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Measuring the Economic Risk of Epidemics

Abstract

We measure the economic risk of epidemics at a geo-spatially detailed resolution. In addition to data about the epidemic hazard prediction, we use data from 2014-2019 to compute measures for exposure, vulnerability, and resilience of the local economy to the shock of an epidemic. Using a battery of proxies for these four concepts, we calculate the hazard (the zoonotic source of a possible epidemic), the principal components of exposure and vulnerability to it, and of the economy's resilience (its ability of the recover rapidly from the shock). We find that the economic risk of epidemics is particularly high in most Africa, the Indian subcontinent, China, and Southeast Asia. These results are consistent when comparing an ad-hoc (equal) weighting algorithm for the four components of the index, with one based on an estimation algorithm using Disability-Adjusted Life Years associated with communicable diseases.

JEL-Codes: E010, Q540.

Keywords: epidemic, influenza, risk measurement, economic impact.

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1. Introduction

There is a well-documented global increase in zoonotic disease emergence. It has been linked to the intensification of human activity in previously sparsely inhabited locations and the increasing interactions between humanity and the natural world (Jones et al., 2013; Naicker, 2011; Wolfe et al., 2005). Around 60% of Emerging Infectious Diseases (EIDs) are zoonotic and there is a long observed upward trend in the frequency of outbreaks.[1]

Zoonotic epidemiology experts have attempted to identify regions that present a greater risk of experiencing an EID event (EID hotspots). A recent analysis of 335 emerging infectious disease events between 1940 and 2004 found that EIDs are significantly correlated with environmental, socio-economic and ecological factors (Jones et al., 2008). Specifically, the frequency of EIDs is correlated with increased human population density, mammalian species density and human population growth. This implies that highly biodiverse areas into which the human population rapidly expands exhibit high and increasing incidence of EIDs (Allen et al., 2017). The key EID risk regions identified by Allen et al. (2017) include most of Southeast and East Asia, the Indian Subcontinent, the Great Lakes region in Africa, and the Niger Delta (Figure 1).

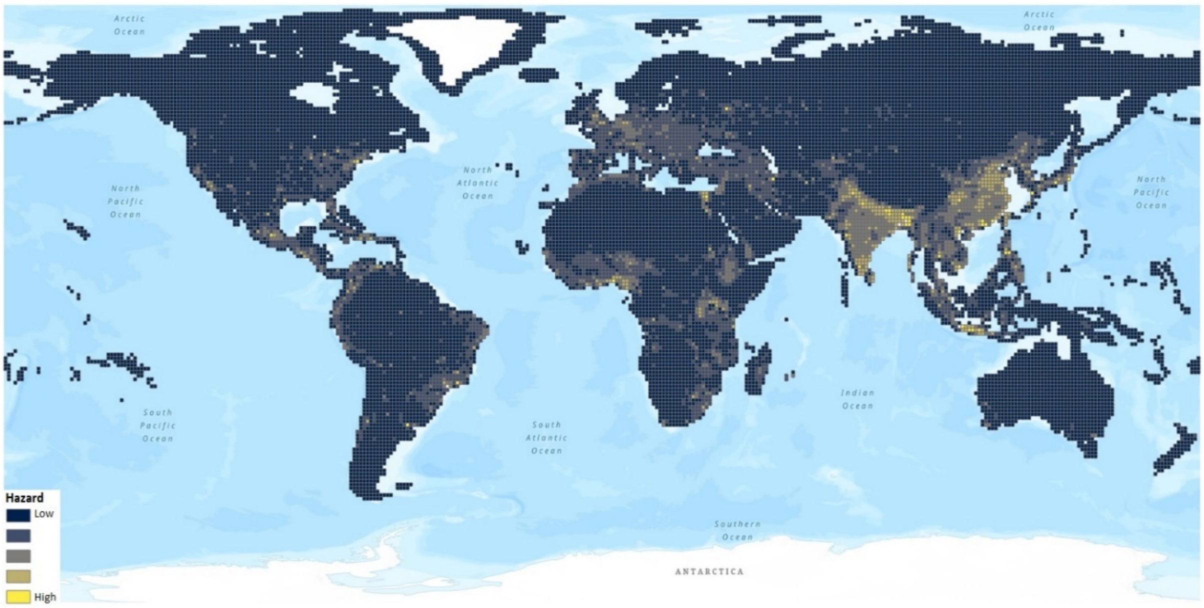

Fig. 1 Global Hotspots for Emerging Infectious Diseases. Source: Allen et al. (2017)

We aim to measure the economic risk that is associated with this hazard of epidemics. This risk is distinct from the mortality and morbidity risk associated with epidemics, and plausibly has very different spatial variability. For example, even an epidemic with no mortality associated with it can lead to significant behavioural changes that can have very adverse

[1] Animal-to-human transmission is the primary conduit to the emergence of epidemics, and probably needs to occur repeatedly before the pathogens mutate sufficiently to enable human-to-human transmission. This implies that agricultural intensification (specifically animal husbandry) in areas previously inhabited by wildlife present an increased risk of EID transmission; as can the installation of irrigation, which increases the spread of disease vectors.

economic impacts. Given the paucity of data on epidemic cases in the recent past (the period for which comprehensive economic and demographic records are available), our aim here is not to measure the consequences of past events, but to evaluate where the economic risk of epidemics are currently located.

Our risk measure is premised on the observation that a disaster, including an epidemic, occurs when a hazard (in this case the disease) interacts with an exposed population that is vulnerable to this hazard, thus causing harm to people. Epidemics always arise out of a natural pathogen (possibly zoonotic), but the pathogen by itself does not create the epidemic and definitely not its economic consequences. For that, the pathogen must encounter a society, people and an economy, that is both exposed and vulnerable to it. Resilience, in this framework, is conceptualized and measured as the ability of the economy to bounce back given the magnitude of the shock (generated by the intersection of the hazard, exposure, and vulnerability). The degree of resilience in a system (in this case, the economy) is thus determined by the speed in which the recovery process occurs, and when the system reverts back to its pre-shock level (i.e., full recovery is achieved).

Measured at the level of grid cells, g, we model the risk associated with the economic impact of epidemics simply as a linear combination of hazard plus a local economy's exposure and vulnerability to it, minus its resilience or ability to bounce back:

$$\widehat{Risk}_g = \alpha_1 Hazard_g + \alpha_2 Exposure_g + \alpha_3 Vulnerability_g - \alpha_4 Resilience_g \qquad \text{(Eq.1)}$$

We first collect a large group of sub-national and national measures from recent years (2014-2019) to proxy for exposure, vulnerability, and economic resilience. We then use principal component analysis (PCA) to compute a standardized index for each exposure, vulnerability, and resilience. Using the first component of exposure, vulnerability, and resilience index, in addition to the hazard data of Allen et al. (2017), we compute a risk index in relation to the economic risk of epidemics. In our simplest specifications, we assume $\alpha_i = \alpha_j$ for all *i* and *j*.

Our results suggest that the economic risk of epidemics is especially high in most of America, Africa, the Indian subcontinent, as well as in China and Southeast Asia. These results remain consistent even when we employ an alternative functional form that entails greater weights being placed one hazard and vulnerability, and less on exposure and resilience.

2. Results

Figure 2 shows descriptive information and PCA results of all variables we use to measure exposure, vulnerability, and resilience. The new principal component variable is the output of linear combination of the original variables. We use the first principal component for each exposure, vulnerability, and resilience index. As the first component accounts for most variation in the data and contribute the most explanation in the combining procedure. The proportion of eigenvalues indicates the explanatory importance of the factor, which are 4.0, 5.9, and 2.4 for exposure, vulnerability and resilience respectively. Economic activities, demographic measures, and infrastructure density all positively explain exposure. High income areas with better healthcare quality (as measured by vaccination rate, health spending, sanitary infrastructure) are less vulnerable. Agricultural areas and high numbers of the young are associated with more vulnerable. For resilience, areas with higher geographic, social, and cultural disparity (e.g., time to travel to a metropolitan area) have a lower index. Countries receiving more overseas incomes are more resilient. The results for the all principal components, as calculated using PCA, are presented in Supplementary Table A3.

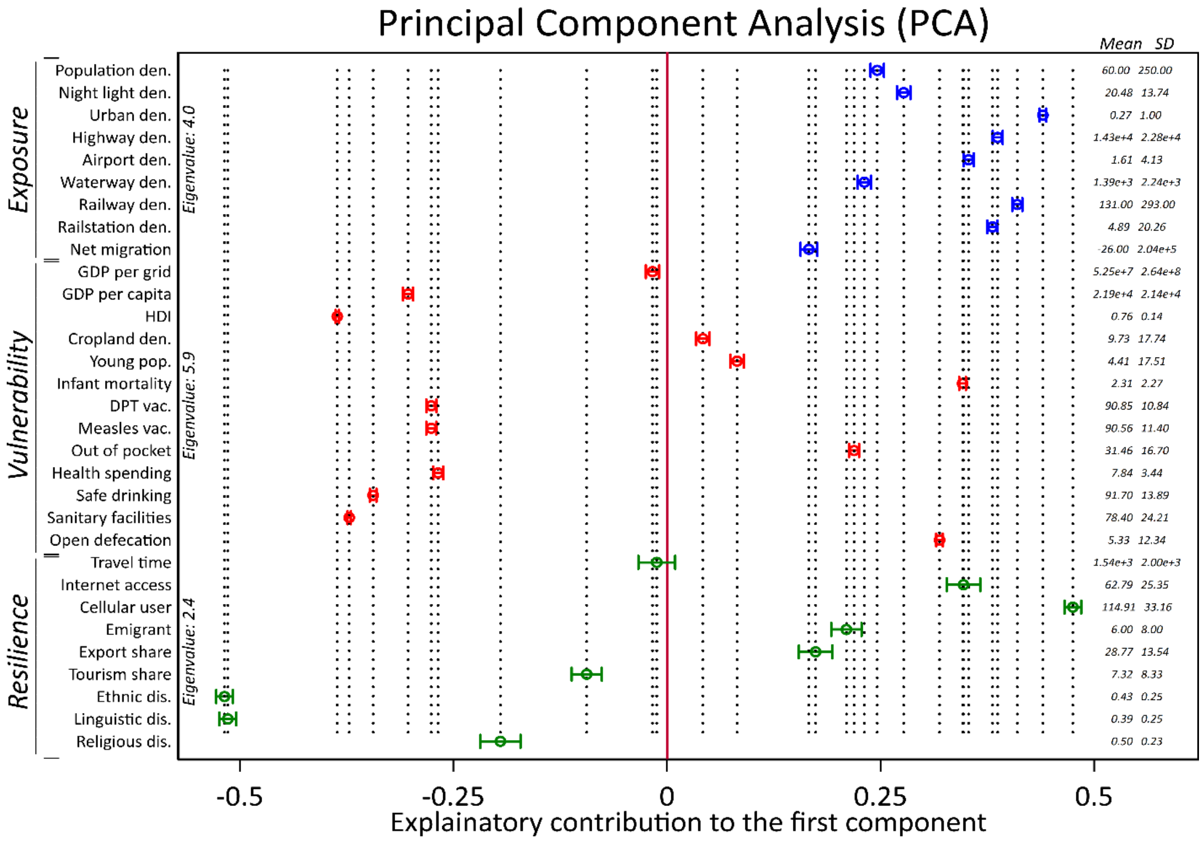

Fig. 2 Descriptive data and principal component analysis (PCA) results. The lower and upper caps represent standard errors of each variable in the first component.

We normalize all exposure, vulnerability, and resilience indices. Figure 3 presents the cumulative distribution of main results for: Hazard, exposure, vulnerability, resilience, and economic risk. For hazard, we use the zoonotic EID events prediction of Allen et al. (2017) directly. We calculate the economic risk by an equal-weight linear combination. Using these results, we can then map, in the Supplementary Figure A1, the exposure, vulnerability, and resilience indices.

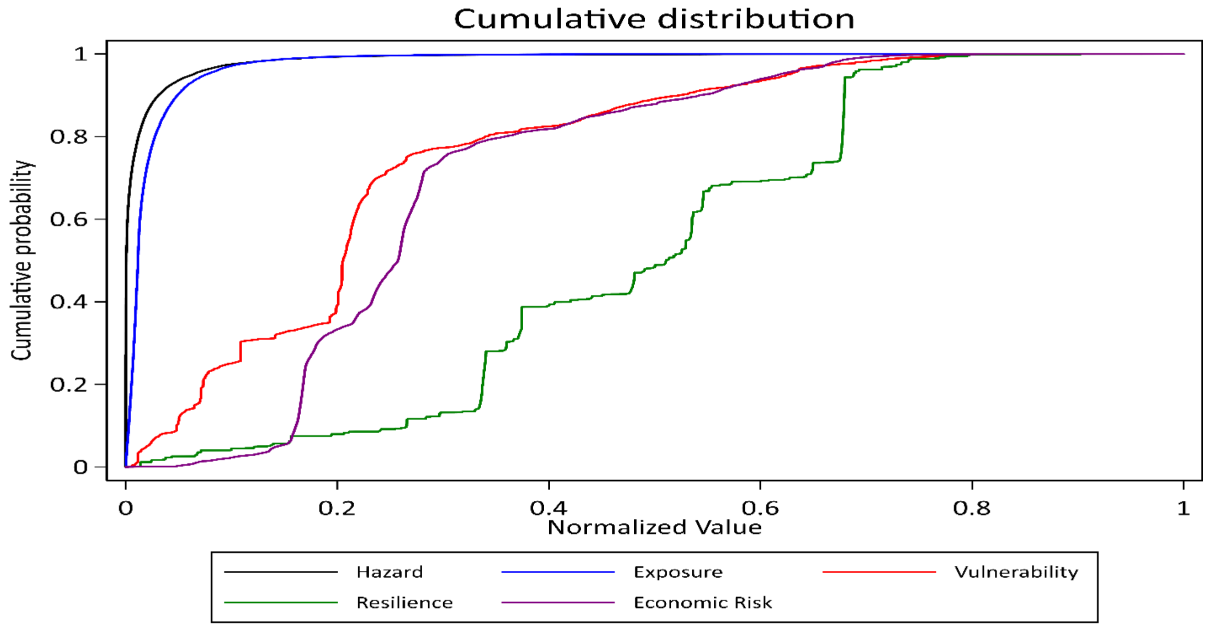

Fig.3 The cumulative distribution of indices

We find that the economic risk of epidemics is especially high in most of Latin America (except for the Southern Cone countries), most of Africa, South Asia, China, and much of Southeast Asia (Figure 4). Fundamentally, countries of the greatest exposure to EID events prediction by Allen et al. (2017) align with the high economic risk: India is the highest in Asia, followed by China. The economic risk is high in Africa and Southeast Asia, as these are the most vulnerable areas with low income and healthcare quality. Resilience, intentionally or otherwise, plays a role in reducing the economic risk from epidemics. For example, in Southern Cone countries (Argentina and Chile) the resilience is higher than neighbourhood countries due to less fractionalized socio-cultural characteristics (lower ethnic, linguistics, and religious disparity). While Saudi Arabia and Russia have lower economic risks because their domestic economies are focussed on huge amounts of (oil) exports, and hardly rely on tourism.

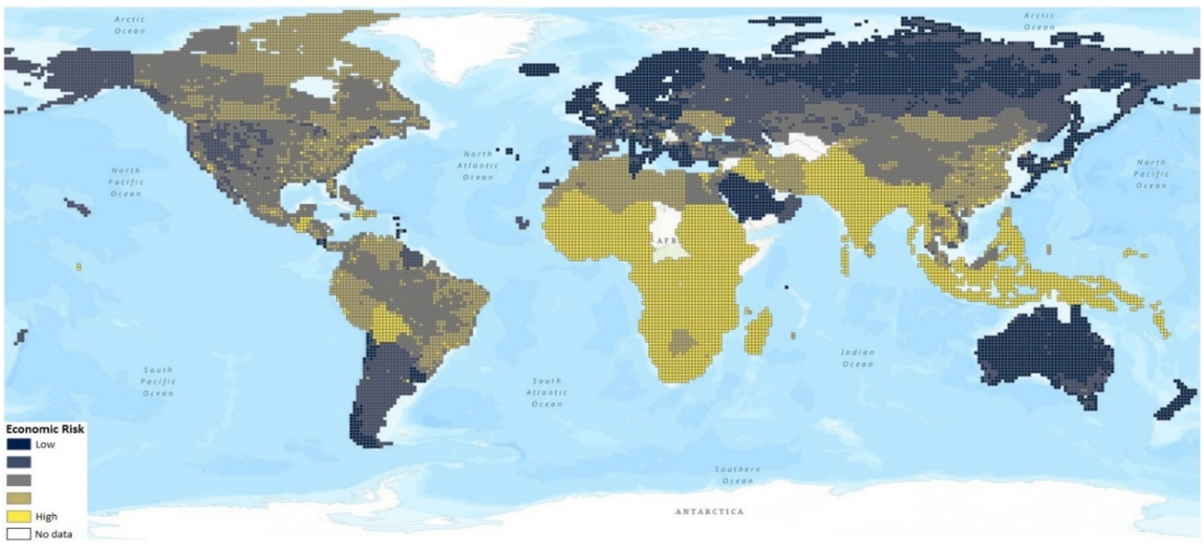

Fig. 4 Economic Risk of Emerging Infectious Diseases. The lowest economic risk value represents for 20th percentile. The value of 20th, 40th, 60th, 80th percentile are: 0.168, 0.233, 0.266, and 0.358 respectively.

A less ad-hoc weighting scheme, instead of equal-weights, for the economic risk index relies on the Disability-Adjusted Life Years (DALY) measure of overall disease burden. DALYs are the sum of years lost due to ill-health, disability or premature death from various causes. Weights for each of the four dimension components—aggregated by countries i—are derived by OLS regression on DALY:

$$DALY_i = \beta_0 + \beta_1 Hazard_i + \beta_2 Exposure_i + \beta_3 Vulnerability_i + \beta_4 Resilience_i + \varepsilon_i \qquad \text{(Eq.2)}$$

The estimated weights (coefficients) and the constant are plugged into the risk function (i.e., $\alpha_i = \beta_i$) which now places considerably less weight on exposure and resilience, than on hazard and vulnerability:

$$\widehat{WRisk}_g = -0.04 + 0.42Hazard_g + 0.05Exposure_g + 0.34Vulnerability_g - 0.15Resilience_g$$

(Eq.3)

The spatial patterns of the DALY-weighted risk map in Figure 5 are similar to those observed in the unweighted map. As before, the areas at highest risk of economic losses from epidemics remain Sub-Saharan Africa and South Asia. By contrast, the DALY-weighted approach assigns lower risk to the American region, where fewer are predicted to be exposed to EID events.

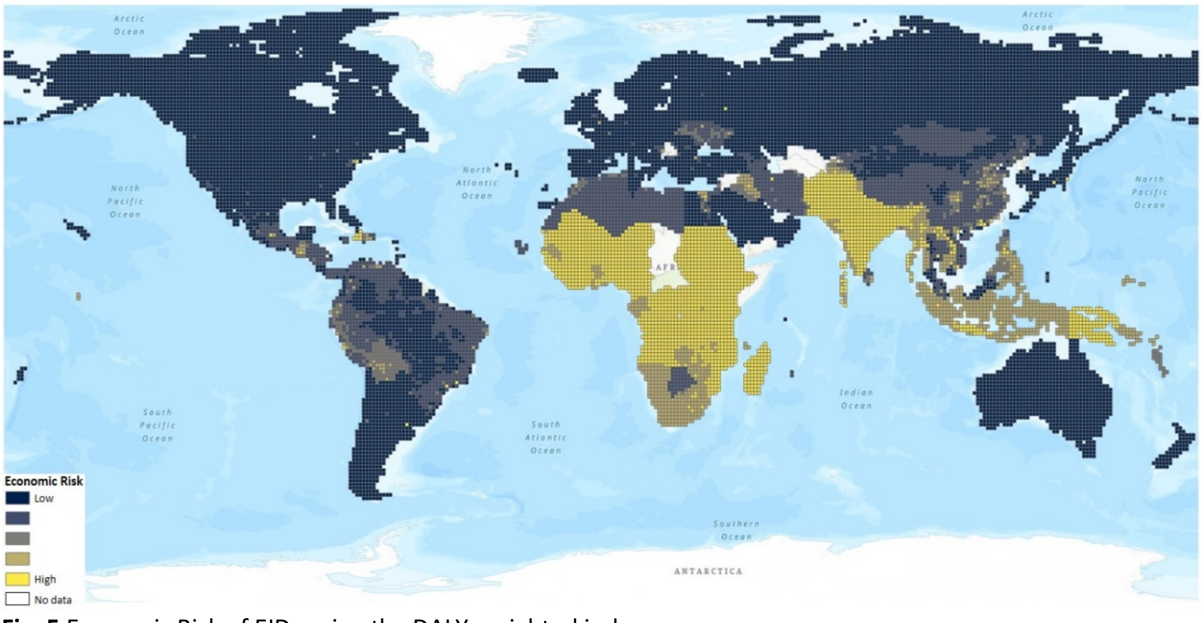

Fig. 5 Economic Risk of EIDs using the DALY-weighted index.

3. Discussion

We developed a method to estimate the economic risk of epidemics. With growing globalisation and inter-connectedness among far flung populations comes increased exposure to the risk of epidemics, with implications also for the world economy. Potentially important epidemic threats to the world's economy include the Crimean-Congo haemorrhagic fever, Ebola, Marburg virus, Lassa fever, MERS, SARS, Nipah disease, Rift Valley fever, and Zika. Other damaging epidemics are also possible, especially influenza of various types, and the emergence of other pathogens that are currently unknown to science is also highly probable (Bloom et al., 2018).

The economic implications of an epidemic

The economic consequences of an epidemic, like any other natural hazard shock, can be delineated into damages, direct losses, and indirect losses (Noy, 2016). Direct losses included lost income and output due to death and symptomatic illness as well as increased healthcare costs. The direct costs due to illness and mortality are measured by the World Health Organisation when it measures the Disability-Adjusted Life Years (DALYs) associated with various diseases (WHO, 2018). DALY calculations are not intended to measure, however, the direct and indirect economic losses, in terms of lost incomes and disruptions to economic activity. As such, they fail to acknowledge the potentially important economic significance of epidemic events.

When we account for the ways an epidemic creates economic losses, we need to measure not only the direct reductions in economic activity that is attributable to changes in behaviour of infected individuals (e.g., their inability to work), but also measure behavioural changes that are caused by changing subjective judgements about the risk of contraction among the still healthy population. These behavioural changes may be influenced not only by the characteristics of the epidemic contagion process and the disease virulence, but also by its media coverage and the fear it might generate.

For example, the Severe Acute Respiratory Syndrome (SARS) outbreak was the first epidemic of the 21st century to spread rapidly across 26 countries in a matter of weeks (Keogh-Brown and Smith, 2008). Several studies have suggested that the behavioural response was disproportionately large in relation to the actual contraction and mortality risks associated with SARS (Noy and Shields, 2019).[2] Fortunately, the SARS epidemic was also contained relatively rapidly, infecting only around 8500 people, but with a mortality rate of around 11% (Noy and Shields, 2019). Nevertheless, the SARS epidemic did lead to some short-term declines in economic activity in various vulnerable sectors, in infected and even in un-infected countries, most notably through interruptions in international tourism flows. Had the SARS outbreak occurred in countries less equipped to manage an epidemic of this virulence, however, it is likely that its health and economic consequences would have been far more devastating.

The risks of indirect losses caused by changing behaviours and policies (like border closures or increased quarantine requirements) have led to concerns that some disease outbreak could result in a major impact on the global economy driven by amplified behavioural

[2] The SARS outbreak generated substantial attention. One reflection of this panic was the early economic projections on the impact of SARS, which generally predicted losses to be far greater than what eventually transpired (Keogh-Brown and Smith, 2008). The most significant economic losses occurred in: (1) China; (2) Hong Kong; (3) Singapore; and (4) Taiwan (Brahmbhatt and Dutta, 2008). During the height of the epidemic, international visitor arrivals fell dramatically in these four economies and resulted in an estimated GDP loss amounting to US$ 13 billion (Noy and Shields, 2019). These losses, however, did not affect any of these economies for more than a couple of quarters and even the most heavily affected countries started recovering by the third quarter of 2003.

responses. Intriguingly, it seems little research has been done on these economic losses, and even less on the longer term losses arising from epidemics.

Risk as a function of hazard, exposure, vulnerability, and resilience

As defined by UNDRR (2017), a disaster is "a serious disruption of the functioning of a community or a society at any scale due to hazardous events interacting with conditions of exposure, vulnerability and capacity, leading to one or more of the following: human, material, economic and environmental losses and impacts. The effect of the disaster can be immediate and localized, but is often widespread and could last for a long period of time."

Exposure in the UNDRR definition refers to the population and the economic activity that is located in areas that are being exposed to the pathogen or that is indirectly exposed to the changing behavior that is induced by the presence of this pathogen, changes that can also impact the disease trajectory (e.g., Epstein, 2009). Vulnerability, in this case, refers to the ability of the pathogen to adversely affect the exposed entities (human, social, and economic). A higher degree of vulnerability will lead to a more adverse outcome for the same pathogen characteristics and exposure to it.[3] As an example, in the SARS affected economies, domestic consumption of leisure activities, leisure-related local and international transport, and tourism, were the most significantly affected sectors. Whether the SARS epidemic generated any long-lasting demographic impact has not been investigated, but we assume this has not been the case.

More broadly however, economic impacts will depend not only on the characteristics of the disease, but also on the ways the economy is exposed to it, the vulnerability of different sectors in the economy to the shock, and their resilience (their ability to bounce back). Prager et al. (2017), in their modelling of influenza in the United States, define 'economic resilience' as the capacity "to maintain functionality and dampen business interruption losses in the aftermath of a disaster" (p. 6). For some (maybe most) epidemics, they point out, some resilience policies are not really plausible given the rapid and short-term nature of the epidemic. What is most plausible is to make up for lost production once the epidemic has abated.

SARS, for example, was quite contagious, so that people attempted to minimise face-to-face interactions and physical proximity with possibility infected persons. This manifested in significant changes to consumer behaviour due to individual judgements about the risk of contraction, and resulted in a significant portion of GDP loss attributed to social avoidance by millions. Exports of goods, in contrast, were relatively unaffected as the disease was

[3] These distinctions are imperfect, as even the basic epidemiological parameter, R_0, may be a function of the socio-economic environment, as the contact rate, the probability of transmission upon contact, and the duration of infection are all also determined by social factors (e.g., poverty or nutrition) – see Janes et al. (2012). For example, Laffargue (2012) investigate the impact of an epidemic on fertility. While he elucidates the potential demographic impacts of an epidemic, his model results depend crucially on assumptions regarding the nature of the epidemic (the R_0) and the most vulnerable cohorts to it. We assume that the epidemics whose economic risk we measure do not have any long-term demographic impact (which will imply long-term economic effects as well).

transmissible only through human to human contact (the disease pathogen did not exhibit the longevity outside of its human host that would have allowed for its spread via cargo).

There are multiply reasons why economic activity might be adversely affected. They range from the direct impact on labour (as workers are symptomatic), to behavioural responses that might arise out of over-reactions, panics, and scientific misunderstandings. Indirect losses arise from the lost productivity of those directly affected, and more indirectly from aggregate behavioural changes driven by the public's reactions to the outbreak.

Boucekkine and Laffargue (2010) describe three channels through which an epidemic might have long term impact on economic development. First, mortality of labour will increase wages and lead to a lower fertility (as women enter the workforce). Second, the expected mortality will increase fertility if women optimise for the number of children expected to survive to adulthood. Mortality will create orphans, who will be less able to invest in their education and will therefore experience a relative decline in lifetime income.[4] Damon et al. (2015) find that there are ambiguous effects of increased mortality risk on investment decisions of households (specifically in conservation of environmental resources), since there are two opposing channels of causality (through the discount rate, and through labour productivity). An even longer-term indirect channel of economic impact was identified in Almond (2006). He found that U.S birth cohorts who were in-utero during the 1918-1919 influenza epidemic exhibited reduced educational attainment, higher rates of physical disability, lower lifetime income, lower socioeconomic status, and higher transfer payments when compared to other birth cohorts born in similar locations and personal circumstances.

Caveats and conclusions

As public health systems continually evolve and improve, future epidemics are unlikely to be of the magnitude of the largest epidemics of the past (e.g., the 1918-19 Influenza pandemic); though they may still be of catastrophic scale. However, what remains equally salient, in contrast, are the economic consequences of future epidemics. The exposure, vulnerability, and resilience to these economic consequences were not ameliorated as much when public health systems developed throughout the last century. In contrast, potentially, the more recent advent of social media is likely to have amplified behavioural responses, and thus potentially exacerbated the economic affects generated through behavioural channels.

The extensive behavioural reaction to SARS could be typified as a high prevalence-elasticity response to a disease outbreak; when the public response to an epidemic results in significant behavioural changes that increase in severity with the number of infected persons. The SARS case fits with the argument of Philipson (2000), that when private behaviour is strongly prevalence-elastic, the main economic cost of a disease outbreak is likely to arise out of individual preventative actions rather than directly from infections. Much of this analysis is based on the assumption that individuals make systematic and rational (or predictably irrational) judgements about the disease prevalence rate and the associated mortality risks. There is significant evidence from previous epidemics that individuals under prevailing circumstances of little reliable information can arrive at biased subjective assessments

[4] Chin and Wilson (2018) claim to find an increase in fertility in Sub-Saharan Africa as a result of the AIDS epidemic; while Karlsson and Pichler (2015) find no fertility effect.

concerning the risk of disease contraction. This can lead to panic and consequently worse decisions, which in turn result in an excessively high cost of preventative private actions. A better accounting of these risks of over-reactions and panics that lead to dramatic behavioural change, while important, remain outside the scope of what we measured here.

In addition, a study by Perrings et al. (2014) highlights the importance of government intervention which targets the private costs and benefits of disease avoidance so that they induce individual behavioural responses which align with the interests of the wider society. This concerns the trade-off that individuals make regarding their respective costs and benefits from (for example) public interaction in an epidemic situation. If the benefits of social interaction for an individual are high (e.g.., interaction is necessary to earn the income required to meet daily subsistence costs) then this could result in continued interaction during an epidemic and, while reducing the economic impact, can potentially increase the disease reproduction rate. This can also work in the opposite direction; if the individual costs of public avoidance are very low and benefits very high, then mass public avoidance in an epidemic where the mortality and contagiousness are not significant enough to warrant such a response, will lead to unnecessarily large economic and welfare losses (Perrings et al., 2014). Improved understanding of the dynamics of individual trade-offs could help to prioritise public health interventions beyond what is suggested from our measure of economic risk.

Another factor that cannot be adequately included here are government interventions that can dramatically affect the magnitude and time profile of losses, and the public's likely compliance with any government interventions, (Perrings et al., 2014).[5] Perrings et al. (2014) advocate for a more nuanced approach toward public management of epidemics that recognises that individual cost and benefits of social interactions can have a direct effect on the disease reproduction rate. Such targeted interventions could offer a more cost effective solution which will change the economic evaluation of the existing risks.

Several suggestions that can minimise the economic risk of epidemics, as is measured here, include: Investment in prediction of disease emergence and appropriately designed Early Warning Systems that can shorten the period in which there are declines in economic activity; active minimization of transmission pathways thereby reducing exposure to the disease in areas that were not exposed to the initial hazard (for example, by timely global reporting); reducing vulnerability to disease outbreaks by improving public health systems or decreasing other 'root causes' of vulnerability (such as poverty); and facilitation of recovery planning by increasing economic resilience to the epidemic shock (for example, by curtailing mis-information). All of these remain relatively neglected parts of the global attempts to reduce the economic risks of epidemics, attempts that are mostly shaped by the 2015 agreements on the Sustainable Development Goals and the Sendai Framework for Disaster Risk Reduction.

4. Methods

Principal components analysis

[5] For example, travel restrictions or bans and quarantines were widely used by governments in the SARS outbreak (Balinska and Rizzo, 2009) See a more complete example in (Noy and Shields, 2019).

Before going through the dimensionality reduction procedure, we standardize all variables and analyse the correlations to choose a proper set of variables. The correlation matrices for exposure, vulnerability, and resilience indicators are available in Supplementary Table A2. To compute a coherent index for exposure, vulnerability, and resilience separately, we use principal components analysis (PCA), an algorithm to compress a large set of variables while retaining most of information in the initial data (Ringnér, 2008). The eigenvalues, latent roots, capture the variations in the set of variables for that component. PCA bases on the eigen decomposition of positive semi-definite matrices and the singular value decomposition of rectangular matrices (Abdi and Williams, 2010).[6] Mathematically, PCA is executed on a square symmetric matrix: (i) Pure sums of squares and cross products (SSCP matrix); (ii) scaled sums of squares and cross products (covariance matrix); (iii) sums of squares and cross products from standardized data (correlation matrix). Correlation matrix performs well when there are significant differences in the variances and the units of measurement of original variables.

DALY weighting method

Based on DALY data from the Institute for Health Metrics and Evaluation, we calculate the average of DALY in the period 2012-2017 from three communicable causes: (i) Diarrhea and common infectious diseases; (ii) Malaria and neglected tropical diseases; (iii) Other communicable diseases. We use this aggregate measure of DALYs lost to these infectious diseases as an alternative proxy for the risk of epidemics. One DALY equals one lost year of healthy life, either from year of life lost or year lived with a disability. Since the DALY aggregates are calculated for each country (*i*), we also aggregate the hazard, exposure, vulnerability, and resilience measures to the country-level. We then estimate the following model by Ordinary Least Squares (OLS):

$$DALY_i = \beta_0 + \beta_1 Hazard_i + \beta_2 Exposure_i + \beta_3 Vulnerability_i + \beta_4 Resilience_i + \varepsilon_i$$

where $Hazard_i$ is the predicted probability of epidemics in country i. $Exposure_i$, $Vulnerability_i$, and $Resilience_i$ is the first component of principal component analysis for exposure, vulnerability, and resilience in country i.

Table 1: Estimation results for National DALY

Hazard	117.07**
	(54.98)
Exposure	14.99
	(37.14)
Vulnerability	92.55**
	(37.57)
Resilience	-41.06
	(42.27)
_cons	-10.139
	(24.94)
Obs.	156
R^2	0.156

[6] Abdi and Williams (2010) provide proof and statistical inference of PCA.

In Table 1, the result of three causes shows that a 1-percentage-point in the probability of hazard is positively related to 117 DALYs. Comparably, a 1-percentage-point of vulnerability is positively associated with 93 DALY points. The relation between exposure and DALY is smallest, the slope is almost 15. Whereas a 1-percentage-point increase of resilience relates to 41-DALY-point decrease. Building on these results, an alternative functional form to measuring economic risk uses the weights implied in the coefficients described in Table 1. The weights are calculated by $\hat{\beta}_j / \sum_{j=0}^{4} |\hat{\beta}_j|$, then:

$$\widehat{WRisk}_g = -0.04 + 0.42 Hazard_g + 0.05 Exposure_g + 0.34 Vulnerability_g - 0.15 Resilience_g$$

Hazard indicators

Allen et al. (2017) provide a comprehensive map of zoonotic disease epidemic at a geo-spatially detailed grid-cell level, whereby each grid cell size is 1 degree x 1 degree. The data includes: (i) Total number of emerging infectious disease events from 1970 to 2008; (ii) the probability of EID risk by reporting effort; (iii) the predicted risk of event location after adjusting for reporting bias.

Table 2: Hazard indicators

Variable	Mean	ST. Dev	Obs
EID event counts	2.16	2.19	18,361
EID event probability (reporting effort)	0.50	0.14	18,361
EID event prediction (weighted output and population)	0.000026	0.000084	18,361

Table 2 shows the descriptive statistics of EID events from Allen et al. (2017). On average, there are more than 2 events happening per grid cell over the period. The event probability, also related to reporting effort, is about 0.5. The predicted risk is more comparable spatially after controlling for reporting bias. We overlay all other spatial data to the map of EID event prediction weighted by output and population.

Exposure indicators

In terms of economic exposure, we use population and nighttime light density to measure human presence and economic activity. Nightlight data is used as a proxy for economic wealth; the data is described in Román et al. (2018). Transport density provides another relevant indicator for population density. An urban metropolitan area likely has a denser network of highways and air links. To get a coherent layer of transportation density, we use all types of transport as described in Lloyd et al. (2017). Transport databases from Open Street Map (OSM) include: Highway, waterway, railway network, railway station and airport. Last, we use the number of net incoming migrants to proxy for external economic exposure. Data for each variable to proxy for exposure are collected as raster format with higher resolution than data for hazard. Hence, we can plausibly merge with data about epidemic into grid 1 degree by 1 degree by WGS84 projection.

Vulnerability indicators

Likewise, we use a set of data on economic outcomes, human development, agriculture, and health quality to measure vulnerability. Drake et al. (2012) argue that the vulnerability to infectious disease outbreak is much higher in low- and middle-income countries, especially the vulnerability to mortality and morbidity risk. The United Nations' Human Development Index (HDI), per capita Gross Domestic Product (GDP), and total GDP in each grid cell, are collected from the data described in Kummu et al. (2018). Kummu et al. (2018) estimate Gross Grid-Cell Product by multiplying country-level GDP per capita (PPP) with 30 arc-sec population data.[7] To get sub-national data on HDI, Kummu et al. (2018) develop scaling factors to combine sub-national and national data.

Tatem et al. (2012) survey the need and availability of sub-national detailed demographic data that might be useful in understanding disease exposure and vulnerability. They argue that for improvement in our understanding of disease transmission and control, we require detailed spatially-referenced demographic data (for example, distinguished by cohorts and gender). This data is only available in low frequency in countries that conduct a comprehensive census.

We lack data on health quality at the sub-national level; except for spatially-detailed data on the young population density and infant mortality rate, we use country-level measures of child vaccination rates, healthcare spending and sanitary conditions. These data are from the World Bank Development Indicators (WDI), the United Nations Children's Fund (UNICEF), and World Health Organization (WHO). We merge the country-level data into the grid cell data by assigning the same value for all grid-cells within the same country.

Resilience indicators

We obtain spatial data about travel time to a settlement with more than 50,000 inhabitants. Lloyd et al. (2017) provide a raster layer depicting the number of hours to travel to the nearest big city. Fundamentally, travel time is a function of distance and the quality of the transport network. Hallegatte et al. (2016) argue that early warning systems possibly reduce asset losses. We assume information about epidemics is accessed via the internet and mobile phones, so we associate higher penetration rates of these with higher resilience. We use data from the WDI and the International Telecommunication Union.

Next, we calculate the number of outmigrants per 100 persons for each country. We assume that the ability to migrate and the availability of remittances, associated with a larger number of outmigrants, are both related to higher resilience. The average share of exports of goods and services (as share of the national economy), and tourism spending (as share of national economy) both are also assumed to be associated with resilience (tourism negatively). Last, we use data about ethnic, linguistic and religious diversity to measure socio-cultural disparity (Alesina et al., 2003). We assume that the diversity plausibly affect the behaviour of individuals and communities in a hazard event.

[7] The strategy to estimate Gross Cell Product is very similar to Nordhaus and Chen (2016), but the Kummu et al. (2018) data were updated more recently, and are available at a higher resolution.

Table 3: Details of variables

	Variable name	Description	Unit of measurement	Kind of indicators	Spatial availability	Year released/ updated	Data coverage by grid	Source
1	Emerging infectious disease (EID)	Zoonetic disease events in the period 1970-2008	Number of events	Hazard	Resolution: 1° WGS84	2017	100%	Allen et al. (2017)
		Emerging zoonotic diseases event probability	Percent					
		EID event prediction	Index					
2	Population density	Number of persons per square kilometre in 2015	Number of people per km^2	Exposure	Resolution: 0.5' (1 km)	2017	100%	(CIESIN, 2018)
3	Night time lights	Night-time light intensity in 2016	Index	Exposure	Resolution: 1.5' (3 km)	2017	100%	Román et al. (2018)
4	Urban built-up	Human impact on land by urbanization activity	Index	Exposure	Resolution: 0.5' (1 km)	2014	100%	Tuanmu and Jetz (2014)
5	Transport networks in 2016	Highway density	Index	Exposure	Resolution: <1 km	2016	100%	Lloyd et al. (2017)
		Airport density						
		Waterway density						
		Railway network						
		Rail station density						
6	Net migration	Number of in-migrants minus out-migrants	Number of people	Exposure	Resolution: 0.5' (1 km)	2015	100%	de Sherbinin et al. (2015)
7	GDP	Gross Domestic Product (PPP) per grid in 2015 (constant 2011 USD).	USD	Vulnerability	Resolution: 0.5' (1 km)	2018	100%	Kummu et al. (2018)
8	GDP per capita	Gross Domestic Product per capita (PPP) per grid in 2015 (constant 2011 USD).	USD	Vulnerability	Resolution: 5' (10 km)	2018	98%	World Bank (WDI)

9	HDI	Human Development Index [0-1]	Index	Vulnerability	Resolution: 0.5’ (1 km)	2018	100%	Kummu et al. (2018)
10	Crop land	Percentage of land use for crop	Percent	Vulnerability	Resolution:5’	2019	100%	Klein Goldewijk et al. (2011)
11	Young population density	Number of children aged 0-4 per square kilometre in 2010	Number of people per km^2	Vulnerability	Resolution: 0.5’ (1 km)	2018	100%	(CIESIN, 2018)
12	Infant mortality rate	The number of children who die before their first birthday per 1,000 births in 2017	Proportion	Vulnerability	Resolution: 0.5’ (1 km)	2018	100%	(CIESIN, 2019)
13	Immunization rate	The percentage of children ages 12-23 months who received DPT/ measles vaccinations	Percent	Vulnerability	Country level	2017	96%	UNICEF
14	Out-of-pocket	Share of Out-of-Pocket Expenditure on Healthcare	Percent	Vulnerability	Country level	2014	96%	World Bank (WDI)
15	Health spending	Total health care expenditure as GDP	Percent	Vulnerability	Country level	2014	96%	World Bank (WDI)
16	Improved drinking water	Share of population with access to improved drinking water	Percent	Vulnerability	Country level	2015	99%	World Bank (WDI)
17	Sanitary facilities	Share of population with improved sanitation facilities	Percent	Vulnerability	Country level	2015	98%	World Bank (WDI)
18	Open defecation	Share of population practicing open defecation	Percent	Vulnerability	Country level	2015	99%	WHO and UNICEF
19	Travelling time	Travel time to nearest city with population more than 50,000	Hour	Resilience	Resolution: <1 km	2016	100%	Lloyd et al. (2017)
20	Internet access	Share of population using the Internet	Percent	Resilience	Country level	2017	99%	World Bank (WDI)
21	Cellular user	Mobile cellular subscriptions per 100 people	Numeric	Resilience	Country level	2017	99%	International Telecommunicat ion Union
22	Out-migrants	Number of emigrants per 100 population	Number of people	Resilience	Country level	2015	99%	United Nations (2015)

23	Export	Share of goods and services export to GDP	Percent	Resilience	Country level	2018	98%	World Bank (WDI)
24	Tourism	Share of travel and tourism to export	Percent	Resilience	Country level	2018	94%	World Bank (WDI)
25	Socio - Cultural disparity	Ethnic disparity [0-1]	Index	Resilience	Country level	2016	99%	Alesina et al. (2003)
		Linguistic disparity [0-1]	Index	Resilience	Country level	2016	99%	Alesina et al. (2003)
		Religious disparity [0-1]	Index	Resilience	Country level	2016	99%	Alesina et al. (2003)

References

Abdi, H., and Williams, L. J. (2010). Principal component analysis. Wiley interdisciplinary reviews: computational statistics, 2(4), 433-459.

Alesina, A., Devleeschauwer, A., Easterly, W., Kurlat, S., and Wacziarg, R. (2003). Fractionalization. Journal of Economic growth, 8(2), 155-194.

Allen, T., Murray, K. A., Zambrana-Torrelio, C., Morse, S. S., Rondinini, C., Di Marco, M., Breit, N., Olival, K. J., and Daszak, P. (2017). Global hotspots and correlates of emerging zoonotic diseases. Nature communications, 8(1), 1124.

Almond, D. (2006). Is the 1918 influenza pandemic over? Long-term effects of in utero influenza exposure in the post-1940 US population. Journal of political Economy, 114(4), 672-712.

Balinska, M., and Rizzo, C. (2009). Behavioural responses to influenza pandemics: what do we know? PLoS currents, 1.

Bloom, D. E., Cadarette, D., and Sevilla, J. (2018). EPIDEMICS & ECONOMI. Finance & Development.

Boucekkine, R., and Laffargue, J.-P. (2010). On the distributional consequences of epidemics. Journal of Economic Dynamics and Control, 34(2), 231-245.

Brahmbhatt, M., and Dutta, A. (2008). Economic Effects during Outbreaks of Infectious Disease. World Bank Research Digest, 2(2), 7.

Chin, Y.-M., and Wilson, N. (2018). Disease risk and fertility: evidence from the HIV/AIDS pandemic. Journal of Population Economics, 31(2), 429-451.

CIESIN. (2018). Center for International Earth Science Information Network, Columbia University. Gridded Population of the World, Version 4 (GPWv4): Population Density Adjusted to Match 2015 Revision UN WPP Country Totals, Revision 11. Retrieved from: https://doi.org/10.7927/H4F47M65

CIESIN. (2018). Center for International Earth Science Information Network, Columbia University: Gridded Population of the World, Version 4 (GPWv4): Basic Demographic Characteristics, Revision 11. Retrieved from: https://doi.org/10.7927/H46M34XX

CIESIN. (2019). Center for International Earth Science Information Network, Columbia University: Global Subnational Infant Mortality Rates, Version 2. Retrieved from: https://doi.org/10.7927/H4PN93JJ

Damon, M., Zivin, J. G., and Thirumurthy, H. (2015). Health shocks and natural resource management: Evidence from Western Kenya. Journal of environmental economics and management, 69, 36-52.

de Sherbinin, A., Levy, M., Adamo, S., MacManus, K., Yetman, G., Mara, V., Razafindrazay, L., Goodrich, B., Srebotnjak, T., Aichele, C., and Pistolesi, L. (2015). Global Estimated Net Migration Grids by Decade: 1970-2000. Retrieved from: https://doi.org/10.7927/H4319SVC

Drake, T. L., Chalabi, Z., and Coker, R. (2012). Cost-effectiveness analysis of pandemic influenza preparedness: what's missing? Bulletin of the World Health Organization, 90, 940-941.

Epstein, J. (2009). Modelling to contain pandemics. *Nature* 460, 687

Hallegatte, S., Bangalore, M., and Vogt-Schilb, A. (2016). Assessing socioeconomic resilience to floods in 90 countries: The World Bank.

Janes, C. R., Corbett, K. K., Jones, J. H., and Trostle, J. (2012). Emerging infectious diseases: the role of social sciences. The Lancet, 380(9857), 1884-1886.

Jones, B. A., Grace, D., Kock, R., Alonso, S., Rushton, J., Said, M. Y., McKeever, D., Mutua, F., Young, J., and McDermott, J. (2013). Zoonosis emergence linked to agricultural intensification and environmental change. Proceedings of the National Academy of Sciences, 110(21), 8399-8404.

Jones, K. E., Patel, N. G., Levy, M. A., Storeygard, A., Balk, D., Gittleman, J. L., and Daszak, P. (2008). Global trends in emerging infectious diseases. Nature, 451(7181), 990.

Karlsson, M., and Pichler, S. (2015). Demographic consequences of HIV. Journal of Population Economics, 28(4), 1097-1135.

Keogh-Brown, M. R., and Smith, R. D. (2008). The economic impact of SARS: how does the reality match the predictions? Health policy, 88(1), 110-120.

Klein Goldewijk, K., Beusen, A., Van Drecht, G., and De Vos, M. (2011). The HYDE 3.1 spatially explicit database of human-induced global land-use change over the past 12,000 years. Global Ecology and Biogeography, 20(1), 73-86.

Kummu, M., Taka, M., and Guillaume, J. H. (2018). Gridded global datasets for gross domestic product and Human Development Index over 1990–2015. Scientific data, 5, 180004.

Laffargue, J.-P. (2012). Epidemics and fertility in a Malthusian economy. Mathematical Population Studies, 19(1), 4-26.

Lloyd, C. T., Sorichetta, A., and Tatem, A. J. (2017). High resolution global gridded data for use in population studies. Scientific data, 4, 170001.

Naicker, P. R. (2011). The impact of climate change and other factors on zoonotic diseases. Archives of Clinical Microbiology, 2(2).

Nordhaus, W., and Chen, X. (2016). Global gridded geographically based economic data (G-econ), version 4. In NASA Socioeconomic Data and Applications Center (SEDAC).

Noy, I. (2016). Tropical storms: The socio-economics of cyclones. Nature Climate Change, 6(4), 343.

Noy, I., and Shields, S. (2019). The 2003 Severe Acute Respiratory Syndrome Epidemic: A Retroactive Examination of Economic Costs.

Perrings, C., Castillo-Chavez, C., Chowell, G., Daszak, P., Fenichel, E. P., Finnoff, D., Horan, R. D., Kilpatrick, A. M., Kinzig, A. P., and Kuminoff, N. V. (2014). Merging economics and epidemiology to improve the prediction and management of infectious disease. EcoHealth, 11(4), 464-475.

Philipson, T. (2000). Economic epidemiology and infectious diseases. Handbook of health economics, 1, 1761-1799.

Prager, F., Wei, D., and Rose, A. (2017). Total economic consequences of an influenza outbreak in the United States. Risk Analysis, 37(1), 4-19.

Ringnér, M. (2008). What is principal component analysis? Nature biotechnology, 26(3), 303.

Román, M. O., Wang, Z., Sun, Q., Kalb, V., Miller, S. D., Molthan, A., Schultz, L., Bell, J., Stokes, E. C., and Pandey, B. (2018). NASA's Black Marble nighttime lights product suite. Remote Sensing of Environment, 210, 113-143.

Tatem, A. J., Adamo, S., Bharti, N., Burgert, C. R., Castro, M., Dorelien, A., Fink, G., Linard, C., John, M., and Montana, L. (2012). Mapping populations at risk: improving spatial demographic data for infectious disease modeling and metric derivation. Population health metrics, 10(1), 8.

Tuanmu, M. N., and Jetz, W. (2014). A global 1-km consensus land-cover product for biodiversity and ecosystem modelling. Global Ecology and Biogeography, 23(9), 1031-1045.

UNDRR. (2017). Terminology on Disaster Risk Reduction, UNDRR. https://www.unisdr.org/we/inform/terminology.

WHO. (2018). WHO methods and data sources for global burden of disease estimates 2000-2016. World Health Organisation, Geneva.

Wolfe, N. D., Daszak, P., Kilpatrick, A. M., and Burke, D. S. (2005). Bushmeat hunting, deforestation, and prediction of zoonotic disease. Emerging infectious diseases, 11(12), 1822.