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Anticipating drought-related food security changes

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Food insecurity early warning can provide time to mitigate unfolding crises; however, drought remains a large source of uncertainty. The challenge is to filter unclear or conflicting signals from various climatic and socio-economic variables and link them to food security outcomes. Integrating lag-1 autocorrelation diagnostics into remotely sensed observations from the Soil Moisture Active Passive (SMAP) mission and food prices, we found dramatic improvement in anticipating the timing and intensity of food crises, except in conflict settings. We analysed drought-induced food crises globally in the SMAP record (since 2015; approximately five per year). The change in soil moisture autocorrelation, which we term the Soil Moisture Auto-Regressive Threshold (SMART), signalled an accurate food security transition for all cases studied here ($P < 0.05$; $n = 212$), including lead time of up to three to six months for every case. The SMART trigger anticipates the timing of the transition and the magnitude of the food security change among small to large transitions, both into and out of crises ($R^2 = 0.80$–0.83). While we do not evaluate out-of-sample forecast accuracy using our model, our findings suggest a significant advancement in the capabilities of food security early-warning diagnostics and could save lives and resources.

In the last decade, there have been valuable applications of tipping point theory to climate and ecological systems. Socio-ecological systems such as food security, while not traditionally considered systems that experience tipping points, may still benefit from analytical approaches from tipping point theory—there are critical transitions in environmental systems with potentially large implications for society. The general principle is that nonlinear systems are expected to have states that respond abruptly to gradual changes in a given variable[1]. Food systems have some similarities to ecological tipping points in that variables that trigger food crises can exhibit characteristics of abrupt transitions. For instance, a gradual decrease in soil moisture results in stress of agroecological systems until agricultural production is no longer viable, triggering a transition towards a food crisis[2]. Recent work has highlighted the potential of applying elements of tipping point theory to remotely sensed environmental datasets to identify thresholds and early-warning signals for food security transitions[3]. These recent advancements in tipping point theory offer the motivation to use autocorrelation in environmental variables to anticipate transitions in food systems and enhance food security early-warning capabilities, for example, by refining trigger thresholds.

Trigger thresholds can inform early action and prevent humanitarian crises[4]. A threshold, such as below-average seasonal precipitation during the agricultural growing period, can signal the need for emergency food assistance[5]. Drought triggers, in particular, are in great need of refinement; in East Africa alone, droughts are associated with more than two-thirds of the food insecurity crises that are not anticipated in a timely manner[6]. Thresholds, based on Earth observation products such as soil moisture, rainfall anomalies, photosynthetically active radiation[7] and other vegetation indices[8] have already been established as drought early warning indicators[9,10]. But there is scope for improving

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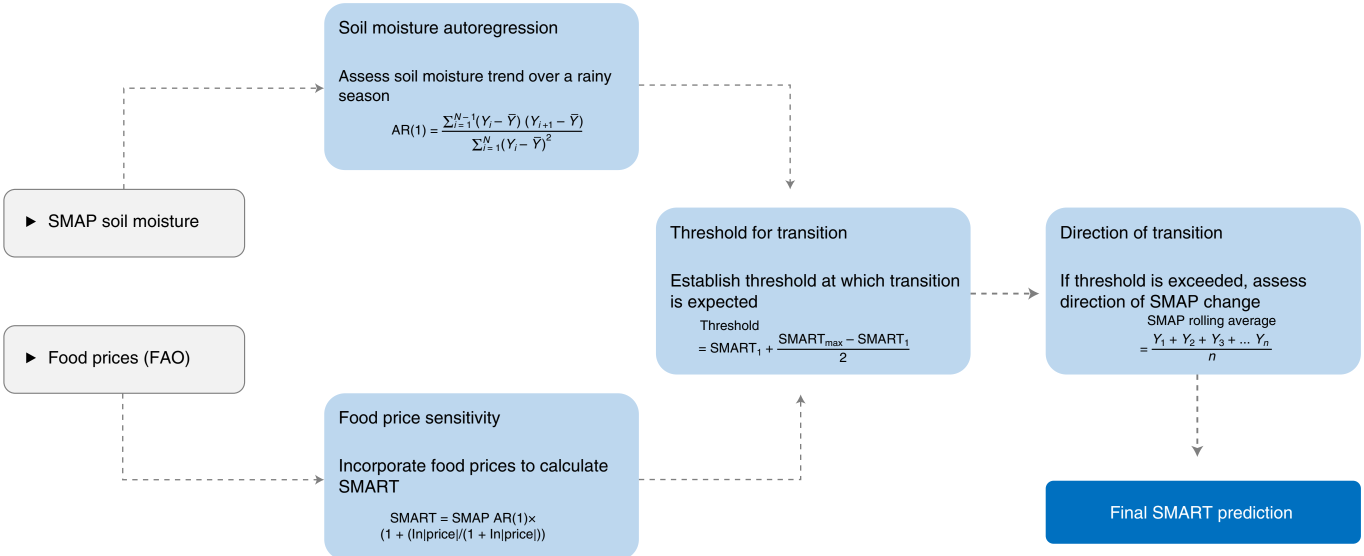

Fig. 1 | SMART uses lag-1 autocorrelation of remotely sensed soil moisture and food prices to anticipate food security transitions. Autocorrelation coefficients and rolling averages for SMAP values are calculated for individual full rainy seasons. Nonlinear effects of food prices are then incorporated into the autocorrelation coefficient. The transition threshold is from the initial and the maximum SMART coefficients. The model is applied to every case study without individual calibration for specific cases, allowing for universal replication. FAO, Food and Agriculture Organization of the United Nations; N, number of observations; i, observation i; Y_i, value ith observation; $\bar{Y}$, average value.

the performance of thresholds in areas prone to food insecurity. If a trigger indicator warns of an impending crisis when there is none (false positive), this misdirects limited resources; conversely, if a trigger indicator fails to anticipate a food crisis that does occur (false negative), people will unnecessarily suffer[5].

Current famine early warning systems rely on consensus-based probabilistic seasonal forecasts and real-time remote sensing data that primarily translate rainfall patterns into food security outcomes[11]. Substantial work has been done to improve seasonal forecasts and interpretation of remote sensing datasets. For example, vegetation indices such as the normalized difference vegetation index have been used to estimate drought impact[12,13]. Rainfall anomalies derived from Earth observation products have also been used to assess the severity of drought[14]. Recognizing that food security depends on a variety of indicators, research has focused on food systems and their interaction with droughts[15,16] (and other climate hazards), agricultural production[10], food prices[17] and household-level dynamics[18]. To complicate matters, other unquantifiable characteristics—such as political instability, currency volatility and disease outbreaks—might also result in sudden changes in food security states[19].

Each of these approaches, whether they are based on hydroclimatic parameters, vegetation indices or socio-economic indicators, contributes to an improved understanding (and prediction) of food security outcomes. We examine the role of the new generation of satellite-based indicators that may provide additional improvements in early-warning systems. The relatively new (2015) indicator of soil moisture from the Soil Moisture Active Passive (SMAP) mission shows particular promise as a potential predictor of food crises[20]. Soil moisture deficit is an indicator of drought that highlights where water shortages could affect crop or pasture output, especially during key growing seasons[21]. Evidence suggests that soil moisture deficits can be a better predictor of crop failure than reductions in rainfall alone[22]. In the absence of robust access to markets and trade, prolonged soil moisture deficits can signal a potential food security crisis[23]. The spatial and temporal resolutions of SMAP soil moisture observations offer unprecedented access to a valuable dataset to monitor drought conditions in near real-time, opening new opportunities to enhance famine early warning[24].

New remote sensing data alone are not enough to enhance early-warning capabilities. We also need analytical frameworks for the analyses of these new data. Initial analysis has suggested that incorporating elements of tipping point theory into food security early warning can prove useful[3,24]. Applications of tipping point theory have shown that lag-1 autocorrelations, the correlation between values that are one period apart, can be used to detect a critical slowing down (the tendency of a system to take longer to return to equilibrium, or 'normal' conditions) before major transitions in ecological systems[1]. We investigate lag-1 autocorrelations to anticipate food security transitions. Lag-1 autocorrelations are associated with critical slowing down whereby a variable becomes less sensitive to small perturbations before transitioning to a different state[25]. In the context of soil moisture, a period of depressed rainfall over multiple months will result in a smooth decline, with the absolute smallest soil minimum water content as a lower asymptote. This kind of curve will inevitably have high autocorrelation. Conversely, high sustained rainfall will lead to soil becoming saturated, resulting in strong autocorrelation. We therefore hypothesize that higher autocorrelation would be expected as soil moisture decreases and reaches a critical agricultural threshold—this is because observed SMAP values would be more similar to each other over a prolonged period as a drought event unfolds.

We tested the approach across drought-induced food crises in the SMAP soil moisture record (since 2015), for a total of 212 cases analysed. The food crises occurred across a broad swath of environmental and socio-economic conditions, specifically in Guatemala, Kenya, Uganda, Somalia, Ethiopia, Sudan, Zimbabwe, Mozambique, Malawi and Cambodia. Through this analysis we provide empirical documentation of a link between the magnitude of the soil moisture autocorrelation change and the severity of the ensuing food security transition. We also evaluated if the autocorrelation could be used to anticipate both deteriorations and improvements in food security conditions. Our study investigates how elements of tipping point theory can enhance detection of food security transitions to a new state and transitions back to the original (or an improved) state.

Early warning model

The model, hereafter referred to as the Soil Moisture Auto-Regressive Threshold (SMART) model, is based on early-warning systems for

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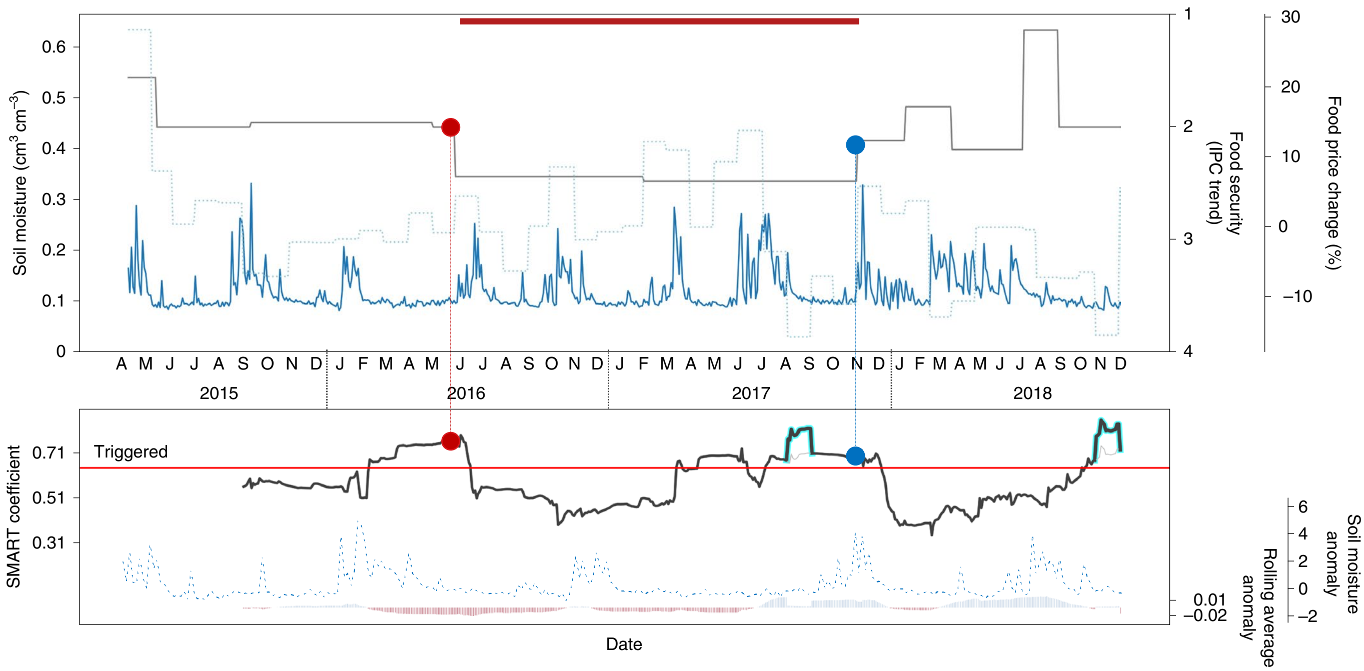

Fig. 2 | Data visualization dashboard showing how food security transitions are detected by the SMART. Top panel: IPC (grey line), remotely sensed soil moisture (solid blue line) and food price anomalies (dashed blue line). Bottom panel: SMART indicator (black line, with blue highlight when price influenced), trigger threshold (red line) and soil moisture rolling average (light red/blue bars). When the SMART indicator exceeds the triggered threshold by at least 60 days, a food security transition forecast is signalled; the indicator provides skill of up to three to six months lead time. The period of state change is indicated by the maroon bar in the top panel. The red dot denotes the exact point when the threshold has been exceeded, suggesting a deterioration of food security conditions, and the blue dot highlights the point in time at which the threshold for an improvement in food security conditions was met. The example shown above is for the northeastern region of Kenya; the other individual case studies are shown in the Supplemental Information. Months are identified by first letter.

tipping point detection. Our approach takes two variables as inputs: soil moisture (a key determinant of agricultural productivity in rain-fed systems) and food prices (a key determinant of access to food). Together, these two variables help in forecasting prolonged food security transitions. The SMART model considers lag-1 autocorrelation values (AR(1)) associated with SMAP soil moisture data (SMAP Level 3 Radiometer Global 36 km Grid Soil Moisture Version 6 (SPL3SMP)) and includes price sensitivity to detect transitions in food security conditions (Fig. 1, Methods, Supplementary Methods and Supplementary Table 2). Food security state transitions take place once the threshold level, determined based on the initial and maximum SMART values, is exceeded for at least three months. Transitions can occur in both directions—deterioration or improvement in food security conditions—as in other environmental systems[26] and are signalled by autocorrelation exceeding the threshold level. The direction of change is determined by the direction of the soil moisture anomaly: a negative rolling average is indicative of a deterioration of food security conditions while a positive rolling average suggests an improvement (Supplementary Methods provide additional analysis of model validation).

We define a transition in food security conditions according to prolonged changes in Integrated Food Security Phase Classifications (IPC) phases (Methods). Food security is a broad concept encompassing availability (ensuring sufficient food of appropriate quality), access (ensuring sufficient entitlement to food), utilization of food (ensuring adequate diets and nutritional well-being) and stability (ensuring that communities do not lose access to food during shocks). The IPC standardizes these complex food security metrics[27], classifying the severity of food insecurity according to a five-class system based on technical consensus that uses on-the-ground and remote monitoring of food-consumption patterns, nutrition trends, access to food and water resources, destitution, displacement and access to critical livelihood assets (1: minimal insecurity, 2: stressed, 3: crisis, 4: emergency, 5: famine). IPC classes are reported every four months for the smallest administrative division or at the livelihood-zone level in the case of Somalia (the average size of these analytical units is 150 km^2). We use the IPC 'current' classes, which are based on explicit on-the-ground monitoring (not to be confused with the 'forecast' classes that also use similar types of data to our analysis). Our interest in this study is on the more severe forms of food insecurity driven by acute undernutrition—but addressing food insecurity effectively requires a longer-term strategy to improve the quality of diets to eliminate micronutrient deficiencies and hidden hunger[28]. For our analysis we do not focus solely on transitions to crisis conditions (IPC 3 or higher); instead, we use the established and defined food security transition as a prolonged period, that is, longer than six months (ref. [29]), of area-averaged food security conditions that change by more than 0.5 in IPC classes.

Results

Across our sample of 212 sites, the SMART metric describes sustained transitions in food security conditions—both in terms of deterioration or improvement—with no less than three months of anticipation. In addition, our model provides an indication of the magnitude of change. This information can be important for food security planning.

Detecting food security state transitions

For each case study, diagnostics and thresholds are shown through a 'dashboard' (Fig. 2 and Supplementary Fig. 1). In the upper panel, food security conditions (IPC) are denoted by the solid grey line, while soil moisture values (SMAP) are shown by the solid blue line and food price changes (relative to the previous month) (Global Information and Early Warning System on Food and Agriculture (GIEWS)) are shown by the dotted blue line. The period of interest is the prolonged shift in food security conditions (a change in IPC class of at least 0.5 sustained for at least six months), denoted by the red bar at the top of the plot. The

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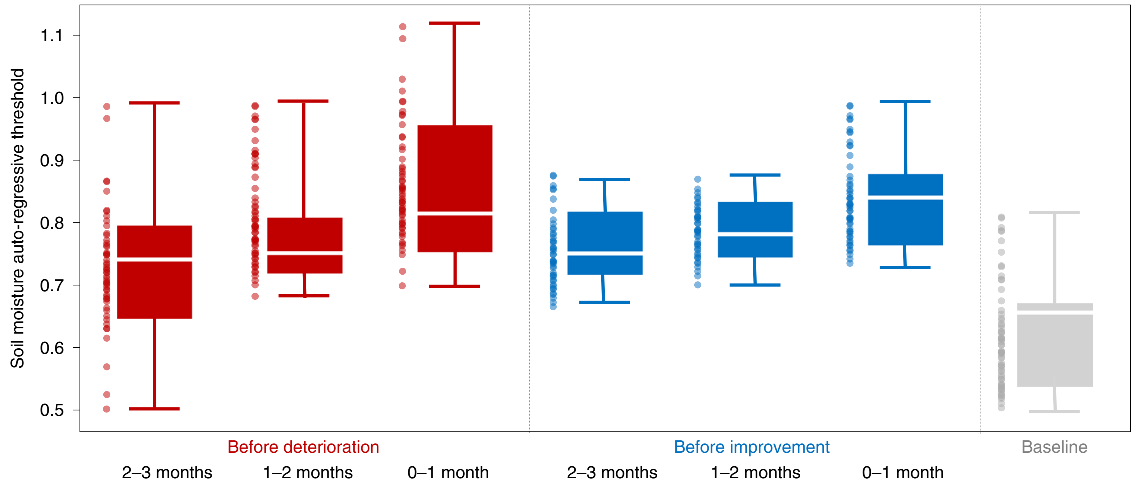


Fig. 3 | Sustained periods of SMART values are indicative of a potential food security state shift. Across all case studies considered here, when the transition approaches, SMART coefficients increase, providing greater certainty about impending shifts in food security conditions. Baseline SMART coefficients are significantly lower than the values associated with periods before transitions (Kendall's $\tau > 0.5$; $P < 0.05$). White lines = median values (50th percentile); upper line = maximum; upper whisker = upper quartile; upper box = third quartile (75th percentile); lower box = second quartile (25th percentile); lower whisker = lower quartile; lower line = minimum.

period starts with a transition towards deteriorating food security conditions (at the beginning of the bar) and improvement in conditions (at the end of the bar).

In the case of Kenya, for example, a food crisis began in June 2016 and lasted more than 18 months following a prolonged period of below-average rainfall[30]. Over 1.3 million people were affected. Food security conditions improved in December 2017 and continued to improve. Minor fluctuations in 2018 are not considered state transitions as food security conditions were not sustained for at least six months. In the lower panel, the SMART indicator (thick solid black line) exceeds the threshold by at least three months before the crisis transition and then stabilizes below the threshold during the crisis. During periods of extreme price changes, the AR(1) also changes—this is illustrated by the blue outline—although, in this case, the prices did not affect the trigger as it had already been exceeded. Before exiting the crisis, the SMART indicator exceeded the threshold by at least three months signalling a new transition. The direction of the transition is determined by the rolling average, shown at the bottom by red (negative rolling average) and blue (positive) bars.

Across all case studies, SMART coefficients increased before a shift in IPC class (Kendall's $\tau > 0.5$; $P < 0.05$) (Methods and Supplementary Results). Furthermore, we found that the SMART, once triggered, provides a lead time of no less than three months and as much as six months before a major transition both towards a food crisis or away from a crisis. As the lead time to a transition decreases, the signal becomes stronger, providing greater confidence that a transition is increasingly likely. In contrast, during periods of no transition ('baseline'), SMART coefficients are lower ($P < 0.05$) (Fig. 3). These results suggest that the SMART indicator is a useful metric for anticipating when a major transition will occur and when conditions are likely to be stable.

In addition to enabling forecasts of when a transition might occur, SMART coefficients are correlated with the magnitude of the food security shift, that is, the change in food security conditions as measured by IPC classes (Fig. 4). The implication is that SMART not only indicates when a deterioration or alleviation is likely to occur but also provides a quantitative indication of how large the shift in food security conditions is likely to be. The median values of SMART in the three months preceding a transition are strongly correlated with the change in IPC classes, with a larger SMART value indicating a larger transition. The skill is nearly equal for exits ($R^2 = 0.83$, $P < 0.05$) and for transitions towards crises ($R^2 = 0.80$, $P < 0.05$).

Discussion

Not all remotely sensed indicators are created equal

Food security early warning systems tend to rely on consensus-based seasonal forecasts, which tend to perform with lower accuracy in periods with complex climate phenomena. During El Niño/Southern Oscillation (ENSO) years, for example, the accuracy rate of seasonal forecasts is 55–58% compared with the average accuracy rate of 69–72% (ref. [31]). Consequently, food security forecasting skill in current systems (that is, the ability to successfully predict IPC categories) is lower in years with strong ENSO cycles (64%) compared with years without a strong ENSO signal (84%) (ref. [6]). Part of the challenge has to do with local sensitivities that drive food insecurity at smaller geographic scales, and part of the issue is related to the need for updating forecasts on a regular basis. Platforms such as the Climate Outlook Forums, whereby analysts interpret information from a range of national, regional and international seasonal forecasts are expensive and therefore meet infrequently, for example, three to four times per year[32], though other climate services such as those provided by International Research Institute for Climate and Society (IRI), the Centre Regional de Formation et d'Application en Agrométéorologie et Hydrologie Opérationnelle (AGRHYMET) and IGAD's (Intergovernmental Authority on Development) Climate Prediction and Applications Centre (ICPAC) are available on a more frequent basis. Recognizing the challenge of consensus-based forecasts, major changes have been suggested: for instance, the Greater Horn of Africa Regional Climate Outlook Forum now uses an objective method based on calibrated dynamical model output alone, with no additional subjective modification.

Earth observation data are increasingly being used to provide regular monitoring updates and develop automatic triggers that activate funding mechanisms and famine prevention activities[33]. Remote sensing products have different characteristics in terms of the types of variable they measure, temporal and spatial resolutions, historical availability, spatial coverage and accuracy (Supplementary Table 3) (ref. [24]). In our analysis, SMART based on SMAP soil moisture outperforms other existing drought indices, including the commonly used Palmer Drought Severity Index (PDSI) and Normalized Difference Vegetation Index (NDVI) metrics, because it quantifies 'critical slowing down' in the agricultural system and can therefore be used to anticipate when a drought-related food security change might take place and how severe it might be (Supplementary Methods and Supplementary Discussion). However, caution is warranted in interpreting results as

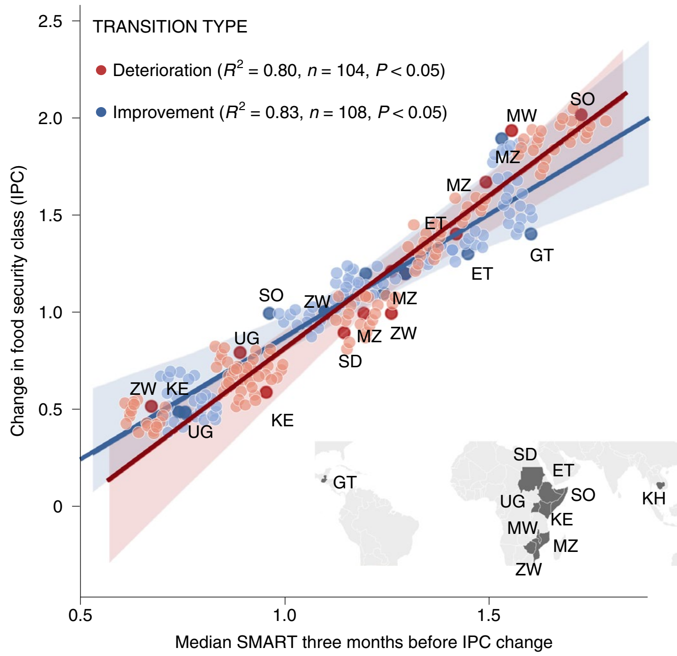


Fig. 4 | The three-month median SMART values forecast the size of the transition for both crises and exits (P < 0.05). Data include all major drought-induced food crises over the SMAP soil moisture satellite record. Darker colours represent averages for the first administrative level (equivalent to the state level) whereas faded colours represent values for second-level administrative divisions (equivalent to districts). The lines represent the best-fit model for each transition, and shaded colours around the lines represent the 95% confidence interval. The inset map shows the location of countries included in this study (ET = Ethiopia, GT = Guatemala, KE = Kenya, KH = Cambodia, MW = Malawi, MZ = Mozambique, UG = Uganda, SD = Sudan, SO = Somalia, ZW = Zimbabwe).

we have been unable to conduct an out-of-sample evaluation given the short time series.

Across our case studies, food security transitions are more sensitive to soil moisture than to food prices. Seventy percent of transitions were anticipated with soil moisture autocorrelation triggers alone sans food prices. But incorporating food prices helps capture the remaining 30 percent, especially in southern African and Asian countries where extreme food price changes are a major trigger of food insecurity (Supplementary Methods and Supplementary Table 2). IPC food security classifications are based on real-time observed characteristics of the population, that is, incidence of malnutrition or sale of critical livelihood assets. Ultimately, our analysis shows that the combination of early soil moisture and price statistics can enhance anticipation of when these adverse food security impacts are likely to be observed. The result of combining the two indicators allows improved detection of the incubation of a food crisis when food price signals begin to worsen or improve synchronously with potential drought stress, especially in countries where rain-fed agriculture and livestock production are predominant sources of livelihoods and food security[34]. At the same time, food prices are not the main contributor to SMART, though it is sensitive to them under rare but extreme swings. The method may not work as well in detecting urban food insecurity or food crises that are more politically driven, such as those seen in the aftermath of the Arab Spring.

Our approach has shown promise in contexts where livelihoods are primarily dependent on rain-fed agriculture, agropastoralism and pastoralism and where connectivity to global markets is limited. In addition to being useful across various livelihood zones, the results also suggest that SMART is a useful indicator across various soil types and geographies; our analysis included nine different types of soil, suggesting a wide applicability of the approach. These are the types of context that are most likely to experience food security crises driven by drought. In more developed markets, such as in Europe or the United States, soil moisture is not likely to result in a food crisis because of social-protection systems[35], more interconnected markets[36] and complex trade relationships with various countries that offer a buffer against localized agricultural deficits[37]. The SMART model is not designed for such contexts.

Our results also indicate an empirical relationship between the magnitude of the SMART indicator value and the change in food security conditions. To our knowledge, this is the first documented analysis of a relationship between autocorrelation and the magnitude of change in the system in the context of food security. If this relationship between magnitude of autocorrelation metrics and magnitude of change in food security holds up in future crises, it would have huge value in responding to food crises—the response could be scaled to the size of the crisis. A humanitarian operation that does not match the scale of the crisis either squanders resources or fails to protect lives. Currently, analysts rely on metrics of food consumption, nutrition patterns and precipitation anomalies to make assumptions about the number of people who will require humanitarian assistance[38]—but the SMART model might provide an additional layer of information to *anticipate* humanitarian needs.

A layered response for enhanced food security early warning

Food crises depend on multiple factors such as availability of crops and grazing land, food prices, governance regimes, health conditions and conflict—so even if an early warning correctly predicts that some thresholds (for example, sufficient food) are not met, a crisis can still unfold because another event triggered it (for example, political instability)[39]. On top of this, there are a multitude of factors that early warning systems are not meant to capture: governance structures, legal frameworks, feasibility of providing humanitarian assistance or the effects of pandemics[16]. A layered early warning system with multiple data streams providing information at different times can reduce uncertainty about the intensity and timing of food crises: for instance, seasonal forecasts might not suggest deteriorating trends, but monitoring of political stability might suggest an impending crisis[15,19]. Moreover, combining multiple Earth observation products can enhance the quality of early warning signals[40]; for example, research has shown that combining vegetation indices such as NDVI with remotely sensed weather parameters improves accuracy of yield forecasts in the US Midwest[41]. Modelled approaches such as the water-requirements satisfaction or the water-satisfaction indices, which are routinely used to monitor agricultural drought in sub-Saharan Africa[42], also hold great potential to enhance early warning capabilities. Approaches that rely on multiple data sources ultimately increase the effectiveness of early warning for early action. Exploring synergies between the various approaches should be the subject for further work.

Our results show the opportunities for integrating analytical statistics used in tipping point applications to complement triggers that feed into existing early warning systems, such as seasonal forecasts (available at least three to four months before a potential crisis), vegetation and drought impact models (constantly being updated) and real-time monitoring. With food security challenges increasing due to climate-related events and conflict incidence[43], our approach offers an additional layer of information before a major food security transition. When all triggers indicate an upcoming crisis, the SMART coefficients can help enhance early interventions by providing greater confidence about the signal and by informing on the severity of the crisis. On the other hand, when all other triggers fail to predict an unfolding crisis, the framework presented here offers a warning signal with a three-month lead time to inform early action. The SMART approach presented here has limitations, however. We tested the SMART approach in other contexts where sustained food security changes took place—and our initial findings suggest that the model does not perform well in cases where food insecurity is primarily driven by conflicts, pandemics, hurricanes/flooding or in areas where large-scale irrigation can offset droughts (Supplementary Methods). Still, the results show promise in rain-fed regions that are prone to food insecurity problems and where current early warning systems occasionally miss food crises.

The SMART model we present here is based on universal criteria applied to open-source information and can be replicated across all geographies. The main data sources, SMAP soil moisture and food prices, are collected regularly through existing systems. At the same time, the thresholds utilized for the triggers are based on the context-specific characteristics of soil moisture dynamics (the maximum and initial values). The advantage of defining thresholds through a universal equation is the possibility of simplifying the analysis of threshold levels while also taking into account the local context. In countries where no early warning systems are in place, it can signal an emerging crisis. And in countries with existing systems, our approach can provide increased confidence about the accuracy of signals detected through other indicators.

Our approach provides a potential step change in food security early warning, given the temporal associations between detected early warning signals and the timing and intensity of food security transitions. The lead time of the signal will allow governments and the humanitarian community to prepare for a crisis and potentially avert it. At the same time, the SMART indicator provides a signal on the severity of food security transitions—another piece of critical information for reducing humanitarian impacts.

Methods

The method used for this analysis consisted of three steps. (1) The first step consisted of downloading food security trend data for locations where major crises occurred, retrieving food price data for the major food staples and downloading remotely sensed data (below). (2) The second step consisted of calculating autocorrelation, variance, skewness and rolling average diagnostics associated with each remotely sensed variable and defining thresholds. Food price data were used to refine the diagnostics and the associated thresholds. (3) The final step involved determining logic rules to quantify what constitutes a food security transition and a trigger to perform further assessment of early warning skill.

The analysis was then conducted for all major droughts since 2015 as defined by the World Food Programme (WFP) and the Food and Agriculture Organization (FAO) for which food security metrics since 2015 were available.

Data sources

Food security crises. The regime shift of interest is the transition between a stable state of minimal food insecurity to a prolonged period with heightened food insecurity. All of the major food crises triggered by drought, identified jointly by the FAO and WFP since 2015, and for which food security metrics were available (below), were included in this analysis (Supplementary Fig. 1). Reports on food crises were collected from ReliefWeb, the UN Office for Coordination of Humanitarian Affairs' repository on humanitarian assessments and data, which represents an independent source of data for identification of food crises. The countries identified for this work are: Cambodia, Ethiopia, Guatemala, Kenya, Malawi, Mozambique, Somalia, Sudan, Uganda and Zimbabwe.

Food security metrics. Food security metrics are available through the IPC approach, which consists of protocols to classify food insecurity and provide information for decisionmaking according to five categories that are comparable across countries: minimal food insecurity, stressed, emergency, crisis and famine (Phases 1 through 5, respectively). A Phase 1 classification is assigned when households are able to meet essential food and non-food needs without engaging in atypical and unsustainable strategies to access food and income. Phase 2 indicates that households have minimally adequate food consumption but are unable to afford some essential non-food expenditures without engaging in stress-coping strategies. Phase 3 represents a situation where households either have food-consumption gaps that are reflected by high or above-usual acute malnutrition or are marginally able to meet minimum food needs but only by depleting essential livelihood assets or through crisis-coping strategies. Phase 4 indicates more severe food gaps because households have large food-consumption gaps that are reflected in very high acute malnutrition and excess mortality or are only able to mitigate large food-consumption gaps by employing emergency livelihood strategies and asset liquidation. The final phase classification (Phase 5) indicates famine and is declared when households have an extreme lack of food and/or other basic needs even after full employment of coping strategies, with starvation and death being visible[27].

Phases are assigned to administrative units or livelihood zones based on consolidated evidence on food-insecure communities to provide information on: (1) the severity of food insecurity, (2) the distribution of food insecurity and (3) the factors contributing to food insecurity[27]. IPC phases are assigned through technical consensus-based on-the-ground and remote assessments that collect information on: food-consumption patterns, anthropometric data on the severity of malnutrition, levels of food and water access, rates of destitution and displacement and availability of livelihood assets (such as agricultural land or grazing land for livestock); the relative importance of the indicators is adapted to the context. Current IPC food security classifications for countries that experienced drought-induced food crises were downloaded from the Famine Early Warning System Network (FEWS NET) Data Portal (https://fews.net/data). Here we test the utility of our proposed approach to reported IPC values averaged for the first- and second-level administrative division in areas impacted by droughts (Supplementary Methods). For Cambodia, FEWS NET does not provide food security analyses, so the number of people receiving food assistance from the WFP was used as a proxy for the severity of food insecurity. Data were retrieved from WFP's standard project and annual country reports (https://www.wfp.org/operations). Data reported here are province-level (first administrative-division level) estimates of people receiving food assistance.

Remotely sensed data. For each of the identified case studies, we used area-averaged time series from the following datasets:

Surface soil moisture (to a depth of 5 cm) was derived from the SMAP Level 3 Radiometer Global 36 km Grid Soil Moisture Version 6 (SPL3SMP), available from April 2015 onwards (https://nsidc.org/data/SPL3SMP/versions/6). The dataset provides global coverage every 2.5 days for soil pixels; all water bodies are already pre-processed and eliminated by the Level 3 product. Soil moisture data are filtered to exclude observations in urban areas, areas with high surface water content and areas impacted by radio frequencies in the same microwave wavelengths as SMAP—all of which are known to affect the quality of SMAP data[44].

Precipitation was derived from the TRMM and GPM missions Level 3 0.25° gridded products, available from 1998 until April 2015 (Tropical Rainfall Measuring Mission; TRMM) and from February 2014 onwards (Global Precipitation Measurement; GPM) (https://pmm.nasa.gov/data-access/downloads/gpm). GPM is an advanced successor of TRMM with additional channels on the dual-frequency precipitation radar and on the GPM Microwave Imager to enable detection of light precipitation and snowfall. Because the two datasets are inter-comparable, a long-term dataset starting in 1998 is available[45].

Evapotranspiration is from the MODIS Level 4 500 m Version 6 product (MOD16A2), available from January 2001 until present (https://modis.ornl.gov/cgi-bin/MODIS/global/subset.pl). Pixels are screened for cloud and aerosol cover to provide more accurate estimates of evapotranspiration rates[46]. Evapotranspiration (ET) pixel values are the sum of all eight days within the composite period.

Normalized difference vegetation index (NDVI) values are from the MODIS Level 3 250 m Version 6 product (MOD13Q1), available from January 2001 until present (https://modis.ornl.gov/cgi-bin/MODIS/global/subset.pl). Imagery is available for every 16-day period using using the two eight-day composite surface reflectance granules (MOD09A1) in the 16-day period. The imagery is filtered for water bodies to improve accuracy of NDVI estimates[46].

Equivalent water heights are from processed Gravity Recovery and Climate Experiment and Follow-On (GRACE/GRACE-FO) data, available from March 2002 until October 2017 (GRACE) and from May 2018 until present (GRACE-FO). Monthly mass grids are processed by the Centre national d'études spatiales/Groupe de Recherche de Géodésie Spatiale (CNES/GRGS) group and provided as 1° × 1° grids through the GRACE-plotter (http://thegraceplotter.com/)[47]. Unfortunately, there are continuity issues given that no measurements were obtained from October 2017 until May 2018, which limits the skill of GRACE measurements for detecting food security transitions.

Our analysis revealed that soil moisture was the indicator with most promise for detecting drought-induced food crises in our analysis (Supplementary Fig. 2).

Food prices. Prices of the dominant food staple in the nearest market (Supplementary Table 2) were retrieved from the FAO's Global Information and Early Warning System food price monitoring tool (http://www.fao.org/giews/food-prices/tool/public/#/home). Price data were downloaded in the local currency for a kilogram of the selected staple. Food price data are collected on a monthly basis for diverse staple crops in various markets. For our analysis, we match the case study locations to the nearest market using nearest neighbour analysis in QGIS to allow for integration in the SMART model. Food price data are routinely collected; an exception, however, is in cases where data collection is unfeasible due to safety concerns (such as during protracted conflict).

Early warning signals, diagnostics and thresholds

Previous studies have demonstrated the utility of using at least four diagnostics for detecting sudden transitions in systems:[24] increasing lag-1 autocorrelation[48], increasing variance[49], increasing skewness[50] and threshold exceedance[51]. The literature recommends defining the rolling window based on the number of observations before the transition occurs (usually half of the observations)[52]. This approach is preferred when the timing of the transition is known. For our analysis, we tested the ability of our model to anticipate food security transitions and assumed that the timing of the crisis transition is not known. We used a consistent rolling window (100 SMAP observations), which is equivalent to at least one rainy period in every country. While a larger window size would be preferred, transitions occurring in 2016 would have been missed.

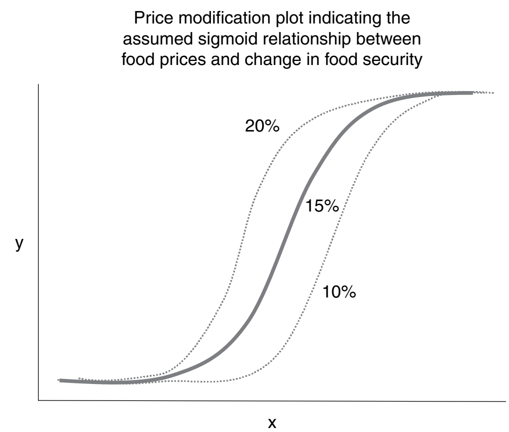
After evaluating the skill associated with each diagnostic, we focused the analysis on lag-1 autocorrelation (AR(1)) coefficients and rolling averages associated with SMAP measurements (Supplementary Fig. 2). The AR(1) value provides an indication that a transition is likely to occur but does not indicate the direction of change. A similar challenge was found elsewhere in climatological applications of tipping point theory[53]. In our analysis, the rolling average diagnostic indicates the direction of change and therefore is a useful metric for early warning protocols. Lag-1 autocorrelation is calculated using the following equation:

$$\mathrm{AR}\,(1) = \frac{\sum_{i=1}^{N-1}(Y_i - \bar{Y})(Y_{i+1} - \bar{Y})}{\sum_{i=1}^{N}(Y_i - \bar{Y})^2} \quad (1)$$

Where Y_i refers to the ith observation of soil moisture, $\bar{Y}$ is the average soil moisture value and N refers to the number of observations.

The initial analysis revealed that some crises were missed by soil moisture measurements alone and that sudden food price increases were implicated. Our analysis revealed that food prices have nonlinear effects on food security, with higher increases in food prices resulting in exponentially more severe food security consequences that plateau[54]. For example, minor food price swings have minimal impacts on food security trends. Conversely, increasing food prices past a certain point do not make people more food insecure as they are already maximally food insecure, though the specific threshold warrants further research. To account for this relationship, nonlinear food price sensitivity is described as:

$$\mathrm{SMART} = \mathrm{SMAP\ AR}\,(1) \times \frac{\ln|\mathrm{price}|}{1 + \ln|\mathrm{price}|} \quad (2)$$



In studies for detection of major climatic shifts such as glaciations[50], the threshold is defined based on the initial AR(1) value, which, in turn, is based on the rolling window size—with an increase in autocorrelation after this baseline indicating an approaching tipping point. We build on this foundation and apply a threshold based on the difference between the initial and maximum SMART. The denominator value is set to 2 to define the halfway point between the initial and maximum values such that the data are evenly distributed between triggering too often (if the threshold is set at the initial SMART value) and not triggering (if the threshold is set at the maximum SMART value), as shown in equation (3):

$$\mathrm{Threshold} = \mathrm{SMART}_1 + \frac{\mathrm{SMART}_{\max} - \mathrm{SMART}_1}{2} \quad (3)$$

This threshold is applied to all cases without calibration for individual cases, making this approach applicable for every location where a food crisis unfolded in our study.

Towards an early warning model. A set of logic rules were developed to identify transitions and triggers. A state transition is considered where there is a change in IPC class in either direction that is greater than 0.5 that is sustained for at least two FEWS NET report periods, which is defined as more than one season with a sustained transition (for example, >150 days), resulting in two types of regime shift—deterioration of food insecurity and improvement in food security conditions. In other words, short-term fluctuations in food security are not considered regime shifts. For instances where food security conditions changed gradually, a regime shift is defined as two or more consecutive changes in IPC class in the same direction if the change is greater than 0.5 IPC classes since the first transition and is sustained for at least two FEWS NET reporting periods. In the latter case, a transition begins at the first change in IPC conditions. For our analysis, we exclude transitions that occurred within the first year of the observational record of

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SMAP (because of insufficient historical measurements to establish a threshold) and those transitions occurring at the end of the record (due to the absence of food security data to verify that a transition has occurred thereafter).

The trigger is important for signalling when an intervention should take place and is therefore an essential element of quality and skill. In our analysis, the trigger is activated when the diagnostic exceeds the threshold level for >60 days (that is, the duration of anomalous dry conditions that are documented to have negative impacts on agriculture and livelihoods).

Reporting summary
Further information on research design is available in the Nature Research Reporting Summary linked to this article.

Data availability
All data used in this study are publicly available through the NASA National Snow and Ice Data Center (NSIDC) website (https://nsidc.org/data/smap/smap-data.html), the FEWS NET Data Portal (https://fews.net/fews-data/333) and the FAO Food Price Monitoring and Analysis (FPMA) Tool (https://www.fao.org/giews/food-prices/price-tool/en/).

Code availability
All code used in this study is available upon request or at https://github.com/Krishna2609.

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Author contributions

P.K.K.R. first conceptualized the study, conducted all data analysis, performed all statistical tests and generated the figures; P.K.K.R., J.B.F. and P.M.K. contributed to designing the methodology. All authors wrote and edited the manuscript.

Competing interests

The authors declare no competing interests.

Additional information

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