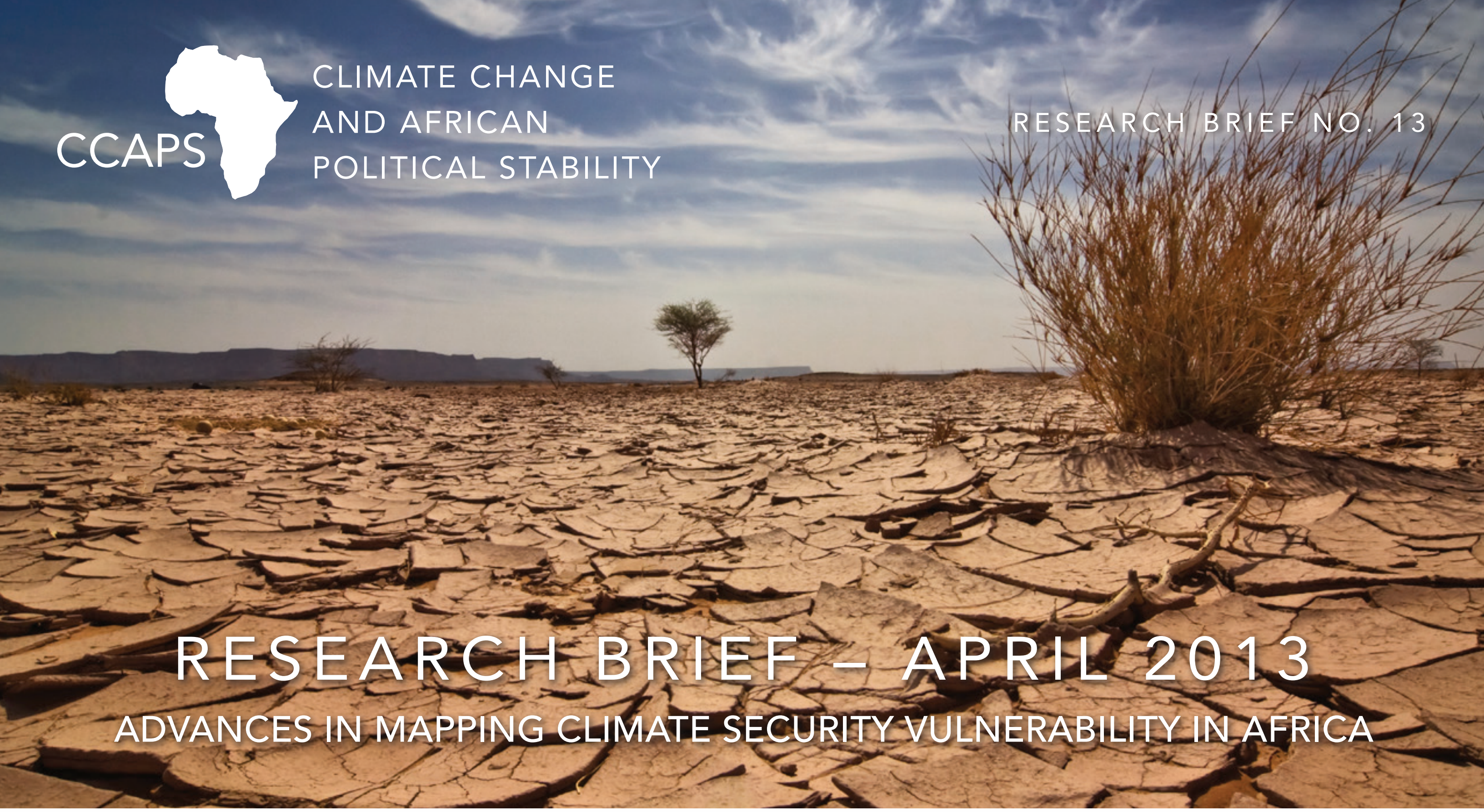

CCAPS CLIMATE CHANGE AND AFRICAN POLITICAL STABILITY

RESEARCH BRIEF NO. 13

RESEARCH BRIEF – APRIL 2013

ADVANCES IN MAPPING CLIMATE SECURITY VULNERABILITY IN AFRICA

EXECUTIVE SUMMARY

The CCAPS Climate Security Vulnerability Model identifies the locations of chronic vulnerability to climate security concerns in Africa. In development for several years, the latest version of the model incorporates updated and new data sources, scales the data in a new way to capture subtle differences in local vulnerabilities, and experiments with alternative formulas to determine how these various risk factors coalesce to impact local vulnerability. The model is also provisionally externally validated by comparing model results with the EM-DAT International Disaster Database. Aligning with the best available knowledge on disasters, the CCAPS model offers a nuanced way to model the security vulnerabilities associated with climate change in Africa and the potential intervention points to build resilience.

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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 differential 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.[1]

The continent of Africa is thought to be among the locations most vulnerable to climate change, given both high exposure to climate change and relatively low community resilience and governance capabilities.[2] However, even within Africa, vulnerability is not equally distributed. With climate change adaptation looming ever larger as an important policy area, decisions must 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.[3]

This CCAPS research aims to identify subnational locations of “climate security” vulnerability in Africa. Going beyond mere livelihoods-based analyses of vulnerability, this mapping project identifies the places where the worst consequences of climate change are likely to hit and put large numbers of people at risk of death. Such situations could become humanitarian emergencies that require the mobilization of emergency resources by local governments and donors alike, sometimes involving military mobilization by both or either to rescue affected people. Such situations may or may not escalate into incidences of armed conflict.

Over the past several years, CCAPS developed a model aiming to capture the factors that contribute to climate security vulnerability.[4] Now in its third iteration, the CCAPS model is called the 3.0 version of the Climate Security Vulnerability Model (hereafter CSVM 3.0). This policy brief details the advances in the underlying methodology in this third iteration of the model.

MAPPING CLIMATE SECURITY VULNERABILITY

The CCAPS model seeks to identify the places most likely vulnerable to climate security concerns within Africa at the subnational level. These are maps of chronic vulnerability, of places likely to be of perennial concern, rather than seasonal maps of emergent vulnerability like those produced by the Famine Early Warning Systems Network.[5] Unlike some global maps of vulnerability,[6] CCAPS maps are relative to the rest of Africa, rather than the rest of the world, and have an explicit security focus, emphasizing situations where large number of people could be at risk of death from exposure to climate related hazards.

The CCAPS model starts with four baskets or processes—physical exposure, population density, household and community resilience, and governance and physical violence—that capture the salient sources of vulnerability. Each of these baskets, save for population density, is composed of multiple indicators. Subnational data with fine-grained resolution were used wherever possible. The initial CCAPS model weighted each basket equally and created a composite index by adding the four baskets together.[7]

Version 3.0 of the CSVM incorporates a number of changes to the existing approach.

More Localized Data

First, CCAPS was able to integrate more subnational data in this iteration of the model. For a number of indicators, particularly in the household and community resilience basket, data from the USAID Demographic and Health Surveys (DHS) among other sources were used to calculate subnational indicators. As a result, the CSVM 3.0 includes subnational data for six of the eight indicators in the household and community resilience basket.

CCAPS maps are relative to the rest of Africa, rather than the rest of the world, and have an explicit security focus on situations where a large number of people could be at risk of death from exposure to climate related hazards.

Second, in previous iterations, the model relied on subnational boundary units from the Global Administrative Areas dataset.[8] For this version, drawing on the latest boundaries that were available from multiple sources, the team created a master set of updated administrative boundaries across Africa, typically corresponding to regional boundaries of states or provinces.

A New Scale

The five-category, one to five scale used in previous model iterations had some disadvantages. Collapsing vulnerability scores into five whole numbers resulted in lost information. Standardizing scores in this way made it easy to visualize the data, but it proved less useful for trying to understand if a particular score lay closer to one whole number or another. As a consequence, in the 3.0 version of the model, all indicators are normalized on a scale from zero to one, using either percent rank to convey where a value fell between the minimum and maximum for that indicator[9] or percentiles.[10] Here, a value of one reflects no vulnerability (high overall resilience) while a value of zero reflects maximal vulnerability (no resilience).

Functional Form

Though the team has prepared alternative versions of the model with different formulas to aggregate the data,[11] this policy brief presents a simple additive index, used in previous iterations of the model, and reflected by the equation:

$$\text{CSVM}_{\text{additive}} = \text{Climate Related} + \text{Population Density} + \text{Household Resilience} + \text{Governance}$$

INDICATORS IN CSVM 3.0

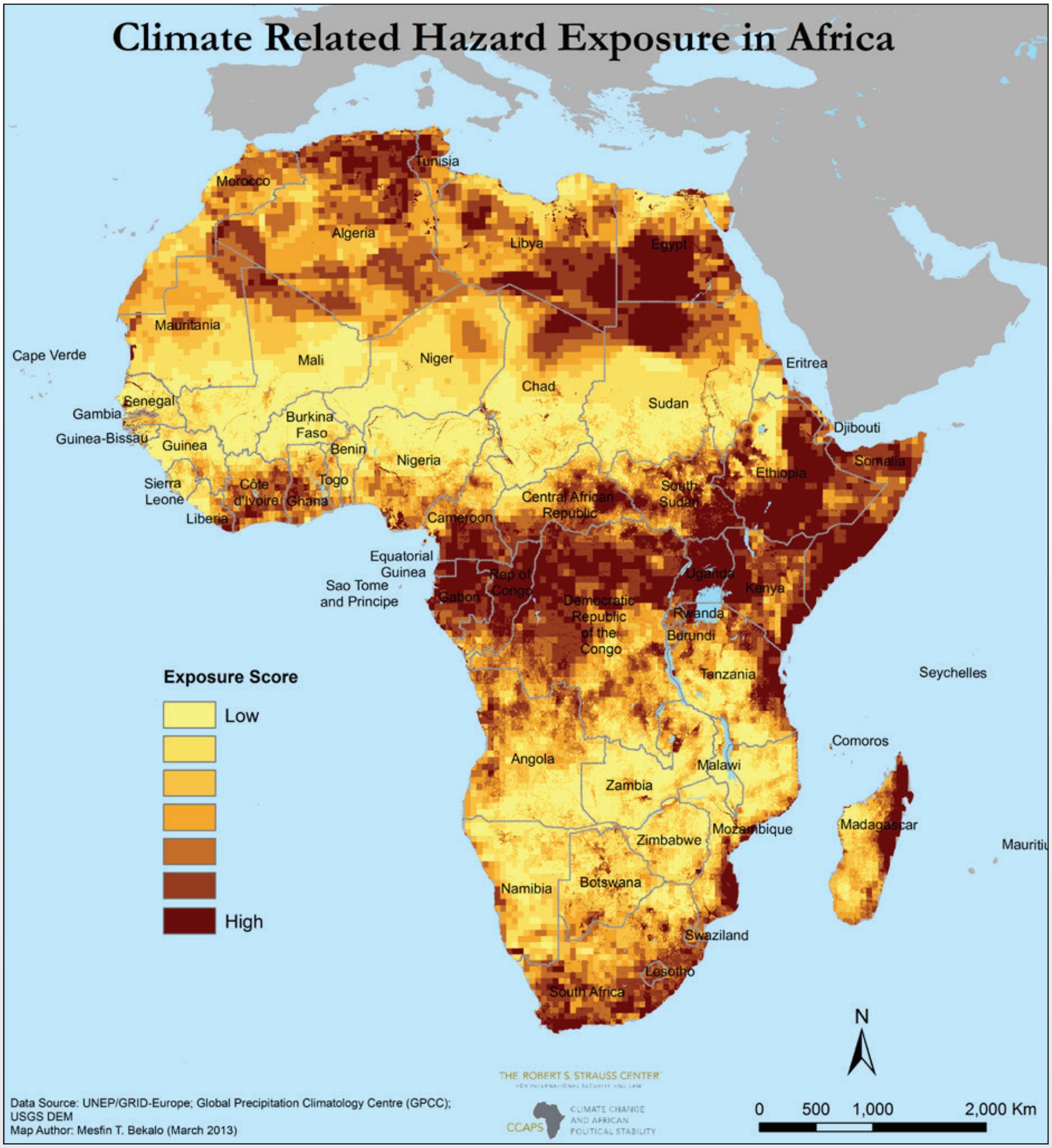
Climate Related Hazard Exposure

CSVM 3.0 includes indicators for rainfall anomalies, chronic water scarcity, cyclones, wildfires, floods, and low-lying coastal zones (see Appendix A).

In terms of rainfall-related indicators, the previous version relied on a count of events and intensity of the Standardized Precipitation Index over the entire period 1980-2004.[12] Rather than create a drought frequency count over the entire period of study, CSVM 3.0 uses *rainfall anomalies* of monthly observations of accumulated rainfall for the previous six months compared to a rolling twenty-year average for each calendar month. Thus, if the accumulated rainfall deviates strongly from the previous patterns over the last twenty years, this could have a major impact on the ability of farmers and other water users to plan, plant, and execute their operations, with potential follow-on consequences for food production. Using data from the Global Precipitation Climatology Centre (GPCC), the research team calculated whether or not a given six-month period deviated strongly from the twenty-year average for the same six months. A rolling six-month standardized precipitation measure of anomalies was calculated for the period 1980-2009.[13] While this indicator captures deviations from normal rainfall, the model also seeks to identify areas with *chronic water scarcity* by calculating the average monthly coefficient of variation.[14] Again, CSVM 3.0 uses GPCC data, updated for the period 1980-2009. Values across the entire continent were generated for both of these indicators.

For the *cyclone indicator*, CSVM 3.0 uses 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. It is measured in kilometers per year and provides values for the period 1970–2009. Previous versions of the model utilized data from UNEP/GRID-Europe on physical hazards. UNEP/GRID-Europe has since updated data sources, including *wildfires*. CSVM 3.0 includes a wildfires indicator for the period 1995-2011, which provides several additional years of data. In terms of the other indicators, the *flood* indicator and the *low-elevation coastal zones* indicator

Figure 1.

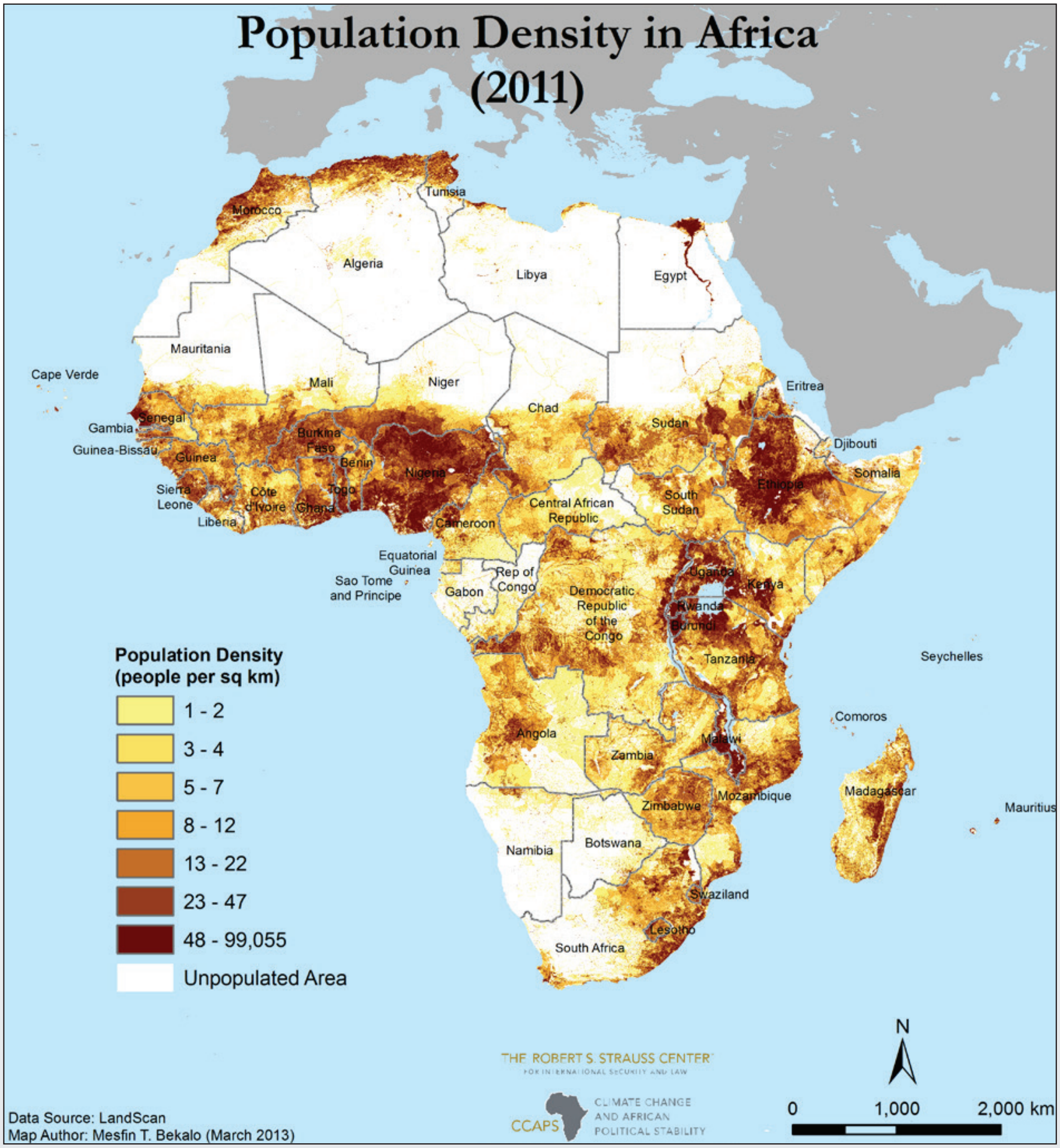


remained unchanged from the previous iteration of the model.

Given that both the *rainfall anomalies* and *chronic water scarcity* indicators were meant to capture similar phenomena related to the effects of changes in rainfall, CSVM 3.0 divides the weight between them. Where *floods*, *cyclones*, *wildfires*, and *low-lying coastal zones* indicators each represented 20 percent of the overall climate related hazard or physical exposure basket, that 20 percent was split equally between rainfall anomalies and chronic water scarcity.

Combining these six indicators into a single basket map of climate related hazard exposure yields a map showing a band of high physical exposure extending from Somalia through Ethiopia and South Sudan, extending across parts of the DRC and Congo, and including parts of Gabon and Cameroon. In North Africa, parts of Egypt and northern Sudan, along with parts of Tunisia and Algeria, face high exposure. In Southern Africa, the eastern edge of Madagascar, coastal Mozambique, and pockets in South Africa also face high exposure (see Figure 1).

Figure 2.



Population Density

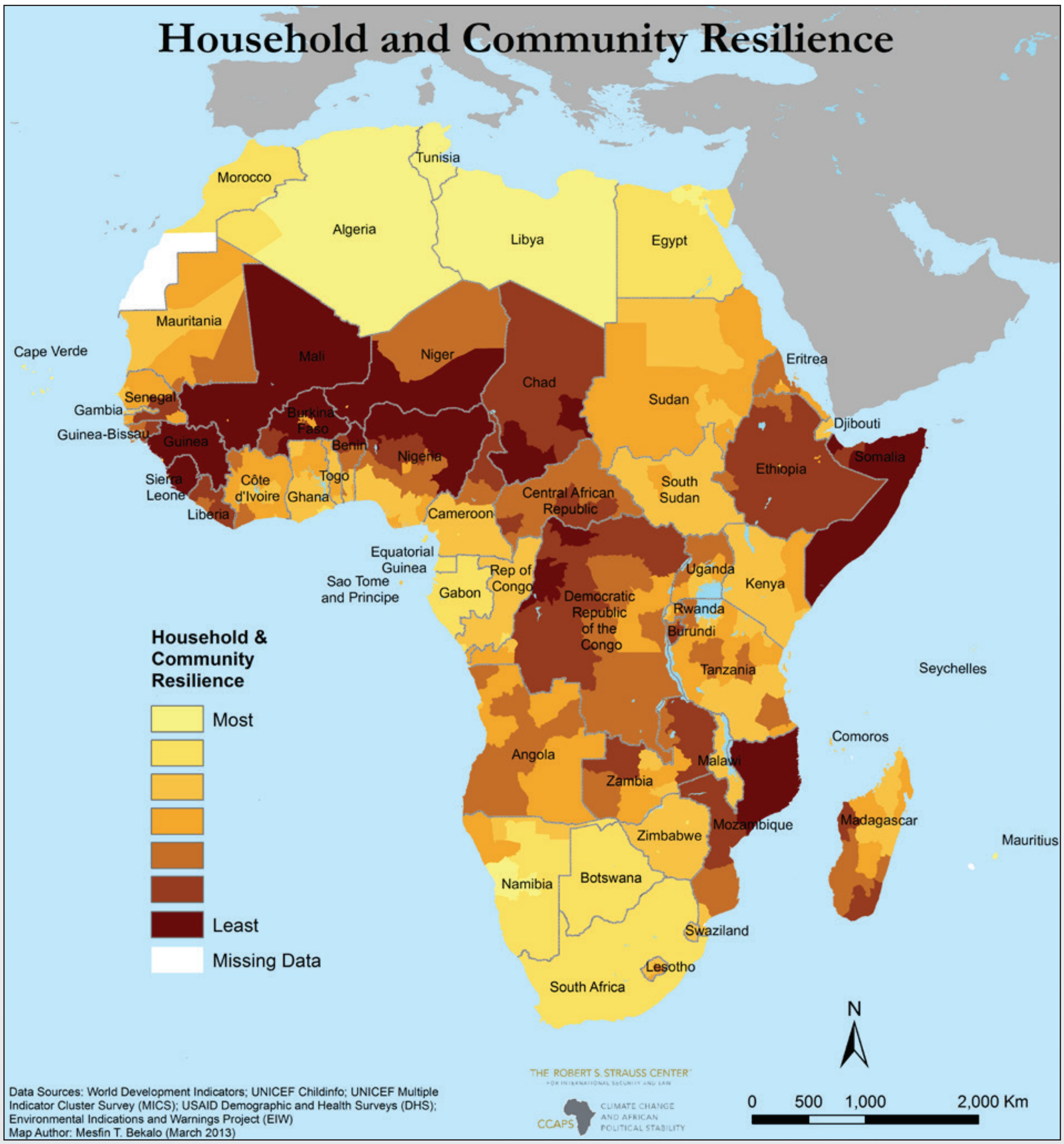
The version 3.0 of the model uses updated 2011 data for LandScan population density data, which were normalized into percentiles on a zero to one scale (see Appendix B).

As Figure 2 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 Figure 2, the range of the most densely populated areas (shown in dark brown) is enormous, from 48 people per square kilometer to 99,055 people per square kilometer.

Household and Community Resilience

This basket contains four categories of paired indicators for a total of eight indicators: two for education, two for health, two for access to daily necessities, and two for access to healthcare. In previous iterations of the model, only three of these indicators contained subnational information: infant mortality, underweight children, and access to

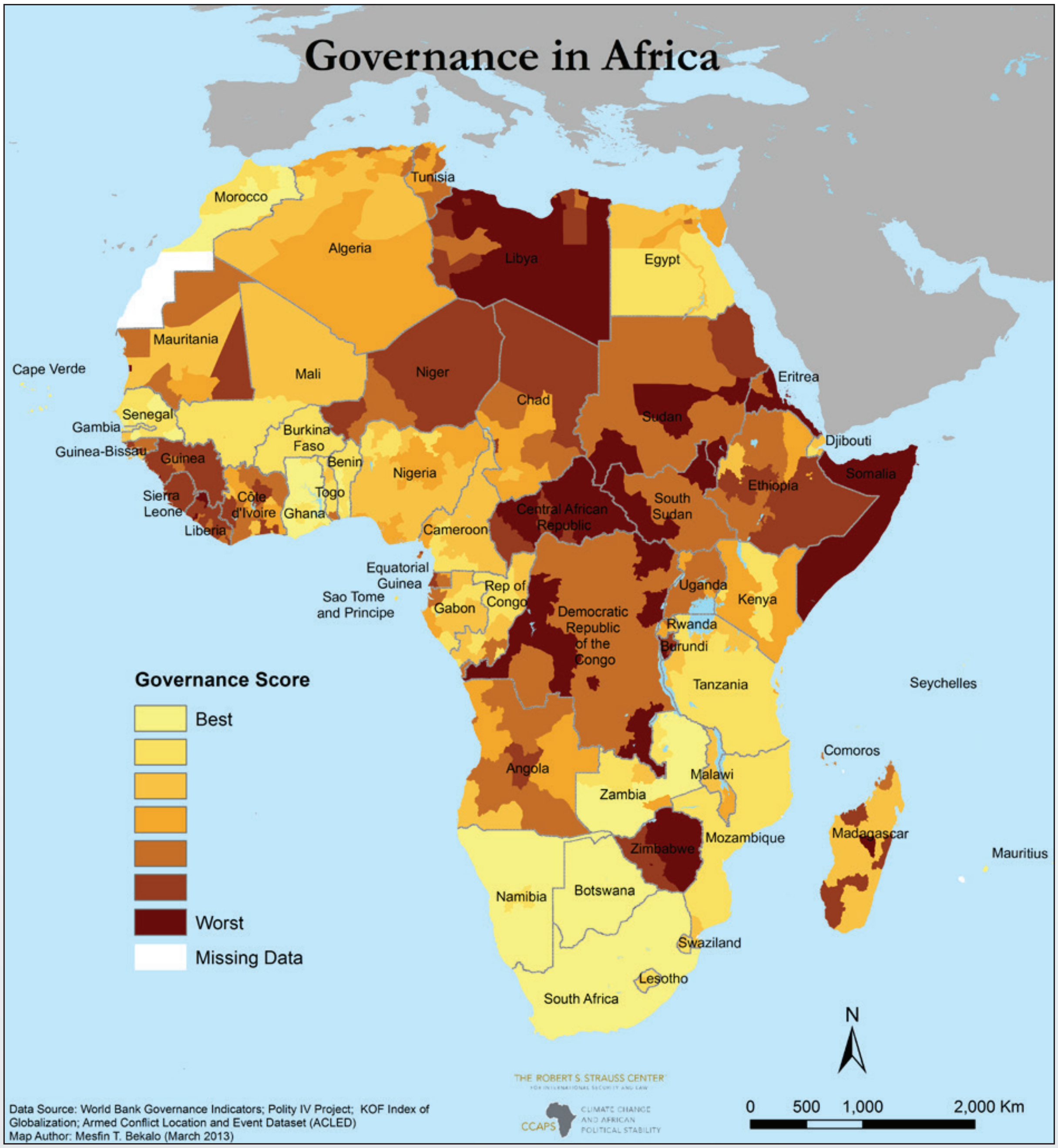
Figure 3.



improved drinking water sources. In this iteration of the maps, CCAPS obtained updated *infant mortality data*, normalized to the year 2008, from the Global Climate Change Research Program.[15] In addition, the team used new data from the USAID DHS program and the UNICEF Multiple Indicator Cluster Surveys (MICS) to derive new subnational indicators for *adult literacy* and *school enrollment* and to update indicators on *access to improved water sources* and *underweight children*. Finally, the new model uses subnational information for *delivery in health facility* from those same surveys, since delivery in a health facility is arguably a better proxy for access to health services than the national indicator of the number of midwives and nurses used in the previous model.[16] CSVM 3.0 thus uses subnational data for six of eight indicators in the household and community resilience basket (see Appendix C).

These data were converted into percent ranks and normalized on a zero to one scale. All four categories received equal weight in the index of 25 percent. Each indicator in the category thus receives 12.5 percent of the weight of the whole basket. In the event a particular indicator was missing

Figure 4.



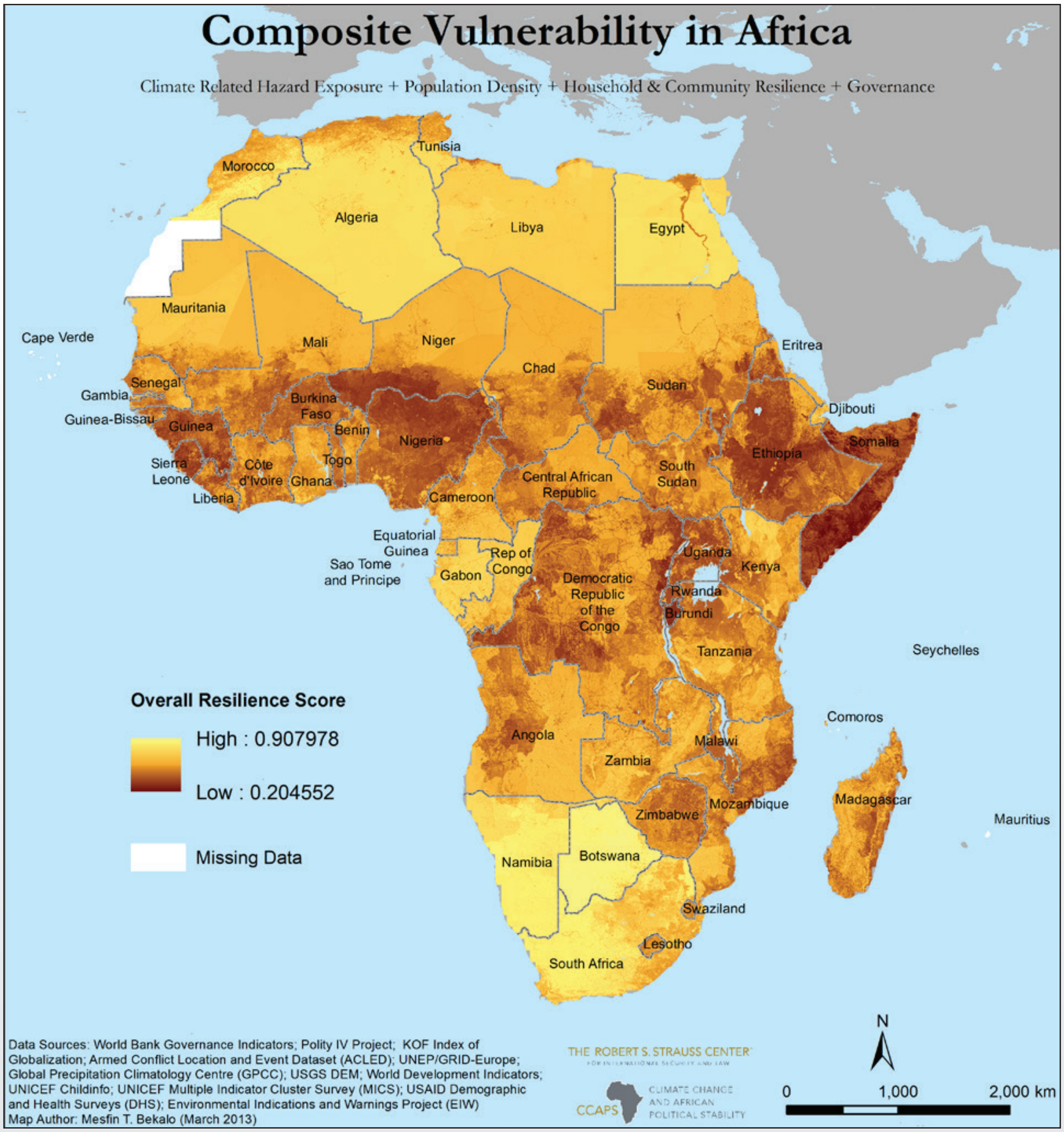
data, the other indicator takes on the full 25 percent category weight.

Combining all these indicators in a single map yields Figure 3, which shows that the areas with the least household and community resilience are located in Somalia, Nigeria, and across the Sahel. The most resilient areas (the areas where communities have the highest levels of education, better health conditions, and access to necessities and health services) are located on the island of Mauritius and primarily in North Africa, including Tunisia, Algeria, Egypt, and Libya.

Governance and Political Violence

The model contains five categories of indicators and six indicators, including government responsiveness, government response capacity, openness to external assistance, two indicators for political stability, and presence of violence (see Appendix D). Of these, only one contains subnational information. In CSVM 3.0, these indicators have been updated to include more recent data. In North Africa, this is particularly important since the region experienced historic transformations in political stability in the last year and a half.

Figure 5.



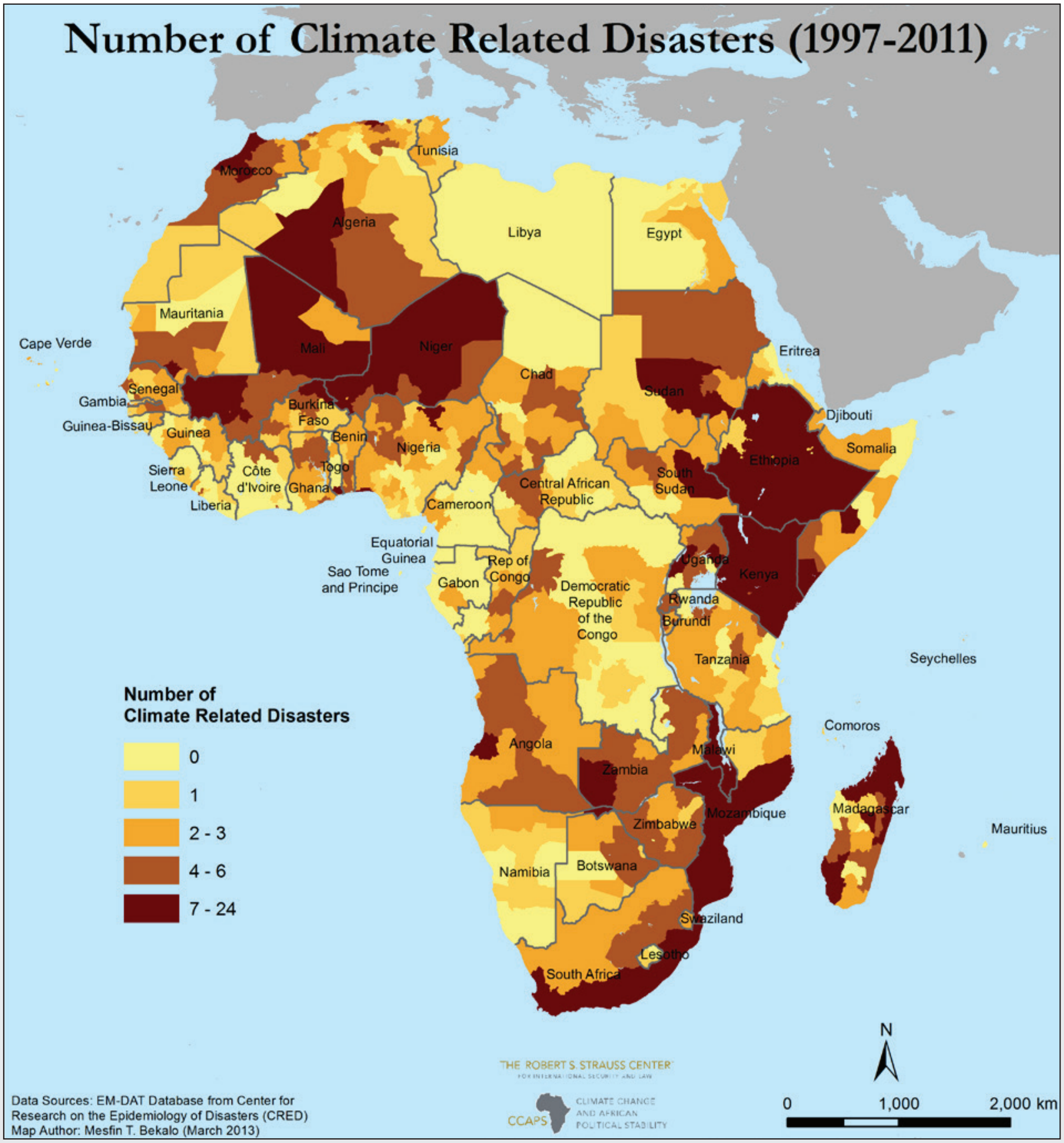
CSVM 3.0 uses indicators for *government effectiveness* and *voice and accountability* updated through 2011. These indicators are represented through a diminishing four-year weighted-average, with data for 2011 assigned the most weight, followed by data from 2010, 2009, and 2008.[17]

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

In terms of political stability, the new model takes advantage of the release of new Polity IV data through 2011. The indicator of *polity variance* now covers the period 2002-2011.

Finally, as before, the sole subnational indicator in this basket is for *political violence* from the Armed Conflict and Location Events Dataset (ACLED). The measure here encompasses all categories of ACLED events for the period 1997-2012. This iteration places more weight on recent events compared to more distant ones.[18] The sum of ACLED events are generated at the level one administrative unit.[19]

Figure 6.



Combining these indicators into a single map yields Figure 4. It shows that the areas with the worst governance include most of Somalia, pockets in both South Sudan and Sudan, parts of the DRC, much of Libya (picking up on civil war and political instability after the Arab Spring), and the Central African Republic. By contrast, areas with the best governance scores include several island countries (Mauritius, Cape Verde, and the Seychelles) as well as much of Botswana, pockets in Morocco (in the Sud region), Namibia, Ghana, and South Africa.

FINDINGS

The model combines all four baskets to produce a composite score, using the additive function used in the previous iteration of the model (see Figure 5).

Somalia, western Ethiopia, and pockets in West Africa (in and around Guinea and Niger) retain the high vulnerability recorded in earlier iterations of the CCAPS model. Northern Nigeria appears more vulnerable in this iteration, a function of more differentiated data on household resilience that shows low household resilience in the north. Patterns in the DRC are similar to earlier versions as well, though somewhat diminished, a function of a more nuanced way of representing the data.

As always, one of the more challenging questions is the extent to which the maps are indicative of any real phenomena in the world. Are the locations identified as most vulnerable the same ones that come up as vulnerable in other studies?

To answer this, it is necessary to find a relevant comparison set of data compiled by others for similar purposes. 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 the CCAPS model. The EM-DAT database records situations that already rise to a certain level of damage to be included in the database.[20] EM-DAT events include a variety of climate related "disasters."[21] The geographic coordinates in EM-DAT are not very precise, with a disaster location usually identified by a town or province name, several provinces or regions, or sometimes the country as a whole. CCAPS geo-coded these events for the period 1997-2012 by linking them to the CCAPS level one administrative regions, with individual events sometimes linked to more than one region or even the country as a whole.[22] Figure 6 shows the patterns in frequency of climate related disaster events in EM-DAT, which can be compared to the patterns in the CCAPS model.

The CCAPS model offers a nuanced way to model the security vulnerabilities associated with climate change in Africa and the potential intervention points to build resilience.

EM-DAT disaster events are concentrated in the Horn of Africa, the Sahel, and coastal Southern Africa. As in EM-DAT, areas in the Horn, Madagascar, coastal Mozambique, northern Nigeria, and southern Niger correspond to high vulnerability areas in CSVM 3.0.

There are, however, also areas of high disaster frequency in EM-DAT (such as some regions in Kenya and South Africa) that the CCAPS model does not show as being highly vulnerable. This underscores the limits to a simple visual correlation.[23] EM-DAT frequency counts do not discriminate between the severity of different disaster events in terms of consequences. Given the vagueness of the geographic details in EM-DAT, connecting EM-DAT events to level one administrative units is still better than nothing. In short, this exercise to compare the CCAPS model findings to EM-DAT is a rough first cut at validating the CCAPS model results. Aligning with the best available knowledge on disasters, the CCAPS model offers a nuanced way to model the security vulnerabilities associated with climate change in Africa and the potential intervention points to build resilience.

CONCLUSIONS

CSVM 3.0 is a welcome advance over 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 between iterations, and compare favorably with other data sources like EM-DAT. At the same time, 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. These maps and the map-making process are an iterative conversation, meant to stimulate discussion about the priority areas in need of attention. The maps do not speak for themselves and are not the final word, requiring a more intense deliberation with regional experts.

APPENDICES

APPENDIX A. INDICATORS USED TO ASSESS PHYSICAL EXPOSURE TO CLIMATE RELATED HAZARDS				
HAZARD TYPE (WEIGHT)	INDICATOR	SCALE	YEARS OF DATA USED	SOURCE
CYCLONE WINDS (20%)	Tropical cyclones average sum of wind speed (km per year)	2 km x 2 km resolution	1970-2009	UNEP/GRID-Europe
FLOODS (20%)	Flood Frequency (per 100 years)	1 km x 1 km resolution	1999-2007	UNEP/GRID-Europe
WILDFIRES (20%)	Number of Events	1 km x 1 km resolution	1995-2011	UNEP/GRID-Europe
CHRONIC WATER SCARCITY (10%)	Monthly coefficient of variation	0.5 degree x 0.5 degree resolution	1980-2009	Global Precipitation Climatology Centre
RAINFALL ANOMALIES (10%)	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 x 0.5 degree resolution	1980-2009	Global Precipitation Climatology Centre
COASTAL INUNDATION (20%)	Low-lying coastal areas within 0 to 10km above sea level	10 x 10 m resolution		USGS Digital Elevation Model

APPENDIX B. INDICATORS USED TO ASSESS POPULATION				
VARIABLE	INDICATOR	SCALE	YEARS OF DATA USED	SOURCE
POPULATION DENSITY	Ambient popluation (avergae over 24 hours)	Subnational at 1 km x 1 km resolution	2011	LandScan Oak Ridge National Laboratory

APPENDIX C. INDICATORS USED TO ASSESS HOUSEHOLD AND COMMUNITY RESILIENCE				
VARIABLE	INDICATOR	SCALE	YEARS OF DATA USED	SOURCE
EDUCATION (25%)	Literacy rate, adult total (% of people ages 15 and above)	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 data from WDI
	School enrollment, primary (% gross)	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 data from UNICEF
HEALTH (25%)	Infant mortality rate adjusted to national 2000 UNICEF rate	CCAPS First Administrative District	2008	Environmental Indications and Warnings project
	Life expectancy at birth (years) both sexes	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	National, CCAPS First Administrative District	DHS 199-2010, WDI 2000, 2004-2008, 2011	Subnational data from DHS; National data from WDI
	Population with sustainable access to improved drinking water sources total (%)	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 data from WDI
ACCESS TO HEALTHCARE (25%)	Health expenditure per capita (current US$)	National	WDI 2001, 2010	WDI
	Delivery in a health facility (% of births)	National, CCAPS First Administrative District	DHS 1999-2008, 2010, UNICEF 2003-2008	Subnational data from DHS, UNICEF; National data from UNICEF

APPENDIX D. INDICATORS USED TO ASSESS GOVERNANCE AND VIOLENCE				
CATEGORY	INDICATOR (WEIGHT)	SCALE	YEARS OF DATA USED	SOURCE
GOVERNMENT RESPONSIVENESS	Voice and Accountability (20%)	National	2008, 2009, 2010, 2011	WDI
GOVERNMENT RESPONSE CAPACITY	Government Effectiveness (20%)	National	2008, 2009, 2010, 2011	WDI
OPENNESS TO EXTERNAL ASSISTANCE	Globalization Index (20%)	National	2009	KOF Index of Globalization
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
PRESENCE OF VIOLENCE	All Conflict Events (20%)	CCAPS First Administrative Division	1997-2012	Armed Conflict Location and Events Database (ACLED)

ENDNOTES

1 A longer version of this paper with more detailed methodology was presented at the 2013 International Studies Association annual conference. Joshua W. Busby et al., "Climate Security Vulnerability in Africa Mapping 3.0" (presented at the International Studies Association Annual Convention, San Francisco, California, April 2013). http://strausscenter.org/images/pdf/Climate Security Vulnerability in Africa Mapping 3.0.pdf

2 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: Cambridge University Press, 2007), 433–467; 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.

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

4 CCAPS has published versions of the Climate Security Vulnerability Model in a variety of outlets, beginning with in-house working papers and policy briefs; see Joshua Busby et al., *Locating Climate Insecurity: Where Are the Most Vulnerable Places in Africa?* (Austin: Strauss Center for International Security and Law, 2010); and 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). The maps were then published in a series of papers and articles in journals and edited volumes, culminating in an article in the Spring 2013 issue of International Security; see 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 Human and Environmental Security and Peace, 8 (New York: 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: University for Peace, 2012); Joshua W. Busby, Kaiba White, and Todd G. Smith, Mapping *Climate Change and Security in North Africa* (Washington: German Marshall Fund of the United States, 2010); and Joshua W. Busby et al., "Climate Change and Insecurity: Mapping Vulnerability in Africa," *International Security* 37 (4) (2013).

5 See www.fews.net/Pages/default.aspx.

6 Maplecroft, for example, has produced a global climate vulnerability ranking at the subnational level; see 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; see David Wheeler, "Quantifying Vulnerability to Climate Change: Implications for Adaptation Assistance," *Center for Global Development*, 2011, www.cgdev.org/content/publications/detail/1424759.

7 In sensitivity tests, the assumption of equal weights was relaxed.

8 See www.gadm.org.

9 The CCAPS team 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).

10 Percentile reflects the percentage of scores below a certain number. The equation representing percentiles is total number of values below X / total number of values.

11 For example, the research team prepared a multiplicative version of the model, whereby the climate hazard basket was multiplied by the addition of the other three baskets. In that model, zero to low climate exposure causes the composite score to approach one or no vulnerability.

12 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.

13 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.

14 The coefficient of variation is the standard deviation divided by the mean. 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.

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

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

17 The value is a diminishing weighted average with 2011 assigned the most weight (.4), followed by 2010 (.3), 2009 (.2), 2008 (.1). The final indicator is then expressed in percent rank.

18 The weighting function is as follows: gen wt_evnts = ((1/16) * v5) + ((2/16) * v6) + ((3/16) * v7) + ((4/16) * v8) + ((5/16) * v9) + ((6/16) * v10) + ((7/16) * v11) + ((8/16) * v12) + ((9/16) * v13) + ((10/16) * v14) + ((11/16) * v15) + ((12/16) * v16) + ((13/16) * v17) + ((14/16) * v18) + ((15/16) * v19) + ((16/16) * v20). v5 is 1997 and v20 is 2012. 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.

19 The other reason for using all level one administrative units is that the smaller the administrative unit that used, the fewer events, all else equal, that are 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 divide 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.

20 For a disaster to be entered into the database, at least one of the following criteria must be fulfilled: ten or more people reported killed, one hundred or more people reported affected, a declaration of a state of emergency, or a call for international assistance. See www.emdat.be/criteria-and-definition.

21 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.

22 Special thanks to Madeline Clark for assisting with these efforts.

23 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.

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