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Key Points:
- Tipping points theory provides a framework to integrate remote sensing into drought and food security early warning
- Some remotely-sensed products have appropriate latency, and spatial and temporal resolutions to identify food security tipping points
- Tipping point signals detected through remotely-sensed products offer an opportunity to improve accuracy of famine early warning systems

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Applying Tipping Point Theory to Remote Sensing Science to Improve Early Warning Drought Signals for Food Security

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Abstract Famines have long been associated with drought. With the severity of droughts growing in association with climate change, there is increasing pressure to do a better job predicting famines and delivering international aid to avert human suffering and civil instability. We examine recent advances in remote sensing technology, focusing on the latency, historical availability and spatial and temporal scales of the data these satellites provide. Because of their global coverage, seven variables derived from satellite observations emerge as especially pertinent to drought and famine: precipitation (TRMM/GPM), groundwater (GRACE/GRACE-FO), snow (MODIS), soil moisture (SMOS, SMAP, Sentinel-1), evapotranspiration (MODIS, ECOSTRESS), vegetation health (Landsat, AVHRR, MODIS, SPOT) and chlorophyll fluorescence (OCO-2). We discuss tipping point theory as a possible framework for taking advantage of long time series of these satellite data where they exist in order to enhance the effectiveness of existing famine early warning systems.

1. Introduction

Droughts have always been part of human history, and when combined with social or political failures they have been linked to civil unrest, famines and even the collapse of civilizations. Droughts occur in many parts of the world, often with disproportionate impacts on the most vulnerable populations (Diffenbaugh et al., 2015; Krishnamurthy et al., 2014; Lesk et al., 2016; Richardson et al., 2018; Schlenker & Lobell, 2010). Most importantly, as a result of climate change, droughts are projected to become more frequent and intense globally (Cook et al., 2018). As drought becomes more common and harsher, society's ability to mobilize relief efforts will be stressed, and the premium of effective early warning systems will be heightened.

Clearly famine has many causes of which drought is only one factor (FAO et al., 2019). But in many places in the world characterized by poor food distribution systems and vulnerable populations, drought tends to be one of the most common instigators of famine (cf. Funk et al., 2019). Famine has many causes, and can occur without any climate drivers. This is particularly true in areas where communities depend on rainfed agriculture or traditional livestock rearing for their livelihood (cf. Brown & Brickley, 2012). These regions are primarily located in sub-Saharan Africa, South and Southeast Asia, and Latin America – all regions that are particularly susceptible to shifts in climatic conditions such as a delay in the onset of the rainy season, or interruptions to the rainy season (Verdin et al., 2005). In these regions, monitoring climatic indicators can offer an opportunity to anticipate and prepare for food crises (Brown & Brickley, 2012; de Perez et al., 2019). This does not mean that a severe drought necessarily must lead to famine – since poor governance, lack of technical capacity or relief capacity, and conflict can exacerbate the impact of a minor drought that might otherwise not result in a crisis (Devereux, 2019; Glantz, 2019). Nonetheless, the nexus of climate change enhancing drought severity and famine poses one of the greatest global challenges we face today.

Existing early warning systems for famine tend to rely on community and household data that can be aggregated up to larger scales, or crop assessments on the scale of kilometers or hectares (e.g., Funk & Verdin, 2010; MDM Sri Lanka and WFP, 2017). In fact, globally standardized classifications of food insecurity are expressed in terms of "*1 in 5 households*" or *"4 in 5 households"* (see Table 2). This makes sense because suffering occurs at the household level. However, this does not mean that early warning data needs to be restricted to the household level or farm field-level. Drought and food security crises can strike at much

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larger scales – at hundred or thousands of square kilometers, and even at the scale of nations (Verdin et al., 2005). Collecting data on a spatial scale commensurate with large-scale drought and famine is a challenge from the perspective of cost and sampling design (see De Sherbinin et al., 2014). Here, the advent of remote sensing instruments offers a possible cost-effective solution – these data provide large areal coverage and can be made available at no (or low) cost to international agencies and scientists (Kogan, 2000).

Although remotely-sensed data currently provide input into drought and food security analysis, their use at the global level is not systematic, partly due to insufficient consideration of end-user needs and technical capacities (Purdy et al., 2019), and partly because in some contexts, climate data are deemed irrelevant given the complexity of food security challenges (de Perez et al., 2019). In an effort to improve this situation, scientists have begun to offer suggestions for how satellite data might be used as an input into early warning decision-making (e.g., Verdin et al., 2005; de Perez et al., 2019). There is evidence that rainfall data over a 12-month period can anticipate drought risks in East Africa as much as six months in advance (de Perez et al., 2019). Here we build off that recent work and develop an additional dimension to the use of satellite data in early warning systems: the theory of tipping points in dynamic systems. Unlike household surveys, or even crop field assessments, data streams from satellites can provide a richness of dynamics, and temporal variability that lends itself to dynamic systems theory (e.g., Dakos et al., 2019; Reyer et al., 2015; van Nes et al., 2014). After summarizing the types of pertinent data available from satellites and existing classifications of food insecurity, we explore "tipping point theory" as a possible framework that could enrich the value of satellite data. More specifically, when the data records are sufficiently long, one might be able to take advantage of changing statistical attributes of environmental time series beyond the 12-month or within-year analyses that have recently shown so much promise (de Perez et al., 2019).

2. The Satellite Data Revolution

Remotely-sensed environmental data are already being used for drought and food security assessments, though their use is still relatively limited. To date these applications of remotely sensed data have been restricted to rainfall or vegetation indices (Otkin et al., 2015; Rojas et al., 2011; USGS 2017), and have tended to focus on the relationship between what has happened in the last twelve months and what might be expected in the upcoming growing season. When these climate data are used, it is widely appreciated that climate data are only part of the picture – there are numerous social, political and economic factors that can determine whether or not a famine occurs, and sometimes over-ride recent precipitation or temperature regimes. However, there is general agreement that rainfall and other climatic factors are an important contributor to food crises, at least in some regions of sub-Saharan Africa, Asia and Latin America (e.g., Brown & Brickley, 2012; Haile, 2005; Verdin et al., 2005).

The ideal or optimal remotely sensed data for early warning systems would: 1) be global in coverage, or at least cover all areas of the globe where drought is likely to be an issue, 2) have sufficient spatial resolution to be relevant to the administrative units responsible for food security and famine relief, 3) have intervals between data collection events short enough that the chance to respond to a food crisis has not passed, 4.) be available at near-real-time so that they can be operational and useful for humanitarian planning, and 5) represent data that are ecologically or environmentally salient to crop or livestock failure.

In Table 1 we identify the satellite sensors for hydrological and vegetation indicators that best meet most of the above criteria. For the purpose of famine and food production, all of the data sources in Table 2 are effectively global in coverage. In terms of spatial resolution – administrative units relevant for food security range from 1,500 m^2 (densely populated areas near urban centers) to 2,100 km^2 (scarcely populated regions in desert regions), with the mean size being 150 km^2 or ~12 km pixels (derived using data from FEWS NET, 2018). Nine of the fifteen satellite data sets have a resolution of 12 km pixels or better, and thus are at a scale that is commensurate with administrative units. Responses to major drought-induced food crises take on average three to four weeks to reach maximum operational capacity. This means that the temporal resolution of environmental data similarly needs to be on the order of three to four weeks. Examining the satellite data in Table 1, thirteen of the fifteen data sets are collected at intervals less than three weeks. Finally, more than half of the remote sensing products examined here are available in near-real-time.). In comparison, the availability of household or crop assessment data depends on the time required to conduct

Table 1
Remotely-sensed environmental indicators that could be related to droughts or the impacts of droughts on food insecurity.

INDICATOR	REGIONAL UTILITY FOR FOOD SECURITY	SENSOR	PRODUCT	NOMINAL SPATIAL RESOLUTION	TEMPORAL RESOLUTION	AVAILABILITY OF DATA
Precipitation	Areas that depend on rainfed agriculture	TRMM/GPM	Rainfall rate	30 km	3 hours	1997-present
Groundwater	Regions with limited rainfall that extract groundwater for irrigation	GRACE/GRACE-FO	Total water storage	300 km	1 month	2002–2017, GRACE-FO: 2018
Snowpack	Areas that depend on snowmelt for agricultural water	MODIS	MOD10 snow cover area	500 m	8 days	2000-present
		MODIS	MOD10 snow water equivalent	25 km	8 days	2000–2008
		MODIS	MOD10 snow depth	24 km	daily	2000–2017
Soil moisture	Arid and semi-arid areas with limited rainfall	SMAP	Soil moisture	36 km	50 hours	2015-present
		SMOS	Soil moisture	35–50 km	23 days	2009-present
		Sentinel-1	Soil moisture	500 m	6–12 days	2015-present
Evapotranspiration	Agricultural regions, particularly irrigated crop land	MODIS	MOD16 ET	500 m	8 days	2000-present
		ECOSTRESS	L3 ET_PT-JPL	70 m	3–5 days	2018-present
NDVI		Landsat	Landsat NDVI	30 m	16 days	Landsat 5–8: 1984-present
		AVHRR	AVHRR NDVI	1 km	daily	AVHRR-3: 1998-present
		MODIS	MOD13	250 m	16 days	1999-present
		SPOT	SPOT-VGT	1 km	10 days	1998-present
Fluorescence		OCO-2	SIF	~2 km	16 days	2014-present

fieldwork,and record and clean the data. Minimally this requires weeks, and usually longer than a month (De Sherbinin et al., 2014).

3. “Tipping Point Theory” as a Framework Applied to Droughts and Food Security

Tipping point theory emerges from the analysis on nonlinear dynamic systems and hence tends to be highly abstract and mathematical (Dakos et al., 2019). Tipping points occur in nonlinear dynamic systems where an incremental change in a variable can lead to a completely different state: a system moves from one equilibrium state to a fundamentally different equilibrium state. These jumps to a new regime can happen because one of the state variables is perturbed, or because a particular input or stress is gradually and incrementally altered (Lenton, 2011). In its simplest form, the idea of a tipping point can be captured by the game “Jenga”, whereby wooden blocks are stacked on top of each other, and players take turns to remove a block and place it on top of the tower. The probability of a player's turn resulting in the collapse of the block tower is low, though the probability increases with each turn. These gradual changes (removal of blocks) inexorably make the structure unstable, until part (or all) of it collapses – game over. In tipping point theory, systems can behave in a similar way, with each day of accumulated environmental stress pushing the system closer to when it all tumbles down.

Because climate and food systems are highly nonlinear, there is merit in asking if tipping point theory might provide ideas for how to analyze remotely sensed datasets. Without any theory, it is obvious that simple increasing or decreasing trends can signal changes in the risk regime. However, droughts and famine need not just be the result of gradual deterioration – they could be dramatic flips in a food system. In particular, there is historical evidence that droughts have triggered abrupt food security crises (Fei & Zhou, 2016; Gupta

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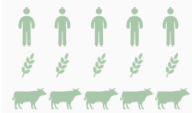
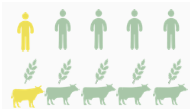
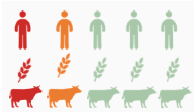
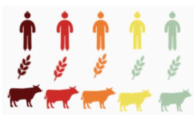
Table 2
Integrated Food Security Phase Classification (IPC). IPC phases are defined based on the classification criteria below (adapted from IPC Global Partners, 2012).

IPC CLASS	FOOD INSECURITY CLASSIFICATION	CRITERIA	
Phase 1	Minimal		At least four out of every five households are able to meet food security needs without resorting to atypical coping strategies.
Phase 2	Stressed		At least one in five households is able to maintain adequate food security but resorts to atypical coping strategies (such as selling livestock or assets) to afford essential nonfood items.
Phase 3	Crisis		At least one in five households have food consumption gaps with high acute malnutrition or are marginally able to maintain adequate food consumption only with sell of assets that will lead to food gaps. National drought response.
Phase 4	Emergency		At least one in five households have large food consumption gaps resulting in very high acute malnutrition or mortality, or resort to coping strategies that will result in large consumption gaps. International drought response.
Phase 5	Famine		At least one in five households have an extreme lack of food or other basic needs. Starvation, death and destitution are evident. International drought response.

et al., 2019). In this regard, flash droughts are especially notable: they occur over shorter periods than seasonal forecasts can anticipate (typically weeks) and can have severe effects on crop yields and grazing lands (e.g., Otkin et al., 2016; Xiong et al., 2018). And even for droughts that develop gradually over seasonal or annual scales, food security impact may manifest abruptly; for instance, the 2011 famine in Eastern Africa occurred after several months of below-average rainfall in the region rather than during the entire period of drought (Ververs, 2011). In such instances, framing impacts as tipping points offers a quantitative approach for early warning analysis.

3.1. Droughts as Tipping Points

What might a famine tipping point look like? An example of a state-variable perturbation that could cause such a tipping point is the addition of too many grazers to a grazer-pasture system. With the addition of too many livestock, intense grazing might degrade the pasture and cause massive soil erosion, which means the livestock cause even more damage because there is less forage, and ultimately a new state is reached that entails semi-arid shrubland or desert as opposed to a fertile pasture (Ellis & Swift, 1988; Fleischner, 1994). In this example, as forage stock is depleted vegetation health indices (such as the Normalized Difference Vegetation Index) would detect lower inter-annual variability in NDVI conditions signaling a transition to a landscape dominated by barren land or shrubs. Another major type of tipping point entails a regime shift that occurs because some climatic stress or input is gradually increased. For instance, the absence of rainfall during the rainy season could trigger a major crop failure and would represent a regime shift.

Currently, the leading metric used in famine early warning is the Integrated Food Security Phase Classification (IPC; see IPC Global Partners, 2012). The IPC approach consists of collecting data on agricultural production, food prices, nutrition rates, weather patterns, and other variables to determine the general food security situation in an area based on five classes (Table 2). The IPC framework was introduced in 2007 and later refined in 2011 and is now used in more than fifty countries to compare food security in a standardized manner (IPC Global Partners, 2012). The standardization of food security measurement provided a

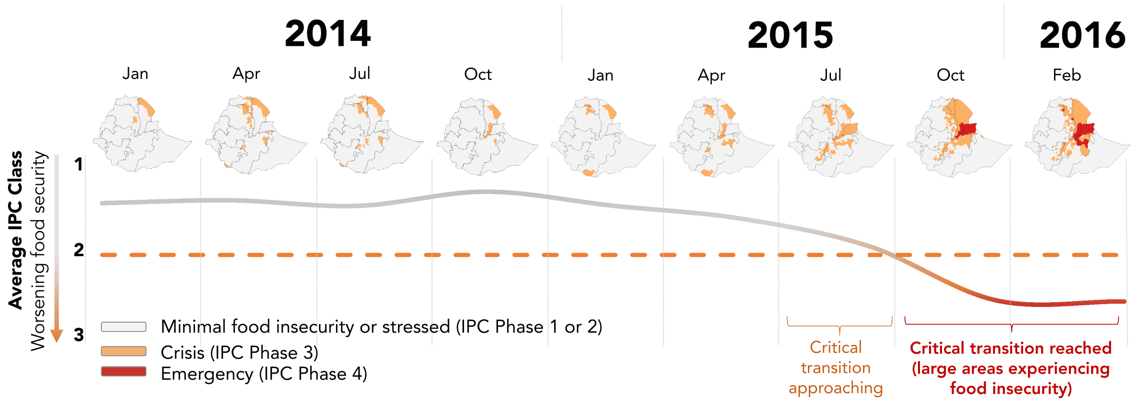


Figure 1. IPC classes provide an opportunity to identify drought tipping points that result in a food crisis. Application of IPC metrics to identify tipping points, showing the transition from stable food security conditions to a food crisis resulting from drought in Ethiopia (derived using FEWS NET, 2018).

breakthrough in famine early warning systems because data quantifying food stress were sufficiently standard that they can now be used to test retroactively whether or not any proposed early warning system has merit. Indeed, leading food security early warning systems – such as the USAID-fiunded Famine Early Warning System Network (FEWS NET) and the FAO's Global Information and Early Warning System (GIEWS) – rely on the IPC classification system to trigger humanitarian responses. An analogous approach, adjusted to crop patterns rather than food security conditions *per se*, is that of the GEOGLAM Crop Monitor which is also based on a five-class system ranging from exceptional to favorable, watch, poor and failure (see Whitcraft et al., 2015).

With this framework, a tipping point in a food system can be thought of as a shift between periods with minimal food insecurity or mildly stressed food security (IPC 1 or 2) to a food crisis (IPC 3 or higher) in the following year (see Figure 1 for an illustration of this concept). We adopt this between-year filter to distinguish from seasonal trends that happen every year (such as drying out through the growing season). An example of a tipping point using the IPC categories is found in East Africa after the 2015/2016 El Niño episode. Usually El Niño events yield extended autumn rains in East Africa, which is good for livestock grazing (Korecha & Barnston, 2007). This was not the case for the 2015/2016 event, which instead was characterized by extremely low rainfall in both the summer and autumns. This trend, combined with insufficient drought preparedness, resulted in crop failures and livestock mortality – and consequently a depletion of livelihood assets and food stocks. As a result, food security conditions deteriorated in large parts of northern and central Ethiopia (see Figure 1), the arid and semi-arid areas of northern Kenya, central Somalia and the Karamoja sub-region of Uganda (FEWS NET, 2017).

Early warning systems that incorporate climatic indicators have some record of success in mitigating major food crises. In June of 2015, for instance, seasonal forecasts suggested that southern Africa would experience drier-than-normal conditions during the rainy season that typically occurs between November and March. Responding to these warnings, several governments pre-positioned food stocks and imported food. By January, data indicated that the region was indeed experiencing its driest rainy season in over 35 years – but effective integration of early warning and early interventions helped avert a far larger crisis. Similarly, predictions of below-average rainfall in parts of Eastern Africa during the 2017 season were instrumental in triggering a multi-agency humanitarian response. Despite the severity of the 2017 drought, relatively few deaths were reported (Funk et al., 2018). Even in cases where drought is not the main contributor to a food crisis, monitoring climatic indicators can provide useful information on the likelihood of potential changes in food prices, conflict, migration and other socioeconomic information that might trigger a crisis as environmental and socioeconomic indicators are intricately inter-connected (e.g., de Perez et al., 2019).

3.2. Early Warning of Tipping Points

Tipping point theory has identified four major statistical diagnostics that might be used as early warning signals of an impending tipping point (e.g., Lenton, 2011):

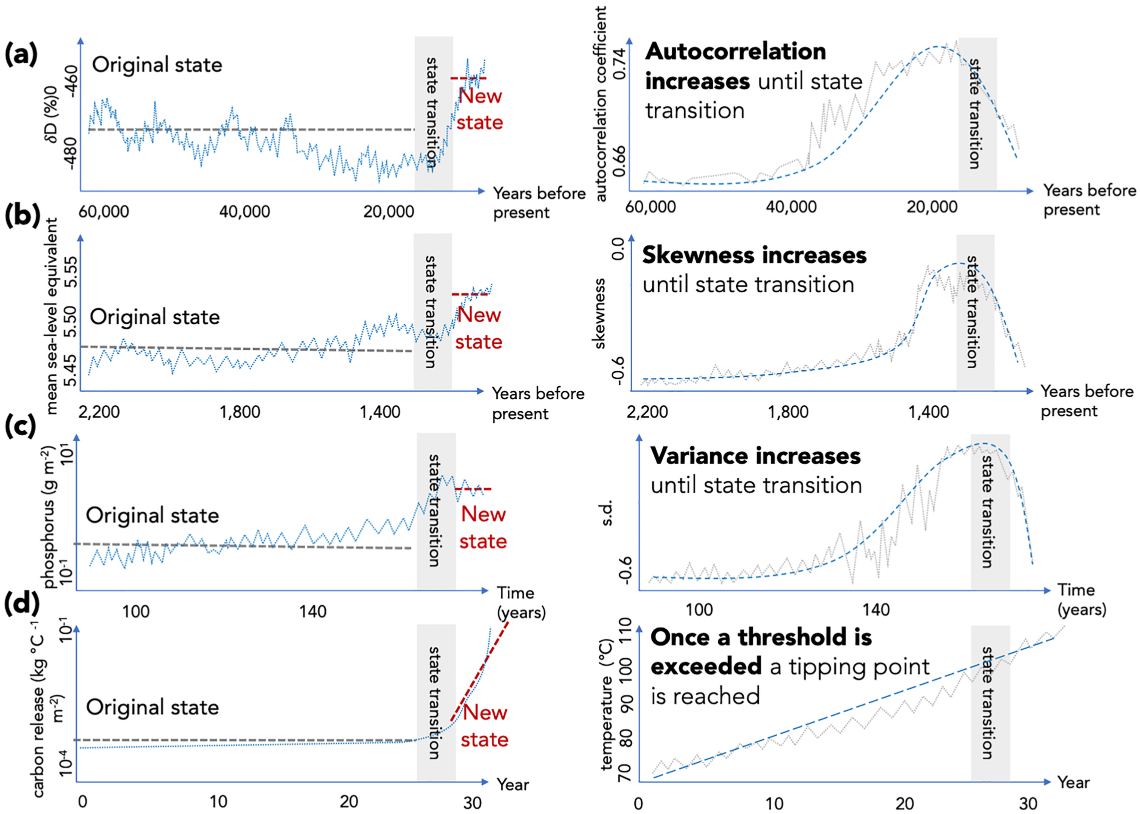


Figure 2. Four main tipping point characteristics may be identified for early warning signals. The examples illustrate an early warning signal identified by (a) autocorrelation towards the end of a glacial period (Dakos et al., 2008), (b) skewness associated with ice melt (Golledge et al., 2017), (c) increased variance with eutrophication (Carpenter & Brock, 2006), and (d) a theoretical example of a rate-dependent threshold for modeled carbon release from peatlands as a temperature threshold is reached.

Autocorrelation: In tipping point theory, dynamical systems that are approaching a transition typically exhibit 'critical slowing down' (on, 2011), which statistically would be manifested as increased autocorrelation. Detection of tipping points through analysis of autocorrelation has been conducted for long-term processes occurring at decadal to century scales, such as the end of glacial phases or desertification of North Africa (Dakos et al., 2008; Figure 2(a)). Decadal and century timeframes are far too long to be useful for early warning of famine, which occurs on sub-annual scales that might not be preceded by critical slowing down signals (cf. Boettiger et al., 2013). However, examples from the ecological equilibrium field have shown that regime changes can be detected through autocorrelation metrics on annual timescales for collapse of quail populations (Hefley et al., 2013), on the scale of months in phytoplankton cycles (Batt et al., 2013), and on the scale of days for plankton populations (Veraart et al., 2012).

Skewness: Some disturbances push a system closer to the boundary of an alternative state, which statistically can be manifested as an increase in skewness and a decrease in the "normalcy" of a data series. (Guttal & Jayaprakash, 2008). Golledge et al. (2017) detected a tipping point in East Antarctic ice-sheet mass during the Pliocene era through increasing skewness. As with autocorrelation analysis, skewness requires consistent data points for long timeseries (Figure 2(b)).

Increased variance: A system characterized by noise, such as a climate system, could exhibit flickering: this is the condition whereby strong disturbances push the system across boundaries of alternative states (Dakos et al., 2012; Scheffer et al., 2009). Flickering and critical slowing down correspond to higher variance prior to a complete transition as shown by increases in standard deviation or amplitude of a particular variable (Figure 2(c)). Using variance, Carpenter and Brock (2006) identified tipping points in eutrophication rates due to phosphorus fertilization, and Takimoto (2009) found transitions in demographic shifts among invasive species.

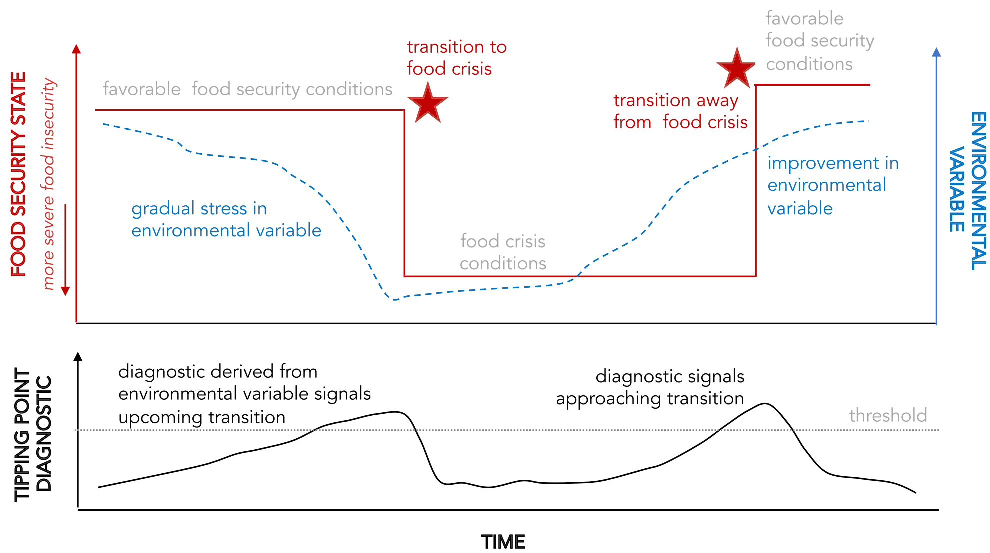


Figure 3. In our conceptual model, the transition of interest is the regime shift from favorable food security conditions into a food crisis, and vice versa. Favorable conditions might include by sufficient (or surplus) food, while a crisis might be characterized by depletion of food stocks or loss of livelihoods. Environmental indicators derived from satellite observations might enable early detection of such transitions through specific statistical diagnostics, such as increasing autocorrelation, allowing governments and the humanitarian system to prepare for food crises.

Thresholds: A fourth methodological approach which holds potential for the identification of tipping points is based on the idea of rate-dependent tipping, whereby the forcing has to exceed a threshold to result in a critical transition (Ashwin et al., 2012; Siteur et al., 2016; Figure 2(d)). In the context of drought and food security, rate-dependent tipping may be quantified as, for instance, the number of days with below-average precipitation during the initial phase of the rainy season, triggering a drought tipping. Rate-dependent tipping is a relatively novel concept and much work is yet to be conducted to determine whether threshold analysis can provide meaningful early warning signals. A working example that has been identified in the literature is that of 'compost bomb instability', whereby there is an explosive release of soil carbon from peatlands after a critical rate of global warming is reached (Wieczorek et al., 2011). As with other diagnostic approaches, rate-dependent tipping requires highly dense timeseries.

3.3. Operationalizing Tipping Point Diagnostics for Famine Early Warning Signals: Combining IPC Metrics, Satellite-Derived Environmental Variables and Tipping Point Theory

The four statistical diagnostics – namely, autocorrelation, skewness, variance and threshold exceedance – offer an opportunity to operationalize an early warning system that detects transitions from one state of food security conditions (e.g., minimal food insecurity, or IPC Phase 1) to a state of a food crisis (e.g., IPC Phase 3). In such a system specific diagnostics associated with an environmental variable would be monitored, and when specific thresholds are met, a famine warning would be triggered (Figure 3).

4. Potential Remotely-Sensed Indicators of Tipping Points

Given the range of hydrological and vegetation indicators available, a key question is which environmental indicators (or combination of indicators) are best-suited for early warning. Below we highlight the utility of the various indicators for drought and food security analysis, and discuss their promise for future analyses.

4.1. Hydrological Indicators

4.1.1. Precipitation

In rainfed agricultural systems, which dominate in much of sub-Saharan Africa, South Asia and Latin America, the main source of water for agriculture is seasonal precipitation and droughts are often associated with below-average rainfall levels (Salmon et al., 2015; Senay et al., 2015). Rainfall monitoring is one of the most direct and simplest methods to assess potential critical transitions. In the context of rainfall, a tipping point might be thought of as a transition towards more variable seasonal rainfall resulting in more extreme rainfall extremes (both high and low) and subsequent crop losses during the agricultural season (cf. Trenberth, 2011). Satellite products, such as those from the Global Precipitation Measurement constellation, offer data at the global level and are useful for identifying such tipping points. The long-term historical dataset available from GPM measurements as well as the high temporal resolution are significant advantages for early warning analysis. But the relatively low spatial resolution (30 km) is likely to limit early detection of tipping points to droughts covering a large geographical area – and decisions based on precipitation data would have to take place at regional scales rather than at the subnational level.

4.1.2. Groundwater

In addition to rainfall, groundwater is a major source of agricultural water. Groundwater extraction is both a response to dry conditions, and a contributing factor to more intense drought (Zaveri et al., 2016). Abrupt decreases in groundwater availability (for instance, through a severe drought) would result in a lower water table, to a point at which water pumps may not be economically or physically feasible (van Lanen & Peters, 2000). Such tipping points would have significant effects not only on seasonal agriculture but on long-term water availability. GRACE/GRACE-FO observations offer estimates of total water storage that can be used as a proxy of groundwater levels, providing unprecedented potential to measure groundwater globally and detect the point at which groundwater shortage may reach the tipping points highlighted here. Droughts associated with groundwater shortages occur over large geographic areas and at seasonal or longer timescales (Li & Rodell, 2015). GRACE/GRACE-FO data have the lowest resolution of all sensors evaluated here – which will pose a challenge for analysis at geographic scales that are relevant for government planning. In addition, temporal resolutions of monthly intervals of remotely-sensed groundwater data (Swenson et al., 2003) do not allow for timely preparedness. However, initial work has shown that assimilation of GRACE/GRACE-FO data into land surface models (e.g. Girotto et al., 2016; Zaitchik et al., 2008) can enhance spatial and temporal resolution, which may prove useful for early detection.

4.1.3. Snowpack

Snow behaves as a natural reservoir for water, particularly in mountainous environments. Monitoring snow is essential for drought assessment, particularly in mountainous environments where snow melt provides the main source of water for agricultural livelihoods (AghaKouchak et al., 2015). A tipping point in snowpack could be linked to rising temperatures. As mountain regions reach temperatures over 0 degrees Celsius earlier in the season, accelerated snowmelt may limit the amount of water available during the agricultural season (Molden et al., 2016). A related but more extreme tipping point is the potential for total loss of snowpack (e.g., Fyfe et al., 2017), which could result in a food security tipping point by reducing availability of water for crops such as paddy and wheat in mountainous regions where no alternative irrigation sources exist – such as in the high mountains of Nepal (Krishnamurthy et al., 2013). The use of snow data for drought assessment is less developed compared to other hyrdological products; in part, this is attributable to the lag between snowmelt and the change in water availability (AghaKouchak et al., 2015). This time lag is a benefit for early warning and identification of tipping points over longer timescales (e.g. Huang et al., 2015), and temporal resolutions of 1–2 weeks is sufficient to detect potential tipping points. However, the lag between snowfall, melt and runoff varies significantly by region and season, so careful analysis is required to translate this lag into meaningful tipping points.

4.1.4. Soil Moisture

Soil moisture is a critical element of the hydrological cycle that directly affects plant water availability, overall plant productivity and crop yields – especially in arid and semiarid areas with limited water and marginal agricultural lands (Martínez-Fernández et al., 2016; Wang et al., 2016; Sietz et al., 2017). In such regions, a tipping point may result from the depletion of soil moisture that in turn places plants under stress, and can even lead to plant mortality (Tietjen et al., 2017). Consequently, measurements of soil moisture through SMAP, SMOS and Sentinel-1 are critical for assessment of drought tipping points, particularly in environments prone to food insecurity (cf. Cleverly et al., 2016; Sohrabi et al., 2015). While soil moisture data are promising for tipping point analysis, the extent of historical satellite measurements is currently too limited to provide baseline dynamics against which a tipping point might be detected. In addition, as with rainfall measurements, soil moisture data are reported at relatively low resolutions (36 km), limiting their utility to regional or large-scale droughts.

4.2. Vegetation Indicators

4.2.1. Vegetation Health (NDVI)

Vegetation indices such as the normalized difference vegetation index (NDVI; Tucker, 1978; Vrieling et al., 2016) and the vegetation health index (VHI; Rojas et al., 2011) are routinely assessed to determine drought impacts on food security (Brown, 2016; Enenkel et al., 2015), particularly in regions with simple topography and well-defined rainfall seasonality (Karnieli et al., 2010). A tipping point measured by **NDVI** (or related vegetation indices) may be identified through a sharp decrease in greenness before the end of the agricultural season (e.g. Zhou et al., 2017). NDVI calculations from Landsat, AVHRR, MODIS and SPOT-VGT observations have been successfully used to monitor drought (and translate drought to food security impact). However, when NDVI anomalies have been detected, they are typically detected while a drought is occurring, which might be too late to be much use in terms of early warning.. But NDVI could confirm a tipping point anticipated by analyses of other data streams.

4.2.2. Chlorophyll Fluorescence

Solar-induced chlorophyll fluorescence (SIF) is a relatively novel indicator used to monitor drought dynamics. Fluorescence measures the biochemical, physical and metabolic functions of plants, including photosynthesis, and can be used to assess changes in these functions during a drought event (Sun et al., 2017). A reduction in photosynthesis (as expected in drought conditions) would translate to lower fluorescence yield (Daumard et al., 2010) and could potentially be linked to drought tipping. The application of SIF from OCO-2 observations on drought assessment has been relatively limited given its novelty; however, initial analyses suggest that fluorescence anomalies are closely related to drought intensity and soil moisture in Texas and the US Mid-West (Sun et al., 2015). However, as with NDVI, metabolic functions of plants are likely to show the characteristics of a transition *after* a tipping point, and hence may be more useful for confirming rather than forecasting a drought.

4.2.3. Evapotranspiration (ET)

ET is a major component of terrestrial ecosystems that links the water, energy and carbon cycles, representing the exchange of water and energy between ecosystems and the atmosphere (Chen et al., 2014). Increased ET rates are linked to higher water stress and therefore reduced net primary productivity and agricultural yield. Monitoring of ET rates has been used in drought assessments (Beguería et al., 2014) and has accurately identified the magnitude of drought events in situations where stand-alone precipitation measurements failed to reflect the extent or seriousness of the drought (Dubrovsky et al., 2009). This is because ET represents the demand for water rather than the supply (for instance, precipitation, snow, groundwater and soil moisture are useful measurements of supply), and an increasing demand for water at the global level necessitates greater consideration of both sides of the supply–demand equation (Fisher et al., 2017). In the context of ET, a tipping point can be thought of as the moment when stomata close to limit water loss through transpiration, stopping carbon uptake. ET measurements are available from Landsat, MODIS and the recently launched ECOSTRESS mission, and provide data to evaluate the risk of drought tipping points in near-real-time. ET measurements occur at the appropriate temporal and spatial resolutions for food security-relevant early warning systems, and moreover link hydrology to vegetation. Therefore, ET is likely to prove an extremely valuable indicator for identifying tipping points.

5. Limitations – Yes, but Too Much Potential to Ignore

In agricultural and livestock systems, tipping point research has been limited by data – the absence of long time series of data at the needed temporal scale and spatial scales. Several of the satellite instruments used for drought assessment have only started collecting data within the last decade, with merely a handful of measurements (primarily precipitation- and vegetation-based) available for more than 20 years. Some of the more recent sensors for soil moisture (SMAP) and fluorescence (OCO-2 SIF) provide time-series data for fewer than 5 years. In addition, efforts such as the NASA MEaSUREs (Making Earth System Data Records for Use in Research Environments) program, which aims to create long-term records by combining data from different missions, will accelerate progress. Moreover, in its 2017–2027 Decadal Strategy, the US National Academies of Sciences, Engineering and Mathematics highlighted the importance of enhancing applications of remote sensing data for water resource management while also stressing the relevance of vegetation stress information for a variety of applications including ecosystem health and agriculture

(NASEM, 2018). As such, the remote sensing data highlighted in this paper will be prioritized and will likely continue to be available, either with existing or upcoming missions (NASEM, 2018).

Though we argue that remote sensing holds great potential for improving early warning systems, this is not to say that the use of remote sensing data is without limits. Remote sensing data are subject to error, largely due to cloud cover, atmospheric interference, geometric distortions and sensor degradation (which can include scanline problems) (Campbell & Wynne, 2011). These errors could lead to inaccurate interpretations of signals Various efforts have attempted to quantify error rates through different approaches – including accuracy rates comparing satellite and ground measurements (measured in percentages, bias, or root mean square error) and uncertainty ranges (measured in the unit of measurement of the satellite). The nature of these errors is different for each measurement. In mountainous regions of Ethiopia, for instance, remote sensors underestimate rainfall (Romilly & Gebremichael, 2011) while MODIS products tend to underestimate snow cover in heavily clouded regions and in areas with thin snow (Hall & Riggs, 2007). Measurements of error suggest high accuracy for SMAP (0.04 cm^3 cm^{-3}, Das et al., 2015), GRACE (8 mm per season, Strassberg et al., 2007), TRMM (84%, Hirpa et al., 2010), and MODIS snow (93%, Hall & Riggs, 2007), NDVI (88%, Lunetta et al., 2006) and ET (70–85%, Velpuri et al., 2013). The relatively high accuracy indicate that the data have utility for detection of tipping points (and other applications); still, taking inaccuracies into account is important when interpreting data and translating them into early warning signals.

Assuming there are sufficiently long-terms and fine scale data, it is not clear that remote sensing data can, in fact, be used to *forecast* a tipping point (cf. Andreadis et al., 2017). Each drought is different. Traditional definitions of drought center around intensity and impacts, ranging from meteorological (based on anomalies from average precipitation) to hydrological (where there is persistently low water availability), agricultural (where there is insufficient water for crops) and socioeconomic drought (when societal demand for water exceeds supply, leading to reduced hydropower and municipal water supply) (Fisher & Andreadis, 2014; Wilhite, 2016). The heterogeneity of droughts means that not every drought will lead to a food crisis: there are years during which the conditions for agricultural drought are met, but there is no food security impact, and conversely there are years during which a less severe meteorological drought results in food scarcity (cf. Lewis, 2017). A fundamental task is therefore identifying the subtle differences in system dynamics that occur prior to a major food crisis triggered by drought compared to other events. In other words, the challenge is whether remote sensing indicators can be used effectively to detect abrupt transitions towards food insecurity rather than simply seasonal trends or inter-annual variability.

A final limitation entails the reality of political and social factors. A variety of famine early warning tools are already in existence (e.g., the USAID Famine Early Warning System, FAO's Global Information and Early Warning System, and WFP's Corporate Alert System). Yet, food crises still occur. In part, this discrepancy arises when the alerts generated by early warning systems are not credible, either because the quality of inputs is questionable or because the different warning systems provide conflicting messages (Lautze et al., 2012). At the same time, early warning systems are political tools and depend on agreement that there is a problem, that it is urgent and that a solution is feasible (Zschau & Küppers, 2013). It is easy to understand why governments may either not want to admit there is a crisis, or – conversely – claim a crisis that was in fact not a crisis (Hillbruner & Moloney, 2012; Maxwell & Fitzpatrick, 2012). That said, any methodological improvements in the effectiveness and credibility of early warning metrics can only help governments make better decisions (Choularton & Krishnamurthy, 2019).

Satellite data are unique in being global, georeferenced, available soon after measurement, and generally inexpensive to end users (Kogan, 2000). Moreover they record a wide variety of attributes—from soil moisture to snow pack. Satellite data will always need ground-truthing, but given the expected increase in droughts, with all the human tragedy these droughts can create, satellite data warrant our attention. In particular, because satellite data are only going to improve, and because we will have an increasing number of droughts for which we also have satellite data with a long lead time – a high priority for research should be testing different ways of processing these data to generate an early warning for droughts that can trigger food crises. Tipping point theory is one possible framework because it generates diagnostics that generate a signal of impending crisis conditions *before* as opposed to during the event. Practical application of tipping point theory requires dense data streams (in time and space) and this is exactly what satellite remote sensing provides. The next step is comprehensive analyses of several droughts around the world along with the time series of remotely sensed data that preceded these events.

Data

Data were not used, nor created for this research.

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