Supplemental Appendix for Food and Water Insecurity as Causes of Social Unrest: Evidence from Geolocated Twitter Data[1]

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Contents

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Overview

In this supplementary material, we first provide a detailed summary of the steps used to obtain our Twitter-based measures of food and water insecurity. This is followed by a summary of relevant protest and food/water insecurity events occurring within Kenya during our period of analysis, alongside a qualitative evaluation of our Twitter data against these on-the-ground benchmarks. We then report summary statistics and additional figures from our main models and robustness models. We next provide a set of robustness models associated with the analyses presented in our main article. We conclude with a set of generalized methods of moment (GMM) models that account for potential endogeneity and serial correlation in our data.

Kenya Twitter Data

Our article sought to collect and code individual tweets related to food insecurity and water insecurity across urbanized areas within Kenya for the August 23, 2017 to March 11, 2019 period. This process encompassed six essential steps that are detailed below:

1. Webscraping a collection of over one million geolocated tweets for urban localities in Kenya based upon a set of food and water-related keywords, in both English and Swahili.

2. Developing a coding scheme for hand-coding all scraped tweets from the scraped sample in terms of whether a given tweet pertained to water insecurity (=1) or not (=0), and/or to food insecurity (=1) or not (=0).

3. Utilizing two human coders for the hand-coding of 5,000 English-language tweets and 5,000 Swahili-language tweets based upon this coding scheme, so as to simultaneously (i) evaluate the reliability of our food and water insecurity coding schemes and (ii) train a set of machine learning classifiers for the coding of all one million+ tweets along these two dimensions.

4. Determining an appropriate set of machine learning classifiers for the supervised classification of food insecurity and water insecurity, though the aid of cross-validation assessments of our human labeled tweets, separately for our Swahili and English language samples.

5. Supervised machine classification of all 906,695 unlabled English language tweets and all 363,386 unlabeled Swahili language tweets via an ensemble of machine learning classifier(s) chosen in step four above.

6. Formatting, aggregating, and merging all classified tweets to an appropriate spatio-temporal level of analysis for use in our anticipated statistical models.

Webscraping Tweets

We begin by collecting a corpus of relevant tweets related to food and water-based keywords for the 13 most populous cities, town councils, or municipal-units in Kenya. Our focus was on urban areas as opposed to Kenya on the whole due to the global urban bias in social media usage, especially across the developing world (Wyche, Schoenebeck and Forte, 2013; Khan and Mehmood, 2017). The 13 most populous Kenyan urban locations in descending order, with their sourced levels of population in parentheses,[2] are as follows: Nairobi (3,375,000), Mombassa (1,200,000), Kisumu (600,000), Nakuru (307,990), Eldoret (289,380), Kenhancha (256,086), Ruiru (238,858), Kikuyu (233,231), Kangundo-Tala (218,557), Malindi (207,253), Naivasha (181,966), Kitui (155,896), and Machakos (150,041). We considered these 13 total localities, as opposed to the 'top 10' localities, because we anticipated that some localities would ultimately be combined due to their geographic overlap (e.g., adjacency). Several localities are indeed collapsed when we combine and deduplicate our Twitter data into a total of 11 PRIO-GRID (Tollefsen et al., 2012) cells further below.

For the 13 geographic locations outlined above, we sought to scrape tweets based upon a set of relevant keywords for the time period of interest (August, 23, 2017—March, 10, 2019). Any tweet that had a geolocation assigned to one of the locations mentioned above—and that contained at least one keyword of interest (listed below) within the body of the tweet itself—was scraped. Note that this scraping step was purposefully designed to be *overinclusive* in terms of the tweets scraped per each geographic locale. That is, we define our keyword list in a manner that is accepting of false positives (with respect to food and/or water insecurity) at the initial tweet scraping stage, given that we will subsequently be using a human coding and supervised machine learning approach that will together substantially

[2] The value for Nairobi was taken from: Kenya Census, 2009. Available at: `https://www.scribd.com/doc/36672705/Kenya-Census-2009`. Accessed on 8/23/2017. The value for Mombasa was taken from: Business Insider, 4/16/2014, "Investors Fault Mombasa's New Master Plan." Available at: `https://www.businessdailyafrica.com/Investors-fault-Mombasa-new-master-plan--/-/539546/2148746/-/fprxkxz/-/index.html`. Accessed on 8/23/2017. Remaining values were taken from: CIA World Factbook. Available at: `https://www.cia.gov/library/publications/the-world-factbook/geos/ke.html`. Accessed on 8/23/2017.

narrow our overall set of scraped tweets to *only* those that actually pertain to food and/or water insecurity. With this in mind, we now describe the keywords used for our English language and Swahili language Twitter-scraping tasks.

We first identified the following English-language keywords after a review of relevant topics discussed in the media surrounding food and water issues in Kenya at the time of the initiation of this study:[3] 'drought,' 'water,' 'food,' 'maize,' 'milk,' and 'sugar.' We then identified a set of comparable Swahili keywords whilst leveraging the same sources cited above, and with the aid of Google Translate, to arrive at the following matching Swahili keywords: 'ukame,' 'maji,' 'chakula,' 'mahindi,' 'maziwa,' and 'sukari.' The latter (Swahili) keyword translations were subsequently verified by a native Swahili speaker, who is also a professor of the language at a major academic institution. We next added two keywords that were invoked in both Swahili and English texts within Kenya in relation to a pair of common Kenyan dishes: 'ugali' (a type of grits or porridge made from maize flour) and 'nyama' (for recovering mentions of 'nyama choma'—a grilled/roast meat dish).[4] We then reviewed an initial pre-coding sample of scraped tweets based upon the keywords mentioned above—alongside a series of additional news media reports—to identify and include a set of five additional keywords for use alongside those presented above (we include meanings and further rationales for these five additional keywords in footnotes to each): 'mimea,'[5]

[3]The Guardian, 6/02/2017 "Drought takes centre stage in Kenya's election campaign as food prices rise." Available at: `https://www.theguardian.com/global-development/2017/jun/02/drought-centre-stage-kenya-election-campaign-food-prices-rise`. Accessed on 8/23/2017. Climate Change News, "Kenya's Food Crisis: With This Kind of Farming, I Only Make a Loss," 7/26/2017. Available at: `https://www.climatechangenews.com/2017/07/26/kenyas-food-crisis-kind-farming-i-make-loss/`. Accessed on 8/23/2017. Chatterjee, Siddharth, 05/2017. "Kenya's Drought: Response Must Be Sustainable, Not Piecemeal" Inter Press Services (IPS) News Agency. Available at: `http://www.ipsnews.net/2017/05/kenyas-drought-response-must-be-sustainable-not-piecemeal/`. Accessed on 8/23/2017. Huho and Mugalvardi (2010).

[4]Food in Every Country, "Kenya," 2011. Available at: `http://www.foodbycountry.com/Kazakhstan-to-South-Africa/Kenya.html`. Accessed on: 8/23/2017.

[5]'Mimea' refers to plants or vegetation, and was a Swahili term that we found to appear frequently alongside discussions of droughts (e.g., "mimea ya kuhimili ukame") within our preliminary set of scraped Kenyan tweets and within several pertinent Swahili-language news stories published in the immediate lead-up to our initiation of Twitter scraping (e.g., Baher Kamal, 06/13/2017. "Mashariki ya Kati: Ukame Kuwageuza Watu kuwa Wahamiaji wa Milele, Waliomo katika Hatari ya Kuvutiwa na Ugaidi?" Available at: `http://cdn.ipsnews.net/documents/Kiswahili_Baher_Kamal.pdf`. Inter Press Service (News Agency).

'unga,'[6] 'millet,'[7] 'sorghum,'[8] and 'kiangazi.'[9] These latter five terms were intended in part to ensure that we had a broad baseline of food/water-related Swahili and English tweets to reference in coding our food and water insecurity tweets, but ultimately did not contribute to a substantial share to the actual water and food insecurity tweets coded below. In robustness Table A.11, we demonstrate that our key findings are robust to our sample's *exclusion* of any tweets that solely contain one of the latter five keywords noted above: 'millet,' 'sorghum,' 'mimea,' 'unga,' or 'kiangazi.'

Drawing upon the keywords mentioned above, we next set up 13 separate Twitter scraping routines—one routine for each of the 13 geographic locations mentioned above. We then

Accessed on: 8/23/2017. Carren Omae, 01/12/2017, "Wakenya kuendelea kuahangaika kutokana na hali ya ukame." Standard Digital. Available at: `https://www.standardmedia.co.ke/article/2000229652/wakenya-kuendelea-kuahangaika-kutokana-na-hali-ya-ukame`. Accessed on: 8/23/2017.

[6] We included 'unga' because we were concerned that the use of 'maize' (English scraping) and 'mahindi' (Swahili scraping) may produce inconsistencies in the relevant tweets scraped across both languages. Specifically, our use of 'maize' in the English keyword sample would ensure that we scraped every English language tweet referencing not only 'maize,' but also 'maize flour'—a staple food for most of the Kenyan population—whereas the same would not be the case for our Swahili keyword sample given that a distinct Swahili word—'unga'—is used to refer to 'maize flour' in Kenya. Hence, adding 'unga' to our Swahili keywords ensures that both our English- and Swahili-tweet samples include tweets mentioning maize flour, in addition to mentions of 'maize' itself. For a reference supporting (i) the exchangeability of 'unga' and 'maize flour' in the Kenyan context and (ii) our claim that maize flour is a Kenyan staple, see: The Guardian, 6/02/2017 "Drought takes centre stage in Kenya's election campaign as food prices rise." Available at: `https://www.theguardian.com/global-development/2017/jun/02/drought-centre-stage-kenya-election-campaign-food-prices-rise`. Accessed on 8/23/2017.

[7] This appeared in our initial sample of scraped tweets, but without comparable instances of 'mtama.' We hence included 'millet' (to identify mentions of both 'millet' and 'millets') in the interest of being over-inclusive in our initial tweet sample, and especially given support for English language discussion of millet as a staple crop in Kenya from some English language sources (e.g., USAID, 2010).

[8] This appeared in our initial sample of scraped English-language tweets. However, we did not find similar appearances of 'mtama' (there is no distinct word in Swahili for 'sorghum' in Swahili—'mtama' is used for both 'sorghum' and 'millet') in our initial scraped sample of Swahili tweets. We hence included 'sorghum' with some degree of caution, given support for English language discussion of sorghum as a staple crop in Kenya from some English language sources such as USAID (2010) and Chatterjee, Siddharth, 05/2017. "Kenya's Drought: Response Must Be Sustainable, Not Piecemeal" Inter Press Services (IPS) News Agency. Available at: `http://www.ipsnews.net/2017/05/kenyas-drought-response-must-be-sustainable-not-piecemeal/`.

[9] Our primary set of Swahili keywords included the default Swahili word for drought in Kenya ('ukame'). Inclusion of 'kiangazi' was intended to ensure that we fully captured any lingering mentions of 'drought' in our scraped Swahili tweets, given that some Swahili sources discuss 'kiangazi' as an alternate term for the word 'drought' (See, e.g., "Kiangazi in English" Available at: `https://en.bab.la/dictionary/swahili-english/kiangazi`. bab.la. Accessed on 8/23/2017). However, because our own discussions with a Swahili expert suggested that 'kiangazi' is instead primarily used for "summer" in Kenya, we include 'kiangazi' with caution and omit it from the more conservative keyword-sample robustness model assessments discussed below.

began scraping our primary sample of candidate tweets for subsequent food and water insecurity coding in real-time beginning on August, 23, 2017, and every 15 minutes thereafter, with the aid of the proprietary version of Twitter Archiver (i.e., Premium Twitter Archiver). For these scraped tweets, we chose to omit retweets during the scraping stage, which is in line with past social science research employing Twitter data (Jungherr et al., 2016; Zhou, Wang and Chen, 2015; McCorriston, Jurgens and Ruths, 2015).

This Twitter scraping approach provides us with a unique daily corpus of scraped, location-specific tweets for each location of interest from August, 23, 2017 until March 10, 2019. All tweets contain the time and date that a tweet was made, the name of the user that initiated the tweet (in terms of screen name and full name), a unique tweet ID, the number of followers and follows for that user at the time of their tweet, the app and/or web interface used to make the tweet, the number of retweets and favorites for that tweet at the time of scraping, an indicator of whether the Twitter user was verified or not, the user's self-reported Twitter biography and location, and the text of the tweet itself, among other meta-data.

For the time period outlined above, these webscraping efforts yielded a sample of 930,278 English-keyword tweets (hereafter, "English tweets") and 385,018 Swahili-keyword tweets (hereafter "Swahili tweets"). That being said, the spatial proximity of several of our 13 urban locations, and the fuzziness of Twitter's internal geolocation assignments, ensures that duplicate tweets can at times arise across our 13 location-specific Twitter scraping routines. This is especially the case for localities in proximity to Nairobi: Ruiru, Kikuyu, and Kitui. We handle these duplicates in multiple manners within the sections discussed further below, including comprehensive deduplication at the final data aggregation stage.

Coding Scheme for Measuring Food and Water Insecurity

After scraping our relevant Twitter sample, we sought to devise a coding scheme for the determination of (i) whether or not a given tweet pertained to food insecurity as opposed to broader food-related issues and (ii) whether or not a tweet pertained to water insecurity as opposed to broader water-related issues. This coding scheme was informed by the relevant literatures pertaining to the measurement and operationalization of food and water (in)security, as well as by several limitations in the types of information conveyed in textual Twitter data (i.e., tweets). Here we discuss these items in full.

Within the extant water and food security literatures, academic studies have adopted varying levels of measurements. Most commonly, these levels of measurement pertain to the household, country, subnational/regional, or global levels of analysis. Here, we seek to build off of these previously explored levels of analysis by initially focusing on the individual level of measurement (via tweets) before aggregating this information to larger spatio-temporal units. As such, our work is informed by past studies of food and water security from each level of measurement mentioned above. We begin by briefly synthesizing the extant measurement literature pertaining to food and water security, before turning to our own definitions that this gives rise to.

With respect to water security, several studies have specifically focused on urban water security by examining the interaction between economic welfare/development, social equity, environmental protection/sustainability, and water-related risks (Romero-Lankao and Gnatz, 2016; Hoekstra, Buurman and van Ginkel, 2018, 45; 3). A number of other studies have considered this construct at the global level by analysing water scarcity, (non)renewable groundwater, groundwater depletion, drought frequency, access to sanitation, access to drinking water, flood frequency, flood risk, and a world governance index (Gain, Giupponi and Wada, 2016, 3-6). Finally, several studies have considered the local and household levels through an investigation of "water needs, perceptions of rainfall, sources of anxiety and stress, and past and future conflict" (Marcantonio, Attari and Evans, 2018, 313).

Within the food security literature, there have been explicit calls for a shift away from the sole focus of the national level and for more individual- and household-level analyses as the latter two allow for better a more precise identification of the actors that are most likely to be adversely affected by droughts, food price increases, and related adverse shocks (Barrett, 2010; Staatz, D'Agostino and Sundberg, 1990, 1311). Upton, Cisse and Barrett (2016) add to this, noting that, to date, aggregate, national-level food availability has dominated food security studies. Leroy et al. survey the 'access' dimensions of food security at the individual and household levels (2015, 167); with a focus on the food insecurity-conflict nexus, Ujunwa, Okoyeuzu and Kalu (2019, 182), Jones, Mattiacci and Braumoeller (2017, 335), and Murshed, Badiuzzaman and Hasan (2018, 1) examine the country-level, and Lele et al. suggest a multi-level analysis by examining "diet quality [and] care practices," and the "whole food system" by recognising the "interdependence between agriculture and the environment, food and social inclusion, nutrition and health that is needed for resilience and sustainability" (2016, 4). There are hence multiple dimensions to both water and food insecurity that have been identified by academics.[10]

Notwithstanding these different levels of aggregation, and across both food and water security, there is an overwhelming focus on access and availability as the most relevant dimensions of interest. More specifically, for food security, scholars have identified access, availability, nutrition, utilisation, stability, and resilience as important components of developing an understanding of food security (Staatz, D'Agostino and Sundberg, 1990; Lele et al., 2016, 5). For water security, scholars have identified similar elements, including access, availability, water quality and quantity (Garrick and Hall, 2014; Gain, Giupponi and Wada, 2016, 621; 3-6). Furthermore, studies of both food and water security have incorporated concern of the management and governance of food and water security systems which seemingly align with a goal-orientated perspective in that they aspire to achieve food and water security.

For our coding scheme, our focus accordingly engages with both access and availability dimensions of food and water security. This is consistent with the anticipated relationships

[10] In specific regard to Kenya, Upton, Cisse and Barrett indicate that the northern part of Kenya has a local population that is both poor and highly vulnerable to weather shocks and. Furthermore, in their study of the Marsabit District (now County) in northern Kenya, they include a variety of questions in their surveys of 924 households. These questions related to "livestock production, risk and insurance, employment, expenditure and consumption, assets, and savings and credit, in addition to anthropometric measures of children under five years of age" and the surveys used recall techniques to "elicit data on seasonal income, livestock production, and other livelihood questions" (Upton, Cisse and Barrett, 2016, 141).

that will be ultimately tested, which focus on the effects of food and water security upon social unrest.[11] It is further informed by the anticipated task of coding discrete instances of water and food security from individual tweets, which limits the applicability of several related 'aggregate' dimensions of food or water security mentioned above, such as the 'stability' component to food security and its requirement that one assesses food (in)security over multiple units of time. Hence, and drawing upon a commonly adopted definition, food security can be initially defined for our purposes 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). However, for our coding scheme, this definition of food security is then more appropriately interpreted as 'a situation that exists when all people, at all times, have physical, social and economic access to sufficient and safe food that meets their dietary needs for an active and healthy life.'

The amended definition above best captures the dimensions of access and availability and removes other elements, such as utilisation, nutrition, and resilience that are not germane to this study. We hence take a cue from Koren and Bagozzi (2016),[12] who similarly define access in the context of food security as "the ability of individuals to obtain food, as well as the presence of absence of safeguards for those who cannot obtain food by licit means." They, in turn, refer to availability as "the total amount of food that can be obtained in a given region" (Koren and Bagozzi, 2016, 1001). This conceptualization is consistent with that of Martin-Shields and Stojetz (2019, 151), who define access as containing "variables that measure physical infrastructure for bringing food to market, as well as individual level indicators of whether people have access to the necessary umber of calories per day." We hence seek to code instances where individuals express concerns over (or report on) the absence of, or threats to, these components of food availability and food access below. That

[11] As opposed to, for example, focusing on the (household or individual-level) caloric or nutritional aspects of food security.

[12] Also see Bagozzi, Koren and Mukherjee (2017).

is, for coding purposes, we conceptually define food *insecurity* as:

- 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.

Relative to extant definitions of food security, water security lacks a degree of consensus regarding a definition. Romero-Lankao and Gnatz define urban water security as "the capacity of urban water actors to maintain a sustainable availability of adequate quantity and quality of water, to foster resilient urban communities and ecosystems in the face of uncertain global change" (2016, 47). Grey and Sadoff (2006) define water security as the availability of acceptable quantities, risks, and qualities of water for peoples (including health and livelihoods), economies (including production), and environments (including ecosystems). More succinctly, Gain, Giupponi and Wada define water security as "the conditions in which a sufficient quantity of water resources is available and accessible of adequate quality" (2016, 3). These conceptualizations of water security are generally in line with those of food security discussed above. However, unlike food security, dual definitions of 'access' and 'availability' have not been widely employed for water security. In this case, we contend that the earlier definitions of access and availability drawn from Koren and Bagozzi (2016) can be transplanted here with 'food' supplanted by 'water.' In terms of a definition of water security that focuses on the access and availability dimensions, we thereby adopts a framework that is in line with Gain, Giupponi and Wada's definition above, leading to the following definition of water *insecurity* for coding:

- 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.

Based upon the literature and definitions discussed above, our coding scheme then sought to represent 'food insecurity,' 'water insecurity' as two distinct and potentially overlapping constructs, as opposed to mutually exclusive categories. Herein, we determined it best to classify each scraped tweet based upon separate binary indicators for the presence (= 1) or absence (= 0) of our water and food security dimensions. By coding each tweet separately for food *and* water security, we were able to accommodate instances where food and water insecurity intersected. While infrequent, such tweets did occur in our scraped sample. For example, one Twitter user tweeted in English "Don't engage me if you can't link politics to drought, unemployment, suicide, food insecurity, insecurity, corruption #DroughtNiReal." Another example of a tweet that features both food and water security expressions was as follows: "After u r done with relief food for flood victims, next will be kenyans4kenyans for drought victims coz floods destroyed their crops." As these tweets illustrate, there is often clear indication of food and/or water insecurity concerns within our sample tweets, but insufficient information within our observed tweets to fully distinguish either water or food security separately across their respective access or availability dimensions. This leads us to employ a coding framework that simply records tweets as water or food insecurity-related (or not) on the whole, as opposed to access and availability separately.

The realities of Twitter data imposed a number of additional constraints on our coding of tweets along each dimension. One such constraint included the interpretation of tweets. Some tweets were written in a somewhat abstract manner, therefore limiting the capacity of the human coder to assign a value of "1" or "0." This is largely the result of tweets being limited in characters, leaving little room for additional context to provide clarification. In these instances of excessive abstraction, tweets were coded as 0 on both the food and water insecurity dimensions to avoid the imposition of subjectivity bias from the coder(s) and to ensure that only tweets that explicitly expressed food and/or water insecurity were coded as "1." Another anticipated coding obstacle entailed tweets that employed combinations of English and Swahili and in some cases additional languages within a single tweet, or tweets that mixed specific assertions with more abstraction discussions. These patterns were not common, but when they did arise the corresponding tweets were difficult to translate and/or decipher in a consistent manner.

The limitations outlined above justified the need for a more detailed and consistent coding scheme. Importantly, one constraint imposed in the interest of consistency was to only code instances where access or availability to a particular resource (food or water) was expressed as being threatened, undermined, or characterized with related levels of worry or pessimism. Tweets that by contrast expressed (food and/or water) access or availability in a positive light, or that suggested that such access or availability was increasing, where not coded as water insecurity or food insecurity. For example, one scraped tweet, noting "Kuresoi residents demonstrate over lack of access to water" was determined to be an example for coding as a "1" because it conveyed an explicit concern for water security. Conversely, another tweet, "No more worries about water shortage" was coded as a "0" because it did not express a present concern for water *insecurity*. This is consistent with the definitions of food insecurity and water insecurity highlighted above.

We then developed a more formal set of coding rules for the coding of a scraped tweet as a "1" on either of our water or food insecurity measures. This first entailed that we outline a set of more specific characteristics of food insecurity and water insecurity tweets for use as a guide by our (anticipated) multiple coders. These more specified characteristics for inclusion included the following specific qualities of individual tweets: anxieties regarding the price of food and/or water, observations of extreme weather conditions with specific linkage to food or water, the unavailability of food and/or water, crop failure, delays in supply (chains), long queues for food and/or water, news of food and/or water scandals (e.g. corruption, smuggling, tainted food, monopolies, cartels, and bribery), reports of adverse food market (or price) volatility, and discussions of problems with market schemes and government policies pertaining to food and water. We then reviewed an initial random sample of 100 tweets with these coding criteria in mind.

Based upon our initial review of this pre-coding random sample of 100 tweets, several more specific coding rules and refinements were then added to the list of criteria outlined above:

1. If tweets only vaguely mentioned the price of food and/or water without additional context, these should be coded as "0," unless there was specific mention of issues regarding threats to availability and/or access (e.g., a particular price being too high or increasing);

2. mentions of climatic drought are only to be coded as water insecurity (=1) unless there is specific reference to an impact on food/crops;

3. tweets concerned about food and/or water insecurity outside of Kenya should be coded "1" for the relevant dimension(s), so as to avoid judgement calls regarding particular Twitter user's expectations of impact upon Kenya via global supply chains or regional trends;

4. any expressed discussion of (potential) contamination of food and/or water (supplies) is considered 'insecurity' and, therefore, coded as a "1" on the relevant dimension(s);

5. negative expressed concerns about sewage and drainage infrastructure (e.g., damage to infrastructure, or descriptions of infrastructure as being insufficient) should be coded as a "1" for water insecurity;

6. mentions of the availability or construction of security-enhancing technologies (e.g. improved irrigation infrastructure or the establishment of a dam) should be coded as "0;"

7. food- and water-related scandals, and accusations of corruption (but only if there is an explicit mention of contamination, rather than, e.g., a general mention of mismanagement or company tensions), market-disruption (including price spikes and volatility but not general non-directional comments on price or the general well-being or stabil-

ity of the market), and related behaviors ascribed to cartels/barons, smugglers, etc., should each be coded as a "1" (i.e., insecurity) on the relevant dimension(s);

8. mention of displacement of people and/or refugees in need of food and/or water assistance should be coded as a "1" on the relevant dimension(s);

9. mentions of food and/or water scarcity in specific shops or market (stalls) should be coded as insecurity in the relevant dimension(s); and

10. mentions of animals dying from contaminated water supplies, drought, etc., should be coded as water insecurity, but not food insecurity, unless the animal was considered livestock with direct linkages to food products (e.g. 'cattle' can be linked, but not 'rhinos' or 'camels').

Hand-coding

We next apply the hand-coding framework outlined above to two random samples drawn from our full samples of scraped (English and Swahili) tweets, employing two human coders for these coding tasks. Specifically, we drew separate random samples of 5,000 tweets from our English and Swahili samples, yielding a total random sample for hand-coding of 10,000 tweets. Given that our Swahili and English tweets are in distinct languages, we complete all human-coding and supervised coding steps for these languages and tweets separately, before combining all classified tweets at the data aggregation stage. As noted above, a number of duplicate tweets arose within each language-specific tweet sample. Accordingly, and prior to drawing the random samples of 5,000 tweets mentioned above, we employed mild deduplication by first collapsing our sample in a manner that assigned duplicate tweets that happened to be scraped for both our Nairobi twitter scraping routine and another nearby locality (e.g., Ruiru, Kikuyu, or Kitui) to the Nairobi tweet sample. Note that we return to our original non-deduplicated English and Swahili tweet samples at the out-of-sample machine classification stage, so as not to impose an assumption that any particular duplicate tweet in our full sample arose from Nairobi. We then fully deduplicate our supervised machine coded tweets at the data aggregation stage, which ensures that we do not have to make judgement calls regarding the assignment of a deduplicated tweet to any one particular urban location or another.

Turning to our random samples of 5,000 (deduplicated) English tweets and 5,000 (deduplicated) Swahili tweets, we next sought to evaluate the reliability of the coding scheme presented above. To do so, two coders separately coded an identical set of 1,000 English tweets, and 1,000 Swahili tweets, from our total random sample of 10,000 deduplicated tweets. Measures of inter-coder reliability were then calculated in `R`, and are reported for these subsamples immediately below. Given that this joint coding exercise employed two separate coders, we specifically used Cohen's Kappa (Cohen, 1960) for our evaluations of inter-coder reliability.

Table A.1: Assessment of Inter-coder Reliability via Cohen's Kappa

Variable	**Cohen's Kappa**
English: Water Insecurity	0.826
English: Food Insecurity	0.756
Swahili: Water Insecurity	0.836
Swahili: Food Insecurity	0.711

Note: $N = 1,000$.

Based on Table A.1, we obtain a high level of inter-coder reliability in all instances. Further, we do not observe any clear trends in higher or lower reliability across our English and Swahili-based twitter samples. However, we do generally find slightly lower levels of inter-coder reliability for our food insecurity cases (0.756 and 0.711) in comparison to our relevant water insecurity cases (0.826 and 0.836) across both languages considered. The lowest level of inter-coder reliability corresponds to a Cohen's Kappa of 0.711 (Swahili: Food Insecurity) whereas the highest level of inter-coder reliability corresponds to 0.836 (Swahili: Water Insecurity). These extremes, as well as the two additional Cohen's Kappa values that fall between them in Table A.1 (0.756 and 0.826), together encompass values for Cohen's Kappa that been discussed as "excellent" or "near perfect" within past social science research

(Steiner et al., 2004; Tang et al., 2015; Bächtiger and Hangartner, 2010, Note: 5). Therefore, there is high inter-coder agreement in the application of our coding scheme among our two coders, leading us to conclude that we have sufficient internal consistency in our underlying coding scheme on the whole.

In light of this, we next turn to our remaining randomly sampled English and Swahili tweets ($N = 8,000$). Two human coders[13] separately coded a share of these remaining tweets, again while employing equal balance in the English and Swahili tweets assigned to each coder. These human codings were next combined with the jointly coded sample of 1,000 English tweets and 1,000 Swahili tweets described above to yield our final human labeled samples of 5,000 English tweets and 5,000 Swahili tweets.[14] Altogether, the human labeled sample of 5,000 English tweets had means of water and food insecurity of 0.090 and 0.093, respectively. This suggests that our food and water insecurity labels are relatively rare in the English twitter sample, corresponding to roughly 10% of all scraped tweets. Likewise, our 5,000 human-labeled Swahili tweets' water security labels had a mean of 0.024 and the corresponding food security labels had a mean of 0.019. This implies that food and water insecurity oriented tweets encompassed roughly 2% of our scraped Swahili tweets, suggesting that these binary labels are rarer in this case than was the case for our English tweets. The hand-coded samples of 5,000 English tweets and 5,000 Swahili tweets represent the final training samples used in all supervised classification efforts. We turn to these efforts immediately below.

Supervised Classification

With our human labels in hand, we next turn to supervised machine learning for the classification of our full English and Swahili tweet samples. Ultimately this will require that we train an ensemble of machine learning classfier(s) on our 5,000 hand-coded English tweets and our 5,000 hand-coded Swahili tweets; leveraging the predictions from these classifier(s)

[13] These were the same human coders referred to above.

[14] After reviewing cases of disagreement for the jointly coded samples, we created a single collapsed version of each jointly coded sample set equal to "1" if either coder assigned a "1" in a given instance, and "0" otherwise, for each food and water insecurity measure.

to in turn classify our 906,695 unlabled English language tweets and our 363,386 unlabeled Swahili language tweets in terms of both food insecurity and water insecurity.

To achieve the above aims, our supervised classification strategy is composed of several intermediate steps. We first utilize our 5,000 hand labeled English tweets and our 5,000 hand-labeled Swahili tweets to identify a tentative set of machine learning classifiers for both tweet samples, and to select appropriate tuning parameters for each classifier therein. For this step, our training samples' human labels of food and/or water insecurity are the (binary) outcomes of interest, and our 'features' correspond to Swahili and English-specific document-term-matrices (DTM's) of unigrams derived from each of our 5,000-document training samples' original tweet texts. Prior to creating these Swahili and English-sample specific DTMs, all tweet texts were preprocessed to remove punctuation, special characters, sparse terms, and numbers; and all remaining words were converted to lower case. Given our sample size, and consistent with extant research (e.g., Pilster and Böhmelt, 2014; Bell, 2016), we then implemented a pair of in-sample supervised machine learning routines—once for our English sample, and once for our Swahili sample—using five-fold cross-validation.

These in-sample cross-validation assessments specifically consider three machine learning classifiers: a logistic regression with a Least Absolute Shrinkage and Selection Operator (LASSO) penalty, random forests, and hyperSMURF. The logistic regression with LASSO penalization implements a logit model using penalized maximum likelihood. For the LASSO specifically, this entails the application of a ℓ_1 penalty to facilitate both covariate selection and shrinkage in parameter estimates in relation to food or water insecurity. Given the large number of (relatively sparse) DTM features for our food and water insecurity classification tasks, the variable selection qualities of LASSO make this approach potentially desirable. We implement the logit with a LASSO penalty (hereafter, logit-LASSO) in `R` using `Glmnet` (Friedman, Hastie and Tibshirani, 2010). The value for the penalization parameter (ℓ_1) is selected for our application using five-fold cross-validation, and areas under the receiver operating characteristic (ROC) curve (AUCs), obtained via `Glmnet`.

Random forests are ensembles of decision trees that flexibly allow for non-linear and interactive relationships between predictors (Hill and Jones, 2014, 662) — an especially appealing set of model features given the expansive and likely conditional associations amongst our DTM predictors. The method leverages classification trees to identify and retain the optimal predictive features (within random subsamples of one's data) for binary partitions that best predicts an outcome variable of interest—in our application, food insecurity or water insecurity. This processes is then repeated, with replacement, for additional random data subsamples and with additional classification trees. We again use five-fold cross-validation and AUCs to select an appropriate number of classification trees for our random forest classifiers. HyperSMURF extends random forests to account for class imbalance (i.e., rarity) in our food and water insecurity codings. It does so via a hyperensemble of random forests, wherein all random forests are estimated in an imbalanced aware manner with the aid of a synthetic minority oversampling technique (Schubach et al., 2017). We use our cross-validation setup, along with AUCs, to select an appropriate hyperSMURF model in terms of the number of random forests used, features selected, and nearest neighbors employed.

The aforementioned steps allow us to select optimal classifiers (in terms of tuning parameters) for each of our binary outcomes of interest (i.e., food insecurity and water insecurity within both language-specific tweet samples). We report a set of cross-validation classification statistics—specifically, AUC, area under the precision recall curve (AUPR), precision,[15] recall,[16] F1-scores,[17] and overall accuracy[18]—that are derived from these optimal classifiers for our language-specific insecurity variables in Table A.2. For each classifier and language-specific insecurity variable, a unique cut-point was chosen for all classification statistics that depend upon dichotomizations of predicted probabilities (i.e., precision, recall, F1-score, and total accuracy). In these instances, we specifically favored a cut-point that minimizes the

[15]That is, positive predicted values.
[16]That is, sensitivity.
[17]That is, the harmonic mean of precision and recall.
[18]I.e., the proportion of all 1's and 0's on each binary outcome that were correctly predicted.

distance between that algorithm-outcome paring's ROC and the (0,1) boundary.[19]

Table A.2: Five-fold cross-validated classification statistics

	AUPR	**AUC**	**Precision**	**Recall**	**F1-score**	**Accuracy**
			English: Food Insecurity			
Logistic Regression with LASSO	31.91	87.21	27.31	84.94	41.33	77.67
Random Forest	31.17	88.49	32.92	75.86	45.92	83.45
HyperSMURF	31.93	88.87	29.51	84.40	43.73	79.89
			English: Water Insecurity			
Logistic Regression with LASSO	32.02	84.38	22.58	77.89	35.01	73.97
Random Forest	31.19	84.81	26.04	75.00	38.66	78.58
HyperSMURF	32.34	83.35	21.81	82.22	34.48	71.89
			Swahili: Food Insecurity			
Logistic Regression with LASSO	49.24	51.13	1.83	5.82	3.54	40.36
Random Forest	12.91	68.08	5.06	47.87	9.16	82.15
HyperSMURF	31.15	78.07	5.31	68.62	9.85	76.39
			Swahili: Water Insecurity			
Logistic Regression with LASSO	30.97	55.89	3.07	35.71	5.66	71.65
Random Forest	16.79	73.19	7.09	58.19	12.65	80.67
HyperSMURF	31.14	82.39	6.20	75.42	11.46	72.26

Note: Thresholds for Precision, Recall, F1-score, and Accuracy are optimized based upon minimized distance between ROC and the (0,1) boundary (Vermont et al., 1991; López-Ratón et al., 2014).

The classification assessments discussed above related exclusively to our 10,000 human-labeled tweets. As noted, these assessments employed five-fold cross-validation, which entailed that we randomly subdivide our 5,000 in-sample cases for both the English-language and Swahili-language Twitter samples into five folds of roughly 1,000 unique cases a piece. Our optimally chosen classifiers were then run on each of these five folds, and their out-of-sample predictions for a given fold were obtained from the 4,000 cases that were held out from that fold. The classification statistics in Table A.2 then correspond to the combined out-of-sample predictions across all five folds, as calculated separately for the English and Swahili samples and both insecurity-outcomes of interest.

Turning to Table A.2, our classifiers generally perform well in classifying each binary outcome of interest. We can first observe this by considering our two classification statistics that do not rely upon a single cutout for dichotomization. Here we can note, for example, that our AUC values for the English tweet sample in the Table A.2 each fall between 83.4-

[19] See Vermont et al. (1991); López-Ratón et al. (2014) for further details.

88.9, suggesting relatively high classification performance by accepted rules of thumb for this metric. There is slightly more divergence across classifiers in terms of AUCs for the Swahili tweet sample, wherein for this metric—as well as for the AUPR—we find that hyperSMURF exhibits substantially higher classification performance relative to random forests or the LASSO-penalized logistic regression. We surmise that this divergence in the context of our Swahili codings of food insecurity and water insecurity is attributable to the higher imbalance in the binary dependent variable labels for the Swahili tweet context.

Our threshold-based classification metrics reinforce these general observations. Total accuracy generally falls between 71%-83% for all outcomes and classifiers in Table A.2, aside from one (Swahili) instance where accuracy falls below 50% in the case of logistic-LASSO classifier. Precision is fairly low in the context of our Swahili tweets, suggesting that all classifiers are yielding a fair number of false positives in these instances. The recall values in Table A.2 suggest that all models are recovering a sizable majority of our 1's for each insecurity measure in the cases of our English tweets. However, in the context of our Swahili tweets, commensurate levels of (high) recall are only observed in the case of our hyperSMURF classifier. Similar patterns arise in our F1-scores, where we observe small differences across classifiers in the context of our English language tweets, but more substantial classifier-based variation in this metric in the context of our Swahili tweets.

Taking the above points into account, we can summarize our in-sample findings as follows. First, in the case of our English tweets, we find comparable overall performance across all metrics for our logistic-LASSO, random forests, and hyperSMURF approaches. Depending on the classification statistic considered, each of these three classifiers at times outperforms the other two, and all three typically perform well in classification (aside from precision). On the other hand, in the context of our Swahili tweets, we find that—for both water insecurity and food insecurity—the logit-LASSO performs noticeably worse than either of our classification tree based approaches. This is especially the case for AUC, Precision, F1-scores, and overall accuracy. Furthermore, hyperSMURF tends to also consistently outperform random forests in the classification of water insecurity and food insecurity within our Swahili sample—especially in the case of AUPR, AUC, and recall.

Given the above findings, we select an ensemble of the hyperSMURF, random forests, and logistic-LASSO classifiers for use in the out-of-sample classification of our English language instances of food insecurity and water insecurity. For this ensemble, we use majority vote to address instances of disagreement between our classifiers' out-of-sample predictions. By contrast, and given that hyperSMURF was the only approach to perform well in the context of our Swahili tweets, we exclusively use hyperSMURF for the classification of food insecurity and water insecurity within our Swahili tweet sample. Before performing these out-of-sample classifications, we preprocess our full set of tweets using the same steps described earlier, and again convert all retained terms (i.e., after preprocessing) to a DTM. We then re-train the aforementioned (ensemble of) classifier(s) on our full human labeled samples of 5,000 English language tweets and 5,000 Swahili tweets. Following this, we use the parameters identified from those trained models to classify all 906,695 unlabled English language tweets and our 363,386 unlabeled Swahili language tweets. In each instance, we continue to employ the cutpoint thresholds and tuning parameter values that we identified within our aforementioned cross-validation efforts.

Spatio-Temporal Aggregation

With our final codings of tweets in hand, we next sought to aggregate these coded cases for effective analysis. This entailed that we collapse our machine-coded and handcoded tweets to the daily PRIO-GRID level (Tollefsen et al., 2012), which allowed us (i) to analyze the effects of these tweets on a level of geographic aggregation that has been characterized as reliable for the analysis of political event data (Weidmann, 2015, 1143) and (ii) to fully address the duplicates in our final supervised-classified tweet samples. With respect to the latter point, we specifically retained only one unique version of each Swahili and English tweet for each PRIO-GRID location in our final collapsed sample. This deduplicates our tweets given that the PRIO-GRID cells are at a higher level of spatial resolution than our tweets, effectively binning together instances where proximate scraped urban localities exhibit geographic adjacency (and hence duplicate tweets). In total, we end up with 11 PRIO-GRID cells based upon our original 13 urban locations and their respective latitude-longitude coordinates.

After deduplicating our tweets in this manner, we create 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 relevant tweets. Note that, for each of these combined counts, we have thus summed together our English and Swahili language tweets. However, we also examine disaggregated instances of these tweets where relevant in our robustness section. As mentioned in the main article, we then calculate lagged one-week moving averages of our combined tweet counts to smooth out our tweet series and to ensure that the expressed concerns about food and water insecurity precede our conflict outcome measures. These lagged averaged counts remain highly skewed, with a mean, median, standard deviation and skeweness of 7.78, 2.43, 14.23, and 3.05 for water insecurity; and of 8.65, 3.00, 14.25, and 2.63 for food insecurity. These levels of skewness lead us to take the natural log of all lagged moving average counts prior to entering these variables into analyses. Ultimately this addresses skewness in each measure, and specifically produces means, medians, standard deviations, and skewness for our logged moving average water (food) security measure of 1.43 (1.55), 1.23 (1.38), 1.11 (1.22), and 0.82 (0.64), respectively.

Kenya Context & Qualitative Validation

This section provides a qualitative overview of (i) food and water insecurity issues, (ii) protests and political unrest, and (iii) relevant Twitter examples from our scraped Twitter sample for Kenya during the August, 23, 2017—March, 11, 2019 sample period. This allows us to evaluate *both* the appropriateness of our analysis' overall sample frame *and* the correspondence between our collected Twitter data and on-the-ground processes in Kenya.

The immediate lead-up to our August 23rd, 2017 period of analysis saw a notable degree of instability in Kenya's urban areas due to (1) Kenya's (anticipated) August 8th general elections, (2) nearly two years of ongoing shortages in maize, sugar and other staple commodities,[20] (3) country-wide droughts and urban water shortages throughout the first half of 2017, and (4) a corresponding rise food prices during the summer of 2017. We next discuss this initial context in detail, before discussing subsequent water- and/or food-insecurity induced unrest in Kenya during our full August, 23, 2017—March, 11, 2019 sample frame.

Kenya's August 8th, 2017 general elections were preceded by a several proximate elections that were each marred by varying degrees of political violence and/or vote rigging.[21] Kenya's 2017 elections also held a heightened political importance, in that they were seen as "the first real opportunity to take stock of whether [Kenya's] 2010 constitution has effectively reduced the stakes of political competition and thus the prospects for political instability" (Cheeseman et al., 2019, 215). Further complicating matters, and as noted above, the immediate lead-up to these 2017 elections saw a period of sustained drought throughout Kenya, which was originally declared to be a natural disaster by the Kenyan government in February of 2017. By mid-summer of 2017, this drought was noted as contributing to a major sugar deficit and rising food prices for many Kenyan staples such as maize flour (unga), milk, and sugar.[22] The drought and its impacts were in turn characterized as raising pre-election political tensions overall.[23] To this end, government opposition parties and groups sought to use Kenya's rising food prices to discredit the Kenya government as the general election approached, wherein "on social media, #UngaRevolution [was] growing in popularity [...]

[20]Mantoe Phakathi, 07/07/2017. "Kenya's food crisis: Drought raises prices and political tensions." Climate Home News. Available at: `https://www.climatechangenews.com/2017/07/26/kenyas-food-crisis-drought-raises-prices-political-tensions/`. Accessed on 2/29/2020.

[21]For example, post-election violence in 2007-2008 saw approximately 1,300 casualties in Kenya (Klaus, 2020, 43); whereas Kenya's Independent Electoral and Boundaries Commission (IEBC) saw street protests in 2016 and accusations in complicity in the rigging of Kenya's 2013 election on behalf of Uhuru Kenyatta (Lockwood, 2019, 542).

[22]Guardian, 06/02/2017. "Drought takes centre stage in Kenya's election campaign as food prices rise." The Guardian. Available at: `https://www.theguardian.com/global-development/2017/jun/02/drought-centre-stage-kenya-election-campaign-food-prices-rise`, . Accessed on 2/29/2020. See also Financial Times, 05/21/2017. "Rising food prices add to political pressures in Kenya." Financial Times. Available at: `https://www.ft.com/content/8d2041ce-19fe-11e7-bcac-6d03d067f81f`, Accessed on 2/29/2020.

[23]Mantoe Phakathi, 07/26/2017. "Kenya's food crisis: Drought raises prices and political tensions." Climate Home News. Available at: `https://www.climatechangenews.com/2017/07/26/kenyas-food-crisis-drought-raises-prices-political-tensions/`, Accessed on 2/29/2020.

with experts describing the drought as becoming a major political ordeal."[24]

The August 8th elections themselves saw the reelection of incumbent President Uhuru Kenyatta. However, with accusations of electoral fraud and Kenyatta's main opponent, Raila Odinga, refusing to accept the results, Kenya entered into several ensuing months of electoral contestation and political unrest. Punctuating this instability, Kenya's Supreme Court nullified Kenyatta's August 8th victory on September 1st, calling for a new election in 60 days. On the day of this Supreme Court ruling, Kenyatta and "other politicians from his Jubilee Party addressed a huge rally at Burma, a popular *nyama choma* (roast meat) market in Nairobi, where President Kenyatta, visibly annoyed, castigated the court and called the judges *wakora* (Swahili for crooks and criminals) [...]" (Kanyinga and Odote, 2019, 235). Concurrently, our twitter sample continued to capture instances of concern over food and water insecurity, with one tweet on this same date (September 1st) expressing concerns that "#WithOrWithoutSugar soon we will be having sugar without sugar and salt without sugar.. " and another on September 6th, 2017 reporting that "#KenyaChat Maize, wheat and other major crops have experienced significant yield reductions," and still another on August 29th, 2017 stating "Governor @MikeSonko please order @NairobiWater to give @Langata NHC water NOW. @NairobiWater games need to be addressed ASAP by your govt!" The ensuing October 26th election was boycotted by Odinga, leading to Kenyatta's ultimate victory and formal reelection—albeit alongside low voter turnout and subsequent formal challenges.[25] The interim period between Kenya's initial August 8th election and the Supreme Court's final ruling in support of Kenyatta's October 26th victory saw substantial political unrest and over 100 killed—albeit a level of violence that has been described as "far less violent compared to [Kenya's] earlier elections" (Klaus, 2020, 43).

With the cessation of electoral violence in late 2017, food and water insecurity issues rose more directly to the fore in contributing to social and political unrest in Kenya. Turning

[24]Guardian, 06/02/2017. "Drought takes centre stage in Kenya's election campaign as food prices rise." The Guardian. Available at: `https://www.theguardian.com/global-development/2017/jun/02/drought-centre-stage-kenya-election-campaign-food-prices-rise`, Accessed on 2/29/2020.

[25]See Kanyinga and Odote (2019, 235-236) for further background and detail.

first to water insecurity in 2018, citizens across Kenya repeatedly protested water insecurity and related water infrastructure concerns. This included protests in Machakos in December of 2018 over failed drainage systems,[26] protesters blocking the Nairobi-Mombasa highway in Emali in July 2018 to protest water shortages,[27] water crises in Kenya's "urban slums" in August of 2018,[28] and an increasing focus on Kenya's major dam projects as a point of contestation and social unrest throughout 2018.[29] Numerous scraped tweets reflect various water shortage concerns that are in line with these trends, including one from August, 29th, 2018 asking "How can the county forcefully turn off water supply without giving notice?" An extensive number of tweets within our scraped sample also underscore the latter discontent over various dams in Kenya and their interplay with the ongoing drought. Two example tweets in our sample from May of 2018[30] are illustrative of Kenyans' frustrations over this (mis)management of water supplies during this period, in noting that "@iGitz_ Somebody cud be stealing th water n putting it in patel dams„„anything is possible in kenya" and "all the dams in kenya are full to capacity...spilling water. all but ndakaini which apparently has a hole at the bottom! cheeeii!! tufiakwa!"

Additional tweets in our sample also reflect Kenya's broader trends towards water insecurity-induced unrest in 2018 with one for example highlighting a study suggesting that "Families displaced by drought likely to face violence" on September 11th, 2018. Other tweets in our sample similarly underscore the degree to which citizens sought to hold their government

[26]The Star, 12/16/2018. "Fed up Mavoko residents hold demo, resolve to 'take over' county projects." The Star (Kenya).

[27]Pius Maundu, 07/09/2018. "Protesters block Nairobi-Mombasa highway in Emali." Daily Nation.

[28]CNBC, 08/22/2018. "Kenya has a water crisis in its slums, this is what you need to know." CNBC Africa. Available at: https://www.cnbcafrica.com/news/east-africa/2018/08/22/kenya-has-a-water-crisis-in-its-slums-this-is-what-you-need-to-know/. Accessed on 2/29/2020.

[29]Business-Human Rights, 01/10/2018. "Kenya: Residents protest against water project; say they were not consulted & informed of its impacts." Business & Human Rights Resource Center. Available at: https://www.business-humanrights.org/en/kenya-residents-protest-against-water-project-say-they-were-not-consulted-informed-of-its-impacts, Accessed on 2/29/2020. Paul Goldsmith, 10/25/2018. "OL' MAN RIVER AND THE DAM STATE: Kenya's misguided Big Water policy." Elephant. Available at: https://www.theelephant.info/features/2018/10/25/ol-man-river-and-the-dam-state-kenyas-misguided-big-water-policy/, Accessed on 2/29/2020.

[30]Specifically, May, 12th, 2018 and May, 16th, 2018.

accountable for these water insecurity concerns, with one twitter user stating for instance that "@UKenyatta @alain_berset Mr President...we people of Onyonka Estate Langata have water shortage issues...we need help" on July 18th, 2018. By 2019, Kenya's sustained (three season) drought was a key contributing factor to much of this civil unrest throughout the 2017-2019 period of our analysis. Beyond the protests and unrest noted above, news reports in March 2018, for example, indicated that Kenya's 2017 drought contributed to a near ten-year low in Kenyan economic growth and that subsequent shortfalls in rainfall increased number of Kenyans faced with food insecurity from 655,800 in August, 2018 to over a million by March, 2019 (the end of our sample frame).[31] Our tweet sample reflected these same sentiments, with one February 27, 2018 tweet noting for example that "The drought in Kenya is leading to a major malnutrition crisis. - @UNICEFKenya @UNICEF #KenyaChat." Accordingly, we next turn to discussing the social and political implications of this food insecurity.

By early 2019, Kenya's sustained 2017-2019 drought was noted as undercutting maize production (a key staple in Kenya) and producing additional food and milk shortages.[32] During this 2017-2019 window, evidence suggests that social unrest in Kenya increased as a result price controls and/or staple food imports that were needed to address these varied food shortages. For instance, the cuts in maize production mentioned above were paralleled by tweets in our sample calling for Kenyan President "@UKenyatta on coming back, address the maize issue in uasin gishu and plan to tour eldoret and kericho regions, you deserted them" on April 17th, 2018. Subsequent tweets then noted rising concern over "[f]irms hired to transport maize by National Cereals and Produce Board say they are owed Sh1b; threaten to paralyse fertiliser distribution" on August 14th, 2018.

[31] Eric Ombok, 03/18/2019. "Drought Leaves 1 Million People in Kenya Needing Food Aid." Bloomberg. Available at: `https://www.bloomberg.com/news/articles/2019-03-18/kenyan-drought-leaves-1-million-people-needing-urgent-food-aid`, Accessed on 2/29/2020.

[32] Eric Ombok, 03/18/2019. "Drought Leaves 1 Million People in Kenya Needing Food Aid." Bloomberg. Available at: `https://www.bloomberg.com/news/articles/2019-03-18/kenyan-drought-leaves-1-million-people-needing-urgent-food-aid`, Accessed on 2/29/2020.

To take a second example, 2017 protests by sugar cane farmers in Kenya[33] were followed in 2018 by major political scandal[34] and public outrage over Kenya's (illegal) import of (contaminated) sugar, with many in Kenya "using the hashtag #sugarylies on Twitter to criticise what they see as misleading and false statements being made about the scandal by politicians."[35] An extensive number of tweets in our sample reflect substantial public concern over this sugar scandal, noting for example that "#ProbeNoorAfresh Honestly people are so inhuman why sell us poisonous sugar..." (June 18th, 2018). The ensuing government crackdown over contraband sugar imports led to anti-government protests by traders in Nairobi, wherein "traders marched in the city streets, carrying placards and chanting anti-KRA [Kenyan Regulatory Authority] slogans."[36] These protest-sentiments were again echoed in our tweet sample, with one user for example remarking on June 21st, 2018 that "We have a government chemist, we have a board that deals with poisons, We have a standards body and yet there is poisoned sugar in supply?" and a second calling for boycotts on June 16th, 2018 in stating that "I stopped buying kabras sugar when I noticed black insoluble materials in its sugar. #BoycottKabras." Compounding these issues, sugar cane farmers then subsequently protested in 2019 against state owned sugar factories over arrears owed to them, with backing from major sugarcane associations and unions.[37]

Prior to the latter 2019 protests by sugar cane farmers discussed in the paragraph above, traders in Voi—near Mombasa—likewise protested rising food prices in 2018, with (e.g.), some protesters violently clashing in "running battles" with police in Voi town over a corresponding 2018 County Finance Act that was argued to have raised taxes on agricultural

[33] FarmBiz Africa, 05/02/2018. "Why sugarcane production is on the decline in Kenya." FarmBiz. Available at: `http://farmbizafrica.com/high-yield/1969-why-sugarcane-production-is-on-the-decline-in-kenya`, Accessed on 2/29/2020.

[34] Martin Siele, 06/21/2018. "Boni Khalwale Backs West Kenya as Contraband Sugar Scandal Rages On." Kenyans.co.uk. Available at: `https://www.kenyans.co.ke/news/30698-boni-khalwale-backs-west-kenya-contraband-sugar-scandal-rages`, Accessed on 2/29/2020.

[35] Ashley Lime, 06/24/2018. "Kenya's 'contaminated sugar' row: What we know." BBC Africa. Available at: `https://www.bbc.com/news/world-africa-44550813`.

[36] The Star, 07/04/2018. "City traders protest over alleged harassment by government agencies." The Star (Kenya).

[37] Kepher Otieno, 02/23/2019. "Cane farmers protest want Sh2.7 billion listed beneficiaries published." The Standard.

commodities in Kenya.[38] Our scraped tweets captured multiple relevant instances of food and water insecurity in the lead-up to these Voi protests, wherein one such tweet on June, 24th, 2018 reported that the "COAST WATER Services Board disconnects supply to Voi town and its environs over unpaid Sh411m bill as standoff with Taita Taveta County escalates."

Contraband rice imports—in a similar fashion to the contraband sugar imports mentioned above—further exacerbated social and political tensions during this period. In Mombasa, for example, government officials were charged over contraband rice imports, with over one million bags of contaminated rice being seized by the Kenyan government in August 2018.[39] Kenya Bureau of Standards (KEBS) officials were subsequently arrested in Mombasa and Nairobi for this scandal, and more specifically for "releasing toxic rice into the country."[40] Twitter users in our scraped sample expressed concern over the compounding problems posed by contaminated rice, asserting for instance that "[f]ollowing today reports of poisonous rice and numerous reports of sugar laced with heavy metals, it's high time a Public Health Authority is formed to check on food and water standards in Kenya" on August 20th, 2018. Meanwhile, in early 2019, potato shortages throughout Kenya's food outlets were also reported,[41] alongside Kenya's persistent drought being implicated as contributing to additional rice shortages that were intertwined with the rice import scandals mentioned above.[42]

With respect to the former (potato) shortages, various tweets in our sample highlighted these concerns prior to the news reports mentioned above, including one on June, 19th, 2018 that reported that "Potato is the second most important crop in Kenya after maize. However, potato farmers continue to face challenges [...]." With respect to the aforementioned rice and sugar import scandals, we can note that these likely contributed to broader citizen concern

[38] The Star, 12/07/2018. "14 Voi traders arrested during protest over tax hike." The Star (Kenya).

[39] Geoffrey Mosoku and Cyrus Ombati, 08/20/2018. "Detectives save Kenyans from one million bags of toxic rice." Standard Digital. Available at: `https://www.standardmedia.co.ke/health/article/2001292575/a-million-bags-of-poison-rice-netted`, Accessed on 2/29/2020.

[40] Hilary Kimuyu, 09/22/2018. "KEBS, KRA officials arrested over contaminated rice scandal." Nairobi News. Available at: `https://nairobinews.nation.co.ke/news/kebs-kra-official-arrested-contaminated-rice-saga`, Accessed on 2/29/2020.

[41] Wachira Mwangi, 02/06/2019. "Kenyan food outlets reel from acute shortage of Irish potatoes." Daily Nation.

[42] George Munene, 02/21/2019. "Rice shortage looms as rivers dry up in Mwea." Business Daily.

and anti-government sentiment over government corruption. This is clearly suggested by a number of tweets in our sample, with some focusing directly on the role of government corruption in the aforementioned sugar scandal, noting for example that "Arati backs war on corruption, claims MP behind contraband sugar" (June 16th, 2018), "Uhuru's brother named in contraband sugar scandal #Goteana" (June 6th, 2018) and "Clearly the soul of our beautiful nation is hurting badly; too much #CorruptionKe cases, illegal #Sugar imports...God have mercy!" (June 19th, 2018). Correspondingly, large anti-corruption protests emerged across Kenya's urban areas in 2018-2019, although the factors that contributed to these broader anti-corruption protests extend far beyond Kenya's food-related import scandals.[43]

Alongside these various food scandals and anti-corruption protests, Kenya's food prices continued to rise in 2018 in response to changes in Kenya's VAT tax for key staple foods such as maize, bread, flour, milk, and sugar.[44] One seemingly sarcastic June 4th, 2018 tweet in our scraped sample captured these concerns succinctly in responding to proposed sugar taxes more generally in stating "We@agree let's tax sugar out of reach" whereas another twitter user similarly remarked in July 19th, 2018 that "@C_NyaKundiH @waweru There is oversupply of sugar yet the self price has gone up almost 40% in the last one month." These broader food price challenges led to rising warnings of civil unrest, with one Muslim organization chairman warning in September 2018 for example that "Peace and hunger do not go together. There can never be peace when people are forced to either pay through the nose to get a meal or go hungry."[45] Immediately following these September warnings, citizens in Western Kenya "called for countrywide protests to oppose plans by millers to

[43]Mohammed Yusuf, 05/31/2018. "Kenya Protesters March Against New Corruption Scandal." VOA News. Available at: https://www.voanews.com/africa/kenya-protesters-march-against-new-corruption-scandal, Accessed on 2/29/2020. Ken Opalo, 05/29/2019. "Why are Kenyans protesting their government?" The Washington Post. Available at: https://www.washingtonpost.com/politics/2019/05/13/why-are-kenyans-protesting-their-government/, Accessed on 2/29/2020.

[44]The Citizen Reporter, 06/06/2018. "Kenya's food prices to rise." The Citizen. Available at: https://www.thecitizen.co.tz/news/business/1840414-4598342-bw3jrfz/index.html, Accessed on 2/29/2020.

[45]The Star, 09/21/2018. "MUHURI warns of civil unrest over high cost of living, taxation" The Star (Kenya).

increase the retail prices of maize flour - the staple diet in the country,"[46] Reflecting these same on-the-ground events, concurrent tweets within our scraped sample noted these same tensions, in reporting for example that: "You are liars and part of cartels, maize farmers lecture senators" on September 30th, 2018 and that "Rift Valley MPs to lead protests if government delays to pay maize farmers :: Kenya" on October 3rd, 2018.

Meanwhile, citizens outside of Mombasa held separate protests over alleged land grabs.[47] Yet these varied protests did little to address rising food prices and subsequent unrest. Indeed, towards the end of our 2017-2019 time window of analysis, it was noted for example that "the wholesale prices of maize in Eldoret, Mombasa, Kisumu and Nairobi [was] at its highest in the last five years, with a significant increase of Sh1,000 per 90kg bag in July 2019 compared the price recorded in the respective towns in July 2018. This is a five year high. The price of rosecoco beans has also significantly increased, from Sh8,000 per 90kg bag in Eldoret in July 2018 to Sh9,000 in July 2019, with Kisumu recording a bigger margin of increase Sh6,500 in July 2018 to Sh10,000 in July 2019, another five-year high."[48] Efforts to implement price controls in response to this continued rise in food prices were confronted with protests by farmers in early 2019.[49] These trends were likewise captured within our scraped tweets, with one January 22nd, 2019 tweet reporting for example that "Eldoret farmers protest NCPB's failure to buy maize despite Uhuru order."

Summary Statistics and Additional Figures

[46] BBC Monitoring, 10/31/2018. "Kenyans threaten protests over proposal to hike food prices." BBC.

[47] The Star, "Protests in Mtwapa as locals allege plot to grab Jumba Ruins land." The Star (Kenya). October, 11, 2018.

[48] Mt Kenya Star Team, 09/09/2019. "Hunger as food prices hit 5-year high." Standard Digital. Available at: `https://www.standardmedia.co.ke/business/article/2001341288/hunger-as-food-prices-hit-5-year-high`, Accessed on 2/29/2020.

[49] James Munyeki, 02/26/2019. "Farmers protest reduction of milk prices." The Standard.

Table A.3: Summary statistics of all grid-day level variables

	Min	**Median**	**Mean**	**Max**	**Std. Dev.**
Social unrest$_t$	0	0	0.055	12	0.390
Food insecurity$_{t-1:t-7}$[1]	0	1.386	1.554	4.693	1.123
Water insecurity$_{t-1:t-7}$[1]	0	1.232	1.427	4.607	1.108
Growing season$_t$	0	0	0.296	1	0.457
Weekend$_t$	0	0	0.143	1	0.350
N.tweets$_{t-1:t-7}$[1]	0	2.659	3.133	7.077	1.937
Travel time[1]	4.501	4.904	5.125	6.089	0.502
Child malnutrition	18.895	22.920	23.415	29.600	3.406
Social unrest$_{t-1}$	0	0	0.0547	12	0.390
Food insecurity (Swahili)$_{t-1:t-7}$[1]	0	0.999	1.254	4.629	1.1263
Water insecurity (Swahili)$_{t-1:t-7}$[1]	0	0.762	1.087	4.273	1.0551
Elections$_t$	0	0	0.106	1	0.308
Nighttime light (2013)	0	1.271	2.853	16.252	4.388
Urbanization	0.009	0.247	1.290	9.491	2.638
Land area[1]	6.312	8.0364	7.735	8.037	0.640
% mountains	0	0.287	0.296	0.568	0.177
% water	0	0.145	17.402	80.194	30.281
Govt. repression$_t$	0	0	0.007	2	0.090
Capital dist.[1]	2.228	5.128	4.887	6.139	1.087
Border dist.[1]	2.843	4.829	4.632	5.272	0.656
Violent unrest$_t$	0	0	0.028	8	0.293
Nonviolent unrest$_t$	0	0	0.0249	5	0.207
Civil resistance$_t$	0	0	0.0223	7	0.247
Food insecurity (robustness)$_{t-1:t-7}$[1]	0	1.350	1.546	4.484	1.118
Water insecurity (robustness)$_{t-1:t-7}$[1]	0	1.273	1.495	4.873	1.153
Food insecurity (Swahili, robustness)$_{t-1:t-7}$[1]	0	0.887	1.225	4.005	1.125
Water insecurity (Swahili, robustness)$_{t-1:t-7}$[1]	0	0.827	1.155	4.389	1.119

All time varying indicators are denoted t.

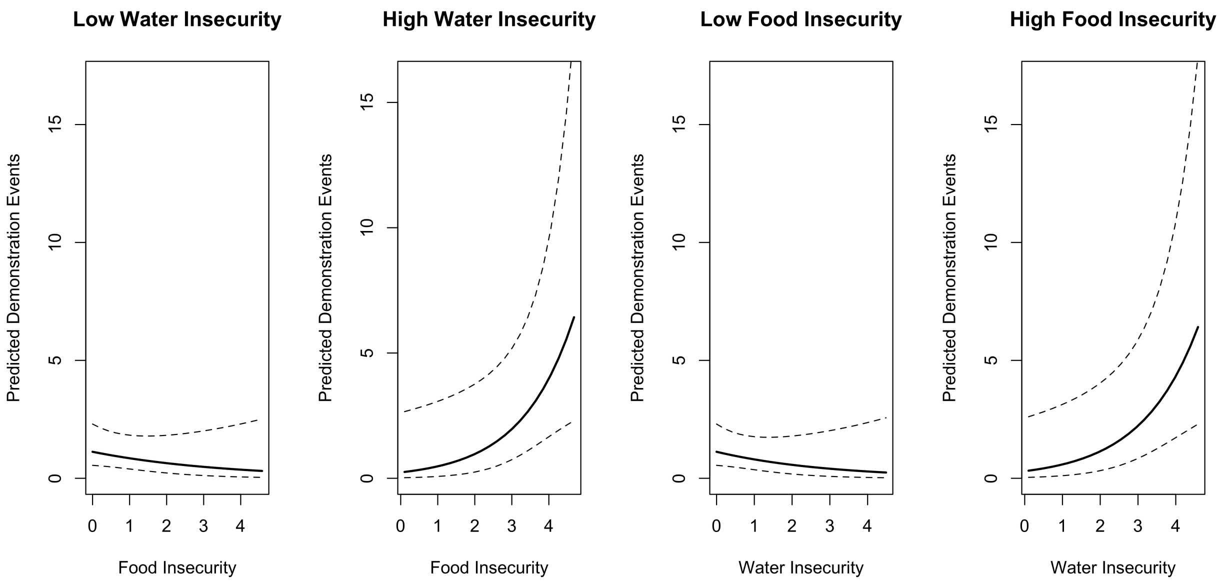
Table A.4: Summary statistics of all grid-month level variables

	Min	**Median**	**Mean**	**Max**	**Std. Dev.**
Social unrest$_t$	0	0	1.568	53	5.253
Food insecurity$_{t-1:t-7}$[1]	0	4.663	4.523	7.484	1.541
Water insecurity$_{t-1:t-7}$[1]	0	4.419	4.324	7.406	1.585
Growing season$_t$	0	0	0.300	1	0.459
N.tweets$_{t-1:t-7}$[1]	2.398	5.974	6.349	9.981	2.115
Violent unrest$_t$	0	0	0.855	37	3.556
Nonviolent unrest$_t$	0	0	0.714	16	2.017
Civil resistance$_t$	0	0	0.659	48	3.829

All time varying indicators are denoted t.

Testing for Multicollinearity

An overriding concern is the possibility that the null findings for the additive (direct effect) models (but not the interactive effect term) observed in the main article are actually due to a high correlation between our key independent variables, leading us to incorrectly conclude



Water Insecurity as the Moderator Food Insecurity as the Moderator

Figure A.1: Predicted change in number of social unrest events for minimum-to-maximum change in each moderator

that the interactive models are preferable to the direct effect staple insecurity models. In this section we accordingly evaluate whether multicollinearity is driving the null findings reported in our main article's direct effect models with the aid of a standard approach: variance inflation factors (VIFs). Briefly, for a given predictor, multicollinearity can assessed by computing a VIF score (for either one's model on the whole, and/or each independent variable therein), which measures the degree to which the variance of a regression coefficient is inflated due to multicollinearity in the model. The smallest possible value of a VIF is one (implying the absence of multicollinearity). As a rule of thumb, a VIF value that exceeds 10 indicates a problematic amount of collinearity (see, e.g., Kutner, Nachtsheim and Neter, 2004; Thompson et al., 2017).

Accordingly, to evaluate multicollinearity, we reestimated our primary direct effect NB model using linear regression—the estimates of which are reported in Table A.5—and recovered that model's VIFs, reported in Table A.6. The VIF scores for water and food insecurity were 8.26 and 8.58, respectively. While these VIF scores suggest a degree of multicollinearity, they each fall below 10, which as noted above is the most commonly used rule of thumb for identifying VIFs that are significant cause for concern (see, e.g., Kutner, Nachtsheim and Neter, 2004; Thompson et al., 2017). Hence, it is unlikely that multicollinearity alone is driving the null results identified here. Additionally, we report raw correlations and a loess-smoothed graph in Figure A.2, which show that correlations with unrest increase where both variables take middle-to-high values. Thus, the results are in line with hypothesis H2 and the overall argument developed in this study concerning the joint impact of acute staple insecurities in motivating social unrest, rather than their being an artifact of multicollinearity.

Table A.5: Multicollinearity test regression estimates (controlled effects model)

Food insecurity$_{t-1:t-7}$[1]	0.0009
	(0.013)
Water insecurity$_{t-1:t-7}$[1]	0.023†
	(0.013)
Growing season$_t$	-0.019†
	(0.011)
Weekend$_t$	-0.038*
	(0.014)
N.tweets$_{t-1:t-7}$[1]	0.014**
	(0.004)
Travel time[1]	-0.011
	(0.012)
Child malnutrition	-0.018**
	(0.002)
Constant (count)	0.459**
	(0.059)
Observations	6,149
R^2	0.037
Adjusted R^2	0.036

Note: $^{\dagger}p<0.1$; $^{*}p<0.05$; $^{**}p<0.01$. Coefficients report average effects with standard errors in parentheses.
[1] In natural log form.

Table A.6: Variance inflation factors (VIFs)

Variable	**VIF**	**1/VIF**
Food insecurity$_{t-1:t-7}$[1]	8.58	0.117
Water insecurity$_{t-1:t-7}$[1]	8.26	0.121
N.tweets$_{t-1:t-7}$[1]	2.46	0.407
Travel time[1]	1.56	0.643
Child malnutrition	1.37	0.728
Growing season$_t$	1.02	0.976
Weekend$_t$	1.00	1.00
Mean VIF	3.46	

All time varying indicators are denoted t.
[1] In natural log form.

Robustness and Sensitivity Analyses

To evaluate the sensitivity of our findings to alternative specifications, sampling, and modeling choices, we estimate a large number of robustness models corresponding to the interactive ZINB model from the main article.

Alternative Dependent Variables

First, in Table A.7, we test to see where the observed effects hold when we disaggregate our *Social unrest*$_t$ variable into violent and nonviolent unrest. We find that the interactive effects observed in our main models are driven largely by nonviolent social unrest. That is, when faced with rising staple insecurity, urbanites prefer to rely on nonviolent methods to pressure the government. This is interesting, considering that historical research tends to highlight the "food riot" phenomenon, i.e., violent mobilization by urban civilians with response to high food prices (Tilly, 1971; Taylor, 1996; Bellemare, 2015). One explanation might be that Kenya is, at least formally, a democratic state, where politicians are potentially more responsive to peaceful protests by urbanites over food prices (Hendrix and Haggard, 2015). Nevertheless, the results from our *Violent demonstrations*$_t$ dependent variables, although not statistically significant, do show the same positive coefficient estimate of *Food*

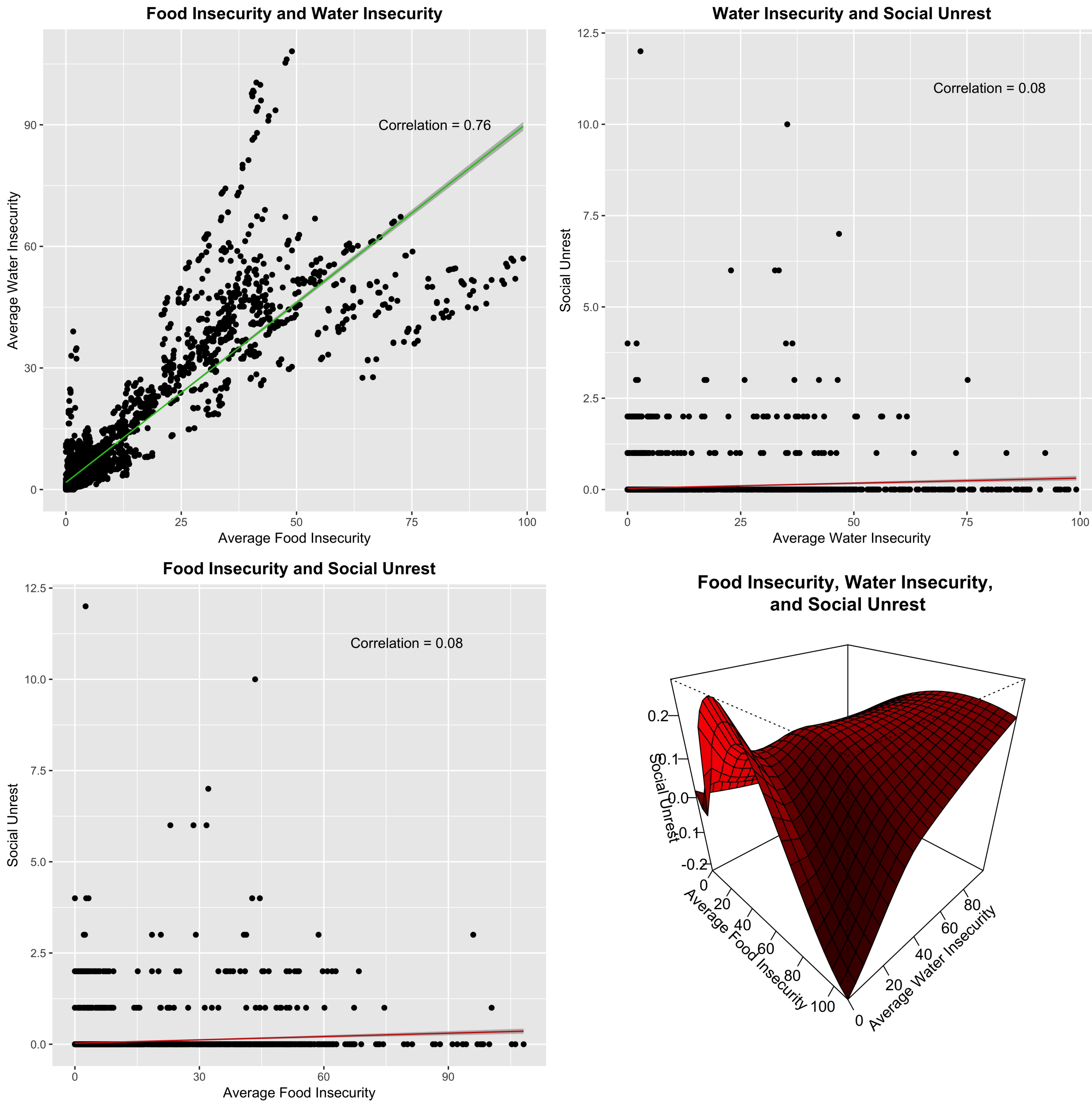


Figure A.2: Correlations between food insecurity, water insecurity, and social unrest

$insecurity_{t-1:t-7} \times Water\ insecurity_{t-1:t-7}$, which means that the "food riot" phenomenon is empirically plausible.

In the last column of Table A.7, we turn to test our model on a dependent variable drawn from a completely different dataset, the Integrated Crisis Early Warning System (ICEWS; Boschee et al., 2015). ICEWS is an entirely machine coded worldwide dataset[50] encompassing

[50] Although it excludes strictly domestic-U.S. events.

both political and cooperative events; with information on each event's day of occurrence and geolocation (if available). Our ICEWS variable, $\textit{Civil resistance}_t$, was coded as a count of the total number of (grid-month) domestic citizen[51] initiated material conflict events (against any domestic Kenyan target) for our sample's time period and geographic units. The concept of "material conflict" events encompasses a range of standard CAMEO (Schrodt, Gerner and Yilmaz, 2009) two digit categories such as "14: Protest" and "18: Assault,"[52] and has been used to study intrastate conflict and violence in a wide variety of existing studies (e.g., D'Orazio, Yonamine and Schrodt, 2011; Bagozzi, 2015; Chiba and Gleditsch, 2017). As can be seen in Table A.7, even when we test our model on a dependent variable drawn from these entirely distinct ICEWS data and coding sources, we find consistent results to Table 1, with a positive and statistically significant (to the $p < .1$ level) coefficient on our interaction term.

Theoretical Confounders

Next, in Tables A.8–A.9 we turn to evaluate our findings' sensitivity to several additional specification choices, alternative confounders, and potential measurement errors. In Table A.8, we start by running a model that omits all controls from the count stage to verify that our results are not due to internal covariation and variable choices, which can bias estimates toward significance (e.g., Schrodt, 2014). Next, note that in coding $\textit{Food insecurity}_{t-1:t-7}$ and $\textit{Water insecurity}_{t-1:t-7}$ we relied on tweets in both English and Swahili. However, relying on English language tweets might cause biases—they are more likely to capture complaints by foreign nationals or NGOs, which are more likely to both be aware of insecurity issues and voice such concerns in manners that are not as bound to the localities that they are tweeting from. To this end, in the second column in Table A.8 we remove all English tweets

[51] Or domestic citizen group/organization, e.g., ICEWS source actors whose source sector designation was "NGO" or "Business."

[52] Along with each two digit category's associated three- and four-digit sub-categories.

Table A.7: Determinants of social unrest – by type

	Violent	**Nonviolent**	**Civil Resistance**
Count stage			
Food insecurity$_{t-1:t-7}$[1]	-0.158	-0.470	-0.161
	(0.314)	(0.305)	(0.557)
Water insecurity$_{t-1:t-7}$[1]	0.014	-0.426	-0.353
	(0.326)	(0.379)	(0.582)
Food insecurity$_{t-1:t-7}$[1] × *Water insecurity*$_{t-1:t-7}$[1]	0.079	0.264**	0.230†
	(0.108)	(0.091)	(0.121)
Growing season$_t$	-0.075	-0.140	-0.977
	(0.323)	(0.312)	(1.747)
Weekend$_t$	-0.374	-0.115	-0.521
	(0.619)	(0.759)	(0.747)
N.tweets$_{t-1:t-7}$[1]	-0.144	-0.455^{**}	-1.399^{**}
	(0.159)	(0.152)	(0.327)
Travel time[1]	0.127	0.287	-26.658^{**}
	(1.145)	(1.120)	(7.152)
Child malnutrition	-0.067	-0.424^{**}	0.379
	(0.102)	(0.079)	(0.277)
Constant (count)	1.738	7.689†	121.359**
	(4.451)	(4.404)	(29.748)
Inflation stage			
Growing season$_t$	0.423	-0.153	2.314
	(0.311)	(0.636)	(1.951)
Weekend$_t$	0.661	2.336†	1.331
	(0.548)	(1.297)	(1.174)
N.tweets$_{t-1:t-7}$[1]	-0.007	-1.267^{**}	-1.421^{**}
	(0.100)	(0.412)	(0.312)
Travel time[1]	1.840*	3.546	-14.240^{**}
	(0.743)	(2.999)	(3.450)
Child malnutrition	0.396**	$-0.436^{\dagger}$	0.295†
	(0.095)	(0.231)	(0.159)
Constant (inflation)	-13.624^{**}	-2.974	66.720**
	(3.825)	(12.137)	(15.728)
Observations		6,149	
Log Likelihood	-503.670	-529.140	-364.133
Akaike Inf. Crit.	1,039.340	1,090.280	760.266

Note: †p<0.1; *p<0.05; **p<0.01. Coefficients report average effects with standard errors in parentheses.
[1] In natural log form.

from our data and rely only on tweets in Swahili. We then illustrate that our findings are not driven by temporal correlation of demonstrations over time by including a one-day lag of our dependent variable, *Social unrest*$_{t-1}$ in both stages of the ZINB model. Another possible important confounder is that the frequency of social unrest events in our sample is driven by elections. As noted further above, the period from August 27, 2017 until October 26, 2017 was a time of electoral contestation following the annulment of Kenya's August presidential vote, with new elections being held on October 26th, 2017. To this end, in the fourth column of Table A.8 we add a variable denoting whether a given day was during said election contestation period, with all days between August 27, 2017 and October 26th, 2017 being given a value of 1, and all remaining days receiving a 0 on this variable. In the final column of Table A.8 we account for additional urban area characteristics that might influence the results by adding into both our count and inflation stages controls for the percent of a grid cell denoted as urbanized by the Globcover database (Bontemps et al., 2009), *Urbanization*; and average nighttime light emission levels for the most recent year available in the PRIO-GRID (2013) to approximate urban development levels in a manner used in past research (Mukherjee and Koren, 2018).

Turning to Table A.9, we first add controls with geospatial features that might influence the propensity of social unrest by adding into both our count and inflation stages controls for grid cell areas (to account for proximity to the equator), and percent area of a given PRIO-GRID cell that is mountainous and covered with water. Next, we recognize the possibility that additional political features might explain the results. The second column in Table A.9 hence add a variable denoting the number of attacks against civilians by the government in a given grid cell during a given day obtained from ACLED (Raleigh et al., 2010). In the third column we then account for other geopolitical confounders by adding to this government repression specification controls for distance to the capital—which might account for the ability of people to organize against the government and the latter to respond—and distance to the nearest country, under the assumption that border areas might also be susceptible to social unrest (both controls were obtained from the PRIO-GRID database). Finally, we combine all of our geospatial and geopolitical confounders as well as protest lags into one control inclusive model, to illustrate that our findings our robust to this host of alternative explanations.

Modeling Choices

Next, Table A.10 accounts for our modeling choices by employing a set of alternative models and serial-control specifications. We begin by relying on the Poisson distribution to model demonstration counts instead of the negative binomial (NB) model. Although the NB model is greatly preferred for overdispersed data such as ours, where the variance of our dependent variable is greater than its mean, our results are robust to this alternative model choice. Next, recall that in our main models we did not cluster standard errors considering that doing so in a sample with a large temporal range and small panel is likely to bias our results toward significance (King and Roberts, 2015). Nevertheless, in the second column in Table A.10, standard errors were clustered by grid cell to account for heterogeneities across time within the same locations.[53] Following this, and considering that our findings might be driven by month-specific factors, we include fixed effects by month in column three. In doing so, $\textit{Growing season}_t$, which is month-constant, is omitted from the models. Our key findings are robust in these instances.

Another potential explanation for our significant findings is the possibility that some locations (i.e., urban grid cells) are naturally more likely to experience demonstrations. To account for this issue, we add fixed effects by grid cell to our standard NB model (considering

[53]Note that the results remain unchanged when clustered standard errors are used for all models in Table A.10, not only the interactive ZINB.

Table A.8: Determinants of social unrest – alternative specifications (pt. 1)

	Baseline	**Swahili Tweets**	**Lag DV**	**Elections**	**Urban Features**
Count stage					
Food insecurity$_{t-1:t-7}$[1]	-0.296	-0.536	-0.227	$-0.431^{\dagger}$	-0.182
	(0.234)	(0.331)	(0.233)	(0.244)	(0.243)
Water insecurity$_{t-1:t-7}$[1]	-0.099	-0.075	-0.360	-0.106	-0.271
	(0.267)	(0.374)	(0.266)	(0.291)	(0.296)
Food insecurity$_{t-1:t-7}$[1]	0.130^{*}	0.257^{**}	0.194^{**}	0.171^{*}	0.176^{*}
× *Water insecurity*$_{t-1:t-7}$[1]	(0.064)	(0.075)	(0.070)	(0.074)	(0.078)
Growing season$_t$	–	-0.441	-0.345	0.108	-0.404
		(0.275)	(0.289)	(0.344)	(0.304)
Weekend$_t$	–	-0.475	-0.474	-0.309	-0.590
		(0.484)	(0.491)	(0.537)	(0.515)
N.tweets$_{t-1:t-7}$[1]	–	-0.410^{**}	-0.317^{**}	-0.120	-0.572^{*}
		(0.111)	(0.110)	(0.131)	(0.255)
Travel time[1]	–	0.565	0.726	1.629	1.175
		(0.914)	(0.910)	(1.050)	(1.064)
Child malnutrition	–	-0.173^{*}	-0.182^{*}	-0.168^{*}	$-0.153^{\dagger}$
		(0.075)	(0.073)	(0.082)	(0.081)
Social unrest$_{t-1}$	–	–	0.144^{*}	–	–
			(0.065)		
Nighttime light (2013)	–	–	–	–	-0.201
					(0.384)
Urbanization	–	–	–	–	0.464
					(0.609)
Election$_t$	–	–	–	1.041^{**}	
				(0.255)	
Constant (count)	-0.026	2.049	1.626	-4.307	-0.662
	(0.297)	(3.886)	(4.118)	(4.919)	(4.721)
Inflation stage					
Growing season$_t$	0.180	-0.116	-0.147	0.154	-0.136
	(0.197)	(0.293)	(0.304)	(0.353)	(0.328)
Weekend$_t$	1.014^{**}	0.706	0.697	0.854	0.635
	(0.322)	(0.494)	(0.512)	(0.555)	(0.538)
N.tweets$_{t-1:t-7}$[1]	$-0.121^{\dagger}$	-0.306^{**}	-0.283^{**}	$-0.206^{\dagger}$	-0.200
	(0.062)	(0.094)	(0.092)	(0.109)	(0.232)
Travel time[1]	2.169^{**}	2.634^{**}	2.439^{**}	3.273^{**}	2.709^{**}
	(0.454)	(0.673)	(0.678)	(0.852)	(0.785)
Child malnutrition	0.307^{**}	0.191^{**}	0.155^{*}	0.193^{*}	0.081
	(0.041)	(0.073)	(0.072)	(0.081)	(0.086)
Social unrest$_{t-1}$	–	–	-0.567^{**}	–	–
			(0.169)		
Nighttime light (2013)	–	–	–	–	-0.101
					(0.358)
Urbanization	–	–	–		0.097
					(0.586)
Constant (inflation)	-14.239^{**}	-13.637^{**}	-11.582^{**}	-17.254^{**}	-11.546^{**}
	(2.387)	(3.085)	(3.263)	(4.021)	(3.639)
Observations			6,149		
Log Likelihood	-905.436	-894.432	-878.602	-887.169	-891.239
Akaike Inf. Crit.	1,832.871	1,820.863	1,793.205	1,808.339	1,822.478

Note: †p<0.1; *p<0.05; **p<0.01. Coefficients report average effects with standard errors in parentheses.
[1] In natural log form.

Table A.9: Determinants of social unrest – alternative specifications (pt. 2)

	Geospatial	Gov. Rep.	Geopolitical	Control Inc.
Count stage				
Food insecurity$_{t-1:t-7}$[1]	-0.287	-0.311	-0.147	$-0.472^{\dagger}$
	(0.250)	(0.248)	(0.253)	(0.241)
Water insecurity$_{t-1:t-7}$[1]	-0.358	-0.458	-0.451	-0.186
	(0.280)	(0.281)	(0.290)	(0.292)
Food insecurity$_{t-1:t-7}$[1]	0.223^{**}	0.258^{**}	0.216^{**}	0.187^{*}
× *Water insecurity*$_{t-1:t-7}$[1]	(0.079)	(0.077)	(0.079)	(0.078)
Growing season$_t$	-0.340	-0.358	-0.364	0.081
	(0.295)	(0.306)	(0.310)	(0.243)
Weekend$_t$	-0.171	-0.366	-0.318	$-0.654^{\dagger}$
	(0.536)	(0.544)	(0.518)	(0.388)
N.tweets$_{t-1:t-7}$[1]	-0.320	-0.377	-0.668^{*}	$-0.535^{\dagger}$
	(0.228)	(0.240)	(0.300)	(0.307)
Travel time[1]	-0.040	0.060	0.136	5.777
	(1.586)	(1.625)	(2.205)	(52.539)
Child malnutrition	$-0.154^{\dagger}$	$-0.174^{\dagger}$	-0.196	-2.764
	(0.090)	(0.098)	(0.164)	(27.490)
Social unrest$_{t-1}$	–	–	–	0.378^{**}
				(0.096)
Nighttime light (2013)	–	–	–	-1.989
				(16.093)
Urbanization	–	–	–	-1.084
				(21.49)
Land area[1]	0.011	-0.031	-0.695	-18.184
	(1.357)	(1.438)	(1.924)	(170.320)
% mountains	1.691	1.639	4.315	-4.653
	(3.702)	(3.791)	(3.973)	(106.377)
% water	0.005	0.003	0.010	-0.326
	(0.024)	(0.026)	(0.046)	(3.274)
Govt. repression$_t$		0.208	0.160	$0.677^{\dagger}$
		(0.293)	(0.296)	(0.376)
Capital dist.[1]	–	–	-0.602	-10.599
			(0.376)	(111.404)
Border dist.[1]	–	–	-1.312	-15.387
			(1.582)	(152.922)
Constant (count)	4.046	4.527	18.534	315.478
	(17.318)	(18.229)	(21.750)	(3,130.205)
Inflation stage				
Growing season$_t$	-0.058	-0.167	-0.200	-0.340
	(0.299)	(0.326)	(0.347)	(0.383)
Weekend$_t$	$0.919^{\dagger}$	0.730	0.784	0.436
	(0.486)	(0.539)	(0.536)	(0.636)
N.tweets$_{t-1:t-7}$[1]	$-0.385^{\dagger}$	$-0.413^{\dagger}$	-0.272	-1.719^{**}
	(0.198)	(0.218)	(0.294)	(0.583)
Travel time[1]	2.360^{*}	2.456^{*}	3.281^{**}	1.230
	(1.063)	(1.092)	(1.236)	(2.129)
Child malnutrition	0.166^{*}	0.145	-0.022	-0.231
	(0.083)	(0.092)	(0.128)	(0.228)
Land area[1]	-0.404	-0.186	-0.617	-6.772^{*}
	(1.000)	(1.077)	(1.753)	(3.064)
% mountains	-0.426	-0.602	-0.911	8.813
	(2.531)	(2.591)	(3.711)	(6.743)
% water	-0.015	-0.011	-0.030	$-0.119^{\dagger}$
	(0.021)	(0.023)	(0.037)	(0.063)
Govt. repression$_t$	–	-2.864^{*}	-2.902^{*}	-3.819^{*}
		(1.120)	(1.141)	(1.924)
Capital dist.[1]	–	–	0.334	0.512
			(0.342)	(1.043)
Border dist.[1]	–	–	-0.352	-2.319
			(1.079)	(1.820)
Constant (inflation)	-7.609	-9.269	-6.373	$65.414^{\dagger}$
	(12.623)	(13.584)	(21.859)	(35.781)
Observations	6,149			
Log Likelihood	-894.486	-883.785	-872.290	-851.066
Akaike Inf. Crit.	1,832.971	1,815.571	1,800.581	1,766.131

Note: †p<0.1; *p<0.05; **p<0.01. Coefficients report average effects with standard errors in parentheses.

[1] In natural log form.

our small panel, it was impossible to do so within a zero-inflated framework, which led to convergence problems). We then add fixed effects for each grid cell and, additionally, each month in our sample, to capture all month- and grid cell-constant effects in the final column. Finally, we account for the possibility that unit specific effects are driving the results. Here, in order to help compensate for the problems with running ZINB with unit of analysis fixed effects, we estimate a Bayesian ZINB model with random effects by grid cell. The priors are normally distributed and assume constant effects with a standard deviation of .01. The model was estimated using 100,000 MCMC simulations, where the first 99,000 were discarded to ensure only converged model estimates were reported. Crucially, the sign and significance of $\textit{Food insecurity}_{t-1:t-7}$, $\textit{Water insecurity}_{t-1:t-7}$, and their interaction holds across these numerous alternative models and specifications in Tables A.7 – A.10, which reaffirms our main article's findings with regards to the interaction of $\textit{Food insecurity}_{t-1:t-7}$ and $\textit{Water insecurity}_{t-1:t-7}$.

Robustness to Twitter Keyword Choices

Finally, as discussed in the initial section above, there are possible concerns regarding the full set keywords we used to code food and water insecurity in English and Swahili. To account for the possibility our choice keywords might affect the results, we re-aggregate our data while omitting any tweets that do not contain the nine "primary" keywords that a native speaker of Swahili—who is also a professor for teaching the language at a large research university—identified as optimal for coding each staple insecurity type. This primary set of more balanced keywords includes the following English keywords: 'drought,' 'water,' 'food,' 'maize,' 'milk,' and 'sugar,' alongside an equal set of comparable Swahili keywords whose one-to-one matches to the aforementioned English set of keywords were determined to be closest: 'ukame,' 'maji,' 'chakula,' 'mahindi,' 'maziwa,' and 'sukari.' We then continue to include two keywords that were invoked in both Swahili and English texts within Kenya

Table A.10: Determinants of social unrest – alternative modeling

	Poisson	**CSE**	**Month FE**	**Grid FE (NB)**	**Grid & Month FE (NB)**	**Bayesian Grid RE**
Count stage						
Food insecurity$_{t-1:t-7}$[1]	-0.193	-0.271	$-0.462^{\dagger}$	-0.141	-0.257	-0.204
	(0.204)	(0.237)	(0.264)	(0.256)	(0.271)	(-0.537 ⇔ 0.166)
Water insecurity$_{t-1:t-7}$[1]	-0.172	-0.415	-0.128	$-0.548^{\dagger}$	-0.295	-0.470**
	(0.218)	(0.269)	(0.301)	(0.311)	(0.339)	(-0.804 ⇔ -0.155)
Food insecurity$_{t-1:t-7}$[1] × *Water insecurity*$_{t-1:t-7}$[1]	0.141*	0.231**	0.214**	0.253**	0.207*	0.218**
	(0.058)	(0.069)	(0.070)	(0.093)	(0.091)	(0.033 ⇔ 0.332)
Growing season$_t$	$-0.374^{\dagger}$	-0.369	–	-0.120	–	-0.320**
	(0.227)	(0.296)		(0.198)		(-0.471 ⇔ -0.214)
Weekend$_t$	-0.346	-0.504	-0.138	-0.853**	-0.761**	-0.020
	(0.371)	(0.496)	(0.492)	(0.297)	(0.288)	(-0.346 ⇔ 0.307)
N.tweets$_{t-1:t-7}$[1]	-0.267**	-0.355**	-0.275*	0.074	-0.189**	-0.283**
	(0.090)	(0.108)	(0.119)	(0.273)	(0.247)	(-0.446 ⇔ -0.054)
Travel time[1]	0.358	0.606	0.979	–	–	1.922*
	(0.662)	(0.910)	(1.062)			
Child malnutrition	-0.146*	-0.189**	-0.154*	–	–	
	(0.058)	(0.073)	(0.078)			(0.542 ⇔ 3.877)
Constant (count)	2.664	6.594	-1.414	-2.460**	-2.351**	-10.610**
	(3.126)	(4.122)	(4.710)	(0.947)	(0.887)	(-15.196 ⇔ -3.452)
Inflation stage						
Growing season$_t$	-0.057	-0.082	0.254			0.123
	(0.245)	(0.305)	(0.317)			(-0.147 ⇔ 0.307)
Weekend$_t$	$0.776^{\dagger}$	0.688	$0.953^{\dagger}$			1.014**
	(0.402)	(0.506)	(0.495)			(0.480 ⇔ 1.765)
N.tweets$_{t-1:t-7}$[1]	-0.257**	-0.301**	-0.250*			-0.307**
	(0.073)	(0.090)	(0.099)			(-0.442 ⇔ -0.133)
Travel time[1]	2.227**	2.540**	2.857**			2.401**
	(0.547)	(0.682)	(0.811)			(1.433 ⇔ 3.530)
Child malnutrition	0.211**	0.178*	0.207**			0.136
	(0.059)	(0.073)	(0.077)			(-0.098 ⇔ 0.261)
Constant (inflation)	-11.557**	-12.608**	-15.232**			–
	(2.784)	(3.297)	(3.715)			
Observations				6,149		
Log Likelihood	-905.825	-896.123	-869.984	-918.726	-891.838	–
Akaike Inf. Crit.	1,841.651	1,826.246	1,791.967	1,871.453	1,837.675	–
Deviance Inf. Crit.	–	–	–	–	–	1,750.594

Note: †p<0.1; *p<0.05; **p<0.01. Coefficients report average effects with standard errors in parentheses.

[1] In natural log form.

in relation to a pair of common Kenyan dishes: ‘ugali’ (a type of grits or porridge made from maize flour) and ‘nyama’ (for recovering mentions of ‘nyama choma’—a grilled/roast meat dish). However, we omit the following more problematic keywords from this robustness sample, for the reasons described in the first section of this Supplemental Appendix: ‘millet,’ ‘sorghum,’ ‘mimea,’ ‘unga,’ or ‘kiangazi.’

The above re-aggregation decisions help to ensure that the retained tweets correspond to a more conservative, but potentially more accurate, set of keywords for the identification of food and water insecurity across both English and Swahili. After re-aggregating our data to contain only the primary keywords mentioned above, we repeated our analyses with this smaller, robustness sample of aggregated tweets.[54] Table A.11 reports robustness models corresponding to our full interactive specification whilst employing the new Twitter measures, both for aggregated English and Swahili tweets, and only for our Swahili tweets (which correspond to the robustness model reported in Table A.8). As Table A.11 illustrates, the sign and statistical significance of the interactive effects observed in our main article’s and appendix’s full keyword models, as well as the coefficient signs of the constitutive terms, all hold when we employ these alternative (more restrictive) keywords when subsetting our coded Tweets, suggesting our findings are robust to this concern.

Accounting for Endogeneity and Serial Correlation

A major limitation of our panel data is that serial correlations in social unrest over time are highly possible. One way of accounting for this concern is by including a temporal lag of our dependent variable in the model, as done in Table A.8. However, doing so is unlikely to address a second pertinent issue—that of endogeneity between our dependent and independent variables. In other words, while food and water insecurities are theoretically

[54]Though we note that the share of total tweets omitted due to the removal of tweets containing only one or more of the following five keywords—‘millet,’ ‘sorghum,’ ‘mimea,’ ‘unga,’ or ‘kiangazi’—was fairly negligible.

Table A.11: Determinants of social unrest – robustness for twitter keyword selection

	All	**Swahili Tweets Only**
Count stage		
Food insecurity$_{t-1:t-7}$[1]	-0.180	$-0.627^{\dagger}$
	(0.249)	(0.380)
Water insecurity$_{t-1:t-7}$[1]	-0.336	0.083
	(0.294)	(0.430)
Food insecurity$_{t-1:t-7}$[1]	0.185^{**}	0.239^{**}
× *Water insecurity*$_{t-1:t-7}$[1]	(0.071)	(0.079)
Growing season$_t$	-0.445	-0.419
	(0.291)	(0.278)
Weekend$_t$	-0.407	-0.410
	(0.486)	(0.483)
N.tweets$_{t-1:t-7}$[1]	-0.318^{**}	-0.398^{**}
	(0.109)	(0.114)
Travel time[1]	0.728	0.757
	(0.914)	(0.887)
Child malnutrition	-0.194^{**}	-0.186^{*}
	(0.074)	(0.074)
Constant (count)	1.870	1.225
	(4.120)	(3.768)
Inflation stage		
Growing season$_t$	-0.124	-0.102
	(0.299)	(0.292)
Weekend$_t$	0.756	0.752
	(0.482)	(0.482)
N.tweets$_{t-1:t-7}$[1]	-0.286^{**}	-0.276^{**}
	(0.088)	(0.092)
Travel time[1]	2.515^{**}	2.782^{**}
	(0.680)	(0.673)
Child malnutrition	0.177^{*}	0.179^{*}
	(0.072)	(0.074)
Constant (inflation)	-12.473^{**}	-14.186^{**}
	(3.255)	(3.051)
Observations	6,149	
Log Likelihood	-897.694	-894.858
Akaike Inf. Crit.	1,827.388	1,821.717

Note: †p<0.1; *p<0.05; **p<0.01. Coefficients report average effects with standard errors in parentheses.
[1] In natural log form.

more likely to be the cause of unrest, demonstrations—especially violent ones—could increase food and water insecurity by limiting individuals' access to these resources or destroying local infrastructure (Bellemare, 2015; Koren, 2018).

Considering these two issues, the next stage of our analysis employs a series of generalized method of moments (GMM) *dynamic* models below (Arellano and Bond, 1991; Blundell and Bond, 1998). A key assumption of these GMM models is that the necessary instruments are "internal" and rely on lagged values of the instrumented variable, $\textit{Social unrest}_t$ in our case. The model is accordingly specified as a system of equations, one per time period, where the instruments applicable to each equation differ (in later time periods, additional lagged values of the instruments are available). Because these are panel models, unit fixed effects are canceled, providing a a straightforward instrumental variable estimator. We accordingly estimate a set of first-differencing GMM models below, and use a two-step estimation approach, which provides a more robust version of these models and allows us to test whether over-identification is a problem

One challenge for such GMM models is that running GMM's on a long time series (such as our own) is not only highly computationally intensive, but also very likely to run into problems with convergence (Sigmund and Ferstl, 2017). This is compounded by a second, related issue, namely that GMM's have a tendency to overfit the data, especially with long time series (Roodman, 2009). Indeed, when we attempted to run specifications corresponding to Table 1 at the urban grid-day level, we ran into both computational and convergence errors. Accordingly, to address these limitations, we collapse our data to the urban grid-month level. This ensures that the resulting series avoids the risk of overfitting while also addressing computational demands. To illustrate our models' robustness to overfitting we then rely on the two-step method, which allows us to test whether overfitting is a concern.

Following the procedure established by Arellano and Bond (1991) for using endogenous instruments in dynamic panel data, we more specifically estimate first-differencing GMM models that rely on the past values of social unrest as instruments for the contemporary effect of food and water insecurity on demonstrations. Research also warns us of the perils "instrument proliferation" in such models (Roodman, 2009, 136). Hence, to further ensure that our models can claim exogeneity and avoid overfitting, we follow Roodman (2009, 148) and "use only certain lags instead of all available lags for instruments" by limiting the *Social* $unrest_t$ lags used for instrumentation to a six-month period ($t-1$ to $t-7$). As a result, and due to our reliance on a higher (i.e., monthly) level of temporal aggregation than our daily level, we could simply use the total the number of tweets for each of our relevant variables rather than moving averages.

Table A.12 presents the results of the additive and interactive specifications from Table 1 on *Social* $unrest_t$ using first-differencing GMM. Note that—as with unit fixed effects models—all time-invariant variables are omitted in these GMM models because they exploit variations between different time periods to identify each variable's *exogenous* effects. Most importantly, as Table A.12 clearly shows, once endogeneity and serial correlations are effectively accounted for, our results become—if anything—more noticeable. The interaction term *Food* $insecurity_{t-1:t-7}$ $\times$ *Water* $insecurity_{t-1:t-7}$ maintains its positive sign and statistical significance, while both its constitutive terms—*Food* $insecurity_{t-1:t-7}$ and *Water* $insecurity_{t-1:t-7}$—maintain their negative sign, but the effect is now highly statistically significant (to the $p < .05$ level). Additionally, Sargan tests results are insignificant ($p \sim 1$), which suggests that the models *do not* overfit the data, thereby allowing us to reject the null hypothesis that they do. The AR(2) test is also statistically insignificant, suggesting that relying on AR(1) terms—which is the standard in GMM models—is defensible, and that higher serial correlations do not exist in the data. Hence, Table A.12 provides an additional degree of strong support to Hypothesis H2, and shows that once the potentially-confounding effects of serial correlations and endogeneity are accounted for the results are, if anything, even stronger.

Table A.12: Determinants of social unrest (GMMs)

	Direct Effect		Controlled Effect	Interaction
Food insecurity$_{t-1:t-7}$[1]	$0.803^{\dagger}$	–	0.383	-2.658^{*}
	(0.460)		(0.417)	(1.126)
Water insecurity$_{t-1:t-7}$[1]	–	0.714	$0.429^{\dagger}$	$-3.214^{\dagger}$
		(0.459)	(0.256)	(1.644)
Food insecurity$_{t-1:t-7}$[1] × *Water insecurity*$_{t-1:t-7}$[1]	–	–	–	0.910^{*}
				(0.376)
Growing season$_{t}$	−0.074	0.187	0.123	−0.571
	(0.921)	(0.962)	(0.969)	(1.229)
N.tweets$_{t-1:t-7}$[1]	0.062	0.376	0.113	0.998
	(0.591)	(0.481)	(0.588)	(1.106)
Observations			209	
Sargan p	1	1	1	1
AR(2) errors p	0.320	0.302	0.304	0.581

Note: †p<0.1; *p<0.05; **p<0.01. Coefficients report average effects with standard errors in parentheses.
[1] In natural log form.

Finally, in Table A.13, we turn to evaluate whether the results are robust when the dependent variable *Social unrest*$_t$ is disaggregated into its violent and nonviolent components or when a different dataset (ICEWS) is used to compile the dependent variable, similar to the exercises reported in Table A.7. Once again, the results of the GMM models provide even strong support for hypothesis H2. Most importantly, the effect of the interaction term *Food insecurity*$_{t-1:t-7}$ × *Water insecurity*$_{t-1:t-7}$ is highly statistically significant (to at least $p < .05$ level) across *all* dependent variables, including *Violent unrest*$_t$, which was not significant in Table A.7. As in Table A.12, the effect of the constitutive terms *Food insecurity*$_{t-1:t-7}$ and *Water insecurity*$_{t-1:t-7}$ is again negative and statistically significant in all interaction models. And as was the case in that Table, the p-values of both the Sargan and AR(2) tests are insignificant, suggesting that the models do not overfit the data and that no higher serial correlations exist. Therefore, these results lend additional support to hypothesis H2 in showing that, once serial correlation and endogeneity are accounted for, the results of our main analysis statistically and substantively hold across these alternative dependent variables.

Table A.13: Determinants of social unrest (GMMs) – by type

	Violent	**Nonviolent**	**Civil Resistance**
Food insecurity$_{t-1:t-7}$[1]	$-1.274^{\dagger}$	-1.057^{*}	-1.250^{**}
	(0.720)	(0.430)	(0.406)
Water insecurity$_{t-1:t-7}$[1]	$-2.001^{\dagger}$	-0.912	-3.092^{*}
	(1.095)	(0.586)	(1.306)
Food insecurity$_{t-1:t-7}$[1] $\times$ *Water insecurity*$_{t-1:t-7}$[1]	0.518^{*}	0.286^{*}	0.716^{**}
	(0.233)	(0.143)	(0.236)
Growing season$_{t}$	-1.092	-0.030	-2.180
	(1.267)	(0.317)	(1.527)
N.tweets$_{t-1:t-7}$[1]	-0.210	$0.810^{\dagger}$	-0.471
	(0.822)	(0.471)	(0.781)
Observations		209	
Sargan p	1	1	1
AR(2) errors p	0.980	0.313	0.994

Note: †p<0.1; *p<0.05; **p<0.01. Coefficients report average effects with standard errors in parentheses.
[1] In natural log form.

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