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The GDL Climate Change Vulnerability Index (GVI)

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Abstract

In this paper we present the GDL Vulnerability Index (GVI), a new composite index to monitor and analyse the human components of vulnerability to climate change for societies and geographic areas across the globe. The GVI is a simple and flexible index designed for use by experts as well as non-experts in the climate field, including researchers, (local) politicians, NGO's, journalists, advocacy groups and grassroot movements. The GVI is based on an additive formula that summarizes the essence of seven socioeconomic dimensions of vulnerability into a single number. This formula approach sets this index apart from other existing indices. Any person who knows the values of the underlying indicators can compute the vulnerability score of an area by filling in these values in the GVI formula. Validity tests show that, in spite of its simplicity, the data-driven GVI measures the vulnerability dimensions coping capacity, adaptive capacity and susceptibility as well as major expert-based indices. This offers great prospects for use in situations where no other vulnerability information is available. Here we explain the construction of the GVI, test its validity and present GVI values for (almost) all countries of the world and for major global regions.

1. Introduction

In this paper we present a new composite index for measuring the vulnerability of countries and regions to climate change, the Global Data Lab (GDL) Vulnerability Index or *GVI*. The GVI focuses on the human aspects of vulnerability without taking physical aspects (like buildings, roads, landscape, soils, natural vegetation, etc.) or human-environment interactions (like agriculture and nature management) into account.

In recent decades awareness has grown that the impacts of climate change cannot be addressed by focusing on climate-related hazards alone, but that also resilience has to be strengthened by reducing vulnerabilities (Birkman e.a., 2013; Parsons e.a., 2016). Vulnerability is increasingly seen as part of a broader climate change and disaster risk reduction framework that distinguishes between (a) exposure-related factors, (b) the sensitivity or susceptibility to harm of societies, regions and ecosystems, and (c) their capacity to cope with changes and disasters and adapt to them (IPCC, 2022; Birkman e.a., 2022). In this perspective, the occurrence of an event related to climate change, together with the degree to which a region is exposed to its effects and the vulnerability of this region, jointly determine the impact that is experienced (Füssel, 2006; UNDRR, 2019). Vulnerability hereby refers to people's and societies sensitivity to harm as well as their capacity to cope and adjust and is defined straightforwardly as "[t]he propensity or predisposition to be adversely affected" (IPCC, 2014; 2022).

In the literature, vulnerability of groups and societies is supposed to encompass several human-related dimensions, including the economy, education, health, the position of women, governance, demographic factors and infrastructure (Hallegatte e.a., 2018, 2020; IPCC,2012, 2022; Muttarak & Lutz, 2014; Cutter, Boruff & Lynn, 2003; Lavell e.a., 2012; Ebi e.a., 2022). To assess the performance of societies on these dimensions, a broad set of indicators has been developed with which the position of a country or region on a specific dimension can be compared to the position of other countries and regions on that dimension (UNDP, 2022; Birkman e.a., 2022; Miola, 2015; Huisman & Smits, 2009; Atwii e.a., 2022).

Besides these dimension indicators, also composite indices have been developed that provide an overall picture of the capacity of a society to face climate change (Garschagen e.a., 2021; Birkman e.a., 2022). These composite indices have the advantage that they summarize different aspects of vulnerability into a single number. This makes them very useful for comparing countries and studying trends and to help steer finances and policies aimed at risk reduction and adaptation towards the most vulnerable areas (Garschagen e.a., 2021; Feldmeyer e.a., 2020; Becker e.a., 2017; Füssel, 2006). The GDL Vulnerability Index (GVI) presented here is such a composite index. It shows the variation in vulnerability with regard to seven socioeconomic dimensions that are measured with eleven indicators.

The GVI is simpler than earlier developed vulnerability indices like the ND-Gain Vulnerability Index of Notre Dame University (ND-GAIN; Chen, 2015), the INFORM Index of the Joint Research Centre of the European Commission (INFORM; Marin-Ferrer, Vernaccini & Poljansek, 2017), or the World Risk Index (WRI; Welle & Birkman, 2015). These country-level indices are constructed on a yearly basis by teams of experts and combine large numbers of underlying indicators (ND-GAIN: 45; INFORM: 54; WRI: 27). They are ingenious and encompassing, but also rather complex and difficult to understand for non-specialists.

With the GVI we aim to present an understandable and easy to use alternative. The GVI focuses on the core dimensions of socioeconomic vulnerability and uses a strictly data driven approach that is not dependent on expert judgement. The resulting index is universal and designed for use by experts as well as non-experts in the climate field. Any area of the world can be ranked on the GVI scale by filling in the underlying indicator values in a simple formula. The same formula can be used to compute the vulnerability of a country, grouping of countries (e.g. East Africa, South Asia, the Arabic world) or subnational region (province, district) at any point in time, as long as the required indicators are available. For the situation that one or two indicators are missing, reduced GVI formulas are available that rank the region as well as possible on the GVI scale given the information that is available.

The GVI scores are very similar to those of the existing vulnerability indices mentioned above. Our validity analyses reveal high correlations (0.77-0.94) with the coping capacity, adaptive capacity and susceptibility subcomponents of ND-GAIN, INFORM and WRI. These correlations are in the same order and even somewhat higher than those between these subcomponents of the three indices themselves. This might be surprising at first glance, given that the GVI is based on far fewer indicators. However, recent evidence indicates that the human aspects of development are highly correlated and that development is in fact a low dimensional phenomenon (Yang & Xian, 2018; Kraemer et al., 2020; Ghislandi et al., 2019). Our finding in the Validation section that GVI scores are hardly influenced by removing any one of the indicators also points in this direction.

The fact that GVI resembles these indices so well offers great perspectives for the use of GVI in situations where no other vulnerability indices are available. In this paper, we demonstrate this possibility by computing GVI values from indicators at the level of 20 global regions. Given that currently more socioeconomic indicators are becoming available for subnational regions like provinces or districts within countries (e.g. Smits & Permanyer, 2019; Mahecha e.a., 2019; Smits, 2016), also new possibilities arise for measuring climate change vulnerability at the small-area level. With its simple and flexible formula-based approach, the GVI might play a pivotal role in extending vulnerability measurement to these levels and in this way add more spatial detail to the global vulnerability analyses of the IPCC and other major players in the climate field.

In the next section, we discuss the major dimensions of vulnerability that are combined in the GVI, together with the indicators that are used to measure them. Thereafter the data and methods used in this paper are presented. The main GVI formula and its reduced versions are constructed by applying Principal Component Analysis on a dataset for 156 countries in the period 2015-2020. The index is subsequently validated by comparing it with the above-mentioned existing vulnerability indices and by testing its dependency on specific indices. In the result section, GVI values are presented for 189 countries and 20 global regions in the period 2000-2020. The paper is concluded with a conclusion section in which the findings are summarized and discussed.

2. Human dimensions of vulnerability

The GVI focuses on the human and societal aspects of vulnerability of communities, countries or other geographic areas of interest. It combines seven major dimensions, which – together with their indicators – are presented in Table 1. Physical aspects (landscape, soils, natural vegetation etc.) as well as exposure-related aspects are not included. Neither are human-environment interactions like agriculture and nature management.

The economic dimension refers to the ability of economic actors, such as households, companies or states, to cope with climate change and related events, as well as the damage and economic loss caused by such events (Birkman, 2013). Both economic development at the level of regions and poverty at the level of households affect the risk of suffering from negative effects of climate change (Lavell e.a., 2012; Cutter, Boruff & Lynn, 2003). Less developed countries tend to be more vulnerable to the impacts of natural hazards (Hallegatte e.a., 2018, 2020), as they have larger vulnerable populations with less possibilities to adapt to the consequences of climate change, or to prepare for or recover from climate-related impacts (Lavell e.a., 2012; Thomas e.a., 2019; Andrijevic, e.a., 2021).

Table 1. Dimensions and indicators on which the GVI is based[a]

Dimension	***Indicators***
Economy	GDP per capita PPP (constant 2017, international $) and Poverty Headcount Ratio at 3.20 US $ a day
Education	Mean years of schooling 25+
Gender	Gender Development Index (GDI)
Health	Life expectancy at birth
Infrastructure	Access to clean water, electricity and (mobile) phone
Governance	World Governance Indicator
Demography	Urbanization and Dependency Ratio

Education affects the risk of suffering negative consequences of climate change since a well-informed population will be more aware of the possible risks of and the best ways to respond to climate change events (IPCC, 2012). People and societies with a higher level of education are better prepared for disasters and respond better to them and consequently tend to suffer less negative impact and recover faster (Muttarak & Lutz, 2014). Lack of knowledge and lower levels of education increase social vulnerability and reduce recovery capacity and the ability to receive and understand warnings (Cutter, Boruff & Lynn, 2003).

Gender has been found to be an important factor determining the degree of vulnerability to climate change (Eastin, 2018; Cutter, Boruff & Lynn, 2003). Women and girls often are at greater risk of dying in disasters, they are less included in decision making and may even be acted against in recovery and reconstruction projects (Houghton, 2009; Sultana, 2021). Gender does not make people vulnerable through biology, but as a consequence of societal structures and roles (Lavell e.a., 2012; Birkmann e.a., 2013), for example by discouraging women from participating in survival training.

A weak health status of the population and inadequate health systems, including poor hospital and laboratory infrastructures, may increase vulnerability to climate change events considerably (Ebi e.a., 2021). Specific groups, such as the (very) young and old, and people with underlying health conditions might be more vulnerable to disasters and in the aftermath of such events. People with underlying health conditions, such as diabetes and obesity, and the elderly are at greater risk during heat waves (Watts e.a., 2021). Children are particularly susceptible to dehydration and infectious diseases (Hellden e.a., 2021).

Inferior infrastructure may act as a driver of vulnerability to climate change. People without access to clean drinking water and sewage systems are more susceptible to disease in the aftermath of a hazard (Miola, 2015). Electricity is essential for preparing and acting in times of emergencies. Communication means such as mobile phones and internet may help reduce the impact of climate change. People with limited access to information are more vulnerable since they might not be aware of the full scale of the imminent hazard, unaware of how to respond, or might not be alerted about it in the first place (Hansson e.a., 2020). Mobile phones may help spread early warning signals in areas prone to disaster and support the organization of post-event responses (Dujardin e.a., 2020).

Governance is essential for reducing climate change vulnerability and improving coping capacity of countries and regions (Andrijevic e.a., 2020). Good quality governance makes it easier to develop strategies and implement policies to deal with the impacts of climate change and to act in times of crisis.

Demographic factors like age structure and population density are important factors related to climate change vulnerability (Lavell e.a., 2021; Son, Coco Liu & Bell, 2019). Certain population groups, such as the very young and old are more vulnerable than others due to 'biological sensitivity' (Thomas e.a., 2019; Cutter, Boruff & Lynn, 2003; Miola, 2015). Another relevant demographic factor is urbanization. Rapid and unplanned urbanization may increase vulnerability, particularly in low and middle income countries (LMICs) where it associated with slums and informal settlements, often located on peripheral lands and areas more at risk of climate-related events (Lavell e.a., 2012; Son, Coco Liu & Bell, 2019). Rural communities are potentially more vulnerable because rural areas often have lower priority for governments (Lavell e.a., 2012). The demographic dimension is measured by the percentage of the population living in urban areas and the Dependency Ratio (Crombach & Smits, 2022), which is computed by dividing the size of the dependent population (0-15 and 65+) by the size of the working age population (15-65).

3. Methods

3.1 Data

To construct the GVI, a database for the period 2000-2020 was built with indicators for 189 countries derived from three reputable international sources. From the World Development Indicators of the World Bank (WDI, 2022) we derived GDP per capita PPP (in constant 2017 international dollars), the poverty headcount ratio at US$ 3.20 (2011 PPP) a day, the percentages of people using safely managed drinking water services, with access to electricity and living in urban areas, the number of mobile cellular subscriptions per 100 people, and the Dependency Ratio.

From the Human Development Index Database of the Human Development Report Office of the UNDP (UNDP, 2022), we derived mean years of schooling of the adult (25+) population, life expectancy at birth and the Gender Development Index (GDI), which indicates the level of human development of women relative to men (Permanyer & Smits, 2020).

To indicate governance, we use the Worldwide Governance Indicators from the WGI Database of the World Bank (WGI, 2022). This database includes six governance indicators -- voice and accountability, political stability, government effectiveness, regulatory quality, rule of law and control of corruption – measured with standardized variables. To obtain a single figure indicator, the mean of these six indicators was taken. As the

WGI values were lacking for 2001, for that year the WGI values were interpolated between the years 2000 and 2002.

The mobile cellular subscription indicator was adjusted, because in many countries people on average have more than one subscription, up to over two per person. After a certain number, more subscriptions do not mean more communication possibilities. We consequently choose to maximize this indicator at 125 subscriptions per 100 people, which is in the order of the numbers found in EU countries and among the values with the highest explained variation in the PCA analysis.

The dataset constructed on the basis of World Bank and UNDP data still contained some missing values, in particular for LMICs. This can be problematic, as for obtaining comparability over time, the same indicators should be used for each year. We therefore imputed the missing values in the *GVI Start Dataset* with indicators derived or estimated from databases of the Global Data Lab (GDL; www.globaldatalab.org). This was done in the following ways. Mean years of schooling for Somalia (2006, 2011) was derived from the GDL Area Database; the Gender Development Index (GDI) for Fiji (2015), Myanmar (2015) and Papua New Guinea (2015), was derived from the GDL Human Development Database (version 5.0): GDP per capita for Somalia (2006, 2019) was estimated based on the GDL International Wealth Index (IWI); the poverty headcount ratio at US$ 3.20 a day for Afghanistan (2010, 2015), Barbados (2012), Belize (2006, 2011), Cambodia (2000, 2005, 2010, 2014), Guyana (2006, 2009, 2014, 2019), Kosovo (2014, 2020), Kuwait (2014), Libya (2014), Somalia (2006, 2019), Suriname (2006, 2010, 2018), Trinidad and Tobago (2006, 2011), Turkmenistan (2006, 2015, 2019), Tuvalu (2019) and Turks and Caicos Islands (2019) was estimated on the basis of the GDL Poverty50 measure; the GDI for Djibouti (2006), Guinea Bissau (2006, 2014, 2019), Myanmar (2016), Papua New Guinea (2017), Turkmenistan (2015, 2019), Vanuatu (2007) and Samoa (2019) was estimated on the basis of mean age difference between spouses, mean age at marriage, IWI and the Human Development Index, all derived from the GDL website (38).

Because not all missing data could be imputed with GDL indicators, some additional measures had to be taken to complete the database. First, if values were missing for in-between years, the missing values were imputed by linear interpolation between the nearest lower and higher years for which information was available. Second, if this was not possible because no values for an earlier and a later year were available, we allowed the use of neighbouring values for up to four years. For the poverty headcount ratio this period was extended to ten years, because this indicator had substantially more missing values than the others. For a few countries we allowed neighbouring values for more years if this would lead to better comparability within country over time. For poverty this was the case for Algeria, Barbados, Myanmar, Papua New Guinea, Serbia, Seychelles, United Arab Emirates and Zimbabwe; for GDI for Bosnia and Herzegovina, Djibouti, Guinea Bissau and Turkmenistan; and for electricity Liberia. If this procedure did not lead to comparability over time for an indicator, that indicators was removed and a reduced set of indicators remained for computing GVI. If this did not yet solve the issue for a country, the data for the problematic years were removed and the GVI had to be computed over less years. With these steps, we were able to obtain indicator values for 189 countries in our database.

For the construction of the GVI formula in the PCA analysis, data from our database for the period 2015-2020 was used. Given the universal nature this formula should have, the requirements for country selection were even stricter than for the complete 2000-2020 database. All included countries were required to have values for all indicators in all years of the 2015-2020 period, so that all countries could have the same weight in the analysis. Missing values within this period were imputed by linear interpolation for in-between years and with the values of neighbouring years for end years. For indicators with missing values for all years in the 2015-2020 period, values were taken from the most recent earlier year after 2010 for which valid information was available. If no valid information was available after 2010, the country was removed from the analysis. After making these selections, 156 countries from all regions of the globe remained.

To validate the GVI, its values at country level are compared with those of (the subindices of) three established climate vulnerability indices: ND-GAIN, INFORM and World Risk Index. For this purpose, data with the values of those (sub) indices for the year 2020 were downloaded from the following websites: ND-GAIN: https://gain.nd.edu/our-work/country-index/download-data/ (downloaded on 6-2-2023); INFORM: https://drmkc.jrc.ec.europa.eu/inform-index/INFORM-Risk/Results-and-data/moduleId/1782/id/453/controller/Admin/action/Results (downloaded on 6-2-2023); World Risk Index: https://weltrisikobericht.de/weltrisikobericht-2022-e/ and https://weltrisikobericht.de/download/2977/ (downloaded on 10-2-2023). The validation dataset contained GVI values for 187 countries, ND-GAIN values for, depending on the (sub)index, between 176 and 192 countries, INFORM values for 191 countries and WRI values for 193 countries. Because of missing values, the validation analyses were performed on between 174 and 186 countries.

3.2 Index construction

The simplest way to construct an index is to give the same weight to all the underlying indicators (McKenzie, 2005; OECD, 2008; Howe e.a., 2012). However, this would imply that all indicators have the same effect on the final index, which in most cases is not very realistic. It therefore is recommendable to use a more advanced method to determine the relative weights of the included indicators (Filmer & Pritchett, 2001; Sahn & Stifel, 2003; OECD, 2008). Here we use an empirically based method and apply principal component analysis (PCA) for computing the weights. This has the advantage that the weights are not affected by subjective judgements of experts and are completely determined by the data.

PCA is a multivariate statistical technique that reduces the number of variables in a dataset by converting them into a smaller number of components; each component being a linear weighted combination of the initial variables (Bartholomew e.a., 2002; Nardo e.a., 2005; Vyas & Kumaranayake, 2006). The first component, which explains the largest part of the variation, can then be chosen as the central index (compare Filmer & Protchett, 2001; Smits & Steendijk, 2015) for similar approaches in the field of wealth measurement). For GVI the first component explains 67.1% of the variation in the underlying indicators. Compared to the construction of wealth indices, where the first factor generally explains 25-35% (Smits & Steendijk, 2015; Howe e.a., 2012), this is a very satisfactory explanatory power.

Table 2. Mean and standard deviations of the indicators, raw indicator weights, and coefficients of the GVI formula

Indicators	Mean	Std. Deviation	Raw indicator weight	GVI Formula weight
GDP per capita	18605	19047	0.10408626	-0.00010686
Poverty	22.858	26.971	-0.12524258	0.09081646
Years schooling	8.6810	3.2817	0.11967215	-0.71308829
Gender Development Index	0.9446	0.0674	0.08825844	-25.59264906
Life expectancy	71.900	7.6887	0.12382514	-0.31492412
Access to clean water	87.446	15.590	0.12484200	-0.1565931
Access to electricity	82.934	26.230	0.11904323	-0.08874772
Phone subscriptions	107.33	33.298	0.09781305	-0.07288862
World Governance Index	-0.0686	0.8653	0.10287776	-2.32477119
Dependency Ratio	60.470	16.401	-0.11096747	+0.13230595
Urbanization	57.818	21.900	0.09663833	-0.08628689
Constant	-	-	-	-22.63157686

Table 2 presents an overview of the mean and standard deviation of the indicators included in the construction of the GVI (columns 1 and 2), plus the ‘raw’ indicator weights produced by PCA analysis on this database (column 3). These PCA weights reflect the possibility that a country that has a high (low) value on one of the indicators also has a high (low) value on other indicators (Vyas & Kumaranayake, 2006; OECD, 2008). The weights show that all indicators contribute substantially to the index. The highest weights are observed for poverty, life expectancy and access to clear water. The lowest weights for the Gender Development Index, phone subscriptions and urbanization.

On the basis of the raw indicator weights we computed a raw vulnerability score by multiplying the indicator variables with their indicator weights and summing them up. This procedure is shown in the following equation, where y_r is the raw vulnerability score, β_n the estimated raw indicator weight of the n^{Th} indicator and x_n the (standardized) indicator value of the n^{Th} indicator.

$$y_r = \sum \beta_n \cdot x_n$$

When applying this formula to our data, we obtained a country vulnerability distribution with a minimum score of -2.58671677 and a maximum score of 1.76018853. To get a scale with a more intuitively appealing range, we transformed the distribution to values in the 0-100 range. This was done in such a way that some room was left for lower and higher values in the data for earlier and later years than the period for which the index was constructed (2015-2020). To construct this scale, we used the following formula:

$$GVI' = L - \frac{\left(\sum \beta_n \cdot x_n - \text{abs(Min)}\right)}{(\text{abs(Min)} + \ Max + \text{H})/100} = -22.63157686 + \sum \beta_n' \cdot x_n$$

Where *Min* is the lowest possible value of the distribution (-2.58671677), Max the highest possible value of the distribution (1.76018853), *L* the lowest value we would like to give the scale, and *H* a constant chosen strategically to obtain a preferred highest value of the scale. On the GVI' scale constructed in this way higher values refer to countries that are less vulnerable, which is not very intuitive. We therefore have reversed the scale to create the final GVI scale in the following way:

$$GVI = 100 - GVI'$$

The values of *L* and *H* were chosen in such a way that the final GVI scale runs from 10 to 95 in the period 2015-2020. In this way, countries at the lower (least vulnerable) end of the scale keep ample space for future improvements, while at the upper (most vulnerable) end some room remained for more extreme vulnerability levels in past data. Future or past values below zero or above 100 have to be recoded to zero or 100 to keep the scale in the zero-100 range. The final GVI scores are rounded to one decimal place.

4. Validation

4.1 Correlations with existing indices

To validate the GVI and position it in the climate vulnerability field, we compare its performance with the three widely used vulnerability indices mentioned in the introduction: ND-GAIN, INFORM and WRI. All three indices include a number of subindices that aim to measure different aspects of vulnerability. ND-GAIN assumes two broad dimensions, called vulnerability and readiness, whereby vulnerability is defined as the propensity of societies to be negatively impacted by climate hazards and readiness as the degree of safety and efficiency of the business environment in making efficient use of adaptive actions (Chen e.a., 2015). The vulnerability dimension is most relevant for our work. It consists of three subcomponents, 1) exposure, which captures the external physical aspects that contribute to vulnerability, 2) sensitivity, which indicates to what extent a society is affected by climate-related hazards, and 3) adaptive capacity, which refers to the possibilities to respond and adapt to the negative consequences of climate change.

The INFORM index is presented as a tool for understanding the risk of humanitarian crises and disasters (Marin-Ferrer, Vernaccini & Poljansek, 2017). It covers three dimensions of risk: 1) hazards and exposure, referring to averse events that can occur, 2) vulnerability, signalling the susceptibility of societies to those averse events, and 3) coping capacity, indicating the availability of resources that may reduce the impact of those events.

Risk is also a central element in the WRI. Within this framework, risk is defined as the interaction of exposure and vulnerability (Atwii e.a., 2022). Exposure relates to the (natural) circumstances in which populations live and the degree to which these circumstances subject them to natural hazards and other negative consequences of climate change. Vulnerability refers to the predisposition of those populations to be affected by those hazards and their negative consequences. Vulnerability in the WRI context is considered to include three dimensions: 1) Susceptibility, which relates to characteristics of a society that affect the probability of suffering damage from a disaster and being able to overcome its negative consequences, 2) coping capacity, which refers to the possibilities and resources available to reduce these negative impacts by direct actions, and 3) adaptive capacity, which specifies the availability of long-term strategies and activities that may help counteract negative consequences in future (Atwii e.a., 2022).

Hence all three indices include an external dimension -- referring to the presence and intensity of climate-related influences and shocks – and an internal dimension – referring to characteristics of societies that may or may not help them to resist and overcome the consequences of those influences and shocks. The GVI as a socioeconomic composite index is aimed at measuring the second – internal – dimension. This dimension can be further divided into two subdimensions. On the one hand there is a sensitivity or susceptibility aspect that refers to the strength with which the external factors are felt by the affected society. On the other hand a coping or adaptive capacity aspect that reflects the resources available in a society that help reduce negative consequences and build resistance against future shocks.

To validate the GVI, we have computed Pearson correlations between the national GVI values in the year 2020 and the national values of (the subindices of) ND-GAIN, INFORM and WRI for that year. These correlations are shown in Table 3. We see that GVI is very highly (-.89) correlated with ND-Gain, its vulnerability subdimension (.90) and the adaptive capacity component thereof (.89). It is also highly correlated with the INFORM index (.82), its vulnerability subdimension (.84) and particularly strong with its coping capacity component (.94). Correlations between GVI and the exposure component of ND-GAIN and INFORM are with values around .47 clearly lower, but not neglectable. GVI is uncorrelated with the WRI (.09), but this is mainly due to its lack of association with the WRI exposure component (-.12). In fact, it is strongly correlated with the vulnerability subdimension (.77) and particularly its susceptibility (.78) and adaptive capacity (.80) components.

Table 3. Pearson correlations between national GVI values in the year 2020 and the national values of (the subindices of) ND-GAIN (G), INFORM (I) and WRI (W) for that year, including two-tailed significance levels and number of cases on which the correlations are based.

		GVI	Gain	G_Vulnerability	G_Exposure	G_Sensitivity	G_AdapCap	INFORM	I_Exposure	I_Vulnerability	I_CopingCap	WorldRisk	W_Exposure	W_Vulnerability	W_Susceptibility	W_CopingCap
Gain	Correlation	**-0.894**														
	Significance	0.000														
	N	180														
G_Vulnerability	Correlation	**0.896**	-0.902													
	Significance	0.000	0.000													
	N	180	182													
G_Exposure	Correlation	0.458	-0.473	0.634												
	Significance	0.000	0.000	0.000												
	N	184	182	182												
G_Sensitivity	Correlation	0.659	-0.649	0.744	0.227											
	Significance	0.000	0.000	0.000	0.002											
	N	180	181	181	182											
G_AdapCap	Correlation	**0.893**	-0.914	0.917	0.448	0.576										
	Significance	0.000	0.000	0.000	0.000	0.000										
	N	174	176	176	176	176										
INFORM	Correlation	**0.824**	-0.811	0.730	0.409	0.503	0.741									
	Significance	0.000	0.000	0.000	0.000	0.000	0.000									
	N	186	182	182	189	182	176									
I_Exposure	Correlation	0.478	-0.490	0.401	0.289	0.250	0.386	0.846								
	Significance	0.000	0.000	0.000	0.000	0.001	0.000	0.000								
	N	186	182	182	189	182	176	191								
I_Vulnerability	Correlation	**0.835**	-0.783	0.736	0.402	0.532	0.739	0.924	0.642							
	Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000							
	N	186	182	182	189	182	176	191	191							
I_CopingCap	Correlation	**0.935**	-0.930	0.859	0.407	0.608	0.908	0.826	0.470	0.801						
	Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000						
	N	186	182	182	189	182	176	191	191	191						
WorldRisk	Correlation	0.087	-0.162	0.101	0.276	-0.096	0.103	0.424	0.664	0.257	0.114					
	Significance	0.237	0.029	0.174	0.000	0.195	0.174	0.000	0.000	0.000	0.119					
	N	185	182	182	192	182	176	190	190	190	190					
W_Exposure	Correlation	-0.116	0.079	-0.086	0.220	-0.228	-0.115	0.166	0.458	0.021	-0.094	0.858				
	Significance	0.116	0.291	0.246	0.002	0.002	0.127	0.022	0.000	0.769	0.198	0.000				
	N	185	182	182	192	182	176	190	190	190	190	193				
W_Vulnerability	Correlation	**0.774**	-0.719	0.666	0.350	0.478	0.685	0.913	0.803	0.830	0.716	0.416	0.130			
	Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.071			
	N	185	182	182	192	182	176	190	190	190	190	193	193			
W_Susceptibility	Correlation	**0.778**	-0.719	0.685	0.388	0.489	0.700	0.881	0.747	0.814	0.707	0.374	0.131	0.943		
	Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.070	0.000		
	N	185	182	182	192	182	176	190	190	190	190	193	193	193		
W_CopingCap	Correlation	0.589	-0.533	0.486	0.257	0.349	0.488	0.809	0.808	0.698	0.544	0.443	0.166	0.923	0.783	
	Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.021	0.000	0.000	
	N	185	182	182	192	182	176	190	190	190	190	193	193	193	193	
W_AdaptiveCap	Correlation	**0.804**	-0.776	0.691	0.301	0.500	0.764	0.753	0.479	0.760	0.792	0.205	-0.040	0.765	0.726	0.548
	Significance	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.004	0.580	0.000	0.000	0.000
	N	185	182	182	192	182	176	190	190	190	190	193	193	193	193	193

These correlations are in the same order and even a little higher than those between these subcomponents of the three indices themselves. The correlation of adaptive capacity of ND-GAIN with coping capacity of INFORM is .91 and with susceptibility and adaptive capacity of WRI .70 and .76 respectively. The correlations of coping capacity of INFORM with susceptibility and adaptive capacity of WRI are .70 and .79 respectively. Susceptibility and adaptive capacity of WRI are themselves correlated .73.

The high correlations of GVI with the vulnerability dimensions and in particular the coping capacity, adaptive capacity and susceptibility components of the three established indices – also in comparison with the correlations between the subcomponents of these indices themselves – show that despite its simplicity the data-driven GVI represents the human or societal components of climate vulnerability very well.

We therefore can conclude that with the simple and flexible approach used for the construction of GVI, a picture of the global distribution of climate change vulnerability is obtained that is very similar to the outcomes of these more sophisticated indices. This offers great prospects for the application of the GVI to other regional subdivisions and aggregates for which no other vulnerability index is available. In particular the possibility to apply the index to subnational areas like provinces and districts within countries might be very helpful for adding more spatial detail to the global vulnerability analyses of IPCC and other important players in the climate field.

4.2 Reduced GVI versions

While the PCA analysis made clear that all indicators contributed substantially to the index, it remains to be seen to what extend the GVI depends on the inclusion of specific indicators. This is an important question, not only for validation reasons, but also because it regularly happens – in particular for LMICs – that not all indicators are available for a specific region. If the dependency on specific indicators is not very strong, reduced version of GVI might be constructed that might place a region with missing data as well as possible on the GVI scale given the available information.

To address this issue, we use an approach developed by Smits and Steendijk (2015), who performed additional PCA analyses for creating reduced versions of their wealth index. Following them, we conducted a number of additional PCA analyses, each time with one or two of the indicators removed. On the basis of the outcomes of these analyses, new GVI formulas were developed for creating reduced vulnerability indices that were scaled in a similar way as the main GVI. The reduced formulas are presented in the *GVI-Dataset.SPS* syntax file.

To test the quality of the reduced indices, Pearson correlations between these indices and the original GVI were computed. All correlations turned out to be higher than 0.99, which is so high that hardly any difference between the original and reduced versions of the GVI seems to exist. We therefore are led to the conclusion that the GVI is barely influenced by the removal of specific indicators and that none of the underlying indicators seems essential for assessing the vulnerability of a country.

This finding, together with the relatively high explained variation in the PCA analysis and the fact that all indicators contributed more or less similar to the PCA model, suggests that socioeconomic vulnerability is a low-dimensional phenomenon. This may also imply that sub-versions of the GVI based on restricted information might still provide a reasonable picture of climate change vulnerability in situations with weak data infrastructures, like in resource-poor regions of LMICs.

5. Results

5.1 National GVI values

In the Supplementary Information, yearly GVI values for each year in the 2000-2020 period are presented for all 189 countries for which the GVI is available, together with information about the indicators on which the GVI values are based. In Figure 1, GVI values for 2000 and 2020 are displayed on world maps. As could be expected, socioeconomic vulnerability is low in the most developed countries and high in the poorest countries. Particularly high GVI values, indicating very high levels of vulnerability, are found in Sub Saharan Africa and South and South East Asia, whereas low values are found in West European countries – predominantly North West Europe – and North America and Australia.

Between 2000 and 2020 the level of socioeconomic vulnerability improved in all countries for which we have data for both years. Whereas in 2000 50 of the countries had a GVI-value above 75, indicating very high levels of vulnerability, in 2020 this had dropped to 16 countries.

The map at the bottom of Figure 1 shows the changes in GVI values that countries experienced over the 2000-2020 period. Countries which already had a low level of vulnerability in 2000, i.e. most Western countries, experienced the lowest levels of change. However, while absolute levels of improvement were relatively minor in these countries, relative levels of improvement could still be large. Luxembourg for instance almost halved its GVI-value from 20 in 2000 to 10.5 in 2020.

The largest levels of improvement in socioeconomic vulnerability were experienced by some of the countries with the highest levels in 2000, i.e. countries in South and South East Asia, and the South East and North West of Africa. However, other countries with high initial levels of vulnerability, in particular some landlocked African countries, experienced little improvement. Niger, Chad and the Central African Republic for instance were among the countries with the highest levels of vulnerability both in 2000 and 2020.

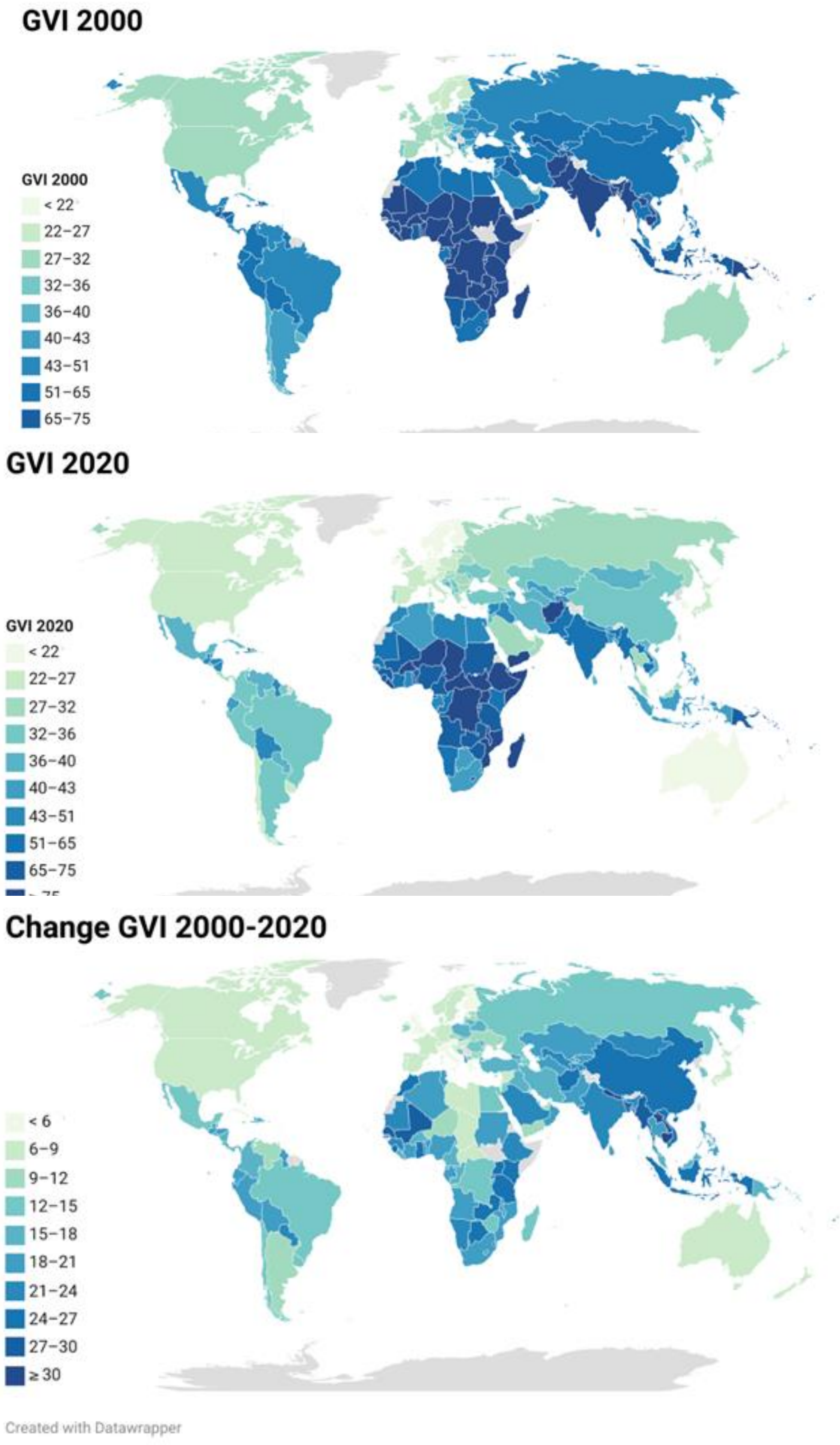
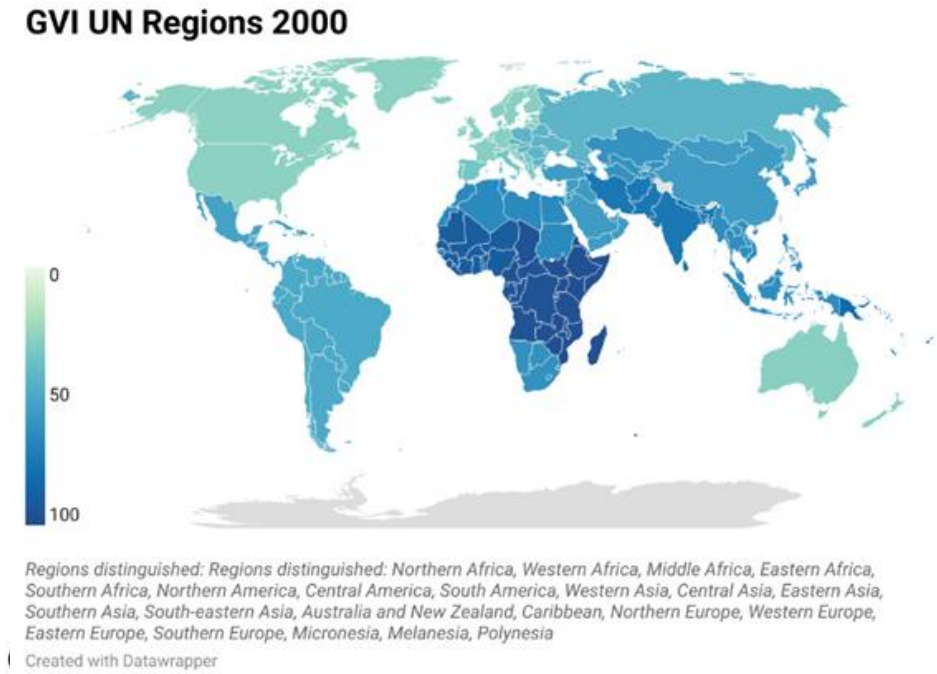


Figure 1. World maps with the distribution of the GVI at country level in 2000 and 2020, plus the change in vulnerability between 2000 and 2020.

5.2 GVI values for global regions

The formula approach underlying the GVI makes it possible to compute GVI values for any regional (sub)division for which the required indicators are available. To demonstrate this possibility, we have computed GVI values at the level of 20 UN Geoscheme Regions (the M49 standard; UN, 2023), whereby Micronesia, Melanesia and Polynesia where combined into one region. To create the GVI values, we first have computed values for the eleven underlying indicators at the level of these regions. This was done by taking the population weighted mean of the country values. After that, the GVI values were computed by entering the regional indicators in the GVI formula.



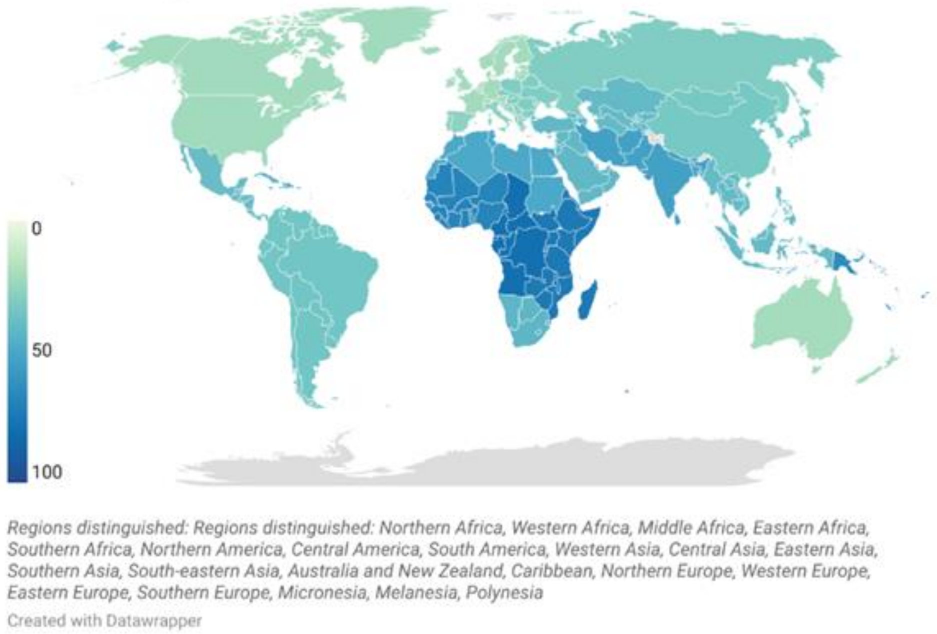


Figure 2. World maps with the distribution of the GVI at the level of 20 UN Geoscheme Regions (M49 standard) in 2000 and 2020. The UN Geoscheme code was slightly adjusted by combining Micronesia, Melanesia and Polynesia into one region.

Not surprisingly, the conclusion on the basis of Figure 2 is rather similar to that of Figure 1. Sub Saharan Africa, with the exception of the Southern part, is clearly the most vulnerable region of our globe, followed by the island states in the Pacific Ocean, South Asia, North Africa and the Caribbean. Northern America, Western

Europe, Northern Europe and Australia/New Zealand are again from a socioeconomic perspective the least vulnerable regions. The GVI values and underlying indicators for the UN regions in the period 2000-2020 are available in the Supplementary Information.

6. Conclusions

Composite vulnerability indices are widely used instruments for measuring the sensitivity, coping capacity and adaptive capacity of regions regarding the impact of climate change and of climate related disasters. Established indices like the ND-GAIN, INFORM and WRI are created by teams of experts and released on a yearly basis for most countries of the world. They are ingenious and encompassing – combining large numbers of underlying variables – but at the same time also complex and not computable by non-specialists. Given their institutional/expert based origin, their scores have to be taken at face value and are only available for the countries and regions for which they are produced.

With the GVI, we aim to present a simple and flexible alternative. GVI uses a strictly data driven approach that is not dependent on expert judgement. It focuses on seven core dimensions of vulnerability -- the economy, education, gender, health, infrastructure, governance and demography – which are measured with eleven indicators. The resulting index is universal, encompassing and easy to use. Any person who knows the values of the underlying indicators for a specific area or community can determine the area's or community's GVI score, by entering the indicator values in a simple additive formula.

The GVI summarizes the human components of vulnerability in a number between 0 and 100, with higher values indicating higher levels of vulnerability.

Correlations between GVI scores and subcomponents of ND-GAIN, INFORM and WRI reveal that GVI is an effective indicator of the subcomponents coping, adaptive capacity and sensitivity. The mutual correlations between the coping, adaptive capacity and sensitivity subcomponents of the three indices themselves are even lower than the correlations of the GVI with these subcomponents. This suggests that that GVI may come close to the greatest common denominator of these components and thus to a large extent represents what these indicators aim to measure.

The finding that a restricted index based on far fewer indicators than these established indices has similar performance in vulnerability measurement might seem surprising at first glance. However, using more indicators is not necessarily better. The selection, normalization and weighting of a larger number of indicators involves more arbitrary choices than of a smaller number of indicators and hence may reduce instead of increase the quality of the resulting index (OECD, 2008). This is particularly the case with the human aspects of development, which are known to be highly correlated (Yang & Xian, 2018; Kraemer et al., 2020; Ghislandi et al., 2019). The PCA approach used for the GVI may also be better fitted for constructing an overall index than the min-max approach used for the other indices, as PCA analysis as technique is designed to extract the common denominator of sets of correlated indicators (OECD, 2008; Nardo et al., 2005; Vyas and Kumaranayake, 2006).

The GVI scores at country and regional level reveal high levels of vulnerability in the poorest countries, particularly in Sub Sahara Africa, the Pacific island states, and South and South East Asia. In contrast, low GVI scores, indicating low levels of vulnerability, are found in developed countries, particular in North West Europe, North America and Australia. Between 2000 and 2020 vulnerability improved in all countries for which we have data. As might be expected, countries and regions which had already low levels of vulnerability in 2000 showed the smallest improvements, while some countries and regions with the highest levels of initial vulnerability showed the largest improvements. However, the landlocked African countries improved disappointingly little and remain among the most vulnerable countries of our world.

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