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Food and water insecurity as causes of social unrest: Evidence from geolocated Twitter data

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Abstract

Research often fails to account for the specific pathways by which climatic factors can cause social unrest. One challenge lies in understanding the distinct effects of food insecurity and water insecurity – which we term 'staple insecurities' – while accounting for their interrelated nature, especially at high-resolution spatio-temporal scales. To unpack these dynamics, we leverage geolocated Twitter data across urban areas in Kenya and deploy a supervised machine learning approach to separately identify geolocated tweets concerning food and water insecurity, in both English and Swahili. The data are then aggregated to create daily measures of food and water insecurity for standardized grid-cells to examine how perceived food insecurity moderates and/or reinforces perceived water insecurity's impacts on social unrest, and vice versa. Our findings suggest that food and water insecurities' respective effects should be interpreted as mutually reinforcing – in compelling citizens to take to the streets – rather than as independent. Those concerned with climate change's impact on conflict should hence endeavor to jointly account for both forms of insecurity, and their interactive effects.

Keywords

civil disobedience, food security, protests, social conflict, water insecurity

Can food and water insecurity – both of which we term, for simplicity, 'staple insecurities' – cause social unrest? Extant research underscores strong linkages between food prices and civilian mobilization (Tilly, 1971; Taylor, 1996; Bellemare, 2015; Hendrix & Haggard, 2015). Yet, despite these findings, we know relatively little, in both theoretical and empirical terms, about the ways in which environmental stress can generate overt dissent in urban areas.

Theoretically, the effects of environmental stress – and especially the effect of climate change – are complex, operate through multiple pathways, and often vary according to actor and context (Theisen, Gleditsch & Buhaug, 2013; von Uexkull et al., 2016; Döring, 2020; Koren & Bagozzi, 2017). Such relationships are often *moderated*, in that environmental factors have a dampening or intensifying impact on different socio-economic determinants of social conflict, rather than a simple direct effect. There is also the possibility that where effective capacities are available, people will adapt to climatic impacts, thus mitigating their severity (Chen, 1991). Moreover, these impacts are rarely disaggregated by type of insecurity, and most existing studies only

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implicitly equate water insecurity (e.g. via drought) with food security (e.g. via lower agricultural output). Finally, there is the possibility that climatic variations can have different – even opposite – impacts in different contexts, perhaps most importantly across urban and rural settings (Theisen, Gleditsch & Buhaug, 2013). Empirically, researchers rely on a variety of proxies to approximate staple insecurity, which – notwithstanding the insights provided by studies that have relied on such variables – remain limited in their ability to capture the exact effects of staple insecurities on unrest, especially as these effects unfold in real time.

Given that staple insecurities occupy a place of increasing importance in the global policy discourse (e.g. IPCC, 2018; Bellemare, 2015; Berazneva & Lee, 2013; FAO, 2014), this article takes a closer look at the relationship(s) between food insecurity, water insecurity, and social conflict. In doing so, we choose to focus on urban settings rather than rural areas, considering that the former constitute a clear potential – arguably most-likely – scenario for how climate change will impact politics in the future. In focusing on urban settings, we consider two important issues. First, we evaluate whether the relationship between staple insecurities is *unconditional* – that is, whether higher levels of each insecurity directly cause more social unrest – or *moderated* – namely whether the different types of staple insecurity exacerbates the other's impact(s). Second, we rely on daily geolocated Twitter data to identify the causal effects of each type of staple insecurity on social unrest in *real time* and *place*, using urban centers in Kenya as the focus of analysis. Communication technologies in Kenyan cities are well developed, and millions of residents have access to Twitter (Dowd et al., 2018; Sumbeiywo, 2018), ensuring these data capture perceived food and water insecurity levels and their local prevalence in a given day.

Based on daily data at the urban 0.5-degree PRIO-GRID level (Tollefsen et al., 2012), the empirical results indicate that between 23 August 2017 and 11 March 2019, rising food and water insecurity did not – independently – lead to a noticeable increase in the number social unrest events. However, we do find that, together, food insecurity and water insecurity greatly reinforce the other's impact on social unrest, with high degrees of *both* insecurities increasing the expected counts of unrest events by approximately one or more events per day, on average.

Considering the grave possibility that both staple insecurities will increase in the coming decades due to changing climate, especially in tropical developing states (IPCC, 2018; FAO, 2014; Maxmen, 2018), our findings suggest social unrest might correspondingly become more prevalent. Indeed, climate change will also contribute to ongoing urbanization, as more people relocate from the rural countryside to the cities (Gleick, 2014), meaning that social conflict is more likely to erupt in urban areas. If there is an immediate causal relationship between staple insecurities and social unrest, this could ultimately mean that episodes of social unrest will occur simultaneously across countries. Therefore, in addition to the irreversible damage staple insecurities cause to the health of affected populations, these insecurities also have the capacity to be a destabilizing geopolitical force (Bellemare, 2015). As such, and because dissent can be highly destabilizing and can generate more violent types of conflict such as civil war and mass killing (Lagi, Bertrand & Bar-Yam, 2011), these results are relevant to both conflict scholars and policymakers working to prevent violence.

Of course, this article's findings do not imply that staple insecurities are the only – or predominant – cause of social unrest, as ample research has established (Chenoweth & Stephan, 2011; Ritter & Conrad, 2016). Rather, the objective of this article is to evaluate whether – and when – staple insecurities can contribute to social unrest, while theorizing about the precise mechanism(s) through which they do so. Considering that multicollinearity between the two insecurity types is not an overriding concern (see Online appendix), our findings suggest scholars and policymakers should address food and water security jointly when studying their effects on unrest.

Theoretical argument

Environmental stress, staple insecurities, and social conflict

Extant research primarily analyzes environmental stress and its impact(s) on social conflict through three main pathways: (i) direct, (ii) indirect, and (iii) threat multiplying. In the first pathway, social conflict arises as an immediate response to a stressor's effects (Martin-Shields & Stojetz, 2019). For instance, environmental stressors can cause sharply diminishing returns in agricultural outputs by depleting resources and reducing the number of daily work hours for rural labor (e.g. Cline, 2007; FAO, 2014). This, in turn, limits the amount of food and water available in urban areas, causing food and water shortages and increasing the prices of staple goods.

Although this direct pathway is often analyzed in studies that link rises in (most often) food prices and social conflict (Bellemare, 2015; Hendrix & Haggard, 2015; Linke et al., 2018; Lagi, Bertrand & Bar-Yam, 2011), it may not be the most pernicious or common way by which environmental stress can impact social conflict. Indeed, the effects of environmental stress are more commonly indirect and *highly contextual* (Theisen, Gleditsch & Buhaug, 2013). In this case, environmental stress is not the direct reason individuals mobilize. As staple stocks dwindle, some governments have the capacity to 'smooth' these adverse effects and provide safety nets to their citizens – thus mitigating adverse impacts on the latter's consumption levels – while others lack such capacities (Wintrobe, 2000; Nooruddin & Simmons, 2006). Indeed, as Amartya Sen (1999) famously argued, famines are most often caused not by environmental decline but by incapable governments. For governments that fail – or struggle – to address the sudden onset of staple insecurities, the resulting crisis sends a strong signal to their constituents of their incapacity, causing further discontent and dissent. Hence, in this scenario, the object of public resentment is not environmental stress and the consumption shock it generates, but rather the government and its ineffectiveness (van Weezel, 2019; Lagi, Bertrand & Bar-Yam, 2011).

Finally, along the third pathway, environmental stress works as a 'threat multiplier', exacerbating ongoing social strife by further straining actors already facing the pressures of existing conflict (Scheffran, Ide & Schilling, 2014; von Uexkull et al., 2016; Koren & Bagozzi, 2017). For instance, among groups that already have a negative perception of each other, increased environmental stress, 'could lead to insecurity and increased threat perceptions, driving a security dilemma that increasingly diverts resources into the spiral of violence' (Scheffran, Ide & Schilling, 2014: 381). In the case of social unrest – our analytical focus – the onset of acute environmental stress and its impact on consumption during ongoing peaceful campaigns could turn nonviolent protests into violent riots, or make civilians mobilize and act on pre-existing grievances against their government.

An important aspect of studies that focus on these three pathways is the reliance on empirical proxies to evaluate observed effects of environmental stress, including food prices (Bellemare, 2015; Hendrix & Haggard, 2015), rainfall (Ritter & Conrad, 2016; Jones, Mattiacci & Braumoeller, 2017), temperature (Burke et al., 2009; Jones, Mattiacci & Braumoeller, 2017), droughts (von Uexkull et al., 2016), cropland coverage (Fjelde, 2015), staple crop productivity (Koren, 2018), water reservoirs (Sarsons, 2015), and surveys (Linke et al., 2018). Some of these proxies, especially precipitation, are empirically problematic (Sarsons, 2015; O'Loughlin, Linke & Witmer, 2014). Other proxies, while more empirically valid, have one important limitation: they are unable to capture the *real-time* effects of environmental stress. For instance, agricultural measures are often constant over time due to the reliance on satellite images (Ramankutty et al., 2008; Bontemps et al., 2009). Changes in agricultural productivity and food prices are likewise often measured over the span of years or, at best, months (Ray et al., 2012; Bellemare, 2015). And survey data, while effective at measuring individuals' sentiment about the impact(s) of environmental stress, are rarely measured in a manner that allows for dynamic evaluations. Another limitation of many of these proxies is the potential for measurement biases – for instance due to poor coverage in some areas or for some indicators – as well as potential differences between how these proxies are measured and how people actually experience their impact (Salehyan, 2014; Scheffran, Ide & Schilling, 2014).

As a result of these issues, we are still short on research that evaluates how different staple insecurities directly affect the near-instantaneous (i.e. daily) decisions of individuals to engage in social conflict. We develop such a measure by preprocessing and analyzing Twitter data in multiple relevant languages, a process we discuss in greater detail below and in our Online appendix. Unlike most said indicators, Twitter data capture the impact of staple insecurities as *perceived* by affected individuals. Although this means this approach is different from measuring food or water insecurities in terms of observed effects (e.g. an *X*% decrease in bushels of wheat or milliliters of rain), the main advantage of using Twitter data is that, if done well, these data actually indicate *the exact sentiment* among people regarding how their lives are impacted by staple security, free of the aforementioned biases. Moreover, they allow one to empirically operationalize a very broad definition of staple insecurity, including – for example – stress resulting not only from climatic variability but also from social and economic shocks (e.g. speculation in food prices).

There is precedence for using Twitter data in these settings. Dowd et al. (2018), for instance, compare Twitter data to 'old' types of data to evaluate their effectiveness in social conflict prediction. Likewise, Anderson & Huntington (2017) conduct a quantitative content analysis of 4,094 tweets concerning the 2013 Colorado floods to examine how sarcasm and incivility is adopted in Twitter discussions of climate change. However, to our knowledge, the approach of utilizing Twitter data on environmental stress has not yet been applied to developing states and countries particularly susceptible to the impact of environmental stressors, such as those located in the tropics – especially not in languages other than English.

In this study, we do exactly this. We develop two separate Twitter-based indicators measuring food and water insecurity, respectively, that rely on tweets in both English and Swahili (the two lingua franca and official working languages of Kenya). Following this, we test our real-time indicators of food and water insecurity against high resolution data on social unrest to assess how real-time food and water stress impacts its prevalence. Thus, this analysis provides an effective framework for modeling of the 'direct' effects of environmental stress as discussed in pathway (i) above, while also having important implications for theory and research on pathways (ii) and (iii), as we discuss in detail further below.

An important feature of climate change is that its impact varies across contexts, perhaps most distinguishably in urban and rural settings. Indeed, much past work on the climate–conflict nexus focused on civil wars between armed combatants in rural areas (e.g. Burke et al., 2009; Buhaug, 2010; O'Loughlin et al., 2012). Yet, climate change's adverse political impacts in urban settings also constitute a viable scenario, arguably one that is more likely (Gleick, 2014; Bellemare, 2015; Hendrix & Haggard, 2015), especially considering that climate change will contribute to increases in urbanization, meaning that social conflict is more likely to erupt in these locations. Accordingly, and considering the volume and variability of Twitter data, we chose to center our analysis on cities and the type of social conflict that occurs predominantly in these settings, namely social unrest (Hendrix & Haggard, 2015; Bellemare, 2015). This focus minimizes several biases specific to Twitter data, such as the tendency to vastly overrepresent urban areas, especially in eastern Africa (Dowd et al., 2018). Next, we focused on a specific country that offers an effective test case for the scenario outlined above. We hence applied the approach proposed by Seawright & Gerring (2008) to identify a 'typical' case of a developing nation-state using three relevant parameters: (i) location, (ii) regime type, and (iii) urbanization levels. We chose to focus on the 'typical' case to illustrate the potential impacts on political stability in developing states if climate trends hold true (IPCC, 2018), and to 'probe the causal mechanisms that may either confirm or disconfirm [*sic*]' (Seawright & Gerring, 2008, 297) our theory.

Accordingly, we identify Kenya as a viable case for our micro-level analysis. Kenya is located in eastern Africa, a region that is expected to experience lower precipitation over time and to become increasingly susceptible to the effects of environmental stress (IPCC, 2012). It is a developing semi-democratic state, which past research suggests to be especially likely to experience social unrest during periods of food and water insecurity (Hendrix & Haggard, 2015). Finally, Kenya is a rapidly urbanizing state – indeed, one of the fastest urbanizing countries in Africa (Otiso & Owusu, 2008). This fact not only provides Kenyan citizens with ample opportunity for dissent, but also suggests that the country's ability to adapt to more extreme climate variability and develop effective coping mechanisms is limited (Chen, 1991; Hendrix & Haggard, 2015; Bellemare, 2015).

Kenya also offers an advantage with respect to our ability to effectively operationalize our anticipated Twitter data. Dowd et al. (2018: 13), for instance, write that Kenya has 'one of the highest levels of telecommunications and internet infrastructure development on the African continent. In 2017, there were 39.1 million registered mobile phone users in Kenya, and an estimated 40.5 million Internet users, out of an estimated population of 44 million.' In terms of social media, usage is high with an estimated '2.2 million monthly active Twitter users' (Dowd et al., 2018: 13). Sumbeiywo (2018: 42) records similar figures, adding that one million Kenyans use Twitter daily, and that these users are located primarily in the cities, with approximately 85% of daily tweets referencing Nairobi, 6.1% Mombasa, 3.8% Nakuru, 2.5% Kisumu and Uasin Gishu. We therefore believe that urban areas in Kenya provide a valuable case study on which to test our Twitter data-driven approach to food and water insecurity and their impact(s) on social unrest.

Defining food and water insecurity

Relying on Twitter data allows us to conceptualize the immediate effects of environmental stress in terms of the real-time insecurities affecting urban residents' well-being and the resulting impact on social unrest. While there are multiple types of potentially relevant insecurities, we focus on two types that extant research deems the most relevant: food insecurity and water insecurity (e.g. von Uexkull et al., 2016; Linke et al., 2018; van Weezel, 2019). This allows us to specifically capture the impact of these stressors while ensuring exogeneity with respect to our dependent variable.

By 'food insecurity' we refer to contexts and situations where food security levels decrease. Most often, food security is defined as 'a situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life' (Barrett, 2010: 825). There are multiple aspects of food security (also called 'pillars') that might be relevant in social conflict analysis. Koren & Bagozzi (2016), for instance, focus on both availability[1] and access.[2] Environmental stress is traditionally associated with the availability aspect, and as a result, most climate–conflict research focuses on this specific pillar. There are, however, situations where food security might be reduced due to limitations on access, if floods wash away roads or reservoirs and dams are destroyed by severe rains or faulty engineering. An advantage of our proposed set of measures is that it captures food insecurity precisely and comprehensively (although in perceived rather than absolute terms), whether it is reduced due to lower availability (e.g. staple crop production) or impediments on food access (e.g. distribution pathways into urban areas are destroyed).

Although extant findings on the broader impact(s) of food insecurity on conflict vary,[3] there is a growing consensus that where urban unrest, specifically, is concerned, scarcity – often operationalized in terms of rising food prices and food price volatility – is an important driver (Bellemare, 2015; Hendrix & Haggard, 2015). Considering our empirical focus on cities in Kenya, which – as discussed above – represent a test case of this scenario, we incorporate this direct effect notion into the first part of our first hypothesis:

> *H1a:* (Higher levels of) perceived food insecurity will be associated with (a higher frequency of) social unrest.

Interestingly, how water insecurity, in and of itself, impacts social conflict has attracted less scholarly attention than food insecurity. Often, water insecurity is understood with respect to its impact on agriculture and food prices. Burke et al. (2009: 20672), for instance, argue that high temperatures 'can affect agricultural yields both through increases in crop evapotranspiration (and hence heightened water stress in the absence of irrigation) and through accelerated crop development'. Similarly, von Uexkull et al. (2016: 12395) state that, '[a] severe drought threatens local food security, aggravates humanitarian conditions, often triggers large-scale human displacement, and as our results indicate, may also provide the breeding ground for sustained fighting'.

That is not to say research completely ignores water insecurity's impact on conflict. One strain of research examines how water insecurity impacts international war and cooperation (Koubi et al., 2014; Mitchell & Zawahri, 2015), while other studies analyze some of its impacts on civil conflict (Selby & Hoffmann, 2014; Döring, 2020). For example, Döring (2020) recently analyzed the impact of access to groundwater on communal conflicts in Africa and the Middle East, and found that in these contexts water insecurity increases the risk of communal conflict. Water insecurity's impact on social unrest, however, remains surprisingly less studied.

Like food insecurity, water insecurity can be caused by natural factors (e.g. droughts, heatwaves), human behaviors (misappropriation or contamination of water resources), and population dynamics (Bakker, 2012; Hoekstra, Buurman & van Ginkel, 2018; Döring, 2020). Bakker (2012), for instance, identifies four individual pathways of water insecurity's impact: (i) drinking water supply, for example by disconnecting individuals from access to water, (ii) economic growth, for example by contracting the agricultural sector, (iii) threats to ecosystems, and (iv) increased variability due to climate change, which requires more effective means of local and state-level resource governance. Considering that these risks will increase in developing tropical countries in future decades (IPCC, 2012), identifying water insecurity's impact along both natural-climatic and socio-economic political pathways on dissent in urban areas has important implications for both researchers and policymakers.

Thus, our expectation is that individuals in developing urban contexts will pursue dissent when faced with scarcity – that is, high water insecurity – which affects their general well-being. Accordingly, the second part of our first hypothesis is as follows:

> *H1b:* (Higher levels of) perceived water insecurity will be associated with (a higher frequency of) social unrest.

The reinforcing effects of staple insecurities

We mentioned above that – in extant research – water insecurity is often used as an approximation of food insecurity. Yet even when the two insecurity types are analyzed separately, they are usually either juxtaposed alongside one another in the same model, or water

[1] That is, how much food is physically produced in a given area/country.

[2] That is, how much of the produced food actually makes it way to the consumers.

[3] With some studies associating abundance with increased conflict in different contexts (Koren, 2018), and others emphasizing scarcity (Burke et al., 2009; Lagi, Bertrand & Bar-Yam, 2011).

insecurity is used as an instrument. In the first case, food security indicators (e.g. cropland, productivity) are included additively into the model alongside water insecurity indicators (e.g. droughts, temperature) under the assumption that the impact of each staple insecurity will be controlled for statistically (Koren & Bagozzi, 2016; O'Loughlin et al., 2012). In the second case, water insecurity (from natural causes) is used to instrument the effects of food insecurity on social conflict, as the latter two variables are often endogenous (Bellemare, 2015; Koren, 2018; Ritter & Conrad, 2016).

Both approaches suffer from major limitations. Firstly, biased estimates can arise in contexts where one insecurity's effects operate via pathways other than the specific ones controlled for in the first case, or through variables other than the variable instrumented (i.e. by violating the exclusion restriction) in the second case. Perhaps more importantly, both approaches can lead to omissions of each variable's *moderating* effects on the other insecurity, which – we argue below – is crucial to identifying the true effects of environmental stress on social conflict and dissent.

Recently, the role of food insecurity and water insecurity as moderators of *other* potential determinants of conflict gained attention. Van Weezel (2019), for instance, analyzes how annual changes in precipitation levels moderate the impact of population densities and pastoral herding areas on communal conflict in Kenya and Ethiopia. Interestingly, the possibility that food insecurity can moderate water insecurity's impact on social conflict – and urban dissent, specifically – has not, to our knowledge, been empirically explored. Nevertheless, we argue that the moderation – or rather, reinforcement – pathway by which food and water insecurity can relate to each other, in addition to juxtaposition and instrumentation, can have crucial effects on social conflict in developing urban contexts. In leveraging Twitter-based indicators, we are able to test these internally - moderated effects as they unfold in real time and compare them to these indicators' direct and controlled effects.

These moderated effects deserve further investigation for at least three reasons. First, considering their highly interdependent nature, the two insecurity types can *compound* each other's direct effects. Water insecurity can often lead to food insecurity, for example via droughts affecting crops. In this scenario, the onset of a drought generates water shortages that reduce the amounts of staple crops that are grown and harvested. Heatwaves can have similar impacts, as '[s]uch heat will compound food insecurity caused by variable rainfall' (Battisti & Naylor, 2009: 243). For example, 'temperatures in the Sahel can be so high that the rain evaporates before it hits the ground' (Battisti & Naylor, 2009: 243), which adds pressures to a region that is already food insecure due to problematic infrastructure and ineffective governance. Food insecurity can also compound water insecurity, for example if government or private actors move water that could be consumed by urban residents to bolster food productivity in rural areas ('the reverse Chinatown' effect). In cases where food insecurity levels are already high, for example due to drought-induced shortages, a sudden water shortage due to conversion of water reservoirs for irrigation can cause additional 'shocks' to food security (Hoekstra, Buurman & van Ginkel, 2018), which directly translate to sudden and sharp declines in the urbanites' consumption levels, making urban citizens much more likely to object to such measures or to riot against potential scapegoats.

Another possibility is that the two insecurities will *complement* each other in their impacts on perceived relative deprivation. According to this scenario, if people already face food shortages, facing water shortages at the same time produces an acute inability to cope, and thus, increasingly stronger anti-regime sentiment. This case is different from that of having the two insecurity variables included additively in the model because facing one staple insecurity while a different one is ongoing causes more exasperation than if urban residents face only one type of insecurity, since the second resource is unavailable for offsetting or compensating for insecurities in the first. For example, in Tajikistan during 2007–08, citizens had to endure both acute food insecurity due to cold weather and rolling blackouts (resulting from decreased productive capacity), and water insecurity due to damage from natural causes and malfunctioning pumps (Kelly, 2009). The state's response was ineffective primarily because the government and aid agencies could not decide which of the two insecurities required more immediate response, which meant civilians needlessly suffered as a result (Kelly, 2009). In other words, each insecurity's 'marginal returns' (or 'marginal anxieties') are increasing in the other insecurity type. This implies that the more acute the impact of one insecurity type, the greater the impact of insecurities in a second resource on civilians' resolve to stage urban unrest.

Finally, there is the possibility that each insecurity impacts *different types of urban populations*. For instance, as Hoekstra, Buurman & van Ginkel (2018: 3) explain, 'water insecurity often concerns particular groups, which may even be the essence of the whole concern about water security: that it does not reach all in society'. Some urban neighborhoods might lack access to proper sanitation and be more susceptible to shocks and outages, while others in the same city might be perfectly fine. In this case, water insecurity's effects within a given city are geographically disparate. In contrast, food insecurity and food shortages are more likely to affect all urban food consumers similarly, even if their impact will be felt disproportionately more by the poor (Bellemare, 2015; Hendrix & Haggard, 2015). Higher levels of both staple insecurities at the same time galvanize the resentment felt by different population subsets in different locations within a city, creating additional incentives for individuals to dissent.

Importantly, the possibility of a moderated effect is not particular to staple insecurities; there are a host of socio-economic and political conditions that could likewise compound the impact of each staple insecurity, including (but not limited to) interethnic grievances, pre-existing antigovernment sentiment, and geospatial features. Here, we emphasize the interaction of food and water insecurity to test if, similarly to socio-economic and political moderators, staple insecurities play a key role in reinforcing each other's impacts. The conclusion briefly discusses some of other potential moderators and outlines future research directions. Building on the three pathways discussed above, we accordingly derive a second hypothesis concerning how each insecurity type moderates the other's impact on unrest:

> *H2:* Higher levels of perceived water (food) insecurity will be associated with an intensifying effect of perceived food (water) insecurity on the frequency of social unrest.

Empirical analysis

Data, variables, and methods

Our hypotheses associate the effect(s) of food insecurity, water insecurity, and their interaction with a higher number of social unrest events in urban areas. We accordingly use data on civilian-initiated urban unrest measured at the urban grid-cell-day level for the 13 largest cities, town councils or municipal units in Kenya between 23 August 2017 and 11 March 2019 (a total of 574 consecutive days). This grid-cell-day sample has two advantages. First, this empirical framework allows us to carefully and accurately operationalize variations in the impact of food and water insecurity on urbanites' real-time sentiment within and across different cities and towns. Second, relying on the grid-level allows us to effectively operationalize and test the effects of both insecurity types and their interaction on fine-grained, localized civil unrest data. This is a necessary prerequisite for evaluating our hypotheses effectively.

Accordingly, our 574 days of data are first structured into a cell-day-level dataset, where cells are the cross-sectional unit of analysis, and are measured at the 0.5 x 0.5 decimal degree cell resolution for the entire terrestrial globe (Tollefsen et al., 2012). We then keep only cells (i) denoted within Kenya's borders and (ii) which contained at least one of the 13 Kenyan urban localities that were used for webscraping our geolocated Twitter data. Altogether, this retained a total of 11 grid-cells (see the Online appendix for further details).

Data on our dependent variable, *Social unrest*$_t$, comes from the Armed Conflict Location Events Dataset (ACLED), which relies on reports by nongovernmental organizations (NGOs) and the media to code information on political violence incidents (Raleigh et al., 2010). ACLED includes a broad spectrum of dyadic interactions incorporating numerous types of violence, including violent and nonviolent social unrest events, most of which are measured at the village/town and day levels. These data accordingly facilitate the correct identification of our theoretical argument and ensure that our models capture a sufficiently high number of heterogeneous social unrest events.

We constructed this dependent variable in several stages. We began by only retaining ACLED events that occurred in Kenya. We then subsetted this sample to only include those events denoted as 'riots' or 'protests', the two social unrest events coded in the ACLED database. Next, we kept only events where the exact date was known and events whose geoprecision was at the district or village/town level. This was done to ensure that the remaining data correspond to our urban-grid-day framework. We then collapse this sample to latitude and longitude coordinates and merge it to PRIO-GRID using grid centroids. The resulting *Social unrest*$_t$ variable is hence a grid-day count of all urban social unrest events in Kenya that occurred during our period of interest, with a mean of 0.055 and a range of $0 \Leftrightarrow 12$. To ensure our findings are not driven by reliance on ACLED, in the Online appendix we also report a model that relies on the Integrated Crisis Early Warning System (ICEWS; Boschee et al., 2015) to code a comparable civil unrest variable (Table A.5 in the Online appendix).

We now turn to our independent variables. To construct real-time indicators of perceived food and water insecurity – *Food insecurity*$_{t-1:t-7}$ and *Water insecurity*$_{t-1:t-7}$ – we collected and coded individual tweets related to food insecurity and water insecurity across urban areas within Kenya for the same 23 August 2017–11 March 2019 period mentioned previously. Due to space constraints, the details of each preprocessing step for these data appear in the Online appendix and are briefly summarized here.

We first identified and scraped food and water insecurity tweets in English and Swahili based upon an intentionally overinclusive set of English language and Swahili language keywords that are discussed in detail in the Online appendix.[4] All relevant geolocated tweets containing at least one relevant keywords were retained, which purposefully creates a extremely broad sample of candidate tweets – many of which did not pertain to food or water insecurity. We then used a detailed rubric to identify *the subset* of these tweets that corresponded to food or water insecurity. To define whether a given tweet in this set was in fact related to food or water insecurity, we relied on the following overarching definitions:

- *Food insecurity*: instances where any persons or groups lack some level of physical, social, or economic access to sufficient and safe levels of *food* via either (i) barriers in access to crops/food or (ii) the actual unavailability of sufficient food.
- *Water insecurity*: instances where any persons or groups lack some level of physical, social, or economic access to sufficient and safe levels of *water for consumption or crops*, via either (i) barriers in access to water or (ii) the actual unavailability of sufficient water.

In this context, we only coded tweets related to food or water *insecurity*. Tweets positively emphasizing food or water abundance, accessibility, or availability were not coded as insecurity. Nor were tweets that impartially mentioned the price of food and/or water without additional context. Mentions of drought were only coded as water insecurity unless there was specific reference to an impact on crops. Tweets concerned about food and/or water insecurity outside of Kenya were coded as insecurity so as to avoid judgment calls regarding a particular twitter user's expectations of impact(s) upon Kenya via global supply chains or regional trends. Discussion of contamination of food and/or water was considered to be insecurity, as were negative characterizations of water or food infrastructure. Tweets expressing concern over food- and/or water-related market scandals or disruptions were coded as insecurity on the relevant dimension(s). Mentions of displacement of people and/or refugees in need of food and/or water assistance were coded as (food and/or water) insecurity, as were mentions of relevant scarcity in local shops or markets. Likewise, any mentions of animals dying from contaminated water supplies or drought were coded as water insecurity, but not food insecurity, unless the animal was livestock with direct linkages to food.

Using the above coding scheme, 5,000 tweets in each language were hand-coded to serve as a training set for our supervised machine-learning algorithm ensembles, which are at the core of our measurement approach. These algorithms, which are discussed in detail in the Online appendix, were implemented using k-fold cross validation, where $k = 5$. As Table A.2 (Online appendix) shows, our algorithms are effective in classifying each outcome across multiple relevant metrics. Classifiers trained on these two language-specific training sets were then leveraged to classify our 906,695 unlabeled English language tweets and 363,386 unlabeled Swahili language tweets in terms of food insecurity and water insecurity.

We then merged all classified tweets to our relevant grid cells, and only retained one unique version of each Swahili and English tweet for each PRIO-GRID location in our final collapsed sample to avoid duplicates. After merging our geolocated tweets in this manner, we created urban-cell-day counts of all retained tweets, separately in terms of counts of relevant food security tweets, counts of relevant water security tweets, and counts of all scraped tweets in these locations and dates (for use as a control). To ensure that the impact of both staple insecurities precedes our conflict outcome measures, we then calculated lagged one-week moving averages of our combined tweet counts. This produced our main variables of interest, *Food insecurity*$_{t-1:t-7}$ and *Water insecurity*$_{t-1:t-7}$, where a higher number of tweets imply more acute insecurity; as well as a control for the total number of scraped tweets in the same locations and days, *N.tweets*$_{t-1:t-7}$. To address skewness, we take the natural log of each lagged averaged count before entering it into our analysis. Finally, to test Hypothesis H2 and the moderated effect of both insecurities, we create the interaction term *Food insecurity*$_{t-1:t-7}$ $\times$ *Water insecurity*$_{t-1:t-7}$ and add it to the models designed to test for these moderated impacts.

In addition to our variables of interest, our models include several key controls. The first crucial confounders are seasonal and day-specific effects. Accordingly, we account for whether the events of interest took place during the growing season (coded 1) or outside of the growing season (coded 0) of all main staple crops in

[4] See also Table A.11 in the Online appendix.

Kenya (Tollefsen et al., 2012). Considering that social unrest is more likely during weekends, when people have more time to invest in mobilization, we also include a variable denoting whether a given day was a weekend-day (i.e. Saturday or Sunday) or not. Another possibility is that one observes more food and water insecurity tweets simply because the total volume of tweets in a particular day is especially high. We accordingly include a (logged) variable measuring the total moving average of all scraped tweets in a given locality, $N.tweets_{t-1:t-7}$, as discussed above.

Next, while urban areas in Africa are relatively robust to the possibility of underreporting due to availability of cell phone coverage (Weidmann, 2016), we account for the possibility that large cities are more likely to experience unrest than smaller ones by including the (logged) measure of average travel time to the nearest large (500,000 citizens or more) city from each grid-cell in question. Finally, to account for the possibility that any observed effects are actually the result of low development, we include a development proxy variable denoting the percentage of children that suffered from malnutrition in a given urban-cell. The last two controls were obtained from PRIO-GRID. The latter control (child malnutrition) was obtained from the time-constant version of the dataset, while the former control (travel time) was obtained from the time-varying version, but includes only values for 2014, considering that PRIO-GRID does not contain information for our period of analysis (2017–19). Summary statistics are reported in Tables A.3–A.4 in the Online appendix.

Our *Social unrest*$_t$ dependent (count) variable exhibits non-negative integer values, is bounded at zero, and is unbounded above. Considering that the variance of *Social unrest*$_t$ (0.152) is larger than its mean (0.055), we employ a negative binomial (NB) model for our baseline assessments. This dependent variable also includes a disproportionate number of zero-count cases, corresponding to more than 99% of our sample. This extreme number of zeros suggests that, for many days and locations, demonstrations were highly improbable due to a variety of structural conditions. Treating all zero observations as count-stage zeros hence risks biasing our estimates and conclusions. To avoid these biases, we employ a zero-inflated negative binomial (ZINB) in our primary analyses. This allows us to statistically account for the mixture of excess zeros within *Social unrest*$_t$. Accordingly we add to the ZINB inflation equation covariates that might dispose a given urban-grid-day to be able to experience social unrest. To ensure comparability across our NB and ZINB models, we specifically include in the inflation stage of our models the same controls used in the count equation: *Growing season*$_t$, *Weekend*$_t$, (logged) $N.tweets_{t-1:t-7}$, (logged) *Travel time*, and *Child malnutrition*.

Results

Table I reports the results of our main analysis at the urban-grid-day level. We begin with the NB model testing the direct effects of *Food insecurity*$_{t-1:t-7}$ and *Water insecurity*$_{t-1:t-7}$ separately. We then add our zero-inflation determinants to our ZINB model. The results broadly support extant research (e.g. Bellemare, 2015; Hendrix & Haggard, 2015) by illustrating that the coefficients on both insecurity variables are positive – that is, associated with a higher rate of social unrest – and statistically significant (to at least the $p < .1$ level). However, as we argued above, such a specification might overstate the effects of each staple insecurity given their correlations. In other words, and because multicollinearity is not an overriding concern in these specifications – as tests reported in the Online appendix illustrate – such models are likely to be underspecified, for both theoretical and empirical reasons.

For these reasons, the next two columns then report NB and ZINB models that account for the effects of each staple insecurity together in the same specification. The final two columns in Table I then repeat the same NB and ZINB specifications, only this time, our two variables of interest are *interacted* to account for each insecurity's moderating effect on the other via the interaction term *Food insecurity*$_{t-1:t-7}$ $\times$ *Water insecurity*$_{t-1:t-7}$.

The results broadly support H2 but not necessarily either component of H1. In the additive models, both insecurity indicators show the expected positive sign – that is, that higher levels of insecurity are associated with more social unrest – but the results are not statistically significant in either the NB or ZINB specifications once one controls for each staple insecurity's effects on the other. Considering that multicollinearity is not a overriding concern, the explanation for the discrepancy between the direct and controlled effect models can be found in the interactive models: we find that *Food insecurity*$_{t-1:t-7}$ and *Water insecurity*$_{t-1:t-7}$ reinforce each other's effects. Both constituent variables have a negative coefficient estimate but no consistent statistically significant effect. This implies that if urbanites do not feel food insecure, then they will not be more likely than average to take to the streets even if water insecurity levels are high, and vice versa. However, *Food insecurity*$_{t-1:t-7}$ $\times$ *Water insecurity*$_{t-1:t-7}$ has a positive

Table I. Determinants of social unrest

	Direct effect				Controlled effect		Interaction	
	NB		ZINB		NB	ZINB	NB	ZINB
Count stage								
Food insecurity$_{t-1:t-7}$[a]	0.216†	–	0.209*	–	0.091	0.083	−0.232	−0.265
	(0.114)		(0.082)		(0.213)	(0.205)	(0.237)	(0.237)
Water insecurity$_{t-1:t-7}$[a]	–	0.222*	–	0.216**	0.142	0.139	−0.373	−0.374
		(0.111)		(0.083)	(0.208)	(0.207)	(0.288)	(0.275)
Food insecurity$_{t-1:t-7}$[a] × Water insecurity$_{t-1:t-7}$[a]	–	–	–	–	–	–	0.219**	0.220**
							(0.077)	(0.072)
Growing season$_t$	−0.211	−0.161	−0.552*	−0.488†	−0.176	−0.506†	−0.127	−0.372
	(0.196)	(0.196)	(0.267)	(0.274)	(0.199)	(0.278)	(0.196)	(0.295)
Weekend$_t$	−0.859**	−0.845**	−0.457	−0.406	−0.852**	−0.428	−0.830**	−0.460
	(0.297)	(0.296)	(0.457)	(0.458)	(0.296)	(0.460)	(0.294)	(0.493)
N tweets $_{t-1:t-7}$[a]	0.015	0.010	−0.156†	−0.162†	0.006	−0.164†	−0.123	−0.340**
	(0.074)	(0.073)	(0.095)	(0.095)	(0.075)	(0.095)	(0.085)	(0.110)
Travel time[a]	−1.825**	−1.853**	1.241	1.160	−1.838**	1.191	−2.353**	0.690
	(0.361)	(0.361)	(0.871)	(0.873)	(0.363)	(0.875)	(0.400)	(0.926)
Child malnutrition	−0.301**	−0.298**	−0.192**	−0.186**	−0.300**	−0.188**	−0.286**	−0.184*
	(0.037)	(0.037)	(0.071)	(0.071)	(0.038)	(0.071)	(0.037)	(0.075)
Constant (count)	12.110**	12.200**	−1.588	−1.311	12.148**	−1.415	15.316**	1.964
	(1.907)	(1.900)	(3.928)	(3.938)	(1.907)	(3.940)	(2.249)	(4.147)
Inflation stage								
Growing season$_t$	–	–	−0.195	−0.167	–	−0.174	–	−0.085
			(0.287)	(0.288)		(0.289)		(0.304)
Weekend$_t$	–	–	0.704	0.739	–	0.724	–	0.720
			(0.461)	(0.457)		(0.460)		(0.498)
N tweets $_{t-1:t-7}$[a]	–	–	−0.239**	−0.239**	–	−0.240**	–	−0.297**
			(0.084)	(0.084)		(0.084)		(0.090)
Travel time[a]	–	–	2.631**	2.612**	–	2.618**	–	2.511**
			(0.677)	(0.681)		(0.679)		(0.685)
Child malnutrition	–	–	0.186**	0.188**	–	0.187**	–	0.185*
			(0.069)	(0.069)		(0.069)		(0.072)
Constant (inflation)	–	–	−13.260**	−13.204**	–	−13.214**	–	−12.612**
			(3.249)	(3.258)		(3.255)		(3.285)
Log Likelihood Akaike Inf. Crit.	−946.308	−946.178	−901.444	−901.298	−946.089	−901.217	−942.209	−896.339
	1,906.617	1,906.356	1,830.887	1,830.596	1,908.178	1,832.433	1,902.419	1,824.674

N=6,149. $^{\dagger}p < 0.1$; $^{*}p < 0.05$; $^{**}p < 0.01$. Cofficients report average effects with standard errors in parentheses.

[a]In natural log form.

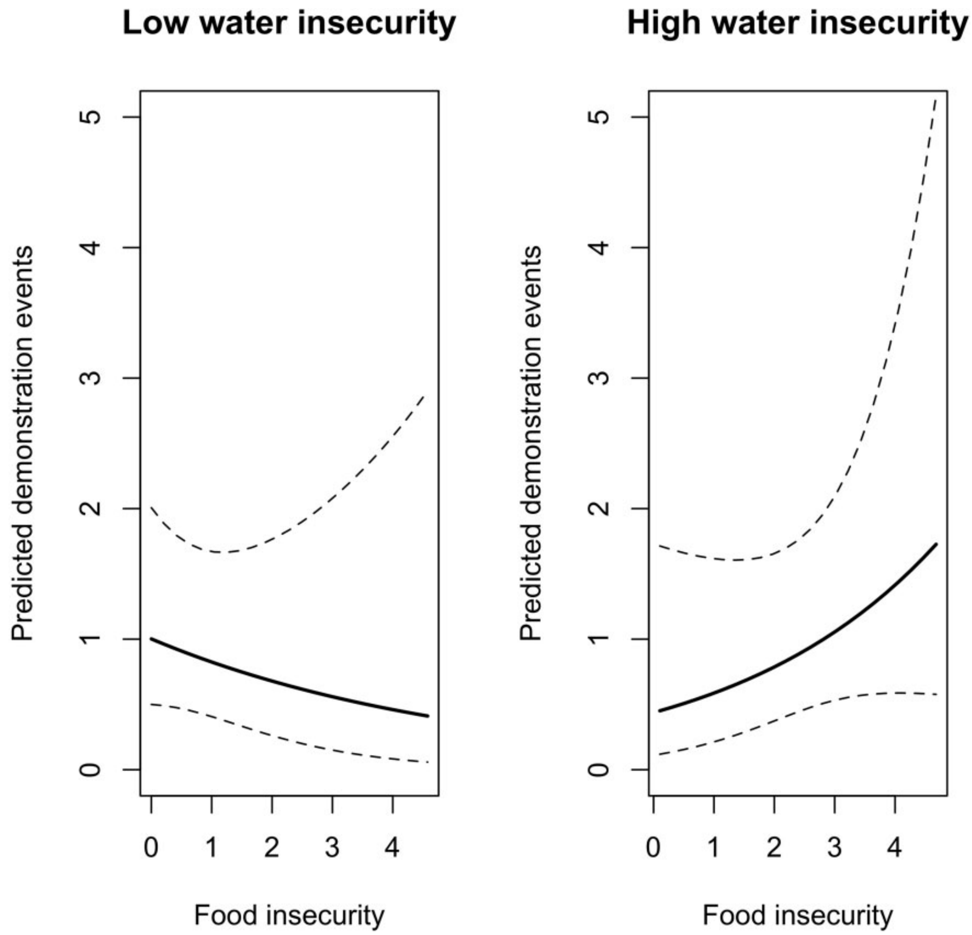

Figure 1. Predicted change in social unrest events for a one standard deviation change in each moderator: (a) Water insecurity as the moderator

and statistically significant coefficient estimate. This suggests that if urbanites experience *both* food- *and* water-insecurity, social unrest ensues, not only because the two staple insecurities are present, but *because they reinforce each other*. Thus, the results are in line with Hypothesis H2 and the broader claim advanced in this study about the joint impact of acute staple insecurities in motivating social unrest. Log likelihood and AIC values suggest the interactive models provide the best fit for the data of all the models reported in Table I. These models hence provide an effective illustration of the importance of accounting for the mutually reinforcing nature of staple insecurities, rather than using one to capture the effects of the other or including both additively in the same specification.

To evaluate whether our interaction provides substantive support for H2, we combine the individual component terms of *Food insecurity*$_{t-1:t-7}$ and *Water insecurity*$_{t-1:t-7}$, along with *Food insecurity*$_{t-1:t-7}$ $\times$ *Water insecurity*$_{t-1:t-7}$, to plot the marginal effect of a one-standard deviation (SD) change from below to above the mean in *Water insecurity*$_{t-1:t-7}$ across the range of *Food insecurity*$_{t-1:t-7}$. We then repeat this process, using *Food insecurity*$_{t-1:t-7}$ as our moderator/reinforcer. To do so, we use our ZINB model interaction estimates to calculate the expected count of demonstrations across the range of (logged) *Food insecurity*$_{t-1:t-7}$ ($0 \Leftrightarrow 4.693$) and *Water insecurity*$_{t-1:t-7}$ ($0 \Leftrightarrow 4.607$) at (i) a scenario where the other staple insecurity is one SD below its mean and (ii) a scenario where it is one SD above its mean, holding all other variables to their means or modes.

We plot these estimated marginal effects, along with their 95% confidence intervals, in Figure 1. As these plots show, *Food insecurity*$_{t-1:t-7}$'s expected effect on social unrest in urban-grid days where water insecurity is low is weak and negative (a predicted decrease of about 0.5 demonstrations), and – at the extremes – not distinguishable from zero. In contrast, when water insecurity is also high – that is, one SD above average – the expected

Figure 2. Predicted change in social unrest events for a one standard deviation change in each moderator: (b) Food insecurity as the moderator

effect is strong and positive (an average increase in the predicted count of social unrest events of ~ 1.2 demonstrations), and always distinguishable from zero.

These observed effects remain when *Food insecurity*$_{t-1:t-7}$ is the moderator/reinforcer (see Figure 2).[5] The predicted impact for high *Water insecurity*$_{t-1:t-7}$ when food insecurity is high is slightly lower (a predicted increase of ~ 0.7 unrest events), but it is still positive and distinguishable from zero. In both cases, the expected increases in social unrest events are far greater than the corresponding sample mean (0.06 daily demonstrations).

These substantive results therefore lend additional support to H2. More broadly, they also suggest that while staple insecurities – independently – are insufficient in motivating unrest in urban areas, especially if people have developed coping mechanisms to the effects of climatic variability, their concatenation can generate a compound shock that does provide a strong enough motivation to protest. This observation is supported by the fact that, as shown in Figure A.1 in the Online appendix, the effect is much stronger for acute levels of insecurity (i.e. a change in the moderator from minimum to maximum values), when the pressure on consumption produced by such combined shocks is far greater. These minimum-to-maximum changes show a predicted increase of ~ 6 events in the frequency of social unrest for *Water insecurity*$_{t-1:t-7}$ as the moderator/reinforcer, and ~ 5 events when *Water insecurity*$_{t-1:t-7}$ is the moderator/reinforcer.

We evaluate the robustness of our results in Tables A.7–A.13 in the Online appendix. Unless otherwise noted, we rely primarily on interactive ZINB specification. These robustness models first disaggregate our dependent variable to violent and nonviolent unrest, and then consider a different event dataset for our dependent variable in Table A.7. Notably, we find that our interactive effect primarily influences nonviolent unrest,

[5] For example, in situations when – due to low food productivity – water is diverted away from cities and toward rural areas.

although our coefficient estimates also show the expected sign when the dependent variable includes solely violent unrest events. Table A.8 illustrates that our findings are robust to: omitting all controls from the model, including only tweets in Swahili to illustrate that our results are not caused by any biases underlying our English language tweets, including lagged dependent variable, accounting for days when disputes over elections occurred, and accounting for the specific features of urban areas. Table A.9 further illustrates our findings' robustness to: including geospatial confounders, accounting for repression by the government, geopolitical confounders, and accounting for all said confounders together in a control inclusive model. Next, Table A.10 illustrates our findings' robustness to alternative modeling strategies, including: a zero-inflated Poisson model, clustered standard errors by grid cell, fixed effects by grid cell (NB model), fixed effects by grid cell and month (NB model), and random effects by grid cell (ZINB). Table A.11 then demonstrates that our findings are robust to a more conservative set of initial keywords used for Twitter scraping.

Finally, social unrest may exhibit both serial correlations over time and endogeneity with our staple insecurity variables. Accordingly, Tables A.12–A.13 employ generalized method of moments (GMM) *dynamic* models with internal instruments to demonstrate that serial correlation is not an overriding concern. We then repeat this exercise using the disaggregated dependent variable discussed above, as well as the ICEWS-based dependent variable. Once endogeneity and serial correlation are effectively accounted for, our results become – if anything – more noticeable and statistically significant.

Conclusion

Our findings illustrate the advantages of using Twitter data, and leveraging different machine learning and statistical approaches, when trying to identify the near-immediate effect of environmental stress on social conflict. Considering the complicated pathways linking environmental stress and social conflict (Martin-Shields & Stojetz, 2019), we believe that employing such data for explaining and predicting the latter's incidence, intensity, and spread will become crucial moving forward. These data allow scholars to create *highly accurate proxies* of how individuals perceive the impacts of a particular phenomenon of interest rather than employ less accurate and/or indirect (observed) proxies. One possible limitation is that – because they capture how people perceive such issues rather than their observed effects – definitions of food and water insecurity might vary across country and context: what is considered food insecurity in Kenya might be different from how people perceive it in Papua New Guinea or Germany. Likewise, our current search terms for identifying food and water insecurity tweets in Kenya are unlikely to be definitive, especially contingent on future crises. Nevertheless, Twitter data, and this study's operationalization procedures, provide major advantages in terms of geotemporal – as well as substantive – measurement by allowing researchers to accurately and effectively operationalize the *exact time and relative geographic location* of the potential trigger, environmental or otherwise. This innovation could have a far-reaching impact on climate–conflict analysis, as well as political violence research more broadly.

Another viable direction for future research is to explore the role of other potential moderators on social unrest and social conflict more broadly. One potentially salient moderator is the pre-existence of ethnic enmity and ethnic grievance, which can become even more acute when a staple insecurity is also present (see e.g. Scheffran, Ide & Schilling, 2014). Another possibility is that in countries and locations where antigovernment sentiment is already widespread, shocks to staple securities can have a greater impact than in more stable states. A third possibility is that geospatial features, for instance the degree of elevation or the existence of natural barriers, can make the impact of staple insecurities on social unrest more likely by hindering effective responses to the sudden onset of the crisis and hence facilitate disillusion with the government.

There are also several pertinent policy implications. Our findings suggest that if climate change trends hold true (IPCC, 2012, 2018) and staple insecurities become more common in some countries, the reinforcing effects we identify here will become more common and more acute. This, in turn, suggests that staple insecurities will, and are, becoming a destabilizing geopolitical force (Bellemare, 2015; Hendrix & Haggard, 2015). That is not to say that one should give in to environmental determinism. Agency on the part of leaders, entrepreneurs, scientists, and local activists can go a long way in combating environmental issues and their impact(s). Such agency also opens doors for abuses of power and non-democratic measures such as providing aid in a politicized manner to appease one's supporters, or preventing it reaching opposition groups. To this end, our findings elicit important staple insecurity-related mechanisms that explain variations in social unrest, such as the compounding and complementary effects of different staple insecurities upon each other and their differential population impacts.

Our findings also suggest that such shocks are more likely to generate nonviolent rather than violent responses. This could be unique to Kenya, a state where politics – while sometimes contentious – have rarely deteriorated to the level of civil war. However, an alternative proposition is that this is how people in urban areas primarily respond to staple insecurity shocks. This illustrates another important role of agency: when people in (developing) urban settings are able to clearly make their grievances over these insecurities known, they do not need violence to achieve an effective policy response. Possibly, by highlighting urban residents' dissatisfaction with a regime's response to the onus of two simultaneous insecurities happening, the residents can actually help shape the government's response to their plight. This view is supported by other cases where multiple staple insecurities were experienced at once; for example, in Tajikistan (Kelly, 2009), authorities were unable to effectively address the adverse effects because they did not know which issue to tackle first. This is another unique aspect of our interactive findings, which may explain why similar civilian responses were not observed in the non-interactive models.

These conclusions are in line with studies emphasizing that supplementing 'standard' environmental resilience programs with assistance directed at building up capacities to 'smooth out' the effects of sudden consumption shocks can enhance political stability, for instance with respect to civil war (e.g. Buhaug, 2010). Another strategy for pre-empting the potentially negative impacts of staple insecurities may be to design economic and political means that will allow governments to make *credible* commitment to their citizens to stabilize food and water supplies *before* a crisis occurs. This will enable governments, even without international assistance, to more effectively address sudden staple shortages, which can help prevent violence and save lives.

Replication data

The dataset, codebook, and do-files for the empirical analysis in this article, along with the Online appendix, can be found at http://www.prio.org/jpr/datasets.

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