Climate Security Vulnerability in Africa Mapping 3.0: An Update

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This paper expands on the data, methodology, and results presented at the 2013 Annual Meeting of the International Studies Association in San Francisco (April 2013) and recently published in our paper "Climate security vulnerability in Africa mapping 3.0", in Political Geography (Issue 43: 2014).

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Climate Security Vulnerability in Africa Mapping 3.0

Climate change is expected to have severe consequences on the lives and livelihoods of millions of people around the world, but its effects will not be evenly distributed. As a result of accidents of geography, different locations face distinct sources of vulnerability based on their different exposure to cyclones, storm surge, drought, intense rains, wildfires, and other physical phenomena. The exposure of human populations to such physical processes varies, with large numbers of people often concentrated along the coasts while other areas are much less densely populated. Whether these populations are able to protect themselves from the worst consequences of exposure to climate related hazards is contingent upon other aspects, including their health status, level of education, and access to services. In many instances, even communities with high living standards and adequate access to information and services will find themselves tested by extreme events; how well they fare will be contingent on the willingness and ability of their governments to come to their aid in times of need.

In this context of multi-layered sources of climate vulnerability, the continent of Africa is thought to be among if not the most vulnerable location, given both high exposure to climate change and relatively low community resilience and governance capabilities.[1] However, even within Africa, vulnerability is not equally distributed. With climate change adaptation looming ever larger as an important policy area,

[1] M. Boko et al., "Africa," in *Climate Change 2007: Impacts, Adaptation and Vulnerability. Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change*, ed. M.L. Parry et al. (Cambridge UK: Cambridge University Press, 2007), 433–467; IPCC, "Fourth Assessment Report -- Chapter 9: Africa," 2007, http://www.unep.org/pdf/ipcc/Ch09.pdf; Reid Basher and Sálvano Briceño, "Climate and Disaster Risk Reduction in Africa," in *Climate Change and Africa*, ed. Pak Sum Low (Cambridge: Cambridge University Press, 2005), 269–281.

decisions have to be made about where to concentrate resources, both from national sources as well as international ones. Understanding where climate vulnerabilities are located therefore has immense practical significance.[2]

Four years ago, as part of the Department of Defense-funded Minerva Initiative, we initiated a mapping project to identify sub-national locations of what we came to call "climate security" vulnerability in Africa. Our intent was to go beyond mere livelihoods-based analyses of vulnerability to identify the places where the worst consequences of climate change were likely to hit and put large numbers of people at risk of mass death. Such situations had become humanitarian emergencies that required the mobilization of emergency resources by affected governments and donors alike, sometimes involving military mobilization by both or either to keep people from dying. Such situations may or may not escalate into incidences of armed conflict.

Over the past several years, we have published versions of those maps in a variety of outlets, beginning with in-house working papers and policy briefs at our host institution, the Strauss Center for International Security and Law at the University of Texas.[3] We then published a series of papers and articles in journals and edited volumes,[4] culminating in an article in the Spring 2013 issue of

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[2] Lisa Friedman, "Which Nations Are Most Vulnerable to Climate Change? The Daunting Politics of Choosing," 2010, http://www.nytimes.com/cwire/2011/02/24/24climatewire-which-nations-are-most-vulnerable-to-climate-95690.html?ref=energy-environment.

[3] Joshua Busby et al., *Locating Climate Insecurity: Where Are the Most Vulnerable Places in Africa?* (Austin, Texas: Strauss Center for International Security and Law, 2010), http://ccaps.strausscenter.org/system/research_items/pdfs/19/original.pdf?1283195613; Joshua Busby, Kaiba White, and Todd G. Smith, *Locating Climate Insecurity: Where Are the Most Vulnerable Places in Africa* (Austin: Strauss Center for International Security and Law, 2011), http://strausscenter.org/ccaps/publications/research-briefs.html?download=97.

[4] Joshua Busby et al., "Locating Climate Insecurity: Where Are the Most Vulnerable Places in Africa?," in *Climate Change, Human Security and Violent Conflict*, ed. Jurgen Scheffran et al., Hexagon Series on

International Security[5]. This current paper represents a major revision in our underlying modeling process, what we are calling the 3.0 version of our Climate Security Vulnerability Model (hereafter CSVM 3.0)[6], which was published in a special issue on climate and conflict in *Political Geography*[7] in November 2014. This paper details the methodological refinements we have made to our model and the rationale for them, our findings, and closes with extensions for future research.

Part I: Mapping Climate Security Vulnerability

The aim of our maps remains consistent, even if our methods and approaches have evolved.[8] Our goal is to identify the places most likely vulnerable to climate security concerns within Africa and go beyond national level vulnerability rankings to identify vulnerabilities at the sub-national level.

Human and Environmental Security and Peace, 8 (Springer, 2012), 463–512; Joshua W. Busby, Todd G. Smith, and Kaiba White, "Climate Security and East Africa: A GIS-Based Analysis of Vulnerability," in *Climate Change, Pastoral Traditional Coping Mechanisms and Conflict in the Horn of Africa*, ed. Gebre Hiwot Mulugeta and Jean-Bosco Butera (Addis Ababa: UPEACE, 2012); Joshua W. Busby, Kaiba White, and Todd G. Smith, "Mapping Climate Change and Security in North Africa," *German Marshall Fund of the United States*, 2010, http://www.gmfus.org/archives/mapping-climate-change-and-security-in-north-africa-full-text/.

[5] See Joshua W. Busby et al., "Climate Change and Insecurity: Mapping Vulnerability in Africa," *International Security* 37, no. 4 (2013).

[6] We also supervised a series of student working papers to test alternative formulations on a regional basis of our vulnerability model. Emily Joiner, Derell Kennedo, and Jesse Sampson, *Vulnerability to Climate Change in West Africa* (Austin, Texas: Strauss Center for International Security and Law, March 2012), http://strausscenter.org/ccaps/climate-vulnerability-publications.html?download=55; Sachin Shah, Sarah Williams, and Shu Yang, *Water Resource Stress and Food Insecurity in Southern Africa* (Austin: Strauss Center for International Security and Law, August 2011), http://strausscenter.org/ccaps/climate-vulnerability-publications.html?download=52; Bonnie Doty et al., *Vulnerability to Climate Change: An Assessment of East and Central Africa* (Austin: Strauss Center for International Security and Law, August 2011), http://strausscenter.org/ccaps/climate-vulnerability-publications.html?download=53; Sanjeet Deka, Glakas, Christian, and Olivier, Marc, *Assessing Climate Vulnerability in North Africa* (Austin, Texas: Strauss Center for International Security and Law, August 2011), http://strausscenter.org/ccaps/climate-vulnerability-publications.html?download=54.

[7] See Joshua W. Busby et al., "Climate security vulnerability in Africa mapping 3.0". *Political Geography*, *43*(0), 51–67. doi:http://dx.doi.org/10.1016/j.polgeo.2014.10.005

[8] *Mapping and Modeling Climate Security Vulnerability: Workshop Report* (Austin, Texas: Strauss Center for International Security and Law, October 2011), http://strausscenter.org/ccaps/climate-vulnerability-publications.html?download=47.m

Beyond subnational vulnerability, among the consistent features of our maps are the following attributes: (1) areas of chronic concern (2) relative to the rest of the continent and (3) composite maps of overall climate security concern. These are maps of chronic vulnerability, of perennial places of likely concern, rather than seasonal maps of emergent vulnerability like those produced by the Famine Early Warning Systems Network (FEWS NET).[9] Unlike some global maps of vulnerability,[10] our maps are also relative to the rest of Africa, rather than the rest of the world. The least vulnerable parts of Africa may be relatively more or less vulnerable to places outside of Africa, but our area of reference is Africa compared to itself.

Finally, our maps are composite representations of climate security vulnerability. Thus, they are different from maps that seek to chart vulnerability in terms of livelihoods. We have an explicit security focus, emphasizing situations where large number of people could be at risk of mass death from exposure to climate related hazards. Unlike other maps with a similar interest in security, our maps seek to capture that phenomenon in a single integrated composite measure rather than a series of maps each documenting different facets of a problem. For example, Marc Levy at Columbia University and colleagues prepared tables of specific security concerns such as dangerous neighborhoods coupled with specific

[9] See http://www.fews.net/Pages/default.aspx

[10] Maplecroft, for example, has produced a global climate vulnerability ranking at the subnational level. Maplecroft, "Cities of Dhaka, Manila, Bangkok, Yangon and Jakarta Face Highest Climate Change Risks," November 15, 2012, http://maplecroft.com/about/news/ccvi_2013.html. The Center for Global Development has produced a global vulnerability ranking at the national level. David Wheeler, "Quantifying Vulnerability to Climate Change: Implications for Adaptation Assistance," *Center for Global Development*, 2011, http://www.cgdev.org/content/publications/detail/1424759/.

climate risks such as chronic water scarcity.[11] The result is a profusion of tables and maps rather than a single consolidated map that can condense all of the information into a single graphic (which has both strengths and weaknesses).

In our original model, we started with four baskets or processes—physical exposure, population density, household and community resilience, and governance and physical violence—that we thought captured the salient sources of vulnerability, though we recognize that in our aspiration to provide continent-wide maps that some likely indicators of interest (such as road networks) might not be available. Each of these baskets, save for population density, was composed of a number of indicators and we sought sub-national data with fine-grained resolution wherever possible. Our initial index weighted each basket equally and created a composite index by adding the four together. In sensitivity tests, we relaxed that assumption of equal weights.

The methods we have employed to map climate security vulnerability have evolved to reflect the opinions we heard from "ground truthing" our first set of maps with local elites in Africa.[12] To date, we have released two major versions of our mapping work, the first 1.0 version is represented by the first working paper we released from the Strauss Center in 2010. Subsequent maps in other published work have largely represented the second iteration 2.0 of our mapping work and

[11] Marc A. Levy et al., "Assessment of Select Climate Change Impacts on U.S. National Security," 2008, http://www.ciesin.columbia.edu/documents/Climate_Security_CIESIN_July_2008_v1_0.ed.pdf.
[12] Berenter, Jared, *"Ground Truthing" Vulnerability in Africa* (Austin, Texas: Strauss Center for International Security and Law, May 2012), http://strausscenter.org/ccaps/climate-vulnerability-publications.html?download=89; Berenter, Jared, *"Ground Truthing" Vulnerability and Adaptation in Africa* (Austin, Texas: Strauss Center for International Security and Law, May 2012), http://strausscenter.org/ccaps/publications/reports.html?download=91.

extensions and applications. As suggested above, this paper represents the 3.0 version of CSVM, which is a new name that we have christened in this paper.

Part II: An Evolving Methodology

Over the course of the last four years, our efforts to map climate security vulnerability have evolved. This section explains our original model, the changes made in 2.0, and then presents the changes made for the current iteration CSVM 3.0.

Vulnerability Model 1.0

To understand what changes we made between the second and third versions of the model, it is helpful to understand where we initially began and what revisions we made between versions 1.0 and 2.0. In the 1.0 iteration of our model, we included several indicators of historic physical exposure to climate related hazards, including floods, fires, drought, cyclone winds, cyclone surge, and low-elevation coastal zones, all of which save for the last one were derived from the UNEP Global Risk Data Platform.[13] With models of future climate change in Africa showing widespread disagreement, the first approximations of the areas likely to face physical exposure to climate related hazards in the future were the areas historically exposed to such hazards. (As an aside, in complementary work, we have collaborated with climate modelers to develop more fine-grained and policy-relevant regional models for Africa).[14]

[13] http://preview.grid.unep.ch/

[14] See Edward K. Vizy and Kerry H. Cook, "Mid-21st Century Changes in Extreme Events over Northern and Tropical Africa," *Journal of Climate* (March 9, 2012): 120309131130007, doi:10.1175/JCLI-D-11-

For population density, we relied on data from Columbia University and the GRUMP model (Global Rural-Urban Mapping Project).[15] In the household basket, we included eight indicators, only two of which included sub-national information (infant mortality and childhood malnutrition). All others (adult literacy, primary school enrollment, life expectancy at birth, drinking water accessibility, healthcare expenditures, and access to nurses and midwives) were at the national level. Finally, our governance basket consisted of two indicators from the World Bank's Worldwide Governance Indicators for 2008, government effectiveness and voice and accountability. We also included two indicators from the Polity IV dataset of political instability through 2008, including the difference between the highest and lowest polity scores in the period 1999-2008 and the number of years since a major change in government (as of 2008). We included a measure of global integration from the KOF Index of Globalization. Finally, we included one sub-national indicator of politically motivated violent events from the Political Instability Task Force for the period 1995-2008.

Changes from the 1.0 to the 2.0 Vulnerability Model

Our 2.0 version of the maps included a number of revisions, including several new data sources and indicators including: (1) a new data source on droughts; (2) a new indicator for areas with chronic low rainfall; (3) an alternate, more fine-grained indicator of population density, (4) a new sub-national indicator of access to

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00693.1; Kerry H. Cook and Edward K. Vizy, "Impact of Climate Change on Mid-twenty-first Century Growing Seasons in Africa," *Climate Dynamics* (March 2, 2012), doi:10.1007/s00382-012-1324-1.

[15] http://sedac.ciesin.columbia.edu/data/set/grump-v1-population-count

improved water sources; (5) a new indicator for sub-national violence; and (6) revised metrics of government effectiveness and voice and accountability which reflect a 3-year weighted average. Here, we explain the changes and rationale for each of them.[16]

In terms of drought data, there were two issues. First, the drought indicator in our original model only covered the period 1980-2001, which was a bit dated. Second, it was based on the Standardized Precipitation Index (SPI), which allows you to calculate deviations from normal rainfall but does not pick up on areas of chronic water deficits. Indeed, it is not a very good proxy for drought as this indicator revealed that one of the most "drought-prone" places in the period 1980-2001 in Africa was the northern part of the Democratic Republic of Congo. This area might have had deviations from normal rainfall such that areas that were normally very, very wet became only very wet.

As a consequence of these two observations, we included an updated measure of SPI from the Global Precipitation Climatology Centre (GPCC) for the period 1980-2004. We also added an alternative measure to capture chronic water scarcity based on the coefficient of variation (which is simply the standard deviation divided by the mean rainfall).[17] This addition was motivated by our fieldwork where respondents noted that our maps failed to capture areas of chronic water scarcity, already at risk to water shortages and likely to fare worse with climate change.

[16] A more detailed discussion of the methodology in the 2.0 model is available as an online appendix for our *International Security* paper.

[17] This helps capture chronic water scarcity quite for the following reason. For areas with low mean rainfall values near zero (like deserts), the value for the coefficient of variation will approach infinity. Small deviations in rainfall will generate large changes in the coefficient of variation.

In addition, we replaced the use of the indicator from GRUMP of population density with a similar measure from LandScan for the year 2008. GRUMP is based on 2000 census data and is based on night-time population whereas LandScan is based on "ambient" populations. LandScan is a modeled dataset based on a variety of inputs such as road networks, elevation, slope, land use/land cover, high resolution imagery. Supporters of LandScan credit it with having more accuracy estimating population concentrations to take into account geographic features such as mountainous areas and rivers.[18]

In our quest for more fine-grained data, we also developed a sub-national indicator of access to improved water sources, using the USAID-funded Demographic and Health Surveys (DHS).[19] For some countries, additional subnational data was available through UNICEF's Multiple Indicator Cluster Surveys (MICS).[20] While this data is collected in the surveys, it takes considerable processing to extract them and have them correspond to specific sub-national administrative units. That meant that the Household and Community Resilience basket had three of eight indicators at the sub-national level.

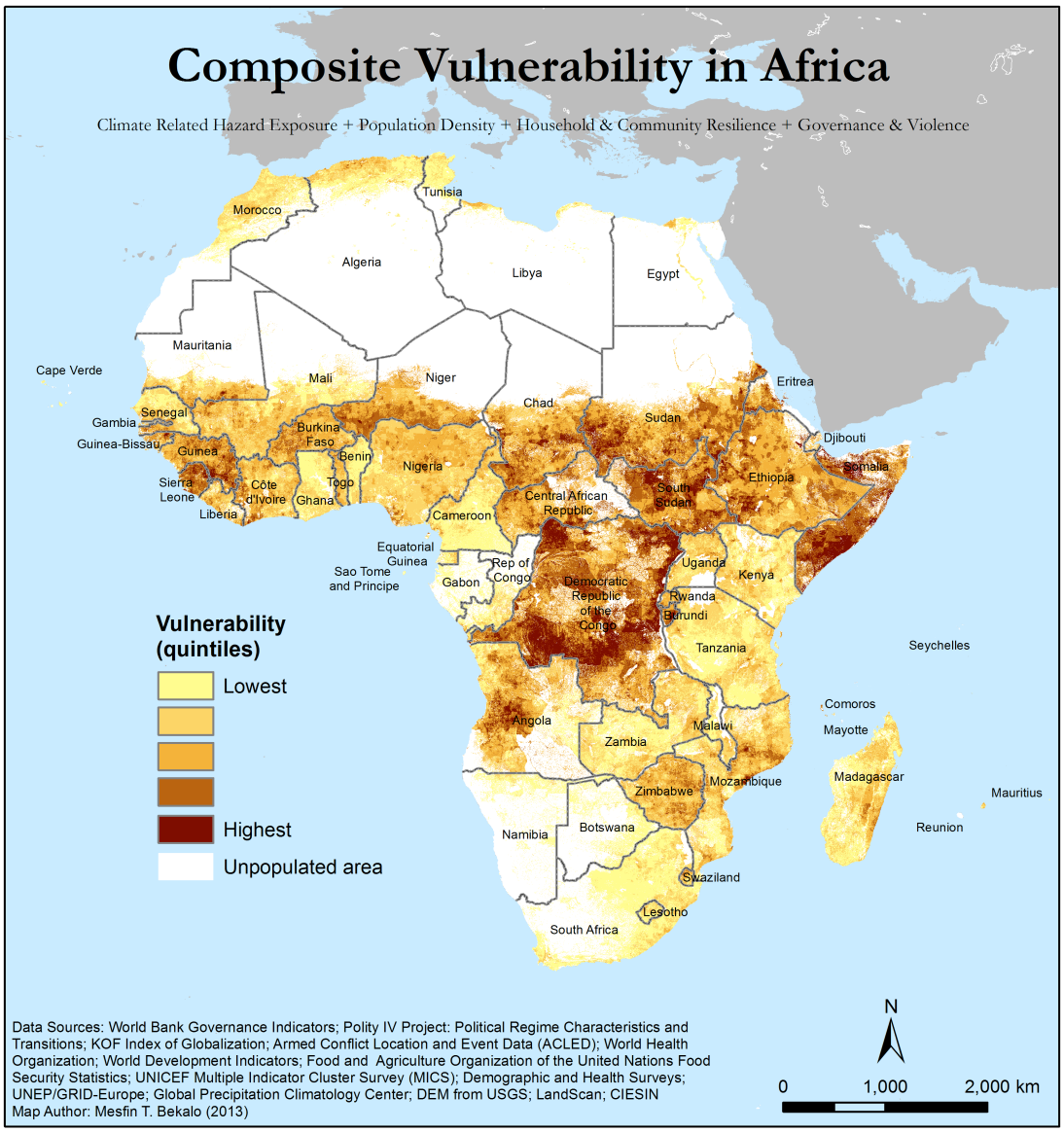
Finally, in terms of the governance basket, we made several refinements. The data on Worldwide Governance Indicators initially reflected a single year 2008, but this is an indicator with some flux and variability, meaning that a value from a single year could drive the results for our measures of government effectiveness and voice

[18] For differences between GRUMP and LandScan, see http://sedac.uservoice.com/knowledgebase/articles/41665-what-are-the-differences-between-gpw-grump-and-la
[19] See http://www.measuredhs.com/
[20] See http://www.unicef.org/statistics/index_24302.html

and accountability. We therefore chose to create a three-year weighted average, weighting the most recent year 2009 the most (50%), the previous year 2008 second (30%), and two year's prior 2007 the least (20%). We also substituted for the Political Instability Task Force indicator of atrocities against civilians a broader measure of conflict from the Armed Conflict and Event Location Dataset (ACLED) for the period 1997–2009. These were assigned to the lowest administrative unit possible to create a frequency count of violent events. The idea here was that governments might not be willing or able to extend aid and assistance to places with a history of violence and conflict in the event of a climate related emergency.

In the base composite vulnerability model, all four baskets were weighted equally and added together. Each indicator was "normalized" into a common scale. We classified them into categories on a scale from 1 to 5, with 1 being the most favorable and 5 being the worst outcome. In the climate related hazard basket, areas with extremely low rainfall are represented by a separate category of 0. In the population density basket, unpopulated areas were represented by a separate category of zero. When we added all four baskets together for the composite map of overall vulnerability, these unpopulated areas were excluded. In some iterations of the 2.0 model, we relaxed the assumption of equal weights to the baskets to see how the maps changed with different weights attached to the baskets. Figure 1 shows the map results for the 2.0 version of our model which shows high vulnerability across Somalia, Sudan and South Sudan, pockets in the Democratic Republic of the Congo (DRC), and in Guinea and Sierra Leone.

FIGURE 1: COMPOSITE VULNERABILITY MAP 2.0



Changes from the 2.0 to the 3.0 Vulnerability Model

We made a number of changes to the indicators and approach in version 3.0, related to the units of analysis, the normalization of data, and the functional form of the model.

Units of Analysis

We sought subnational data wherever possible for use in the model. For a number of indicators, particularly in the Household and Community Resilience basket, we used USAID Demographic and Household Surveys to calculate subnational data. In our previous work, we relied on shapes of subnational units using the data from Global Administrative Areas dataset (GADM).[21] Other available options include data from the Global Administrative Unit Layers (GAUL)[22] and Map Library. As we endeavored to mine the DHS data for this third iteration of our maps for more subnational indicators of interest, we discovered that DHS shapes and GADM do not always neatly coincide. Moreover, we discovered that GADM does not always have files available for the current political divisions of some countries.

For example, in the case of Ghana, GADM has 137 local governments units, but Ghana has reorganized and now has 170 local government units. In the case of Ghana, we now rely on GAUL for the subnational administrative boundaries, of which there are 10 level one administrative units. Our preference was to use the most recent data, wherever possible, or should two data sources be roughly similar in vintage, we rely on the data source that has borders that fit well with neighboring countries, since location of borders may vary slightly by data source. As a consequence, based on the latest shape files that are available from various sources, we created our own master shapefile for all level one administrative boundaries

[21] http://www.gadm.org/
[22] http://www.fao.org/geonetwork/srv/en/metadata.show?id=12691

across Africa, typically corresponding to regional boundaries of states or provinces.[23]

Normalization

The five-category scale 1 to 5 that was used in previous iterations had some disadvantages. We lost a lot of information collapsing the numbers into five whole numbers. Such a normalization exercise made it easy to visualize the data, but it proved less useful for trying to understand if a particularly point lies closer to one whole number or another. Moreover, if we wanted to alter an underlying indicator and see what effect an improvement in, say infant mortality, had on overall vulnerability, having five categories was a blunt instrument. Moreover, our 1 to 5 ranking scheme was meant to capture the range of values from the least vulnerable 20% (a score of 1) to the most vulnerable 20% (a score of 5). In reality, in addition to the loss of information from the 1 to 5 scale, there was quite a lot of clustering so that these quintiles were not evenly distributed, making it harder to interpret what the scores meant.

As a consequence, in this version of the data, all indicators were normalized on a scale from 0 to 1 to three decimals places, using percent rank (a version of dispersion between the minimum and maximum)[24] or percentiles.[25] This gives us a more variegated scale to work with. Instead of 5 whole numbers, we now have a

[23] Smith, T. G., Busby, J., & Agnihotri, A. (2013). *Sub-national African Education and Infrastructure Access Data*. Strauss Center for International Security and Law. Retrieved from https://www.strausscenter.org/images/Subnational_Data_Codebook_final.pdf

[24] We converted the percent rank to show where a given value is in percentage terms between the minimum and maximum score as represented by the equation minmax =1 - (value - min)/ (max – min)

[25] Percentiles reflect the percentage of scores below a certain number. The equation representing percentiles is total number of values below X/ total number of values.

scale to two or in some cases three decimal places with low scores approaching 0 representing maximal vulnerability and high scores approaching 1 representing no vulnerability (high overall resilience). In the legends of the composite maps, we now present the range of values on a zero to 1 score rather than quantiles.

Climate Related Hazard Exposure

We were able to update a number of data sources and develop some new indicators for CSVM 3.0. As Table 1 demonstrates, we include indicators for rainfall anomalies, chronic water scarcity, cyclones, wildfires, floods, and low-lying coastal zones. These correspond to the same concepts we applied in our model 2.0, but in a number of cases, we have replaced the indicator with either an improved data source, an updated set of newer data, or at the very least, the data has been normalized on a 0 to 1 scale rather than a 1 to 5 scale as before.

TABLE 1: CLIMATE RELATED HAZARDS DATA SOURCES

Hazard Type (weight)	**Indicator**	**Scale**	**Years of Data Used**	**Source**
Cyclone Winds	Tropical cyclones average sum of windspeed (km per year)	2 km x 2 km resolution	1970-2009	UNEP/GRID-Europe
Floods	Flood Frequency (per 100 years)	1 km x 1 km resolution	1999-2007	UNEP/GRID-Europe
Wildfires	Estimated frequency of events	1 km x 1 km resolution	1995-2011	UNEP/GRID-Europe
Aridity	Monthly coefficient of variation	0.5 degree	1980-2009	Global Precipitation Climatology Centre

Rainfall scarcity	Number of months between 1980-2009 in which the 6-month accumulated rainfall was 1.5 standard deviations or more below the average for that calendar month over the previous 20 years.	0.5 degree	1980-2009	Global Precipitation Climatology Centre
Inundation (Coastal elevation)	Low-lying coastal areas within 0 to 10km above sea level	3 arc second 1°x1° (90 m)		Viewfinder Panaromas

Rainfall Anomalies and Chronic Water Scarcity. In our original model, we included a single indicator of covering the period 1980-2001 based on the Standardized Precipitation Index (SPI), which calculates deviations from normal rainfall. This measure does not pick up on areas of chronic water scarcity, which fieldwork revealed to be an area of major concern and as particularly climate sensitive. It is also unclear where SPI is a good proxy for drought as this indicator revealed that one of the most "drought-prone" places in the period 1980-2001 in Africa was the northern part of the Democratic Republic of Congo. This area might have had deviations from normal rainfall such that areas that were normally very, very wet became only very wet, but they might not fit other people's definitions of drought as abnormally low rainfall (Lyon, 2011).

As a consequence of these two observations, in our second version of the model, we included an updated measure of SPI from the Global Precipitation Climatology Centre (GPCC) for the period 1980-2004. We also added an alternative measure to capture chronic water scarcity based on the coefficient of variation (which is simply the standard deviation divided by the mean rainfall).[i] This addition

was motivated by our fieldwork where respondents noted that our maps failed to capture areas of chronic water scarcity, already at risk to water shortages and likely to fare worse with climate change.

By the third iteration of the maps, we were not satisfied that the representation by the Standardized Precipitation Index was that meaningful. The previous version relied on a count of events and intensity over the entire period 1980-2004.[ii] Previous studies had suggested that this indicator did a somewhat decent job mirroring patterns of drought, as represented in the EM-DAT disaster database. As our composite model is meant to pick up on other risks that contribute to the occurrence of disasters, we wanted a measure of negative changes in rainfall that is purely physical that together with other indicators should contribute to disaster vulnerability. Rather than create a frequency count over the entire period of study, we created a rolling twenty-year average based on the accumulated rainfall for the previous 6 months.[iii]

The idea here is that people, particularly farmers, will have some appreciation of what the rainfall should look like over a given period (in this case, the previous six months). The memories of adults may stretch back about twenty years. Thus, if the accumulated rainfall deviates strongly from the previous patterns over the last twenty years, this could have a major impact on water users' (including farmers) ability to plan, plant, and execute their operations, with knock-on disruptive consequences. Using data from the Global Precipitation Climatology Centre (GPCC), we therefore calculated whether or not a given six-month period deviated strongly from the twenty-year average for the same six months. We were

able to generate such a rolling six-month standardized precipitation measure for the period 1980-2009.[iv]

As in version 2.0, to get at places with chronic water scarcity, we also calculated the average monthly coefficient of variation. Again, we used GPCC data, and here, we were able to update the data for the period 1980-2009.[v] For both of these indicators, we were able to generate values across the entire continent.

Cyclones. For the cyclone indicator, we elected to use a new indicator from the UNEP/GRID-Europe platform called "sum of winds." It is meant to capture both frequency and speed of cyclone events, thus providing some measure of event intensity. It is measured in kilometers/year. This gave us values for the period 1970-2009. The rationale here was that in our prior version, we had created our own weighting scheme for different categories of cyclones based on the frequency of cyclone severity, giving extra weight to more extreme cyclone events. This weighting scheme and reclassification into five categories was somewhat arbitrary,[26] and we preferred to rely on a measure created by subject area experts explicitly for the purpose of bringing together frequency and severity of cyclone events. Use of this indicator allowed us to bring in two years of additional data for the period 1970-2009.

Wildfires. Since our original use of the UNEP/GRID-Europe data on physical hazards, they also updated other data sources, including wildfires. We now map wildfires for the period 1995-2011, which provides several additional years of data.

[26] These scores are represented as a final cyclone frequency raster using the following equation: cyclone wind frequency = category 1 frequency + (category 2 frequency * 2) + (category 3 frequency * 3) + (category 4 frequency * 4) + (category 5 frequency * 5). This formula assigns greater weight to stronger, more dangerous cyclones.

Floods. In previous iterations of the flood data, we relied on event counts of floods from UNEP/GRID-Europe. Because those areas essentially reflected narrow bands along rivers, we worried that the full effects of flooding on human populations might not show up. One's house need not be flooded for one to be negatively affected by flood. The destruction of riverside crops could lead to food insecurity in surrounding areas; an increase in mosquito populations that breed in stagnant water could lead to an increase in vector-borne diseases; the inability to cross swollen rivers can leave people cut off from jobs or schools. In this iteration, we have drawn 2.5 km buffers around flood zones and collapsed categories on a zero to 1 scale in step-wise 0.1 increments.[vi]

Low Elevation Coastal Zones. We have updated the Digital Elevation Model of low-elevation coastal zones vulnerable to floods. Drawing on more fine-grained data from Viewfinder Panoramas (roughly 90m resolution compared to 1 km resolution in previous iterations), we provide data for low-elevation coastal zones for areas ten meters or lower that are close to the coast.[vii] Scores are normalized on a zero to 1 scale, with 1 being no exposure and with 0 or lower receiving a score of 0 to represent maximal exposure. Each one meter increment reduced an area's exposure by 0.1.[viii]

For all indicators, we normalized the data on 0 to 1 scale with three decimal places. In this iteration of the model, given that both rainfall anomalies and chronic water scarcity indicators were meant to capture similar phenomena related to the effects of changes in rainfall, we divided the weight between them. Where floods, cyclones, wildfires, and low-lying coastal zones each represented 20% of the overall

climate-related hazard or physical exposure basket, that 20% was split equally between water anomalies (6 mo. standardized precipitation measure) and chronic water scarcity (CV).

Combining these indicators into a single basket map of climate-related hazard exposure yields a map, Figure 2 below, showing high climate hazard exposure concentrated along the eastern coastlines of Madagascar and Mozambique, driven in part by their unique exposure to cyclones. Other areas of high exposure include Egypt at the mouth of the Nile and coastal and riverine Nigeria and other edges of West Africa. A band of higher exposure also extends across from Somalia to Gabon, a function largely of droughts and wildfires.

TABLE 2: DESCRIPTIVE STATISTICS FOR EXPOSURE BASKET

	cell size	cell count	mean	sd	min	max
Months of SPI6 <1.5 based on 20 year rolling average (1980–2009)	0.5	12781	7.410	7.626	0	43
Coefficient of Variation (1980–2009)	0.5	12781	1.660	0.996	0	10
Low Elevation Coastal Zone (meters above sea level)	0.00083	3693174751	9.965	0.493	0	10
Cyclone Intensity (sum of wind speeds)	0.01733	8538340	1.650	17.084	0	688
Fire Frequency (1995-2011)	0.1	256865	7.203	19.877	0	589
Flood Frequency (1999-2007)	0.00833	36841664	0.109	0.752	0	38

FIGURE 2: CLIMATE RELATED HAZARD EXPOSURE

Population Density

In version 2.0 of our maps, we used the Landscan values for 2008 and converted them into quintiles. In this version 3.0, we use 2011 data for Landscan and normalize the data into percentiles on a zero to 1 scale (see Table 3).

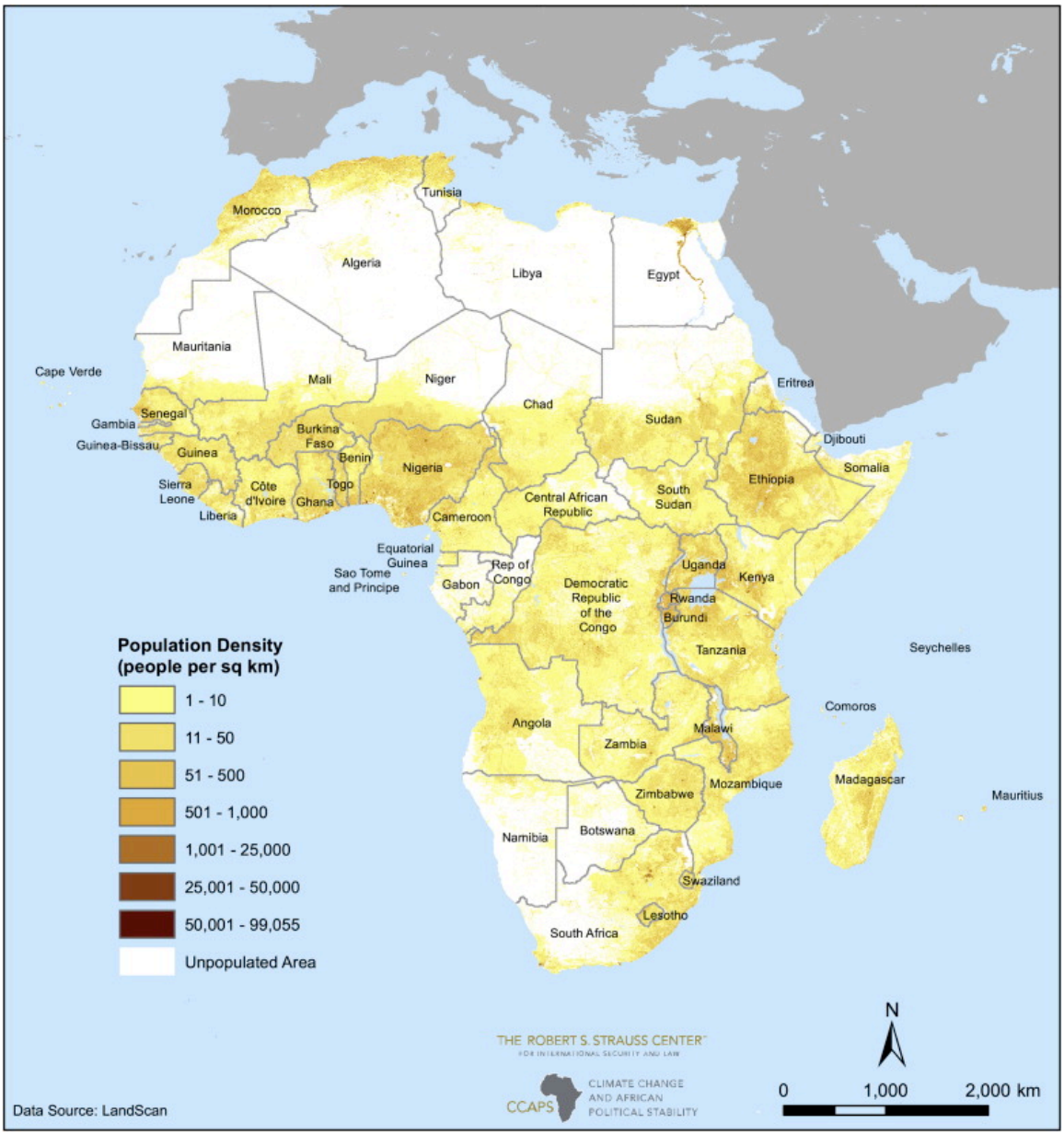
TABLE 3: POPULATION DENSITY DATA SOURCES

Variable	Indicator	Scale	Years of Data Used	Source
Population Density	Ambient population (average over 24 hours)	Subnational at 1 km x 1 km resolution	2011	LandScan Oak Ridge National Laboratory

As Figure 3 shows, population concentrations are found in western Ethiopia, throughout Nigeria and neighboring coastal West Africa, in and around the Great Lakes region, Egypt, along Lake Malawi, and across parts of the Mediterranean coastline of Morocco and Tunisia. It should be noted that in the map below, the range of the most densely populated areas (dark brown) is enormous, from 48 people per square kilometer to 99,055 per square kilometer.

Most of the values continent wide are lower than 50 people per square kilometer, and the highest population concentrations (50,000 people per square kilometer or more) are in a handful of places, in and around major cites in Egypt (Cairo, Alexandria) and Morocco (Fez, Meknes, Rabat, Casablanca), as well Algiers; several cities in Nigeria (including Lagos, Ibadan, Akure, Asaba), several other West Africa cities (Abidjan, Lome, Cotonou), several cities in Central and East Africa (Kinshasa, Brazzaville, Addis Ababa, Nairobi, Kampala, Dar es Salaam), as well as several cities in Southern Africa (Maputo, Durban).

FIGURE 3: POPULATION DENSITY



Household and Community Resilience

This basket contains four categories of paired indicators for a total of eight: two for education, two for health, two for daily necessities, and two for access to healthcare. In version 2.0, only three contained subnational information, infant

mortality, underweight children, and access to improved drinking water sources, developed by our team using the USAID-funded Demographic and Health Surveys (DHS) (see Table 4).[ix]

TABLE 4: HOUSEHOLD RESILIENCE DATA SOURCES

Category	Indicator (weight)	Scale	Years of Data Used	Source
Education (25%)	Literacy rate, adult total (% of people ages 15 and above) (12.5%)	National, CCAPS First Administrative District	DHS 2003-2011, Stats SA 2011, World Development Indicators (WDI) 2006-2010	Subnational data from DHS, MICS; Stats SA; national level data WDI
	School attendance, primary (% gross) (12.5%)	National, CCAPS First Administrative District	DHS 2003-2011, Stats SA 2011, MICS 2006-2010, UNICEF 2003-2008	Subnational data from DHS, MICS; Stats SA; national level data UNICEF
Health (25%)	Infant mortality rate adjusted to national 2000 UNICEF rate (12.5%)	CCAPS First Administrative District	2008	Environmental Indications and Warnings Project
	Life expectancy at birth (years) both sexes (12.5%)	National	2008, 2010, 2011	WDI
Daily Necessities (25%)	Percentage of children underweight (more than two standard deviations below the mean weight-for-age score of the NCHS/CDC/WHO international reference population (12.5%)	National, CCAPS First Administrative District	DHS 1999-2010, WDI 2000, 2004-2008, 2011	Subnational data from DHS; national level data WDI

	Population with sustainable access to improved drinking water sources total (%) (12.5%)	National, CCAPS First Administrative District	DHS 2003, 2005-2011, MICS 2006-2007, 2010, Stats SA 2011, WDI 2001, 2006, 2008-2010	Subnational data from DHS, MICS, Stats SA; national level data WDI
Access to Healthcare (25%)	Health expenditure per capita (current US$) (12.5%)	National	WDI 2001, 2010	WDI
	Delivery in a health facility (% of births) (12.5%)	National, CCAPS First Administrative District	DHS 1999-2008, 2010, UNICEF 2003-2008	Subnational data from DHS, UNICEF; national indicators from UNICEF

Education. In addition, we derived new subnational data for literacy and school enrollment from the USAID DHS surveys and the UNICEF MICS surveys.

Health. In this iteration of the maps, we obtained updated infant mortality data, normalized to the year 2008, obtained from ISciences' Environmental Indications and Warnings Project.[x] Life expectancy data are still drawn from national level data.

Daily Necessities. We also updated data on access to improved water sources and underweight children to take advantage of new DHS and MICS surveys.

Access to Health Care. Finally, we have some subnational information for delivery in health facility from those same surveys, which we thought of as a better proxy for access to health services than our existing national indicator of the number of midwives and nurses.[xi] Health expenditure data is still only available at

the national level. What this means is that we now have subnational indicators for six of eight indicators in this basket (see Table 4).

All of these data sources were normalized on a zero to one scale using a minmax transformation. All four categories received equal weight in the index of 25%. Each indicator in the category would thus receive 12.5% of the weight of the whole basket. In the event a particular indicator was missing data, the other indicator would take on the full 25% category weight.

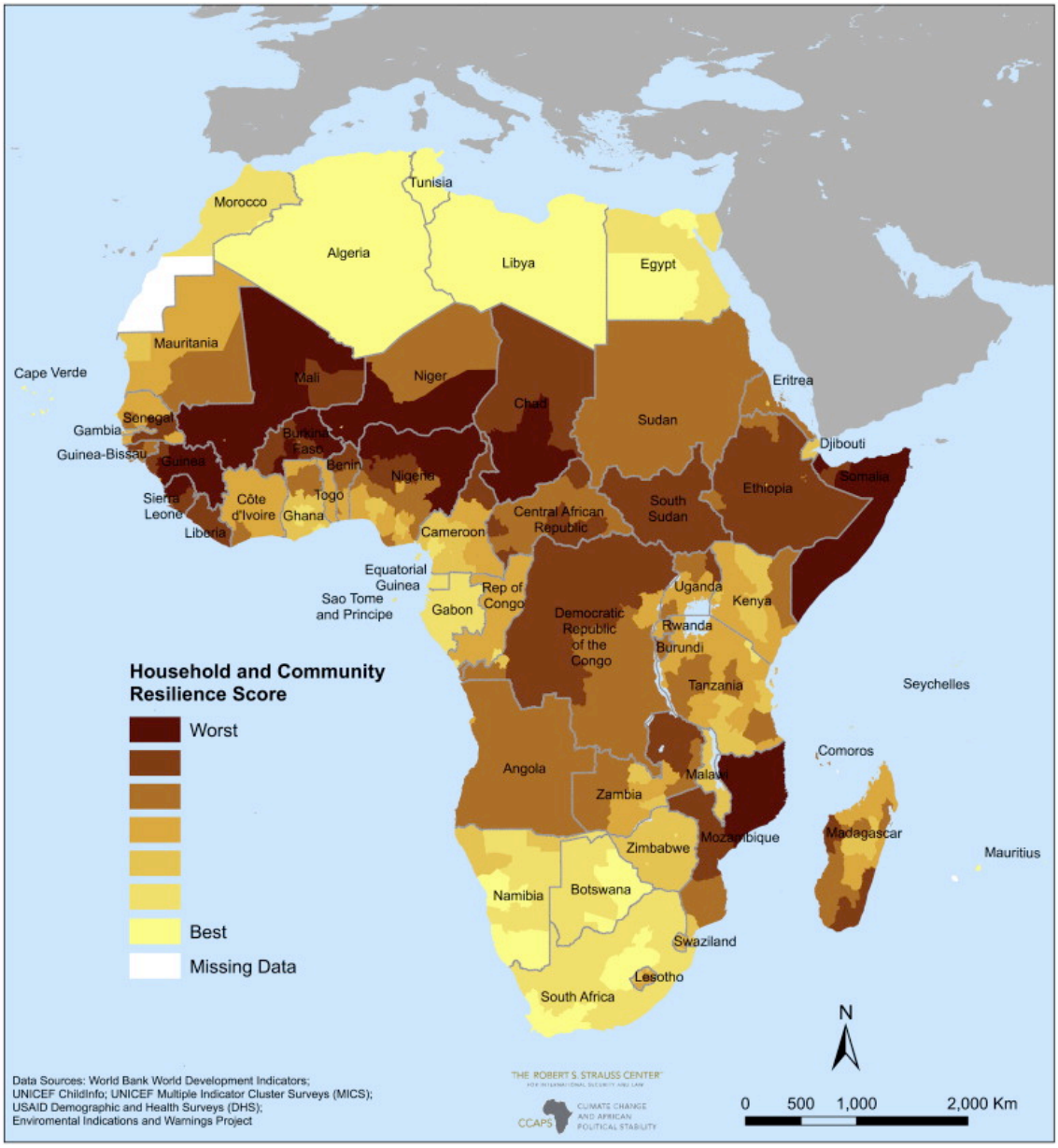
Combining all these indicators in a single map yields Figure 4 which shows that the least resilient areas of the continent are located in Somalia, Nigeria, and across the Sahel while the most resilient areas (the areas where communities have the highest levels of education, better health conditions, access to necessities and health services) are located on the island of Mauritius and primarily in North Africa, including Tunisia, Algeria, Egypt, and Libya.

Table 5 shows the descriptive statistics for the indicators in this basket, with some indicators at their means reflecting extraordinarily poor health, education, and access to daily necessities and basic services.

TABLE 5: DESCRIPTIVE STATISTICS FOR HOUSEHOLD DATA

	count	mean	sd	min	max
Delivery in a healthcare facility (% of live births)	651	53.086	27.655	5	99.7
Health expenditure per capita (current US$)	663	128.887	168.193	11.9	896
Infant mortality rate (per 1,000 births)	692	72.26	35.187	4.29	181
Life expectancy at birth	691	58.933	8.965	47.8	75
Literacy rate, adult (% of people ages 15 and above)	658	65.479	21.551	9.5	98.9
School attendance, primary (% net)	646	77.045	21.992	0.883	103
Access to improved drinking water (% of population)	680	64.013	23.39	0	100
Underweight children (% >2 SDs below mean weight for age)	651	21.057	11.328	2.88	52.6

FIGURE 4: HOUSEHOLD AND COMMUNITY RESILIENCE



Governance and Political Violence

The 2.0 version of our maps contained five categories and six indicators. We included indicators of government responsiveness, government response capacity, openness to external assistance, two indicators for political stability, and presence of violence. Of these, only one contained subnational information. In CSVM 3.0, these

indicators have been updated to include more recent data (see Table 6). In North Africa, this is particularly important since the region experienced historic transformations in political stability after the introduction of our version 2.0.

TABLE 6: GOVERNANCE DATA SOURCES

Category	Indicator (weight)	Scale	Years of Data Used	Source
Government Response Capacity	Government Effectiveness (20%)	National	2008, 2009, 2010, 2011, 2012	WDI
Government Responsiveness	Voice and Accountability (20%)	National	2008, 2009, 2010, 2011, 2012	WDI
Political Stability	Polity Variance (10%)	National	2002-2011	Polity IV Project
	Number of Stable Years (as of 2011) (10%)	National	1855-2011	Polity IV Project
Openness to External Assistance	Globalization Index (20%)	National	2011	KOF Index of Globalization
History of Violence	Subnational conflict events (20%)	CCAPS First Administrative Division	1997-2013	Armed Conflict Location and Events Database (ACLED)

Government Effectiveness and Responsiveness. In this version, we now have indicators for government effectiveness and voice and accountability through 2012 (previously these only covered the period 2007-2009). Again, we represent these indicators through a diminishing weighted-average for the period 2012 dating back to 2008.[27] We chose these indicators based both on the empirical evidence in Brooks et al. and Wheeler, as well as deductive logic about the factors that might

[27] The value is a diminishing weighted average with 2012 assigned the most weight (.33), followed by 2011 (.2667), 2010 (.2), 2009 (.1333), 2008 (.0667). Expressed in percent rank.

impede or facilitate government responsiveness during a crisis (Brooks, Adger, & Kelly, 2005; Wheeler, 2011).

The indicator for openness to external assistance from the 2009 KOF Index of Globalization remains unchanged, as we believe this to be a slow-changing indicator.

Political Instability. We also included two indicators from the Polity IV dataset of political instability, based on the idea that governments experiencing political volatility may be less responsive to their publics in terms of aid provision in a time of crisis, both in terms of will and capability. In terms of political stability, we took advantage of the release of new Polity IV data through 2011. Our indicator of polity variance now covers the period 2002-2011 (it previously covered the period 1999-2008).

This includes the difference between the highest and lowest polity scores in the period 2002-2011 and the number of years since a major change in government (as of 2011). First, we created a measure that we call *polity variance*. The Polity IV Project reports a polity score for most countries in the world on a scale of -10, the most autocratic, to +10, the most democratic. Without preference for democracy or autocracy, this study used the difference between a country's highest and lowest polity scores in the past ten years as a measure for how much a country's government has changed. A zero indicates that the government has experienced no change, while a higher score indicates that the government has changed considerably. For the second metric of *stable years*, this study used a count of the total number of years since a country has undergone a major regime change, defined

by the Polity IV Project as a change of three points or more within three years. In this case, a higher year count indicates a more stable government.

Openness to Globalization. We included a measure of global integration from the KOF Index of Globalization for 2011, an indicator from a single year that tends to change slowly.

History of Violence. Finally, as before, our sole subnational indicator in this basket is the Armed Conflict and Location Events Dataset (ACLED). We also substituted for the Political Instability Task Force indicator of atrocities against civilians a broader measure of conflict from the Armed Conflict and Event Location Dataset (ACLED) for the period 1997–2013. These were assigned to the lowest administrative unit possible to create a frequency count of violent events. The idea here was that governments might not be willing or able to extend aid and assistance to places with a history of violence and conflict in the event of a climate-related emergency.

The measure here encompasses all categories of ACLED events for the period 1997-2013 (in the previous iteration, we had events for the period 1997-2009). In this iteration, we place more weight on recent events compared to more distant ones, based on the same logic applied to the World Bank measures.[xii] In version 2.0, we attached ACLED events to the smallest administrative unit where available, since the original data was point data. However, for the purposes of creating a consistent percentile rank across all subnational administrative units, we needed to have consistent units of analysis across different subnational indicators. We therefore

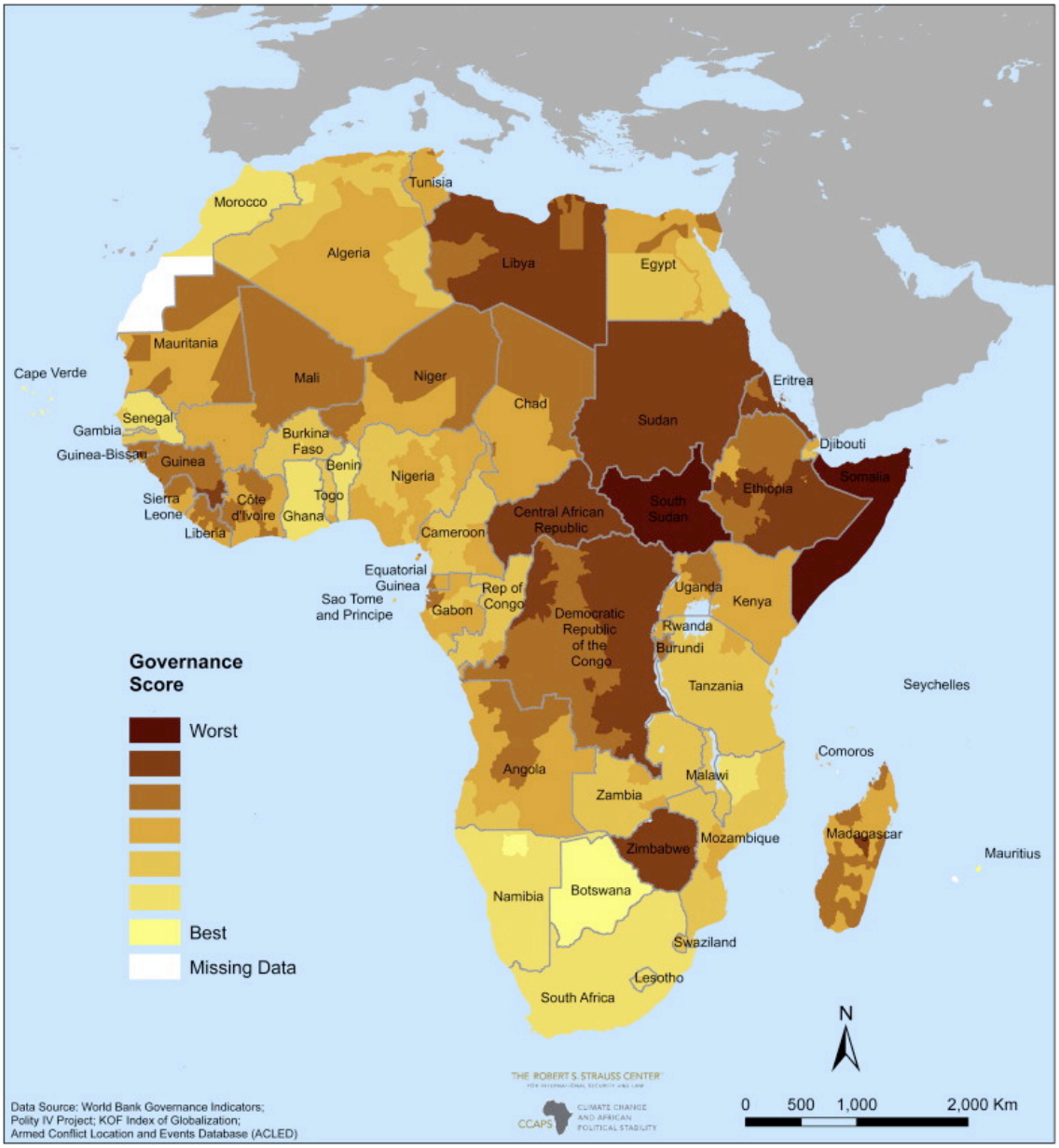
elected to aggregate ACLED events to the level one administrative unit, again corresponding to regional boundaries in most cases.[xiii]

Combining these indicators into a single map yields Figure 5, which shows that the areas with the worst governance include most of Somalia, pockets in both South Sudan, Sudan, parts of the Democratic Republic of the Congo, as well as much of Libya (picking up on civil war and political instability after the Arab Spring), as well as the Central African Republic. By contrast, areas with the best governance scores include several island countries (Mauritius, Cape Verde, the Seychelles) as well as much of Botswana, pockets in Morocco (in the Sud region), Namibia, Ghana, and South Africa. Table 7 provides the descriptive statistics for this basket.

TABLE 7: DESCRIPTIVE STATISTICS FOR GOVERNANCE BASKET

	count	mean	sd	min	max
ACLED Events (weighted sum 1997–2012)	692	57	172.1	0	2444
Voice & Accountability	53	-0.686	0.732	-2.16	0.935
Goverment Effectiveness	53	-0.749	0.62	-2.23	0.821
Globalization Index	53	46.235	8.979	25.9	64.4
Polity Variance	52	2.231	2.84	0	10
Number of Stable Years	52	12.75	11.939	0	46

FIGURE 5: GOVERNANCE



Part III: Findings

Each of these baskets, save for population density, was composed of a number of indicators and we sought sub-national data with fine-grained resolution wherever possible. Our initial index weighs each basket equally and creates a composite index by adding the four together.[xiv] In sensitivity tests in other work, we

relaxed the assumption of equal basket weights.[xv] In CSVM 3.0, we test alternative functional forms with a model multiplying the physical exposure basket by the weighted average of the three other baskets as well as multiplying physical exposure times population multiplied by the weighted average of governance and household resilience. [28]

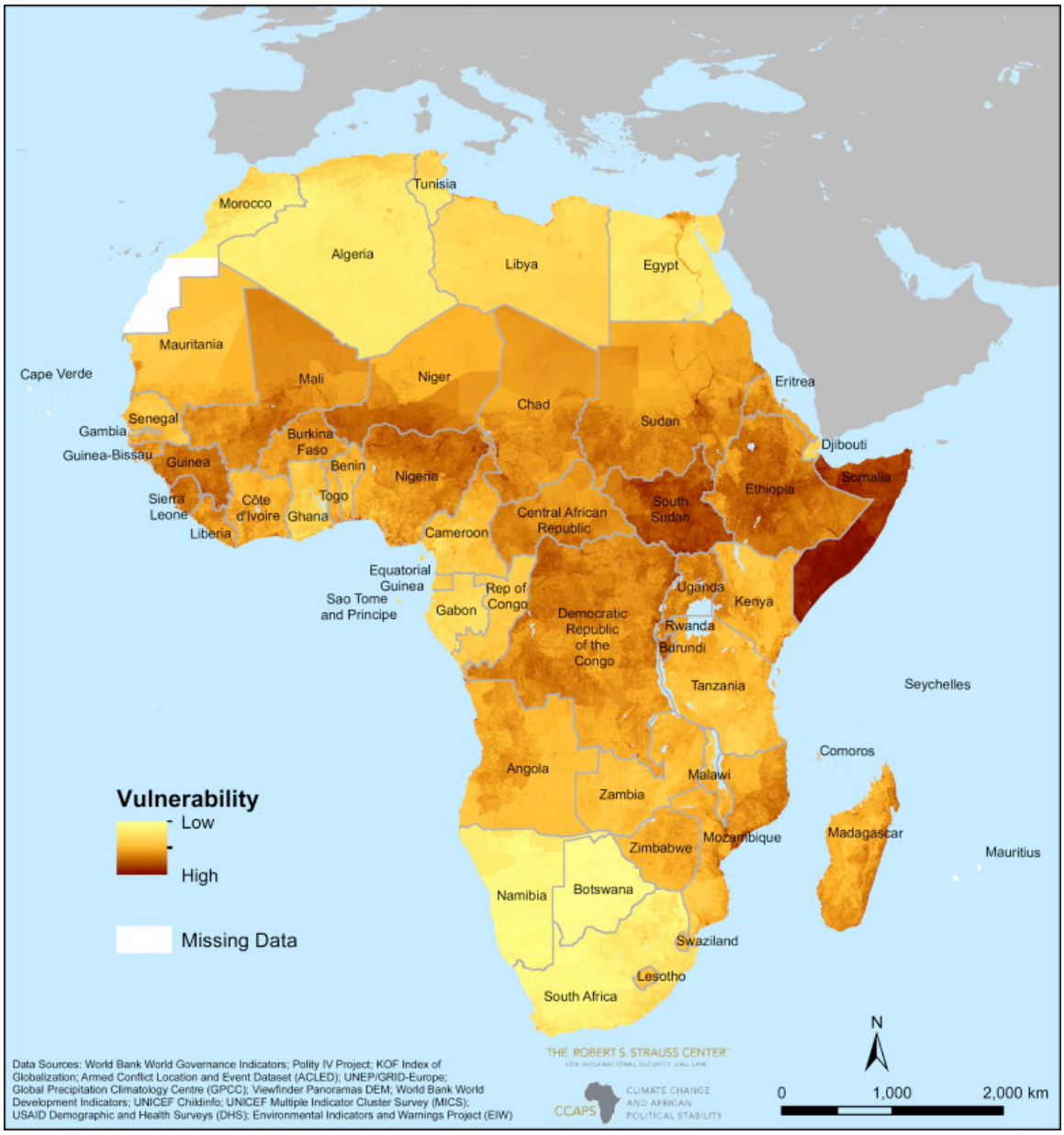
In order to retain the zero to one scale (with zero meaning maximal vulnerability and 1 meaning no vulnerability), we had to re-normalize the data, dividing by the total possible score.

Model 1: $CSVM_{additive} = (C + P + H + G)/4$

The model shows extensive vulnerability across the Horn of Africa (particularly in Somalia and Ethiopia), in pockets around the Great Lakes in Uganda and Burundi, with higher areas of vulnerability through Nigeria and southern Niger, as well as West Africa in Guinea and Sierra Leone.

[28] See Joshua W. Busby et al., "Climate Security Vulnerability in Africa mapping 3.0", *Political Geography* 43 (2014). doi:10.1016/j.polgeo.2014.10.005

FIGURE 6: COMPOSITE VULNERABILITY IN AFRICA



Comparison of CSVM 3.0 with Version 2.0

The patterns we observe in the basic 3.0 additive Model 1(Figure 6) are somewhat different from the 2.0 model results (see Figure 1). Somalia, western Ethiopia, and pockets in West Africa (in and around Guinea and Niger) retain their high vulnerability. Patterns in the DRC are similar, though somewhat diminished.

With an overall score and stretched representation of our results on 0 to 1 scale, the portrait of vulnerability in CSVM 3.0 is more evenly distributed across the continent compared to the 2.0 model which collapsed values into five categories.

Part IV: Implications and Extensions for Future Research

In light of these findings, one of the more challenging questions is the extent to which we can trust the maps as indicative of any real phenomena in the world, especially since the patterns are somewhat different than what we developed in the 2.0 iteration of our maps and because there are sharp differences between them. We also want to know something more about the model's external validity: are the locations we find most vulnerable the same ones that come up in other studies?

Here, we need a relevant comparison set of data that were compiled by others but for similar purposes. To the extent that the patterns we observe in our maps mirror those of others, we are likely to have more confidence that our maps represent an underlying reality.

Our goal is to identify places where large number of people could be exposed to mass death from climate related hazards. Here, the EM-DAT International Disaster Database compiled by the Université Catholique de Louvain in Belgium may be a suitable candidate for assessing the external validity of our model. The EM-DAT database records situations that already rise to a certain level of damage to be included in the database.[29] Since EM-DAT events represent negative outcomes

[29] The criteria include: For a disaster to be entered into the database at least one of the following criteria must be fulfilled: ten (10) or more people reported killed, one hundred (100) or more people reported

where physical exposure intersects with where people live, what resources they have to protect themselves, and how their governments respond, it is a decent proxy for what we are trying to explain. Their database includes a variety of climate related "disasters."[30] The geographic coordinates in EM-DAT are not very precise – usually a field will list a town or province name, several provinces or regions, or sometimes the country as a whole. While EM-DAT has had a decade-long discussion about more accurate geocoded information, [31] they have yet to resolve methodological issues to release a geo-coded version of their own.

We geo-coded these events for the period 1997-2012 by linking them to our CCAPS level-one administrative regions with individual events sometimes linked to more than one region or even the country as a whole.[32] In Figure 10, we plot the patterns of frequency counts of climate related disaster events, and we can compare them to the patterns in our models.

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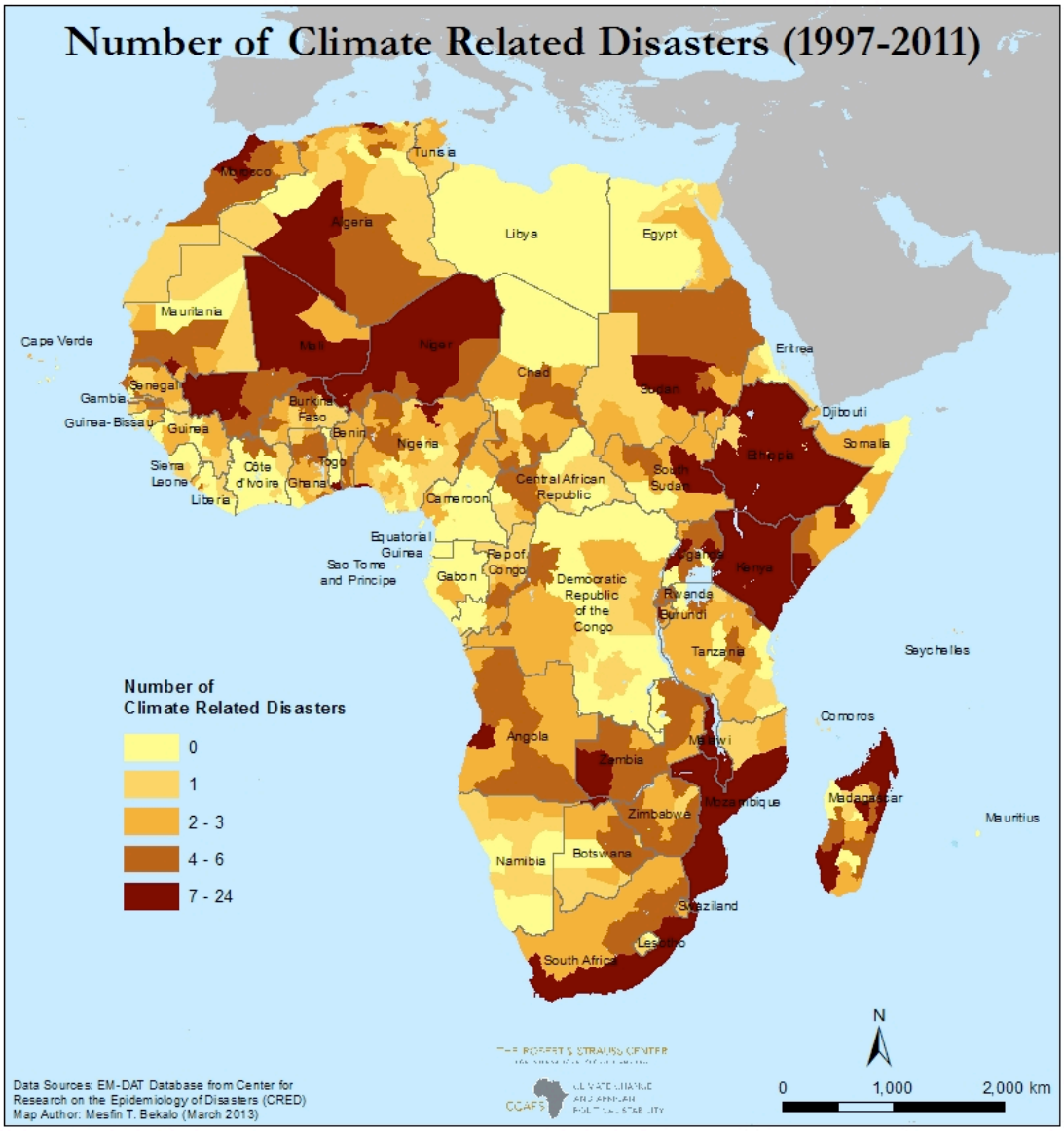
affected, a declaration of a state of emergency, or a call for international assistance. See http://www.emdat.be/criteria-and-definition

[30] This included droughts, floods, storms, wet landslides, wildfires, and extreme temperatures. Centre For Research on the Epidemiology of Disasters - CRED, "EM-DAT: The OFDA/CRED International Disaster Database", 2011, www.emdat.net.

[31] Debarati Guha-Sapir, Jose M. Rodriguez-Llanes, and Thomas Jakubicka, "Using Disaster Footprints, Population Databases and GIS to Overcome Persistent Problems for Human Impact Assessment in Flood Events," *Natural Hazards* 58, no. 3 (March 15, 2011): 845–852; P. Peduzzi and H. Dao C. Herold, "Mapping Disastrous Natural Hazards Using Global Datasets," *Natural Hazards* 35, no. 2 (June 2005): 265–289.

[32] Special thanks to Madeline Clark for assisting with these efforts.

FIGURE 7: EM-DAT INCIDENCE OF DISASTER EVENTS



EM-DAT disaster events are concentrated in the Horn of Africa, the Sahel, and coastal Southern Africa. These patterns closely resemble our additive model (Figure 6). Areas in the Horn, Madagascar, coastal Mozambique, northern Nigeria, and southern Niger correspond with high vulnerability areas in our model. At the same time, there are limits to a simple visual comparison. For one, areas of high disaster

frequency in EM-DAT such as some regions in Kenya and South Africa are not reflected in our model.[33]

Having said that, EM-DAT may not be more accurate than our portrait of vulnerability. Both Kenya and South Africa may possess more developed media and freedom of the press and thus exhibit reporting biases in the frequency of the press reports. Moreover, frequency counts do not capture the severity of different disaster events in terms of consequences. Most EM-DAT events have some geographic data specified and include some estimates of casualties, deaths, and damages. However, the consequences are not connected to individual locations where multiple towns or provinces are mentioned, making it difficult to know how to distribute the losses. Indeed, some of the first administrative divisions are quite large, and it is highly likely that attaching each event to the entire geographic area overstates the extent of the damage.

Given the vagueness of the geographic details in EM-DAT, connecting EM-DAT events to first administrative units is still better than nothing. In short, this exercise to compare our model findings to EM-DAT is a rough first cut and, to the extent that it reveals weaknesses in EM-DAT methods, perhaps it will serve to impel EM-DAT's organizers to develop a more robust geo-coding methodology.

Still, these comparisons between our work and disasters and other climate related outcomes are important for us to assess the external validity of our models. Econometric work would also be a useful complement to the simple visual comparisons generated here.

[33] These results are confirmed when one compares the mean resilience scores by administrative region with the number of EM-DAT events in that region or the percent rank of the number of events.

Moreover, we should note that these analyses depict historical outcomes rather than future consequences of climate change. As we have written about elsewhere, the future geographic distribution of the number and intensity of climate related hazards may be very different from the past.[34] For this reason, as we mentioned earlier, we have also collaborated with climate scientists on a mid 21st century regional climate projection for Africa to identify which regions historically vulnerable to climate related hazards are likely to face similar exposure in the future.

Conclusions

CSVM 3.0, our new maps of climate security vulnerability, is a welcome advance over our previous methodology, benefiting from updated data sources, expanded subnational data, and a refined methodology for calculating and depicting vulnerability. Some areas, namely over the Horn of Africa, show persistent vulnerability across our models, both between and within iterations, and compare favorably with other data sources like EM-DAT. At the same time, we recognize that the stakes for getting this right are important, as resource allocation decisions for adaptation assistance may one day be related to estimates of the relative vulnerability of different regions. At the same time, we should recognize that these maps and the map-making process is an iterative conversation, meant to stimulate discussion about the priority areas in need of attention. The maps do not speak for

[34] Joshua W. Busby et al., "Of Climate Change and Crystal Balls: The Future Consequences of Climate Change in Africa," *Air & Space Power Journal Africa and Francophonie* no. 3 (2012): 4–44, http://www.airpower.au.af.mil/apjinternational/apj-af/2012/2012-3/eng/2012_3_05_Busby.pdf.

themselves and are not the final word, requiring a more intense deliberation with regional experts. We look forward to that conversation.

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[i] This helps capture chronic water scarcity quite for the following reason. For areas with low mean rainfall values near zero (like deserts), the value for the coefficient of variation will approach infinity. Small deviations in rainfall will generate large changes in the coefficient of variation.

[ii] The drought data are represented by a raster with values based on the six-month standardized precipitation index (SPI) according to the severity of drought in a given calendar year. If the SPI does not drop below -1 for at least three consecutive months, the value is set to zero. If the six-month SPI does drop below -1 for at least three consecutive months, the value is set to 1; if it is below -1.5 for at least two consecutive months, the value is set to 1.5. If both criteria are met, the value is set to 2.5.

[iii] We drew inspiration for this approach from (Koubi, Bernauer, Kalbhenn, & Spilker, 2012) who used a 30-year rolling average. We thought a short time frame would correspond to the living memory of people more readily than a longer time frame.

[iv] This is defined as the number of months between 1980-2009 in which the 6-month accumulated rainfall was 1.5 standard deviations or more below the average for that calendar month over the previous 20 years.

[v] In the previous iteration, we received data that suggested rainfall was too low to calculate the SPI or CV across wide swathes of area in the Sahara. Those areas were excluded from the physical exposure basket, lest they skew the rankings. Including those areas but recording a zero for them would have potentially indicated no physical exposure, which would not be right. They did not have enough rainfall to register droughts but were areas that faced perennial water scarcity. While they might not face changes in the climate, the climate conditions were already harsh.

[vi] For floods, we collapsed categories such that the high of 30–38 floods represented maximal vulnerability (a score of 0) and 0 floods represented no vulnerability (a score of 1). Between 27 and 29 floods received a value of 0.1 for floods, 24–26 floods 0.2, 21–23 floods 0.3, 19–20 floods .04, 17–18 floods 0.5, 13 or 14 floods 0.6, 10 floods 0.7, 7 floods 0.8, and 2 floods 0.9.

[vii] See viewfinderpanoramas.org. Data is mostly derived from the 2000 Shuttle Radar Topography Mission.

[viii] We manually excluded some interior areas that are of low elevation including the Afar Depression in Djibouti, the Danakil Depression in Ethiopia, the Qatarra Depression in Egypt, and Chott Melrhir in Tunisia.

[ix] See http://www.measuredhs.com/

[x] Global Climate Change Research Program (2011). Global Subnational Infant Mortality Rates ca. 2008. Environmental Indications and Warnings Project. Central Intelligence Agency. U.S. Government.

[xi] DHS administrative regional boundaries did not always correspond neatly to our level one administrative regions, with borders off slightly. We were able to match these in most cases by using the centerpoint of our regions and applying the value from the DHS regions to our shapes. In the case of Burkina Faso and Rwanda, the differences between DHS regions and our shapes were more severe, with multiple DHS regions corresponding to one of our regions. In such cases, we made a decision to apply a value to our shape that was roughly representative of the DHS values for those regions (for example, if there were three values, we took the intermediate one).

[xii] The weighting function is as follows: gen wt_evnts = $wgt\_events = \sum_{y=0}^{15} \frac{1+y}{16} events_{1997+y}$. This means that events in 2012 gets a full weight of 1 but that diminishes by 1/16 each year until 1997 which gets a weight of only 1/16.

[xiii] The other reason for using all level one administrative units was that the smaller the administrative unit that you use, the fewer events, all else equal, that were likely to take place in a given unit. If a reasonably large level one administrative unit has many conflict events distributed across it, using a smaller administrative unit would then divvy up that larger pool of conflict events among the smaller units, making it appear that a country was less conflict-ridden relative to other geographic units.

[xiv] In the 2.0 version of our modeling, areas with extremely low rainfall are represented by a separate category of 0. In the population density basket, unpopulated areas were represented by a separate category of zero. When we added all four baskets together for the composite map of overall vulnerability, these unpopulated areas were excluded. In CSVM 3.0, we were able calculate values for all indicators and the normalization procedure on a zero to 1 scale avoided the problem of having unpopulated areas dominate the upper quintile of the exposure basket. Thus, unpopulated areas are included in the analysis in 3.0.

[xv] (Busby, Smith, White, & Strange, 2013).