



The impact of flooding on food security across Africa

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Recent record rainfall and flood events have prompted increased attention to flood impacts on human systems. Information regarding flood effects on food security is of particular importance for humanitarian organizations and is especially valuable across Africa's rural areas that contribute to regional food supplies. We quantitatively evaluate where and to what extent flooding impacts food security across Africa, using a Granger causality analysis and panel modeling approaches. Within our modeled areas, we find that ~12% of the people that experienced food insecurity from 2009 to 2020 had their food security status affected by flooding. Furthermore, flooding and its associated meteorological conditions can simultaneously degrade food security locally while enhancing it at regional spatial scales, leading to large variations in overall food security outcomes. Dedicated data collection at the intersection of flood events and associated food security measures across different spatial and temporal scales are required to better characterize the extent of flood impact and inform preparedness, response, and recovery needs.

floods | food security | Africa | disaster | extremes

Record flooding was pervasive across Africa in 2020, affecting millions across national boundaries, damaging infrastructure, and compounding public health concerns amid the accelerating COVID-19 crisis (1–4). While flooding across Africa is a regular, seasonal occurrence in riverine areas (5, 6), the extent, magnitude, and duration of flooding and its subsequent impacts is gaining increased attention, especially from humanitarian organizations and related to relief (ex post) and preparedness (ex ante) operations (7, 8).

The impact of flooding on agriculture and food security is a chief concern, particularly where flood events might be increasing (9, 10) or shifting in seasonality or character (i.e., flood type) (11). This concern is evident in periodic reports issued by the Famine Early Warning System Network (FEWS NET), which is primarily mandated with providing early warning of food crises to decision makers, as well as organizations such as the International Federation of Red Cross and Red Crescent and the United Nations Office for the Coordination of Humanitarian Affairs, which have a broader mandate but one that likewise includes food security. However, few analyses have been conducted on the relationship between floods and food security (12, 13), particularly across sub-Saharan Africa.

Reporting of exactly how flooding impacts food security is standardized neither across the reports issued by operational humanitarian agencies nor across government and nongovernment reporting agencies (14). Furthermore, while remote sensing–based estimates of floods are assessed for accuracy (15), the full magnitude and extent of flood damages, for example, to crop/pasture areas, are often not comprehensively ground truthed or quantified (13, 16). This results in uncertainties in the extent (including both flooded area and depth and duration) to which a flood may have occurred, and, by extension, the assessment of flood impacts on food security (13).

Nevertheless, emerging literature coupled with food security outlooks reveals several possible pathways through which flooding can impact food security. Many of these pathways lead to negative food security outcomes. For example, floods can lead to crop and livestock losses or damages, thereby either directly reducing the amount of food available to a household or indirectly impacting food security by reducing household income (12, 17, 18). Floods may also damage infrastructure, such as roads, bridges, and storage facilities, which can prevent agricultural and pastoral producers from accessing food markets to sell goods and buy food and supplies (19–21). Saltwater intrusion from coastal flooding, such as from storm surge related to tropical cyclones, can prove damaging to crops in various ways, including marsh migration and groundwater contamination (22). Even in the absence of direct damages to food production or livelihoods, floodwaters can exacerbate the public health-related challenges that affect nutritional statuses, such as water-borne illnesses, inclusive of malaria and cholera, and lack of access to clean water (23–25).

Perhaps counterintuitively, however, increases in precipitation and even moderate flooding may also be positively associated with GDP in agriculturally dependent

Significance

Floods impact food security for ~12% of our modeled African population that experienced food insecurity during our study period. Flood impacts on food security vary depending on scale, with declines likely at smaller scales but mixed impacts at national and regional scales. Improved data collection at the intersection of flooding and food security, and at the spatial scales ranging beyond conventional humanitarian responses, is critical to better mitigate food security impacts of flood disasters across Africa and globally.

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economies (26–28). For example, precipitation associated with floods (or even the floods themselves) can, within a certain range, increase soil moisture, thereby facilitating crop and forage growth at later times (29–33). Likewise, floods may also increase water supplies for irrigation by way of farm ponds and other reservoirs. Overall, actions taken by individuals and governments related to flood preparedness, anticipatory postflood management, and building household resilience more generally can help to alleviate the most severe impacts of flooding, particularly in relation to food security (34).

While this past literature has demonstrated myriad pathways by which flooding may affect food security, to date, no analysis has attempted to catalog how widespread these effects are or their magnitude on regional-to-continental scales. Obtaining a better understanding of how flooding impacts regional food security, and the pathways by which this occurs, is critical to both food security assessments and disaster action and response, particularly under accelerating climate and environmental change (9, 35, 36). We herein address key knowledge gaps on how flooding affects food security across sub-Saharan Africa. Specifically, we answer the following research questions which are largely missing from the current literature: 1) Where, and to what extent, do floods impact food security across sub-Saharan Africa? 2) How do floods relate (in magnitude and sign) to changes in regional food security? We address our first research question by adopting an approach relating floods to food security levels in a Granger causality framework. Specifically, we use the Integrated Food Security Phase Classification (IPC) levels at national and subnational scales as a food security indicator (37) and flood metrics from the Dartmouth Flood Observatory (38) as an indicator of where and when impactful/important floods occurred. To address the second research question, we develop a suite of regional and country-specific statistical models of the impacts of flooding on food security and compare them to qualitative descriptions of key flood events compiled from widely used humanitarian reports and sampled across a diverse range of regional climate, social, economic, and political conditions.

Results

Where Do Floods Most Impact Food Security? The flood variables used in our analysis include the number of flood occurrences, the total area affected by floods as a proportion of panel area, and the cumulative duration of flood events in days. Each of these variables is recorded per season and per spatial unit, that is, per panel, here defined as the intersection of FEWS NET livelihood zones and administrative level two regions (see *Materials and Methods*). Flood occurrences can be interpreted largely as an indicator of floods occurring at a particular panel in time, with additional information on the frequency of flood events when multiple events occur in one season. The univariate and bivariate distributions of these variables—over space and time—are visualized in *SI Appendix, Fig. S1*.

Fig. 1 maps the variance for each of the above variables (i.e., number of floods, total flood area, and flood duration), along with food security encoded in the mean IPC, over time. The observed regions of high variance of food security levels often, although not completely, overlap with the regions of high variance for different flood metrics. In particular, southern Niger, northern Nigeria, southern Sudan, South Sudan, Kenya, Mozambique, and Malawi are all regions of high flood metric variance and high variance of food security levels. Regions that have a large variance in food security levels but little recorded flood metric variance are

Mauritania, Mali, Chad, Ethiopia, Somalia, and Zimbabwe. Provided these results, we would expect that the regions of overlapping variance are regions in which floods may be affecting food security levels. We test this hypothesis using Granger causality.

Granger causality was successfully tested in regions that contained sufficient variance over time in both mean IPC and flood metrics (Fig. 1) and was largely unable to be tested in low-variance regions, due to singularities in the linear systems used to conduct the Granger tests (see *Materials and Methods*). Among the regions with sufficient variance, all global tests of Granger noncausality rejected the null hypothesis of universal noncausality between each of the first-differenced flood variables and the first-differenced mean IPC (Table 1). This suggests that floods Granger-cause changes in food security in at least one panel in the dataset.

The spatial heterogeneity of the significance of these relationships is mapped in Fig. 2, where we can see where and by what metrics floods have significant predictive influence over following changes in food security.

Using the 2020 WorldPop data (39), we estimate ~12% of our modeled population, or 5,671,657 people, had their food security status impacted by flooding during the 2009–2020 period. This proportion of impacted population is consistent with data obtained from LandScan (40) and Global Human Settlement Layer (41) for the year 2015, when these products and WorldPop all had data available for our entire domain. More specifically, averaged across these three datasets (i.e., 2015 population numbers from WorldPop, LandScan, and the Global Human Settlement Layer), 12.03% [11.46%, 12.60%] of our modeled population (or 4,751,130 [4,446,008, 5,056,252] people) had their food security impacted by flooding during the 2009–2020 period (*Materials and Methods* and *SI Appendix, Table S6 A and B*). This estimate both is constrained by the regions in which the Granger test could be conducted and uses the conservative assumption that only 20% of the population in a region meets the IPC criteria, which is the minimum threshold for the region to be classified at an IPC level (42, 43).

Some regions stand out as “hot spots” of flood impacts on food security, including along the Niger river in Nigeria, both western and central South Sudan, and northwestern Malawi. While some of these regions are located near or in large river basins, other affected regions are not immediately adjacent to large regional rivers, highlighting the need, in future work, for additional data disaggregation by flood type (e.g., riverine or flash flooding) and/or locality. This may be particularly important for anticipatory action and/or resilience-building programs that often include recommendations and actions specific to flood type.

For many panels, there was insufficient variance in the data to determine whether floods Granger-cause changes in food security. This does not mean that floods are unimportant in these regions, but, rather, it highlights the necessity of long, reliable records of both flood incidence (including valuable detail, such as duration in particular) and food security levels when analyzing the links between the two.

How Do Floods Relate (in Magnitude and Direction) to Changes in Food Security? The full panel model (Fig. 3A), using the entirety of our flood and IPC datasets, allows us to understand any prevailing relationships between flooding and food security, while mitigating potential biases associated with subsetting the data. However, to minimize the risk of concluding potentially spurious flood–food security relationships, we show the

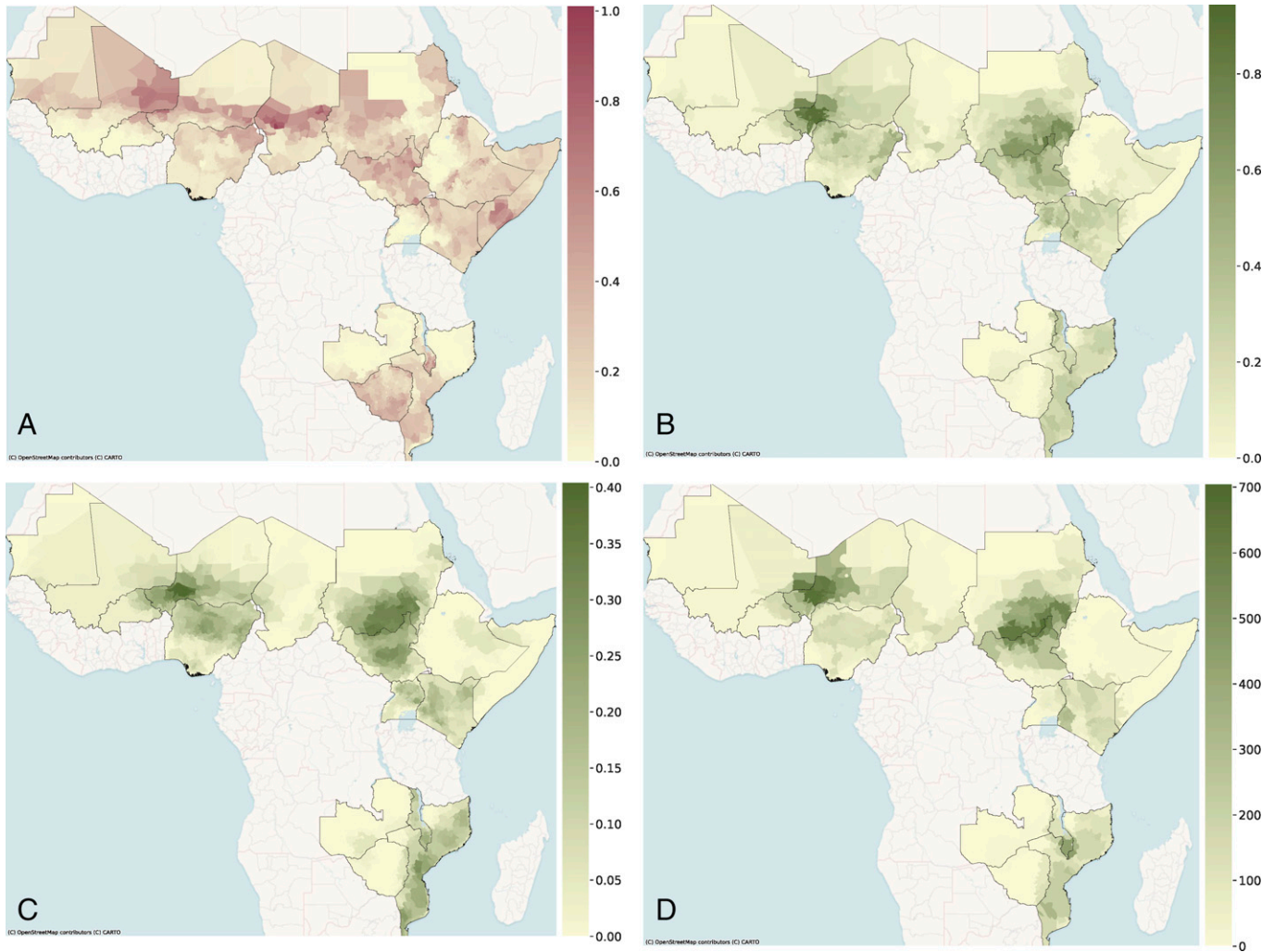


Fig. 1. Plots of variances of covariates over the study period, 2009–2020. Subplots are arranged as (A) variance of first-differenced mean IPC, (B) variance of first-differenced flood occurrences, (C) variance of first-differenced flood area as a proportion of panel area, and (D) variance of first-differenced cumulative seasonal flood duration.

Granger-filtered model, which represents areas where the statistical relation between floods and food security is most likely to be causal. We provide complete model summaries in [SI Appendix, Table S2 A and B](#).

The Granger-filtered and full datasets used in the All-Africa panel models show agreement on the most significant flood variables to impact food security and their direction of change. Flood occurrences, particularly at time lag two (i.e., two IPC reporting periods or 6 mo; see *Materials and Methods* for a description), are significantly related to decreases in food security (i.e., increases in the first-differenced mean IPC score), while cumulative flood duration from time lags zero through

two are linked to improvements in food security (i.e., decreases in the first-differenced mean IPC score). These models suggest that floods have opposing effects on food security that are mostly delayed in time from their occurrence. We note that, while flooded area is not a significant driver of food security changes in these All-Africa models, it is significant in the regional and country-level models described in the case studies below. That flooded area is insignificant as a covariate may be sensitive to the scale of the unit of analysis (here the intersection of FEWS NET livelihood zones and Admin-2 regions) relative to the scale of the flood hazard. Due to the coarseness of flood polygons available in the Dartmouth Flood Observatory (DFO) database, these panels are often smaller in scale than the flood hazards themselves, making the covariate less informative than it might be for larger units of analysis.

The magnitudes of the variance in first-differenced mean IPC explained (i.e., adjusted R^2) by the All-Africa and regional models are broadly similar, spanning 1.85 to 2.95% for the models fit on the full dataset and 5.31 to 9.34% for models fit on the Granger-filtered dataset ([SI Appendix, Table S1](#)). This small percentage of variance explained, even in the Granger models which amplify the signal of flood impact on food security through localization, reflects the many, regionally varied factors, such as pests/diseases, trade, drought, and conflict, that

Table 1. Results of global Granger noncausality test for each of the first-differenced flood variables

X	Y	\tilde{Z}	P value
Δ flood occurrences	Δ IPC	24.2861	<0.00001
Δ total flood area (%)	Δ IPC	7456.8301	<0.00001
Δ cumulative flood duration (days)	Δ IPC	38.6769	<0.00001

The alternative hypothesis is that Granger causality exists for at least one panel in the dataset.

Granger causality map: first-differenced flood variables cause change in first-differenced mean IPC

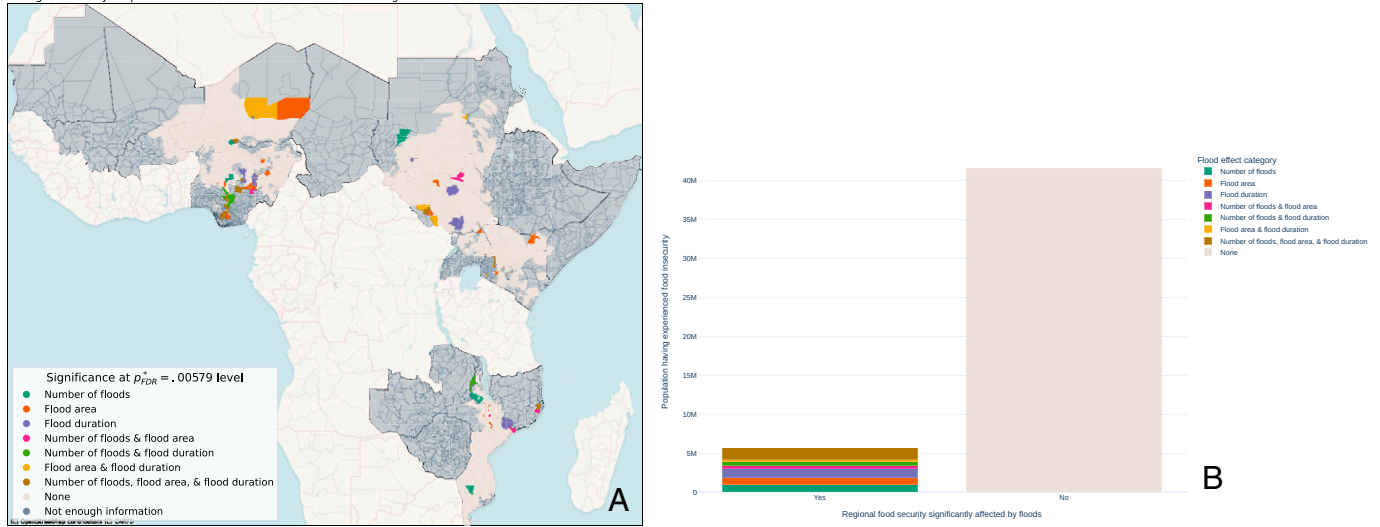


Fig. 2. (A) Map of where first-differenced flood variables Granger-cause changes in food security based on a significance level determined using the false discovery rate method; (B) total population (as of 2020) living in panels indicated as experiencing a Granger-causal relationship between flooding and food security.

may influence food security across broader spatial scopes (39). The effect of model localization on variance in food security explained by floods is more pronounced in the country-specific models, in which adjusted R^2 values span 1.15 to 15.76% and 1.61 to 33.40% for models fit on the full and Granger-filtered datasets, respectively. We also note that, for Burkina Faso, Ethiopia, and Mali, this localization with the Granger-filtered dataset is extreme (i.e., associated with large decreases in sample

size M). As a consequence, we believe the Granger panel models for these countries are less representative of country-scale dynamics than their peer models, and henceforth limit our discussion of their results.

Regional and country-specific panel models (Fig. 3 B–D) are generally consistent with the All-Africa panel models in that they indicate flood occurrences decrease food security, while flood duration increases food security. In contrast to the

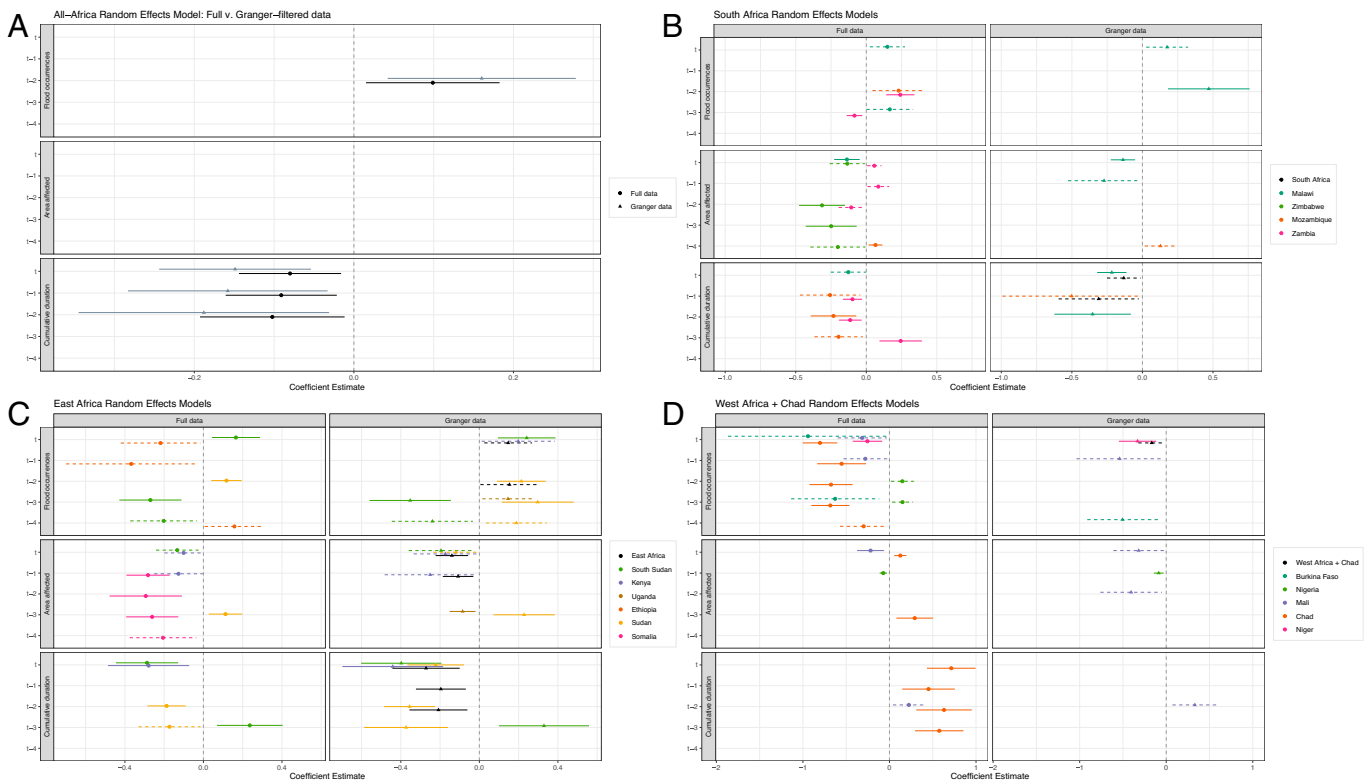


Fig. 3. (A) Significant ($P < .05$) coefficient estimates and 95% confidence intervals of All-Africa panel models for both the full and Granger-filtered datasets. The “Area affected” panel is included to illustrate the lack of statistical significance across all time lags of the area affected coefficients in the models. Also shown are significant coefficient estimates and 95% confidence intervals for regional and country-specific panel models. Solid lines indicate coefficient $P < p^*FDR = .0124$, representing the coefficients which are most confidently nonzero. Dashed lines indicate coefficient $P < .05$, representing coefficients that are confidently nonzero yet which warrant more targeted analysis to confirm. (B) Southern Africa, (C) East Africa, and (D) West Africa and Chad. Countries are indicated by colors in corresponding legends.

All-Africa models above, however, several of the country and regional models also show significant impacts from flooded areas. In most cases, increases in flooded areas tend to be related to improvements in food security, particularly in the east African models. When comparing between regions, east Africa has the greatest number of significant covariates, indicating a comparatively stronger relationship between floods and food security in east Africa as compared to west Africa or south-east Africa.

Southern Africa. In southern Africa, the number of floods degrades food security while the duration of floods is associated with improved food security (Fig. 3*B*). Flood characteristics explain 2.77% of the variance in the IPC metric in the full model and 9.34% of the variance in the Granger model. Similar to east Africa, a greater number of floods is associated with degraded food security, while increased flood duration and increased flood area are generally associated with improved food security. Notably, the Malawi country model has the greatest number of significant relationships between flood metrics and food security levels (Fig. 3*B*) as well as the largest fraction of area in which floods are causally linked to food security levels (Fig. 2). This identifies Malawi as a hot spot for flooding-induced changes to food security levels, and provides another opportunity to explore why flooding does not uniformly degrade food security.

Early 2013 flooding in Malawi and Mozambique led to concerns of possible degradation of food security in the region (Table 2). The subsequent response, however, illustrates how the acute effects of flooding can be mitigated by targeted interventions. In January of 2013, extreme precipitation across southern Africa (*SI Appendix, Fig. S4B*), which was in the 94th percentile of monthly precipitation in Malawi and 98th percentile in Mozambique, led to flooding in both southern Malawi and northern Mozambique. In Malawi, the floods were localized, affecting <1% of national cropland, such that humanitarian aid was able to meet the identified need (Table 2). But, in Mozambique, flooding destroyed 3 to 4% of all croplands, killed thousands of livestock, displaced nearly 150,000 people, and led to an outbreak of cholera (Table 2). Despite this significant damage, the floods occurred during the planting season (with conditions improving still during the planting season), meaning that, while food security was degraded locally, the government was able to distribute new seeds and fertilizer to enable postflood planting and large-scale recovery (from a food security perspective) from the floods.

East Africa. In east Africa, a number of flood characteristics affect regional food security either positively or negatively, depending on the characteristic and lag in question. Overall, flood characteristics explain 2.60% of the IPC metric variance in the full model and 8.18% of the variance in the Granger model (*SI Appendix, Table S1*). A greater number of floods degrades food security in both the regional and country models, except for South Sudan, where food security is degraded initially but improved at a time step of three to four lags (9 mo to 12 mo; Fig. 3*C*). In the regional models, greater flood size and duration lead to increased food security, indicating that wetter years also have net beneficial effects on food security at the regional scale. These regional results are similar to most of the country-level results (Fig. 3*C*). In Kenya, for example, flood characteristics explain 8.16% (5.65%) of the variance in the first-differenced mean IPC level in the Granger (full) model (*SI Appendix, Table S1*). The direction of influence is also similar:

an increase in the number of floods decreases food security in both models, while longer duration and greater area of those floods improve food security.

These modeled results are exemplified by recent (2019–2020) flooding in Kenya. An exceptional Indian Ocean Dipole event (positive sea surface temperature anomalies in the western Indian Ocean with negative anomalies to the east; *SI Appendix, Fig. S4C*) led to extreme amounts of precipitation (>95th percentile) between October 2019 and January 2020 and again in March through April 2020 (spatial distribution of precipitation anomalies is shown in *SI Appendix, Fig. S4C*). The extreme precipitation led to flooding that reduced the planted area of many crops by 10 to 20%, destroyed thousands of acres of floodplain crops, killed tens of thousands of livestock, and damaged roads, houses, irrigation systems, and water and sanitation infrastructure (Table 2). The rainfall between October and January (*SI Appendix, Fig. S3*), however, also provided relief from drought in the previous season and produced generally favorable conditions for pastoralists and marginal agricultural areas. The result was a widespread improvement in estimated levels of food security in early 2020 across the country, except for the region along the Tana River, where 55% of the planted area was destroyed by the flood (50, 51). These floods demonstrate how the acute effects of flooding can directly degrade food security in a confined region while also being associated with a season of above-average rainfall that remains generally favorable for crops and pasture. This situation also highlights the importance of assessing the timing and spatial elements of flood risk in determining which and to what extent areas are increasingly likely to experience negative (or positive—or both) impacts from floods.

West Africa and Chad. The west African regional models show few significant effects of flood characteristics on food security (Fig. 3*D*). Overall, flood characteristics explain only 2.95% of the variance in IPC levels in the full model and only 6.06% of the variance in IPC levels in the Granger model (*SI Appendix, Table S1*). This may be partly due to the presence of several other driving and/or mediating factors influencing food security, in particular, conflict in Nigeria (39). Nevertheless, and in contrast to the All-Africa and other regional models, the number of floods (at lag zero) is shown to significantly reduce variability in food security (i.e., improve food security) (Fig. 3*D*).

This result demonstrates the complex relationship between flooding and food security in countries where the IPC level is causally influenced by flooding per the Granger causality analysis, such as Niger and Nigeria (*SI Appendix, Table S1*). In 2012, flooding in both Nigeria and Niger simultaneously destroyed vast swaths of cropland, damaged infrastructure, and displaced people, but it was also accompanied by good growing conditions elsewhere in the region, created labor opportunities, and was met with effective provision of humanitarian aid. Such competing influences demonstrate how even destructive flooding may not always lead to food insecurity.

The exceptional flooding in 2012 across west Africa was the result of high precipitation, mostly in October 2012 (*SI Appendix, Figs. S3 and S4A*), driven by cool sea surface temperature anomalies in the southern Atlantic, which strengthened the west African monsoon. These wet conditions acted against the backdrop of rising Niger River water levels and streamflows over the last several decades, due, in part, to changing land use patterns (44), making riverine areas across Niger and Nigeria increasingly susceptible to anomalous flood conditions. Compounding these high streamflows, dams were released upstream of the hardest-hit

Table 2. Case studies of regional flood events by country and season-year

Country and season-year	Flood impact			
	Agriculture and food security*	Infrastructure*	Displacement*	Pests/ diseases/ malnutrition
Niger, 2012 (47)	~60% of affected Household (HH) in rice growing areas; ~10,000 ha destroyed; 27,000 tons of crops destroyed; ~33 to 50% of rice and vegetable harvest obtained	“... losses of infrastructure and equipment, with very limited self-financing capacity for the rebuilding of homes destroyed by the floodwaters.”	“Very poor and poor households currently living with host families or in makeshift dwellings have been receiving humanitarian aid. ...they will be facing a housing need over the next two to three months”	Cholera up 19% from last year Malaria up 30% from last year “... in the aftermath of the floods. ... malnutrition trends [have] more than double the usual number of admissions ... to treatment facilities, even in nontraditional outbreak areas.”
Niger, 2012 (83)	N/A*	37,034 houses collapsed	1,733 families evacuated	“To add to the situation, a cholera epidemic spread rapidly in Tillabéry and gradually in Tahoua region. Additionally, malaria incidents increased severely with several deaths.”
Nigeria, 2012 (45, 48)	Several thousand hectares of (mostly floodplain) cropland damaged Losses include (% area): rice (22.4%), maize (14.6%), soybeans (11.2%), cassava (9.3%) and cowpea (6.3%)	“... infrastructure such as roads, dams, and bridges has been destroyed. ...”	1,341,179 people displaced	“There is a widespread outbreak of malaria and typhoid fever . . . in Jigawa state.”
Nigeria, 2012 (45)	481,528.9 naira agricultural losses and damages Market purchase provide food for 60 and 98% of affected households Less than 10% relied on food aid	62,033.2 naira in damages	387,153 people displaced	N/A
Nigeria, 2012 (84)	5,036,972 livestock killed	N/A	2,800,000 people displaced	N/A
Malawi, 2012/2013 (85, 86)	<1% of cropped area damaged	“Possible impact to roads”	N/A	N/A
Malawi, 2012/2013 (87)	19,097 households had crops washed away (95,485 people)	34,000 households damaged (172,955 people)	>33,000 people displaced	Report states no cholera outbreak
Mozambique, 2012/2013 (88, 89)	110,000 ha (3% of planted area nationally) destroyed	Houses destroyed, secondary roads and bridges destroyed, impeding the movement of people and goods	150,000 people reported as displaced by the government	N/A
Mozambique, 2012/2013 (52, 90)	210,587 hectares destroyed (4% of ag land). 890 heads of cattle, about 1,986 goats, 211 sheep, 540 pigs and 11,863 birds were lost	17,000 to 20,000 houses damaged countrywide	>146,000 people displaced	1,771 cases of cholera and 17 deaths
Kenya, 2020 (91)	N/A	N/A	116,000 people displaced	“The Ministry of Health has reported a cholera outbreak in Marsabit county and parts of north-eastern region” “70% of people [displaced by floods] do not have adequate access to clean water”
Kenya, 2020 (50, 51)	Cropped area for beans, maize, and sorghum reduced by 10 to 20% Crop was still majority in good condition 1,606 acres of fodder destroyed (NE pastoral livelihood zone)	N/A	18,000 households displaced	“There is a cholera outbreak in Marsabit with five registered cases in early June.”
Kenya, 2020 (92)	26,636 livestock killed and 5,051 acres of farmland destroyed “foodstocks swept away by the flood”	“significant damage to houses, destruction of irrigation systems, disruption of transport networks / road infrastructure [...] and water sanitation infrastructure”	11,135 households displaced	“Cases of cholera had been reported in flood affected communities. Increased morbidity for malaria were also recorded in ... Baringo, Turkana, and Marsabit counties”

*N/A = not addressed in referenced reports.

regions of Nigeria, including the Kainji and Jebba hydroelectric power dams in Nigeria and Lagdo dam in Cameroon.

The 2012 floods in Niger and Nigeria had immediate negative effects on crop harvests, infrastructure, and displacement (Table 2). Flooding occurred near harvest time in Nigeria and damaged an estimated 12% of all cropped areas for staple crops, although rice-growing regions were hit hardest, with over 22% of cropped areas being damaged (Table 2) (45). In flood-affected areas, low food availability in markets, increased transport costs, and market speculation caused food prices to temporarily increase by 30 to 70%, depending on the locale (45, 46). In Niger, crop losses were also significant, with over 10,000 ha of cropland damaged due to the floods, which amounted to 5 billion CFA francs (approximately USD 9 million) (47).

These acute negative effects of flooding, however, were mitigated by a combination of good growing conditions (e.g., positive moisture anomalies) elsewhere in the region (*SI Appendix, Fig. S4A*) and effective provision of humanitarian aid. In Niger, a priori food security conditions were generally strong, and much of the country was characterized as IPC 1 before the floods (47). During the floods, humanitarian aid amounted to at least USD 19 million in total (48), which met the food needs of at least ~500,000 flood-affected people, possibly attenuating the immediate impact of flooding on food security in the areas directly affected.

Floodwaters in Niger and Nigeria also increased overall water availability, soil moisture, river levels, ponds, and other catchments, for agricultural activities (47, 48). Government and Food and Agriculture Organization of the United Nations aid for agricultural inputs helped farmers to capitalize on this increased water availability, facilitating opportunities for increased agricultural and fishing labor and surplus production in many parts of the country leading to food security benefits (45). In Niger, employment opportunities also increased postflood as a result of infrastructure and equipment repair from flood damage (47). These enhanced labor opportunities may have acted as motivating factors incentivizing household members to migrate within or into the flood-affected areas to garner wages and help acquire food and other household items. However, we also note that migration into a flood zone (e.g., for labor opportunities) could lead to increased physical risks alongside improper risk perception (49).

Discussion

Quantitative analyses of where, when, and to what extent floods affect food security are critical to inform comprehensive assessments of flood impacts and appropriate policy responses. Our results provide quantitative evidence on the relationship between flooding and food security across Africa at larger spatial and temporal scales relevant to preparedness, response, and recovery needs.

The Granger causality analysis, All-Africa, regional, and country-specific panel models, and case studies all indicate that floods, and, more broadly, the meteorological conditions that give rise to floods, can have both positive and negative effects on food security. These effects can originate independently or simultaneously and can manifest at various time steps following their incidence. These divergent effects are mediated by several factors, including flood type and characteristics, location of the hazard, timing, and, importantly, interventions by state and nonstate actors (NGOs, United Nations programs, etc.).

Across our statistical models, the occurrence of floods was associated with degraded food security, a conclusion supported by our case studies that demonstrated how floods destroyed

infrastructure and croplands and killed livestock, which, in turn, led to localized degradation of food security in the reporting period immediately following a flood. The effects of floods on food security as recorded in both the case studies and the statistical models indicate spatially localized effects. The Granger causality map (Fig. 2A) illustrates that, except for Malawi, flooding significantly affects food security in highly localized and heterogeneous ways, as opposed to homogeneously across entire countries. This heterogeneity implies that the relationship of flooding to food security is mediated not by country-scale dynamics (e.g., changes in food prices) but, instead, by context-specific impacts on food production (e.g., subsistence crop loss), food access (e.g., destruction of infrastructure or direct loss of livelihoods), and/or food utilization (e.g., water-borne diseases and sanitation deficiencies), although further research is needed on this point.

In some cases, the negative impact of flooding on food security may be attenuated. One such case was Mozambique in 2012–2013 (52), when state governments and other organizations provided food aid as well as new seeds and fertilizer to recover when flooding occurred during the planting season, thus likely driving lower IPC levels during the same reporting period. In addition, state and nonstate aid and agricultural inputs can help farmers take advantage of elevated soil moisture, resulting from receded floodwaters and/or increased precipitation outside directly flood-affected areas, that extends into subsequent growing seasons exemplified in Niger and Nigeria in 2012. In these water-limited regions, increases in available moisture may help boost food production, lower prices, and improve food security. However, positive precipitation anomalies may likely have diminishing returns or even negative impacts on agricultural growth (53). More extreme precipitation values may lead to flash floods that erode croplands (54) and/or potentially damage critical agriculture infrastructure and transportation networks (55).

People's ability to take advantage of increased water availability associated with flooding is highly dependent on adequate and timely intervention, particularly by state governments and through shifts in governance structures for climate services/programs (56, 57). Resilience to food insecurity may also result from individuals' or households' income and skillset diversification, particularly away from farming activities that stand to be heavily negatively impacted by floods (34). More generally, increases in per capita income may improve adaptation capacity and lead to declines in flood vulnerability (58). To the extent that flooding is associated with precipitation, higher levels of precipitation (and even moderate flooding) have previously been observed to be positively associated with the growth rate of the agricultural sector (27, 59). Future work should further seek to elucidate the variety of pathways that people (individuals and households) may take to meet their food security needs in the aftermath of flood events.

These examples, and our results showing how some flood characteristics can improve food security in some regions, suggest that appropriate and well-timed interventions (government and nongovernment organizations) may increase the rate at which a flood-affected community returns to pre-flood levels of food security, despite localized crop and infrastructure damages and public health challenges. These actions may be distinct from anticipatory actions taken to prevent a decrease in food security; nevertheless, there may be some overlap. For example, short-term anticipatory actions may contribute to long-term planning for better flood management systems (60, 61). We acknowledge that accounting for possible divergent impacts of

flooding at different spatial scales may add complexity to flood response and management. This more nuanced view of flood impacts may, however, facilitate more targeted responses, particularly as the attribution of impacts, including food security, to flooding progresses.

It is important to contextualize our results relative to those of past research, which often is conducted on different spatial scales or using different food security or food production metrics. Studies using household survey data (12, 34) show strong negative impacts of flooding on food security, but these studies were designed to understand how flooding affects local food security, not whether (or how) it does so on regional scales. It is therefore possible that such survey-based studies may disregard areas outside of flood-affected localities that received beneficial moisture for crops and/or the possible benefits that arise from labor opportunities in flood relief and reconstruction. Akukwe et al. (12) analyze food security in flood-affected households between 2012 and 2017 by sampling from four local government areas (administrative unit level two) directly adjacent to the Niger River. Likewise, Ajaero (34) surveyed only households displaced by the flooding in 2012. Both studies provide valuable insights into how flooding can affect food security, but they cannot answer whether, or to what degree, the effects that they detail are widespread.

Regional studies may be comparable to our study in scale, but they often focus on food production rather than food security. Pacetti et al. (18), for example, use remote sensing data and agricultural and water databases to evaluate crop losses in terms of food calories and water use. While this approach can improve assessments of flood damage on food production, metrics like the IPC levels also further consider impacts to food access and utilization and are thus more comprehensive, if subject to other limitations, such as availability of high-quality data inputs, variability of data quality driven by challenges in institutional arrangements, and accessibility to gather data (53, 54). Fiorillo et al. (16) conducted a larger-scale, subnational statistical analysis for Niger identifying areas where floods had a statistically significant effect on infrastructure damage, number of people affected, and crop and livestock losses. In particular, they note that flood impacts on crops and livestock were less significant than on infrastructure and people, which they attribute to difficulties in acquiring adequate, standardized time series data on the former. These challenges also manifest in the work presented here insofar as crop and livestock damages inform the IPC levels used in our analysis.

As highlighted by both our analysis and that of Fiorillo et al. (16), there are still large gaps and needs for flood data as it relates to food security. Firstly, most biophysical measures of floods alone, including those reported by the DFO, are not fully suited to identifying all the ways that floods affect food security. Changing this would require flood data collection to be more detailed and consider a variety of flood impacts over different periods of time. We note that the DFO does document flood severity; however, this is an aggregate measure of flood impacts across sectors and is not reported for all flood events. As such, it can be difficult to establish an association between this measure and different factors that impact food security, which may be impacted differentially (or not at all) by flooding. For example, as we note in our regional case studies, floods ranked as severe may destroy crops directly and/or critical food system infrastructure (storage and transportation networks), thereby leading to decreases in food security. However, for some floods, the local food system may be less directly impacted than, for example, houses, schools, or hospitals,

which may not have direct food security outcomes but nonetheless constitute “severe” flood damages.

Flood data and metrics that capture a range of food security impacts are essential to building predictive capacity because of the classification and typology challenges related to floods. In this way, flood hazards to food security are distinct from droughts. For instance, features of floods indicating whether they occurred on cropland or over key infrastructure (i.e., for food storage and transport) may carry information to help explain subsequent effects on food security in a particular region that is not captured by physical flood metrics alone. While our analysis is place specific, key aspects of how floods in the dataset interact with their locations remain latent in the resulting panel models. We are therefore unable to infer the significance of a location directly and are unable to use this information to predict future impacts of floods on food security. Future research may include the use of computer vision algorithms and volunteered geographic information (60) for flood impact classification that would aid this sort of feature creation, which, in turn, could unlock more-robust analyses that hypothesize and link causal pathways between floods and food security outcomes.

A further limitation of flood data, in its current form, is the process for reporting flood subtypes, which makes identifying the types of floods that affect food security difficult. It is not always a standard operating procedure to report flood subtype, and, when it is reported, the process for doing so may not be consistent from reporter to reporter—especially as turnover can be high in disaster management and reporting roles. Furthermore, the reporting often does not allow for multiple flood types to be selected if they cooccur. If standards are set now, while we are at the earlier stages of exploring the relationships between food security and floods, then there is a heightened chance to better understand how different types of floods, and compound flood events, are affecting food security now and how those impacts may shift over time with climate change (8, 61).

In conclusion, this study quantitatively evaluates where, and to what extent, flooding impacts food security across sub-Saharan Africa. In doing so, and insofar as the available data allow, we have identified potential “hot spots” of flood impacts on food security and revealed that these impacts can both reduce as well as enhance food security at regional and continental spatial scales. As flooding is generally a more localized and spatially constrained phenomenon (e.g., compared to droughts), the impacts of flooding and high rainfall anomalies on food security vary widely, especially when indirect impacts are considered. There is thus a need to consider and compare flood–food security analyses across different spatial and time scales to bracket the extent of impact and to inform response, recovery, and preparedness needs. Our analyses have also highlighted important needs for data collection at the intersection of flood events and food security that will be valuable in informing future study and predictive assessment of flood impacts on food security, which are critical to direct and guide humanitarian and governmental response strategies.

Materials and Methods

Data. Estimates of food security in this analysis are reported to be compatible with the IPC scale, which provides protocols to measure the severity of acute food security using a five-point scale: minimal food security (IPC 1), stressed (IPC 2), emergency (IPC 3), crisis (IPC 4), and famine (IPC 5). These estimates of food security are provided at the subnational level every 3 mo from 2009 to 2016 and every 4 mo from 2016 to the present for countries in west Africa, east Africa, and southern Africa. IPC levels are determined by consensus among

analysts and reflect an integrated, time-varying measure of all available food security indicators and information, including food consumption, changes to livelihood and coping strategies, nutritional status, mortality, food availability, market prices, and exposure to physical hazards (e.g., floods) (42, 43). Furthermore, IPC levels integrate spatiotemporal dimensions of the above information, from metrics like food prices, which are generally available for all months, as well more intermittently available metrics like the reduced Coping Strategy Index (rCSI) (62), which measures household coping strategies to gain access to food. The IPC measurements, therefore, are not entirely independent from measures of flood, but they do represent a consensus-based synthesis of the best available information.

We note that the IPC process was not explicitly developed for research purposes; it is complex and includes many different information streams evaluated by different teams. Furthermore, IPC levels are coarse categorical estimates of the severity of food insecurity at regional scales rather than direct household-level measurements. Nevertheless, IPC levels represent a valuable source of information in that they quantify the multidimensional nature of acute food crises, which evolve continuously in both space and time (63). The IPC levels compare generally well over both time and space with other routinely utilized indicators, which measure more-singular dimensions of food security (e.g., access). For example, IPC levels vary closely (Pearson's $r = 0.76$) with normalized national food prices in Malawi over the 2009–2018 period (*SI Appendix, Fig. S5*). And, while IPC levels are higher in 2016 as compared to 2013, this observation is supported by the household survey data for rCSI in 2013 and 2016 (*SI Appendix, Fig. S6* and description below).

As a further point of comparison, *SI Appendix, Fig. S6* shows a side-by-side comparison of IPC levels and rCSI scores. The rCSI scores were computed using data from the Living Standards Measurement Study (64) in Malawi during the available years 2010–2011, 2013, and 2016–2017. The rCSI and IPC levels compare well, with the regions of highest rCSI corresponding to the highest IPC levels. According to both measures, the greatest food insecurity occurred in 2016–2017, followed by 2010–2011, and 2013. From 2010 to 2011, the highest levels of food insecurity were in the south of the country, as reported by both the IPC levels and the rCSI. In 2013, although the household survey data coverage was limited, food insecurity levels did not reach the severity of that in the south of the country in 2010–2011. In 2016–2017, food insecurity levels were higher across much of the country, particularly in the southern, southeastern, and western areas.

Because past literature has indicated that the IPC levels can be influenced by politics due to the central role of government officials in the process (65), we use the FEWS IPC compatible levels, which minimizes the negative effects of political influence in the process. FEWS IPC compatible levels are determined using the household food economy analysis framework. The lack of available or reliable data on nutrition and mortality, however, still makes IPC levels relatively less certain in regions of ongoing conflict (65).

Determining the true resolution of the IPC data is difficult (or impossible) because analysts may use information from fine spatial scales to infer the food security status of populations at larger spatial scales. We adopt the intersection of administrative level two units and livelihood zones from FEWS NET as the basic unit of analysis, which we henceforth refer to as a “panel.” Both the administrative unit level two shapefiles and livelihood zones are FEWS NET products. FEWS NET produces maps of livelihood zones within each country, based on geographic and climatic zones, and where people generally have similar options for obtaining food, income, and market access. These livelihood zone maps are maintained by FEWS NET and are publicly available as shapefiles for geographic information systems applications (66, 67).

Flood data, including flood location, duration, and area of extent, were obtained from the Global Active Archive of Large Flood Events generated by the DFO (38). The DFO derives information about discrete flood events from news, governmental, instrumental, and remote sensing sources from 1985 to the date of publication, and is the most comprehensive large flood event archive available for sub-Saharan Africa and our study period of interest. Flood data for this analysis were selected from March 2009 to February 2020, such that we had flood data available to align with each available IPC reporting period.

We note that the spatial resolution of these data is coarse, with each flood event represented by a hand-drawn polygon that outlines its area of impact, as opposed to a precise mask that distinguishes its inundation extent. The area/extent of every flood is thus likely overestimated. However, every flood in the

database is subject to such systematic overestimation. Furthermore, as we are concerned more with signal detection and sign of relationship than magnitude of effect size, and given the first-differencing approach used in our models, this flood area overestimation is not likely to significantly influence our results.

The available data were formatted to a common scale in time and space for our analysis. We used a seasonal time period for our aggregations, aligning with the historical release schedule of the IPC data, which were released four times per year from 2009 to 2015, switching to three times per year in 2016. Each “season” in our dataset thus corresponds to the time between the releases of consecutive IPC reports. Additionally, we decided to delineate the data in space using the panels as defined above across all countries included in the IPC data.

For each panel ($n = 6,589$), we averaged the IPC raster data falling within its borders to yield a mean IPC rating for the end of each season. For each season, we then selected flood events from the DFO dataset which either began or ended in the time period between consecutive IPC reporting dates and used overlay analysis between the flood polygons and panel boundaries to calculate the number of floods that occurred, total flood duration in days, and total flood extent as a proportion of the panel area (i.e., taking a value between zero and one). These variables were each normalized to an SD of one to improve the interpretability of results from the static panel models. This process resulted in each panel having its own time series of mean IPC, number of floods, flooded area, and flood duration for each season over the years studied.

To determine whether our IPC and flood variable time series were stationary and suitable for our regression modeling objectives, we performed different transformations of each of the variables and tested them for unit roots using the cross-sectionally augmented Im, Pesaran, and Shin test for unit roots in panel models using up to four lags, mapping onto any annual cycles present in the data (68). We found that differencing the variables, as well as deseasoning (by differencing the previous season's value from the present value) and then differencing, both produced stationary time series that failed to reject the null hypotheses in this test (*SI Appendix, Table S3*). For the sake of parsimony and interpretability, and to avoid inducing false structure in the data through over-differencing, we decided to use the first-differenced variables for modeling purposes in this analysis.

We used population data from the 2020 WorldPop datasets (<https://hub.worldpop.org/doi/10.5258/SOTON/WP00647>) (39) to estimate the number of people who experienced food insecurity and whose food security was significantly influenced by flooding over the study period, to add context to the results of our Granger causality analysis. These data map the spatial distribution of population in 2020 globally at a regular 30-arc (~1 km at the equator) pixel resolution. WorldPop disaggregates census-level data using statistical models incorporating survey, satellite, and mobile phone data, thereby reducing overestimates (underestimates) of population in sparsely populated rural (urban) areas (69). Similarly to the IPC and flood data, we summed the population falling within each panel's boundaries to yield a total population estimate for each panel.

Granger Causality Analysis. We used Granger causality hypothesis tests using both the “plm” package in R and “xtgcause” command in Stata as a way to identify where, across the study region, the different first-differenced flood characteristics had significant predictive power over first-differenced mean IPC (68, 70–72). Given two stationary time series X and Y , we say that X “Granger-causes” Y if predictions of Y based on its own past values and the past values of X are better than predictions of Y based on Y 's past values alone, typically in the context of linear regression models. In our data, Y represents the first-differenced mean IPC classification for each panel over time, while X represents either the first-differenced number, duration, or extent of floods over time. We explicitly consider the linear relationship between present values of Y and past values of X and Y extending up to four seasons backward in time for each panel $i \in \{1, \dots, N\}$ as follows:

$$Y_{i,t} = \alpha_{i,0} + \sum_{l=1}^4 \alpha_{i,l} Y_{i,t-l} + \sum_{l=1}^4 \beta_{i,l} X_{i,t-l} + \varepsilon_t. \quad [1]$$

We elected to use four time periods in our Granger causality tests to reflect the periodicity of the dataset. For each first-differenced flood variable and each panel, we determined whether X Granger-causes Y if the null hypothesis

$$H_0: \beta_{i,t-1} = \beta_{i,t-2} = \beta_{i,t-3} = \beta_{i,t-4} = 0$$

was rejected by a Wald test.

In our dataset, many panels had an insufficient variance in both the first-differenced mean IPC data and the selected flood variables to actually fit a linear model of the form of [1] without encountering issues of singularities. To work around this, we had to filter the original dataset to include panels with at least four seasons of recorded floods and five seasons of changes in the mean IPC across the study period.

This analysis involved 5,379 individual hypothesis tests. To justify the interpretation of local results and minimize the probability of such results being instances of type I error, we additionally conducted a global hypothesis test for Granger noncausality and calculated an adjusted significance level for the local tests to account for multiple testing, respectively. Additionally, we conducted a global test for Granger noncausality among all the panels, which was used to determine whether homogeneous noncausality was present for each flood variable in the dataset, that is,

$$H_0: \beta_{i,t-1} = \beta_{i,t-2} = \beta_{i,t-3} = \beta_{i,t-4} = 0 \quad \forall i \in \{1, \dots, N\},$$

in which the individual test statistics W_i from each Wald test above are averaged to yield a composite test statistic \bar{W} . This composite test statistic is transformed into another, \tilde{Z} , which follows a standard normal distribution and can be used to test the null hypothesis,

$$\tilde{Z} = \sqrt{\frac{N}{2K}} \times \frac{T-3K-5}{T-2K-3} \times \left(\frac{T-3K-3}{T-3K-1} \times \bar{W} - K \right), \quad [2]$$

where K is the number of lags used in Eq. 1, T is the total number of time periods in the dataset, and N is the total number of panels. If \tilde{Z} is greater than the standard critical value, then H_0 can be rejected, and we conclude that Granger causality exists between X and Y in the dataset in at least one panel. To account for cross-sectional dependence, we additionally followed the block bootstrap procedure proposed by Dumitrescu and Hurlin (73), in which a model is fit according to the null hypothesis for each panel, and their residuals are resampled and used to conduct the hypothesis test outlined in the tests above. The critical values of the test statistic, \tilde{Z} , are then calculated from the distributions of the individual, bootstrapped test statistics. We conducted 10 bootstrapped repetitions for each flood covariate.

With the global null hypothesis of noncausality safely rejected for each flood variable (Table 1), we used the method of controlling the false discovery rate proposed by Benjamini and Hochberg (74) and Wilks (75) to account for type I error and avoid overinterpretation of the local Granger causality tests. This procedure involves, first, sorting the P values of the local hypothesis tests and, second, calculating a more conservative P value for rejection of the null hypothesis, P_{FDR}^* , based on a maximum acceptable rate of type I error, α_{FDR} , using the following equation:

$$P_{FDR}^* = \max_{i=1, \dots, N} [p_{(i)} : p_{(i)} \leq (i/N)\alpha_{FDR}], \quad [3]$$

where i is the index of the P value in the sorted order, and N is the total number of hypothesis tests. In our analysis, $N = 5,379$, and we selected $\alpha_{FDR} = 0.10$ based on discussion from Wilks which suggests that approximately correct results can be obtained under moderate to strong spatial correlation of panels when α_{FDR} is twice the significance level of the global noncausality test (76).

This analysis yielded a classification of panels based on the significance of the predictive influence of flood attributes on changes in food security over the study period. To assess these impacts in terms of the number of people potentially affected, we first calculated an estimate of the population having experienced food insecurity in each panel as 20% of the modeled 2020 WorldPop population following the FEWS NET methodology which requires that a minimum of 20% of a region's population meet an IPC level to be classified as such. We note that all panels in the filtered dataset experienced some food insecurity, based on our filtering logic, which required that each panel have at least five seasons of changes in mean IPC across the study period. We binned these populations by their panels' respective Granger causality classifications and present the results alongside a map of the panels in Fig. 2.

To validate our estimate of the population who had their food security impacted by flooding, we additionally calculated populations for each panel in our dataset using gridded population datasets LandScan (40) and Global Human Settlement Layer (41). These datasets were used to construct a mean and 95% CI (assuming a t distribution) for our impacted population estimate based on data

from the year 2015, in which all three products (including WorldPop) contained data for our entire domain (77). The estimated population who had their food security status impacted by flooding was consistent across these products, with a mean of 12.03% [11.46%, 12.60%] (SI Appendix, Table S6 A and B). While the 2015 WorldPop estimate exhibited a slight positive bias over the sample mean proportion, it was not significantly different from the mean ($P = 0.3397$). Although we do not have additional gridded population data for 2020 for contemporaneous validation, this analysis suggests the WorldPop estimate from 2020 data should also be sound.

These additional population datasets were chosen for their contemporaneity with WorldPop—enabling direct comparison—and because they also disaggregate census-level data using different modeling approaches, as opposed to equally spreading population counts across all grid cells within a census unit. However, Smith et al. (78) show that these products struggle to accurately represent concentrations of flood exposure at finer scales, due, in part, to overestimates (underestimates) of rural (urban) populations. Given this, future work mapping food-insecure (sub)populations to flood regions and events at finer scales than the panels in this study may wish to make use of more-resolved population data products such as the High Resolution Settlement Layer (76). In this case, however, we omit the High Resolution Settlement Layer from our analysis, due to its lack of spatial coverage in Ethiopia, Somalia, Sudan, and South Sudan (79).

Panel Model Analysis. We used a linear random effects static panel model to model the relationship between first-differenced mean IPC and first-differenced flood occurrences, total area, and total duration across multiple spatial extents to explore both "global" and "localized" effects of flooding on food security. Specifically, we created models that included various numbers of panels across three spatial extents: 1) with panels across all countries (16) in the dataset, together; 2) with panels partitioned at the regional level corresponding to the regions present in the dataset, defined here as "east Africa" (Ethiopia, Kenya, Sudan, South Sudan, Somalia, and Uganda), "southern Africa" (Malawi, Mozambique, Zimbabwe, and Zambia), and "west Africa and Chad" (Burkina Faso, Chad, Mali, Mauritania, Niger, and Nigeria); and 3) with panels partitioned at the country level. Additionally, each of these models was made using a version of the original dataset filtered by our Granger causality analysis to include only panels in which enough information was present to determine the Granger-causal relationship between any of the first-differenced flood variables and first differenced mean IPC, resulting in $n = 1,793$.

Each model took the form

$$\Delta y_{i,t} = \sum_{k=0}^4 \alpha_{t-k} \Delta f_{i,t-k} + \sum_{k=0}^4 \beta_{t-k} \Delta a_{i,t-k} + \sum_{k=0}^4 \gamma_{t-k} \Delta d_{i,t-k} + u_i + \varepsilon_{i,t}, \quad [4]$$

where Δy is the first-differenced mean IPC rating, Δf is the first-differenced flood occurrences, Δa is the first-differenced flood area as a proportion of the panel area, Δd is the first-differenced flood duration in days, u is the panel-specific random effects, ε is the idiosyncratic error term, i is the panel identifier, and t is a given time period.

Note that, given this method of data processing, the floods that occur in time t precede the publishing of IPC data in time t , as the publishing of IPC metrics corresponds with the end of a season in our dataset's delineation of time. Hence, floods that occur in time t , that is, $k = 0$ in the formula above, precede published changes in IPC metrics, making flood data in those time periods appropriate to include in the multiple regression.

To determine whether random effects were the appropriate specification for each of these models, we conducted a Chow test for poolability on each model, followed by a Hausman test for fixed effects and a Lagrange multiplier test for random effects (80). The coefficients of each model proved sufficiently stable for pooling, and the random effects specification was unanimously preferred over the fixed-effects specification. After fitting each model to the data, we tested the residuals for cross-sectional dependence using Pesaran's cross-sectional dependence CD test (81). This led to clear indications of cross-sectional dependence; therefore, we decided to cluster the SEs for each of the models using the Driscoll and Kraay (82) robust covariance matrix estimator, which is robust to both cross-sectional dependence and serial autocorrelation.

We acknowledge the potential influence of multiple testing on the significance of coefficients in the fitted panel models across the different subregions and datasets. Nevertheless, the number of models included in our analysis

allows us to explore the varying signals of flood impacts on food security more comprehensively at different spatial scales across sub-Saharan Africa. To balance these concerns, we calculated an additional significance level for the coefficients of the regional and country-level models across the full and Granger-filtered datasets using the false discovery rate method described above in the context of the Granger causality analysis using $\alpha_{FDR} = 0.10$ in the presentation of the results.

Case Study Analysis. We further augment our statistical analyses with qualitative descriptions of select flood events for specific country-years to provide regional context of climate, geography, vulnerability and perception of impacts; compare to our quantitative statistical analyses; and elucidate potential mechanisms, for example, biophysical, sociopolitical, and economic, by which flood impacts food security. We note that there can be much variation in the local and country-wide responses to different flood events, given a priori food security conditions and potential concurrent challenges (conflict, migration, etc.). We therefore attempt a more systematic selection of regional case studies based on the Granger causality results. Specifically, we select case studies by choosing the strongest events based on duration, an uncensored variable suitable for rank-ordering events, from the subset of administrative level-two units for which at least one flood variable was significant in the Granger analysis. We then refer to food security and disaster-focused humanitarian reports for these country-years, including those issued by FEWS NET, Office for the Coordination of Humanitarian Affairs, and country teams during and/or after the flood event occurred to better understand the time-varying impacts of floods on food security at the sub-national scale (Table 2). While Table 2 notes quantitative impact values as provided in these various agency reports, the precision in these numbers is unlikely to be fully reliable, as it can be difficult to exactly quantify such impacts during and

even in the year after a disaster event occurs. Given this, we use these values as a broad measure of impact, to highlight whether or not impacts were present, where, and in what form.

Data, Materials, and Software Availability. All data used in this study are publicly available at the following links and databases. Integrated Phase Classification Data are available from FEWS NET at <https://fewsn.net/fews-data/333> (93). Data from the Dartmouth Flood Observatory are available at <https://floodobservatory.colorado.edu/Archives/index.html> (94). Population data from WorldPop are available at <https://hub.worldpop.org/geodata/summary?id=24777> (95). Global precipitation was sourced from the Global Precipitation Climatology Project V2.3 at a 2.5° resolution available from http://eagle1.umd.edu/GPCP_ICDR/ (96). Regional precipitation data from Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Cloud Classification System-Climate Data Record are available from <https://chrsdata.eng.uci.edu> (97). Sea surface temperatures and surface winds from the National Centers for Environmental Prediction/National Center for Atmospheric Research Climate Data Assimilation System/Reanalysis are available from <https://www.cpc.ncep.noaa.gov/products/wesley/reanalysis.html> (98). Topography from ETOPO5 5 × 5 min Navy database giving topography and bathymetry is available from https://iridl.ldeo.columbia.edu/SOURCES/WORLDBATH/dataset_documentation.html (99).

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