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Identifying hot spots of security vulnerability associated with climate change in Africa

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Abstract Given its high dependence on rainfed agriculture and its comparatively low adaptive capacity, Africa is frequently invoked as especially vulnerable to climate change. Within Africa, there is likely to be considerable variation in vulnerability to climate change both between and within countries. This paper seeks to advance the agenda of identifying the hot spots of what we term "climate security" vulnerability, areas where the confluence of vulnerabilities could put large numbers of people at risk of death from climate-related hazards. This article blends the expertise of social scientists and climate scientists. It builds on a model of composite vulnerability that incorporates four "baskets" or processes that are thought to contribute to vulnerability including: (1) physical exposure, (2) population density, (3) household and community resilience, and (4) governance and political violence. Whereas previous iterations of the model relied on historical physical exposure data of natural hazards, this paper uses results from regional model simulations of African climate in the late 20th century and mid-21st century to develop measures of extreme weather events—dry days, heat wave events, and heavy rainfall days—coupled with an indicator of low-lying coastal elevation. For the late 20th century, this mapping process reveals the most vulnerable areas are concentrated in Chad, the Democratic Republic of the Congo, Niger, Somalia, Sudan, and South Sudan, with pockets in Burkina Faso, Ethiopia, Guinea, Mauritania, and Sierra Leone. The mid 21st century projection shows more extensive vulnerability throughout the Sahel, including Burkina Faso, Chad, Mali, northern Nigeria, Niger, and across Sudan.

Aside from low-lying island nations, Africa is frequently invoked as the part of the world most vulnerable to climate change (Low 2005; Boko et al. 2007). Subnational differences in vulnerability within countries are likely to be as significant as between countries.

The policy community has frequently invoked concerns about the capacity of climate change together with other causes to contribute to conflict and state failure (CNA

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Corporation 2007; Campbell et al. 2007; Solana 2008; Fingar 2008; UN Security Council 2007). While the precise connections between climate change and security remain contested (Burke et al. 2009; Buhaug 2010; Feng et al. 2010; Hsiang et al. 2013), identifying the areas most vulnerable to the security consequences of climate change is an important area for both scholars and practitioners. With the countries most vulnerable to climate change potentially eligible for millions of dollars in adaptation funding, identifying the countries and areas within countries that are likely most vulnerable to climate change has taken on added significance (Friedman 2010; de Sherbinin 2014).

This paper seeks to advance the agenda of identifying the hot spots of security vulnerabilities associated with climate change, areas where the confluence of vulnerabilities could put large numbers of people at risk of death from climate-related hazards. It blends the expertise of social scientists and climate scientists.

Previous iterations of this composite vulnerability model relied on historical physical exposure data to climate-related hazards (Busby et al. 2011, 2012, 2013). The major innovation in this paper is the incorporation of results from a coupled Atmosphere-Ocean General Circulation Model (AOGCMs) and a regional climate model (RCM) to generate state-of-the-art projections of late 20th century and mid-21st century indicators of extreme weather events to define the physical exposure basket.

The RCM projections enable us to identify whether areas of future exposure to climate-related hazards are likely to be similar to those that occurred with historic exposure. They use projections of future climate derived from AOGCMs to constrain the lateral boundaries and specify future sea surface temperature, but provide more fine-grained and realistic representations of African climate than are available through AOGCMs.

In this paper, we isolate the likely effects of future climate change on vulnerability by looking at the impact of changes in projected exposure to climate-related hazards. Security vulnerability composites are generated for the late 20th century and mid-21st century with only indicators associated with the physical exposure basket generated by the RCM allowed to change. With all other indicators and baskets held constant, this study therefore addresses how we expect climate change to affect Africa's vulnerability.[1]

The *first section* outlines our definition of security vulnerabilities associated with climate change and describes the methodology. The *second section* describes the regional climate model used to generate the historical and future projections of extreme events that can influence security vulnerability. The *third section* presents our results.

1 Defining and modeling the security vulnerabilities associated with climate change

The literature on vulnerability is diverse with no standardized approach across disciplines. Some scholars focus on physical exposure alone, while others emphasize social factors. Some approaches embed vulnerability in a broader definition of risk, captured by the equation risk= vulnerability×hazard exposure. Many focus on susceptibility to losses, with a strong emphasis on livelihoods (Brooks et al. 2005; Brenkert and Malone 2005; Alcamo et al. 2008; Cardona 2004; Füssel and Klein 2006; Weichselgartner 2001; Alexander 2009).

Here we are interested in a particular understanding of the security vulnerabilities associated with climate change. *By that, we mean situations where large numbers of people could possibly die as a result of exposure to climate-related events.* Whereas most of the literature

[1] This model does not include indirect effects of climate-related extreme events on mortality through changes in diseases such as malaria or meningococcal meningitis.

on climate change and security has focused on the connections between climate change and violent conflict,[2] we are interested in a broader set of security outcomes that include but are not limited to violent conflict. More generally, we seek to identify areas where household and community resilience is overcome and the capabilities of civilian disaster authorities are exceeded requiring the mobilization and diversion of domestic and/or international military response for humanitarian relief purposes.

Existing efforts to model climate hot spots such as the DARA Climate Vulnerability Monitor, the Notre Dame Global Adaptation Index (ND-GAIN), the Maplecroft Climate Change Vulnerability Index, and the OneWorld consultancy often have a different focus.[3] Many focus on effects on livelihoods rather than security outcomes. Some like the ND-GAIN Index map national level rather than subnational hot spots. Some like the Maplecroft Index are subscription-based and somewhat opaque about their data choices and methodology.

Our methodology was informed by previous vulnerability studies, especially Brooks et al. who used Monte Carlo simulations and expert opinions to identify key contributors to climate vulnerability (Brooks et al. 2005; Adger et al. 2004). We also drew inspiration from Levy et al. who incorporated both political stability and physical exposure to climate hazards (Levy et al. 2005) as well as work by (Wheeler 2011; Raleigh et al. 2008; Brenkert and Malone 2005).

Our modeling efforts have been iterative, with the aim of finding more fine-grained sub-national indicators to replace national level indicators. We have externally validated the work through extensive fieldwork as well as sensitivity analysis, which has also led us to make several updates to the model (Busby et al. 2013; Berenter 2012).

Following the work of the IPCC, vulnerability to climate change is more than a function of physical exposure. Two locations may face identical physical exposure to a climate-related hazard but have widely divergent overall vulnerability because different demographic, social, and political conditions may enhance their sensitivity and coping capacity (IPCC 2007).

For these reasons, our model presents a composite index of vulnerability that combines four “baskets” or processes—physical exposure, population density, household and community resilience, and governance and political violence—thought relevant to an area’s overall vulnerability. The results of the index analysis are used to produce maps of vulnerability at the subnational level. This mapping reflects not only which countries should be of concern, but also which locations within countries. Given our interest in identifying places where large numbers of people might die from exposure to climate-related hazards, these maps thus represent proxies of deaths per area rather than the death risk per person.

Unlike the Famine Early Warning Systems Network (FEWSNET) maps of seasonal vulnerability, the maps reflect what Burg called “chronic vulnerability,” the places that consistently possess a confluence of characteristics that make them vulnerable to having large numbers of people at risk of death in the event of exposure to a climate-related hazard (Burg 2008).

We briefly describe the intuitions and data sources below. A more extended technical discussion is available in supporting information and is detailed in (Busby et al. 2013). A discussion of the model construction, data layers, including the option to zoom in are available in an on-line data dashboard.[4]

[2] The January 2012 special issue of the *Journal of Peace Research* is dedicated to assessing the links between climate change and conflict.

[3] DARA Climate Vulnerability Monitor is found at http://daraint.org/. The ND-GAIN Index is available at http://index.gain.org. The Maplecroft index is available at http://maplecroft.com/. The OneWorld is found at http://www.oneworldgroup.co.za/. For a survey of hot spot climate mapping exercises, see (de Sherbinin 2014).

[4] See http://ccaps.aiddata.org/climate

1.1 Physical exposure to climate-related hazards

The base of any climate change vulnerability model ultimately must be physical exposure. Because we are interested in the effects of climate change that could potentially put large numbers of people at risk of death, we focus on climate-related extreme events. For example, the Emergency Events (EM-DAT) International Disaster database estimates that three of the most prevalent extreme weather events types associated with climate-related disasters over continental Africa are droughts, flooding associated with excessive rainfall, and heat waves (CRED 2012). Based on this information three indicators are developed and used; each a proxy for these different weather events. We also include a measure of low-elevation coastal exposure to take into account areas subject to coastal inundation. How these indicators are defined based on the regional climate model projections is discussed in Section 2.

1.2 Population density

All else equal, larger human populations living in physically exposed areas are likely to command more attention from decision-makers than scarcely populated regions. We elected to use Landscan's map of population density in 2008 because it seemed to offer more fine-grained data than alternatives.[5]

1.3 Household and community resilience

In the event of physical exposure, the first line of defense for many communities will be the availability of local resources. Communities exhibit different levels of resilience—the ability to cope with adversity. While income might be a good proxy for local capability, limited subnational income data is available. Indicators were ultimately selected after drawing largely on the simulations and expert reviews of Brooks et al., though we consolidated the number of indicators as they included two highly correlated school enrollment measures as well as two related measures of malnutrition (Brooks et al. 2005). We include eight different measures of attributes of health, education, and access to services. Data for these indicators have irregular temporal and geographic coverage and draw from diverse sources.[6] We sought subnational data where possible, ultimately finding subnational data for infant mortality, child malnutrition, and access to improved water sources (see Supplementary Table 1). Unlike the physical exposure and population baskets, the subnational information for these indicators is only available at the admin 1 or provincial-level.

1.4 Governance and political violence

When the severity of a climate-related event exceeds the capacity of households and communities to cope, governance—the willingness and ability of the government to aid communities in times of need—becomes critical. Drawing on indicators from the World Bank, Polity IV, the Swiss Economic Institute (KOF) Index of Globalization, and the Armed Conflict Location and Events Dataset (ACLED), we include five measures of governance capacity and responsiveness and political violence, only one of which, ACLED, is subnational (see Supplementary Table 2). Because so much of this basket is based on national-level data, the influence of

[5] In earlier iterations, we relied on the Global Rural–urban Mapping Project (GRUMP). LandScan (2008)™ High Resolution global Population Data Set copyrighted by UT-Battelle, LLC, operator of Oak Ridge National Laboratory under Contract No. DE-AC05-00OR22725 with the United States Department of Energy.

[6] Sources include World Development Indicators, Columbia University's Center for International Earth Science Information Network, and USAID Demographic and Health Surveys among others.

governance creates sharp discontinuities at country borders that may be an artifact of modeling rather than a reflection of reality (de Sherbinin 2014, 33). The difference for example between northeastern Kenya and southern Somalia may be less stark than our maps portray.

Because each of the indicators in this vulnerability model is initially measured using different scales, the first step is to standardize the values based on quintiles, from the least vulnerable 20 percent to the most vulnerable 20 percent. All of the variables within a given basket of vulnerability are then summed and mapped to create composite maps for *physical exposure to climate-related hazards*, *household and community resilience*, and *governance and political violence. Population density* consists of a single indicator and is mapped individually. The final maps are classified into quintiles where areas in Africa are compared relative to the rest of the continent.

In the initial iteration of the composite, the four baskets are then summed together to create a composite vulnerability map. Following conventions in the field of vulnerability studies, the four baskets are initially equally weighted in the index. In most circumstances, indicators within baskets are also assigned equal weights. In the absence of an empirical rationale for weighting indicators differently, the equal weights assignment was the least arbitrary, though our on-line tool allows users to adjust basket weights.[7] In supplementary material, we present a multiplicative variation where physical exposure is multiplied by the sum of the three other baskets as a way of comparing with common approaches in risk management. As is common in composite indices, the vulnerability model does not have an econometric basis, as the data come from different years and different scales of resolution, making statistical analysis problematic, though we have attempted to bootstrap an econometric model.

2 A regional climate model for Africa

The climate change projections used in this study result from the integrated application of AOGCMs and a RCM. The RCM used is the National Center for Atmospheric Research/ National Oceanic and Atmospheric Administration (NCAR/NOAA) Weather Research and Forecasting (Skamarock et al. 2005) regional model. Future lateral and surface boundary conditions for the regional model are derived from simulations using AOGCMS[8] that were run in support of the Intergovernmental Panel on Climate Change's (IPCC) Fourth and Fifth Assessment reports (AR4 and AR5, respectively). While the horizontal space scales of AOGCMs, generally about 150 to 200-km, are not ideally suited to evaluate regional changes in extreme weather events (Crétat et al. 2013), they provide information about large-scale changes in the atmosphere and ocean that are needed for constraining the regional model simulation. In addition to providing finer resolution than the AOGCMs, regional modeling allows one to select model physical parameterizations that work well in the region of interest, in this case over Africa.

An ensemble regional modeling approach is used to improve the reliability of the simulations and provide a tool for evaluating confidence. Two ensembles, each consisting of 6 year-long climate-mode ensemble members,[9] are constructed and run using a 90-km domain that

[7] For the virtues of equal weights in composite indices, see (Stapleton and Garrod 2006, 2007). For the problems with equal weight-based indices, see (Chowdhury and Squire 2005).

[8] The 9 AOGCMs used are CGCM3.1, CNRM-CM3, ECHAM/MPI-OM, GFDL-CM2.0, MIROC3.2 (medres), MRI-CGCM3.2, NCAR CCSM3, NCAR PCM, UKMO-HadCM3. The process is detailed in (Cook and Vizy 2012).

[9] Climate-mode boundary conditions include seasonality, but filter out shorter timescales. This process has been shown to be an effective approach to understand climate variability over Africa in other studies (e.g., Vizy and Cook 2002; Patricola and Cook 2007, 2010). A detailed description on the climate-mode ensemble design methodology is provided in (Cook and Vizy 2012).

extends from 61°W to 101°E and from 52°S to 60°N. The first ensemble represents the late 20th century (1981–2000). Initial, surface, and lateral boundary conditions are derived from the 1981–2000 monthly climatology of the National Centers for Environmental Prediction reanalysis 2 (Kanamitsu et al. 2002) linearly interpolated to form the six-hourly conditions needed as described in (Cook and Vizy 2012). Each ensemble member differs only in their initial conditions.

The second ensemble represents the mid-21th century (2041–2060) under the IPCC AR4 mid-line A1B emissions scenario. CO_2 concentrations are adjusted from late 20th century values to 536 ppmv, which represents the 2041–2060 average under the A1B emissions scenario. Initial and lateral boundary conditions are derived by taking AOGCM anomalies, calculated as the differences between monthly-mean, A1B-forced simulations averaged over 2041–2060 and monthly-mean historical simulations averaged over 1981–2000, adding them to the NCEP2 reanalysis climatological monthly values, and linearly interpolated to form the 6-hourly values needed.

It is shown (Cook and Vizy 2012) that the regional model run in this manner (i.e., climate-mode) can realistically simulate the African climate system, including the seasonal evolution of rainfall, important large-scale and regional circulation features, and even the number of growing season days. This includes the boreal summer migration of rainfall into the Sahel, which AOGCMs typically do not realistically represent (Cook and Vizy 2006). Furthermore, the late-20th century ensemble captures the observed distribution of extreme events over Africa (Vizy and Cook 2012). Thus, these ensemble simulations are suited to provide state-of-the-art regional projections of extreme weather for the future for use in assessing security vulnerability.

As discussed in Section 1, three indicators of extreme weather are calculated from the RCM output and used to form the physical exposure basket. Each is discussed below.

The *number of dry days*, i.e. the number of days per year when the daily rainfall rate is less than 1 mm for at least 21 consecutive days, is used to approximate drought. Unlike other comparable dryness measures (Frich et al. 2002; Tebaldi et al. 2006), the days need not all be consecutive as the simulation design is not appropriate for evaluating dry periods that extend multiple years (See Fig. S2–S4).

At the opposite end of the extreme rainfall continuum, the *number of extreme wet days* is the number of days per year when the daily rainfall rate exceeds a threshold of the 95th percentile of wet days (Frich et al. 2002; Zhang and Fang 2004). Here a wet day is defined as when the daily rainfall is greater than or equal to 1 mm. The 95th percentile corresponds to the 20-year recurrence interval (See Fig. S5–S7). The 95th percentile threshold for the historical ensemble is calculated and then is utilized to evaluate the future projections.

A *heat wave* is defined from the RCM output by calculating the daily maximum apparent temperature (Steadman 1979; Steadman 1984), which factors into account the impact of atmospheric moisture and wind speed, and evaluating when this human-perceived equivalent temperature exceeds 41 °C for at least 3 consecutive days. The threshold of 41 °C represents the point when heat exhaustion is likely, with heat stroke probable with continued activity based on the U.S. National Weather Service scale. A duration of at least 3 consecutive days is chosen based on evidence that mortality is more likely by the third day under such conditions (Kalkstein and Smoyer 1993) (See Fig. S8–S10).

Each of the three indicators were converted in ArcGIS to raster files and classified into quintiles, with 1 being the least exposed to the hazard and 5 being the most exposed to the hazard.

In order to represent future risk from rising sea levels, this study used a digital elevation model (DEM) to extract the 1–10 m coastal zone for all of Africa. We selected all cells with values 1–10 and then excluded areas clearly not contiguous to the coast to increase accuracy. It is possible, however, that a few low-lying areas included in the final low-elevation coastal zone dataset would be protected from rising sea levels and storm surges by higher elevation land along the coast. We assigned areas in the 1–2 m coastal elevation zone a value of 5, areas in the 3–4 m zone a value of 4, areas in the 5–6 m zone a value of 3, areas in the 7–8 m zone a value of 2, and areas in the 9–10 m zone a value of 1. The DEM resolution is 30 arc sec (1 km) (USGS 2009) (see Fig. S11).

We summed the four final rasters for exposure to each type of climate-related hazard, with 1–5 scores, to create a composite score of physical exposure to climate-related hazards. The quintile ranking system enabled the combination of different types of events without regard to how their frequency was measured. Each type of exposure received equal weight, so the final equation for exposure was as follows: Exposure to climate-related hazards=dry days+heavy rainfall days+heat wave days+low elevation coastal zone. The highest possible value was 20 and the lowest was 3. We classified this composite raster by quintiles as well and reclassified once more on the 1–5 scale.

In the representations of the three extreme event indicators, unpopulated areas are excluded in the security vulnerability assessment, though the RCM generates projections for these regions. The rationale is that unpopulated areas in the Sahara and the Kalahari Desert would dominate the upper quintile of the physical exposure basket, biasing the ultimate results towards unpopulated areas. Because the goal was to capture the vulnerability of habitable areas, rather than create a mask excluding the unpopulated areas in the final composite map, we excluded these data points from the calculations in the physical exposure basket and the final composite.[10]

3 Results

In this section, we focus first on the changes in the physical exposure basket before turning to the composite vulnerability model (See Text SI for more detailed information).

3.1 Changes in the physical exposure basket

For the late 20th century (Fig. 1), we find the most exposed areas to be concentrated along the southern border of the Sahara extending from Senegal to Mali, the eastern edge of Niger into Chad, as well as much of Sudan and South Sudan.

By the mid-21 century (Fig. 2), the Sahel band of high exposure is projected to widen and become more extensive from the coast of West Africa across to Sudan. Pockets within Mozambique, Malawi, and Zimbabwe are also projected to become more exposed to extreme weather events.

This increase in projected exposure is visible in the following *change* map (see S1). The increasing vulnerability over southern Africa, extending from Angola across to Mozambique and south, is found to be associated with a projected increase in the number of dry days, with parts having as many as 36 to 86 additional dry days a year, and an increase in the number of heat waves.

The increasing exposure over the Sahel (along the southern border of the Sahara desert) is driven largely by increases in the number of heat wave events projected to increase by more than 100 days a year, from a base of between 26 and 74 days a year (see Figure 6 in Vizy and Cook 2012) in addition to an increase in the number of extreme rainfall days (see Figure 10 in

[10] It is possible that some currently unpopulated areas will become habitable as a result of climate change.

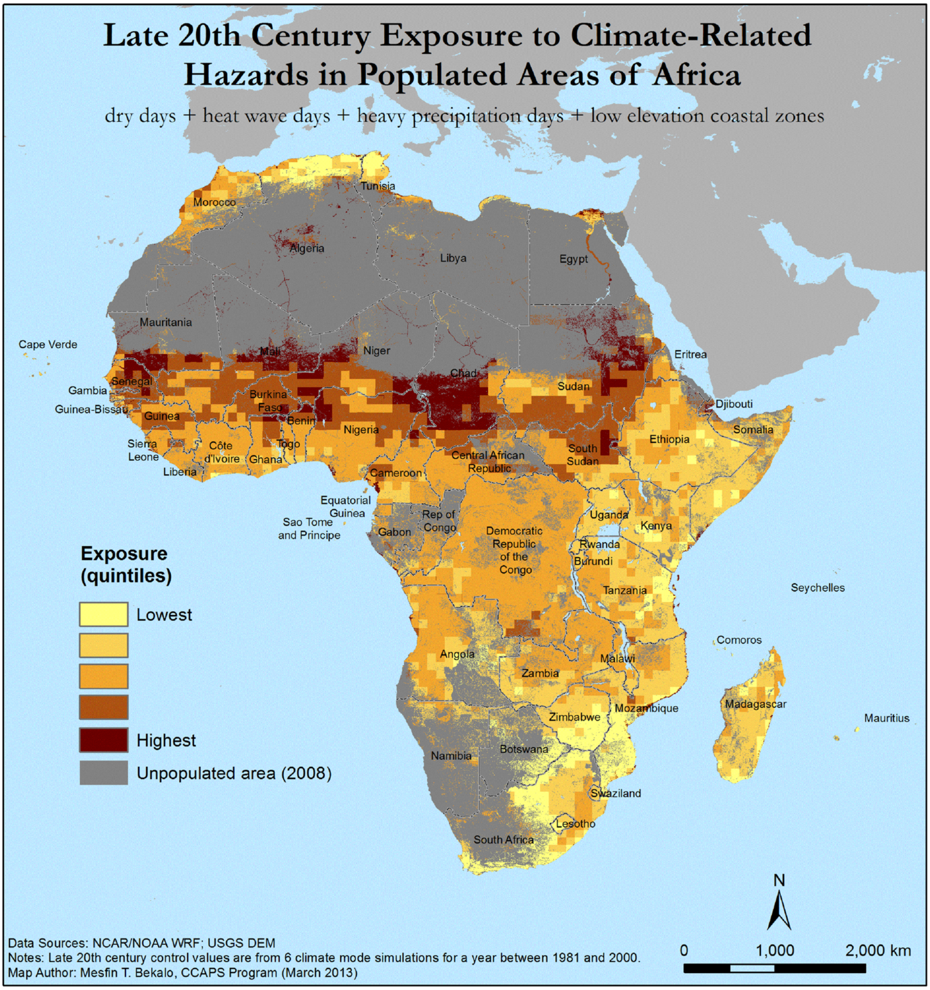

Fig. 1 Late 20th century simulation

Vizy and Cook 2012). Across the Sahel, the number of dry days is projected to change marginally, but for much of the region, more than two-thirds of the year will be dry. Coastal West Africa's increasing exposure is a function of an increase in heavy rainfall days, with the number of days of rainfall falling above the late 20th century threshold for the 95th percentile increasing from approximately 8 days to between 11 and 25 days a year for many areas. Areas of decreased exposure include much of the DRC which is projected to have fewer dry days (between 36 and 54 fewer dry days over much of the north) as well as fewer heavy rainfall days (between 4 and 8 fewer heavy rainfall days over various regions).

3.2 Composite vulnerability

The exposure maps are then combined with the other three baskets—population density, household and community resilience, and governance and political violence—to create a composite index of vulnerability (see Fig. S12–S14 for maps of each of these other baskets).

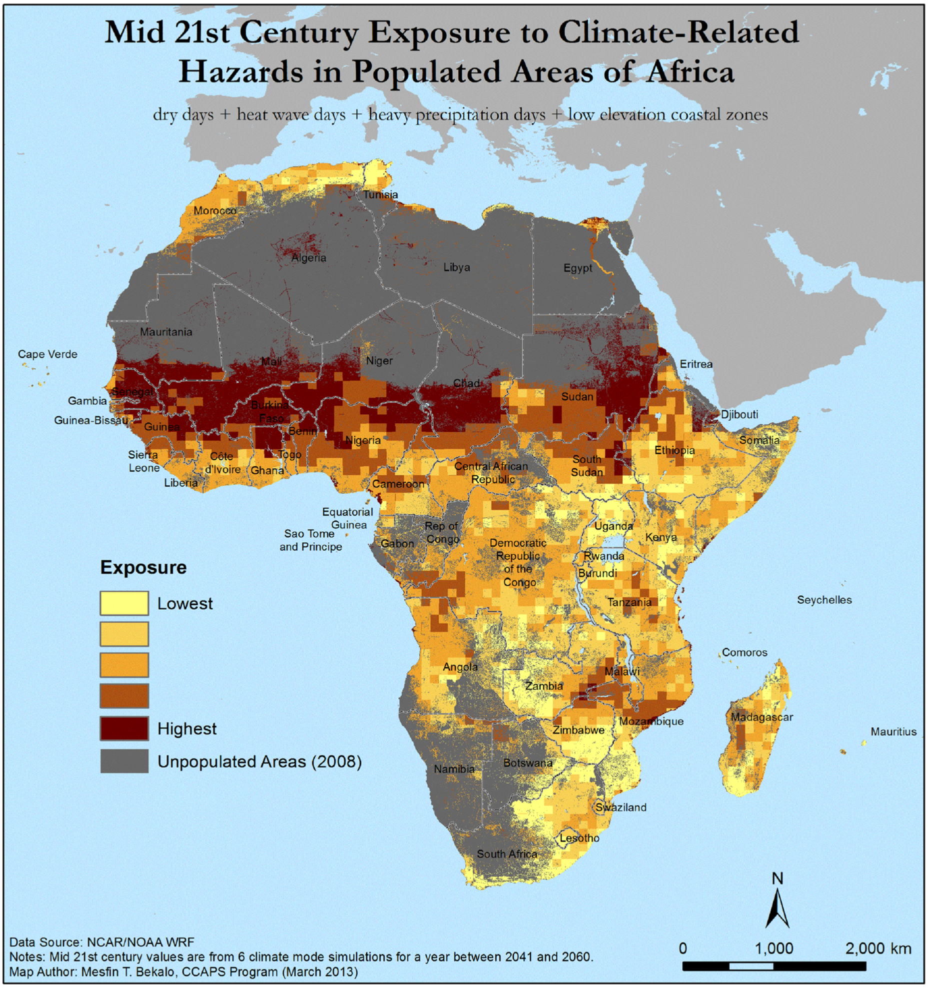

Fig. 2 Mid 21st century projection

Given that we are interested in isolating the expected effects of climate change on overall vulnerability, we hold all three of the other baskets constant.

3.2.1 Late 20th century simulation

The supplementary materials show that the vulnerable areas are concentrated in Chad, the Democratic Republic of the Congo, Niger, Somalia, Sudan, and South Sudan, with pockets in Burkina Faso, Ethiopia, Guinea, Mauritania, and Sierra Leone. The least vulnerable regions for the late 20th century were countries in southern Africa and along the Mediterranean (see Fig. S15).

3.2.2 Mid-21st century projection

The mid 21st century projection shows more extensive vulnerability throughout the Sahel belt in West Africa, including Burkina Faso, Chad, Mali, northern Nigeria, Niger, across through

Sudan and western Ethiopia (see Fig. S17). Throughout West Africa, worsening vulnerability is driven in particular by increases in the projected number of heat wave days and in coastal areas by heavy precipitation days. Increases in the projected number of dry days and the number of heavy rainfall days in northern Ethiopia are largely responsible for the deterioration in vulnerability in that part of the country. Areas within Malawi, Mozambique, and Zimbabwe are also projected to become more vulnerable, largely a function, as noted above, of increases in dry days and heat waves. Much of the DRC, based on changes in physical exposure (namely a reduction in dry days and heavy precipitation days), is projected to become less vulnerable (Fig. 3, Fig. S16).[11] For both the late 20th simulation and the mid 21st projection, the multiplicative model accentuates the vulnerability of Sahel countries (Fig. S18–S19).

4 Discussion and conclusions

How do these results compare with other vulnerability analyses? We conducted several comparisons to other efforts. First, we compared the late 20th century simulation of physical exposure to our previous work, which used data on historic climate hazard exposure (Busby et al. 2011; Busby et al. 2013). Second, we compared our late 20th century findings to the national level vulnerability studies by David Wheeler from the Center for Global Development (Wheeler 2011). In addition, we compared our late 20th composite to three measures of disasters from the EM-DAT database, the number of disaster events between 1995 and 2010, the number of people killed, and the total number of people affected (Guha-Sapir 2012).

In terms of our historic work, there are some differences in the findings for the physical exposure basket. Our previous work showed the highest physical exposure to climate-related hazards in Angola, South Sudan, southern DRC, and Madagascar (see Fig. S20) while the physical exposure basket in the late 20th simulation identifies much of the Sahel to be exposed (see Fig. 1). In part, these are a function of different source indicators. Our previous work included six indicators (wildfires, cyclone risk, two drought indicators, low elevation coastal zone, and floods) while the new simulation only has four (dry days, heavy rainfall, heat wave events, and low elevation coastal zone). Moreover, while the heavy rainfall measure in the climate simulation is meant to pick up on flood risk, our previous flood data closely tracked river basins whereas the heavy rainfall measure has wider geographic dispersion. Nonetheless, there are a few areas in Chad, Mali, northern Nigeria, Sudan, and South Sudan where both maps consistently show the same areas to be in the 4th and 5th (most exposed) quintiles (see Fig. S21 and regional pullout map S22).

A second comparison is between our late 20th century composite (see Fig. S15) and David Wheeler's index which ranks all countries in the world in terms of their vulnerability to climate change (see Fig. S23). We focus on one of his measures, vulnerability to extreme weather events. His index is constructed using an econometric approach, where the dependent variable is the proportion of people affected by a climate-related disaster in the EM-DAT database during the period 1995–2008.[12] His independent variables include the effects of CO_2 forcing and controls for population,

[11] This is based on the assumption that fewer dry days and heavy rainfall events would reduce exposure to extreme events. It is important to produce a more regionally focused assessment that better accounts for the direct and indirect consequences of these imperfect "disaster" proxies, as their impacts may vary considerably from region to region over continental Africa.

[12] Wheeler includes windstorms, droughts, floods, wildfires, and extreme heat events in his measures of climate-related disasters.

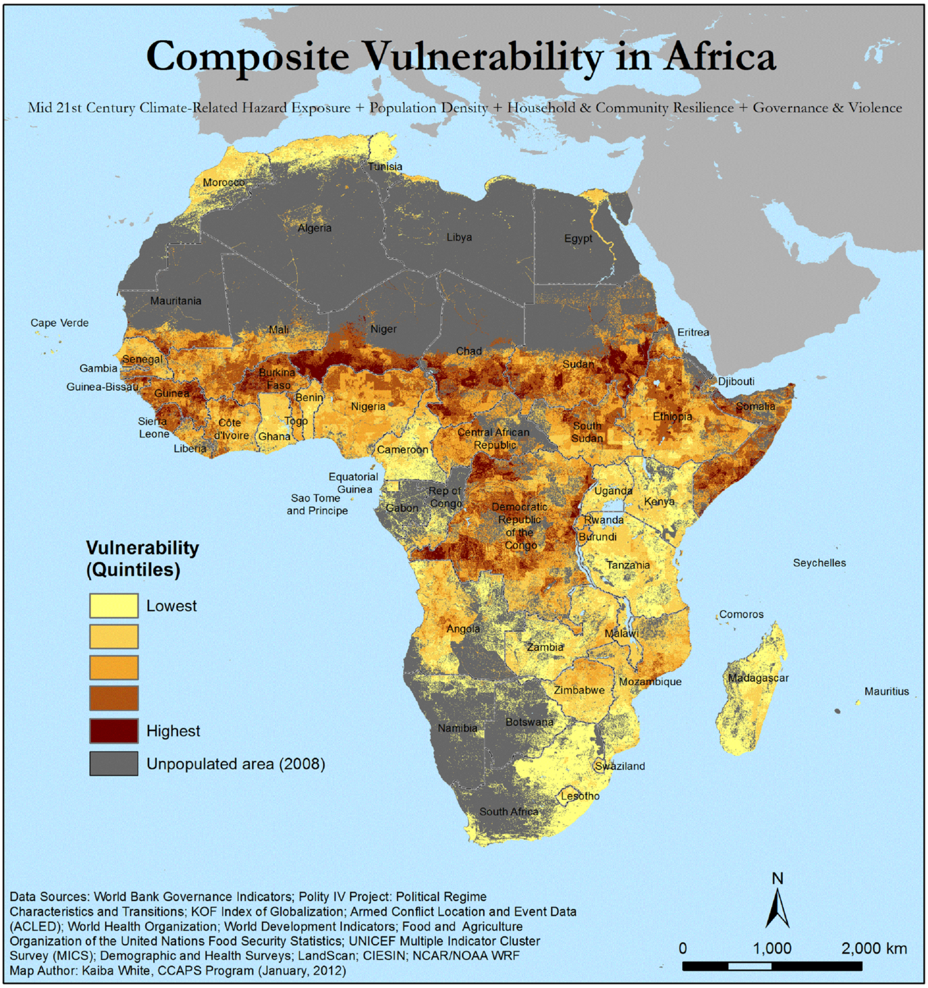

Fig. 3 Mid-21st century composite vulnerability

urban population, measures of information transparency and regulation quality, and dummy variables for regional and country-specific effects. His index projects the trend change in disaster risk for 2015 based on the projected change in CO_2 accumulation by 2015 with all other variables held constant at 2008 levels.

Wheeler finds areas of Kenya, Uganda, Tanzania, Mozambique, and Madagascar to be much more vulnerable than our late 20th century composite. However, we find more vulnerability than Wheeler does for portions of the Sahel in countries like Niger. Unlike Wheeler who uses only changes in CO_2 concentrations to predict changes in disaster events, our physical exposure basket includes indicators of extreme weather events generated from a regional climate model. While we both include a variety of governance measures, we place more emphasis on subnational indicators of violence.

Our final comparison takes three national level indicators of climate-related disaster events from EM-DAT for the period 1995–2010 (see Fig. S24–S26) and compares this to our late

20th century simulation (see Fig. S15).[13] While EM-DAT data is available dating back to the early 20th century, as Wheeler notes, there are a number of reasons including reporting bias to think that data from the earlier period is less reliable. Areas of commonality with our work include Somalia, Ethiopia, and Sudan. Like Wheeler, the EM-DAT data show Madagascar and Mozambique to have experienced high disaster frequency, mortality, and affected populations. Moreover, EM-DAT also shows Kenya and South Africa to have experienced considerable disaster impacts during this period, possibly a function of more media coverage.

Our first pass of multi-study comparison—with our previous work, Wheeler's index, and EM-DAT disasters—suggests there are substantial differences in modeling results between them and the simulation and composite maps generated here.

The inconsistency of results for Madagascar and Mozambique in particular gives us some pause and raise questions for future research. One productive area for future research is the generation of model results for cyclone frequency and severity. The absence of such an indicator in this iteration of our physical exposure basket may account for the difference between our current effort and other studies.

These maps are meant to be points of departure for more extensive research and discussion, including additional field-work validation, modeling, and econometric work. As Sherbinin notes, maps are effective tools to present information, but they can mislead readers to perceive them as "objective" when indicator selection and modeling choices inherently involve some value judgments and trade-offs (de Sherbinin 2014, 34).

The maps are also intended to be iterative. We aim to have greater precision with improved data sources and methods, including new subnational data sources of educational achievement based on the USAID-funded Demographic and Household Surveys as well as revised infant mortality data and new indicators of rainfall anomalies.

We caution against using these maps as the sole source of information to prioritize resources, in part because results across different mapping efforts have not coalesced around a consistent set of results. It is therefore important that maps like these serve to start rather than end the conversation about high priority areas of concern, with analysts and consumers clear about what they are seeking to explain and address.

These concerns notwithstanding, we believe our approach offers a promising beginning for inter-disciplinary collaboration. With this article, we sought to stimulate a conversation among academics and policymakers about how best to understand the confluence of factors that contribute to vulnerability and where those vulnerabilities are concentrated. In our view, the appropriate response from policymakers would be to examine the underlying layers and to question, even challenge, our assumptions and compare our results and approach with others. Our new online information portal allows users to examine the data for themselves. Ultimately, they will be able to change the baskets weights according to their own intuitions about what is important.[14] While there may be some risks of adoption of these maps as totemic guides to direct resources, we are more sanguine about their overall utility.

We held population, social, and governance characteristics constant while using the climate models to simulate and project future aspects of physical exposure, isolating the effects of changes in the physical exposure basket by mid-century. Obviously, all else is highly unlikely to be equal. With rapid urbanization and population growth, Africa in 2050 will not only be

[13] In addition to the five measures Wheeler identified, we also include storms and mass movement wet landslides in our measures of climate-related disasters.

[14] See http://stg.ccaps.aiddata.org.

more physically exposed to climate change but the number of people who face such challenges, particularly in coastal cities, will likely be much larger.

Projecting how these processes will change, beyond extrapolation of current trends, is perhaps beyond the expertise of social scientists, though some scholars have tried by projecting future economic growth and democratic development across Africa (Burke et al. 2009). Population may be easier to project than the other indicators, but we are not aware of high-resolution mid-century projections of population.

For a region where data is limited and of questionable quality, whether the maps of security vulnerability are "true" representations of reality is somewhat beside the point. The more important question is: Does this mapping process represent a methodological advance that enables scholars and practitioners to understand with more geographic specificity the places that are likely to be most vulnerable to the security consequences of climate change? By pulling together the best available information in a hot spots map, we believe our approach provides a single representation of a complex, many-layered problem. More importantly, we believe our work offers an opportunity to begin a conversation about how, where, and why this pressing problem is likely to affect a continent.

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