Technical Analysis to Inform the Trigger Design for Adaptive Safety Nets to Respond to Climate Shocks in Malawi

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1. Background

The Government of Malawi (GoM) has put in place a mechanism to enable its flagship social protection program, the Social Cash Transfer Program (SCTP), to scale up to additional beneficiaries in the event of climate shocks, initially prioritizing drought. This scalable mechanism promotes early action using pre-agreed and transparent triggers for funding, pre-positioned financing instruments linked to those triggers, and pre-targeting of vulnerable households. It also relies on having financial systems (i.e., digital payment accounts) in place to ensure funds reach beneficiaries when needed.

During its first year of implementation, in 2021/22, GoM provided assistance to around 74,000 households in three districts through a scale-up of the SCTP. This scale-up contributed to protecting the livelihoods of poor and vulnerable households in the country. The mechanism triggered due to an unprecedented late onset of rainfall, resulting in failed planting in several areas of Malawi. This situation was followed by a series of cyclones and worsening macroeconomic conditions, which increased food insecurity in the country.

The World Bank partnered with Tetra Tech, a consulting and engineering firm, to provide in-depth technical assistance to the GoM, particularly in designing the trigger to determine when the SCTP should scaled up. This effort was supported by the World Bank's Social Support for Resilient Livelihoods project (SSRLP), with capacity building and technical expertise from the World Bank's Crisis and Disaster Risk Finance team. Funding was provided through the Disaster Protection Program (funded by the UK) and the Global Shield Financing Facility (formally the Global Risk Financing Facility, funded by the UK and Germany).

This assignment included three main steps:

1. **Review available drought data sources in Malawi**, including satellite data (rainfall, vegetation, soil moisture, and evapotranspiration) as well as more subjective and local sources such as food insecurity, crop yields, and market prices.
2. **Review drought risk models** that have been used in Malawi and the region. Based on the lessons from past risk models, compare the performance of different indexes usingsatellite data to identify droughts in Malawi. These indexes were correlated with historical food insecurity and crop yield losses to assess their ability to identify drought conditions.
3. **Develop a framework** for a triggering mechanism in drought-prone districts.

This note summarizes the technical work that was conducted to build the government's capacity to design a trigger mechanism in line with the three steps above. The next section provides a brief overview of the trigger design framework. The two subsequent sections present data sources and screened models. The last three sections describe trigger design options, explain the design selected by the GoM, and provide a forward look at the scalable mechanism in Malawi.

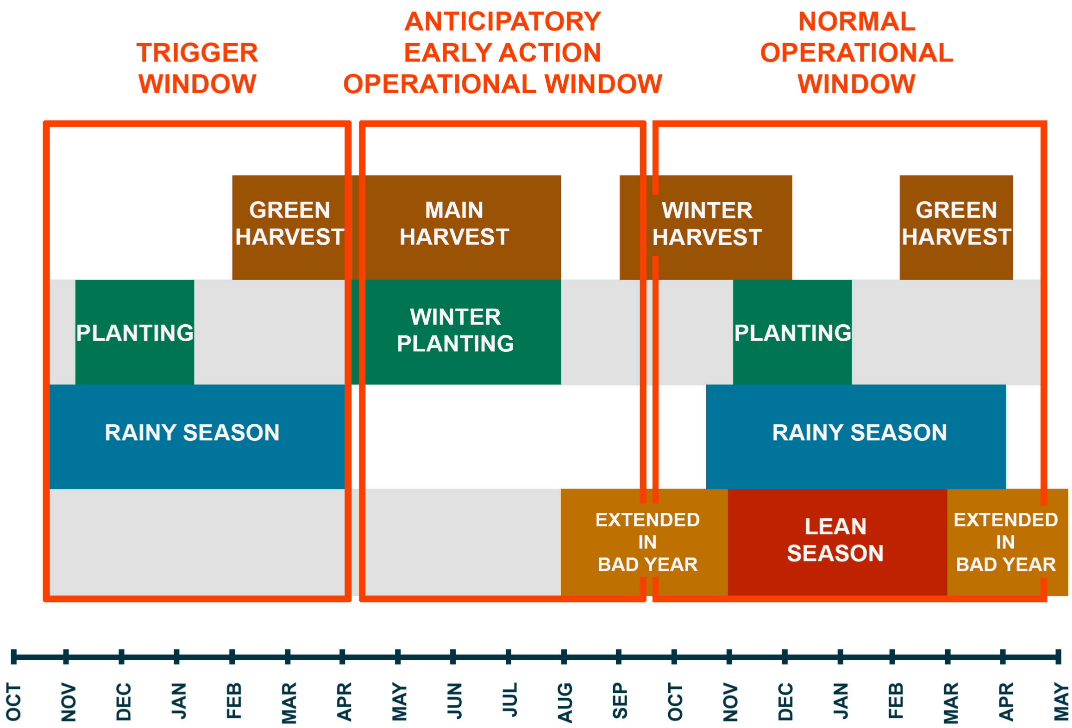
2. Trigger Design Framework

In selecting indicators and designing the triggers for the scalable mechanism, it was essential to understand the links between livelihoods, food security, and drought shocks. In Malawi, food insecurity peaks seasonally during the lean season, in the months from October to March. The lean season precedes the harvest, which occurs between March and May and is the period when rural households obtain their annual income.

Until recently, the government and partners primarily tended to roll out interventions during the lean season. They monitored post-harvest conditions and aimed to intervene during the normal operational response window or lean season months—that is, when households were most food insecure. This is the approach, for example, of the government's Malawi Vulnerability Assessment Committee (MVAC) lean season intervention.

The government's aim in designing the trigger mechanism was to effect an earlier response by monitoring the early indicators of shocks and early signs of food insecurity stress. The design of the mechanism therefore looked for indicators that could be tracked during the rainfall season or triggering window and that were strongly correlated with increases of food insecurity during the subsequent lean season. In other words, the goal was to identify leading indicators, such as rainfall conditions, that would be strongly correlated with trailing indicators, such as drops in agricultural production and food insecurity outcomes. Ultimately, if a scale-up was triggered earlier, assistance could reach households in need during the anticipatory early-action operational window and before the lean season commenced (see figure 1). Providing resources before the lean season could help poor households affected by drought avoid negative coping mechanisms. In addition, receiving additional cash before the start of the lean season would allow them to stock up when food prices are low, hence providing them with more value for money.

Figure 1. Seasonal Timeline and Operational Windows



Source: Government of Malawi, "Social Support for Resilient Livelihoods: Scalable Handbook," 2023, http://www.nlgfc.gov.mw/index.php/the-star/documents/file/135-scalable-handbook-updated-january2023.

3. Review of Available Drought Data Sources

In designing the trigger, the first step was to comprehensively review available data in Malawi in order to identify different data sets that could be used in a trigger mechanism. Following the experience in other countries, the GoM decided to follow a dual trigger approach:

- **The primary trigger** was based on a modeled hard trigger that used satellite data to capture the impact of drought.
- **The secondary trigger** was based on ground conditions or "softer" sources that served as a fail-safe to capture impacts of drought not captured under the satellite-based trigger.

The data review therefore included both remote sensing data to inform the development of the primary trigger and other data that could be used as the basis for a fail-safe secondary trigger. In this initial task, the team identified and assessed a range of remote sensing data and food security indicators against a matrix of evaluation criteria to determine whether these could be used to trigger the scalable mechanism (box 1 below).

Box 1. Selection Factors for Remote Sensing and Food Security Data

- Historical availability
- Temporal resolution or time step (how often the data are released)
- Data latency (time needed to access the satellite data after initial observation)
- Spatial resolution (in square kilometers for remote sensing and administrative area for food security)
- Experience of use for the data source (trusted by government, partners, and financial markets)
- Transparency of algorithm for processing data (in remote sensing) or indicator (in food security)
- Ease and cost of accessing data (for speedy processing of triggered payouts)
- Ease of understanding among and explaining to stakeholders (for acceptance of index performance)
- Expected continuity for future monitoring (for sustainable implementation and future improvements)

For the primary trigger, 15 different satellite data sources were initially analyzed. These included satellite data sources that used a range of indicators, including rainfall (five sources), vegetation (five sources), soil moisture (two sources), evapotranspiration (two sources), and groundwater (one source). For more details on the specific sources reviewed and performance of the selection criteria, please see annex A.

Of the 15 satellite data sources, three rainfall sources performed the best according to the evaluation criteria: TAMSAT, CHIRPS, and ARC2. In addition, background research showed that all the satellite-based data sources used previously for implementing drought index insurance in Malawi were based on rainfall estimates. For this reason, key stakeholders (government, development partners, insurers/reinsurers, etc.) were most comfortable considering rainfall-based indexes, and the three rainfall data sources were short-listed for further analysis. In addition, some data sources that used other indicators were also considered, even when they ranked lower in some of the selection criteria (e.g., historical availability or spatial resolution). The rationale was that globally, some drought index insurance products are being transitioned to non-rainfall parameters to gain higher accuracy. The non-rainfall-related sources chosen for further analysis included one vegetation index (MOD13 NDVI), one soil moisture (SMOS) data set, and one evapotranspiration (ET) data set.

For the secondary trigger, 16 different indicators were reviewed. Malawi has a long history of food security monitoring and early warning, along with a well-established network of food security actors collecting and analyzing data. Most of the indicators reviewed, however, were related to the MVAC, which monitors food security conditions on the ground and is coordinated by the GoM. Please see Annex B for all the secondary trigger indicators considered.

Based on the evaluation criteria, a deeper analysis was carried out for four secondary trigger indicators. These indicators track food insecurity, food prices, and agricultural production and included the following:

- **MVAC data.** The MVAC provides information on the number of households that face food insecurity annually. The disadvantages of using MVAC, however, are that it sometimes faces delays in publication of annual data, and it is perceived to be politically sensitive.
- **FEWS NET (Famine Early Warning Systems Network) Food Security Outlook.** The FEWS NET Outlook includes *Integrated Phase Classification (IPC)* information at subnational level of current and projected food insecurity severity, both of which could be used as a trigger mechanism. However, some accuracy issues arose when historical projections were analyzed against FEWS NET's evaluations of current food security conditions. (See annex E for an assessment of FEWS NET IPC accuracy in Malawi).
- **Staple food prices.** Food prices (especially maize prices) are critical in determining food access for poor households, and robust price data sets exist. Staple food prices are collected by FEWS NET, World Food Programme (WFP), International Food Policy Research Institute (IFPRI), and the Ministry of Agriculture. Options could include
  - Percentage above the five-year average
  - Ratio of food prices to rural labor rates
- **Crop production.** While the primary trigger will most likely work to provide a proxy for crop production, crop production information itself could also be used as a trigger. The release of crop production estimates at the district level often faces delays, however.

4. Screening of Drought Risk Models

Once the government selected a short list of data sources for further consideration, the next step was to develop a risk model for the primary trigger based on a remote sensing data source that could capture the impact of drought in Malawi.

To do this, drought risk models that had been previously used in the country and neighboring countries were reviewed. This analysis found that numerous risk models had been developed with various applications, including climate risk assessment, insurance, and disaster risk finance. Broadly, these models fell into two categories. The first category included statistical analysis of anomalies and variation against climatology for remote sensing products, often layered with other information such as socioeconomic data. The second category comprised index insurance products primarily designed to provide proxy measures of loss for staple crops. These index insurance products have evolved over the last decade, from indexes that measure overall rainfall throughout the agricultural season to more tailored indexes that consider risks to crop production at different points in the season. Newer indexes better reflect rainfall distribution, dry spells, and overall drought conditions.

Based on the lessons from past drought models, eight different drought-related indexes were selected. Annex C provides a description of all the drought-related indexes that were tested and presented to the government. As part of an effort to ensure robustness, each of the eight models or indexes was built for multiple districts in Malawi using the six different remote sensing data sets that were short-listed. These data sets included rainfall (ARC2, CHIRPS, TAMSTAT), evapotranspiration (ET), soil moisture (SMOS), and vegetation (NDVI). For each data source, each risk model or index was tested to assess how well it correlated with food insecurity and agricultural conditions. Specifically, an index's performance was tested against the following criteria:

- Correlation to historical seasonal calendar (rainfall season typically starting in mid-October and ending in mid-April)
- Correlation to agriculture loss using yield data
- Ability to predict lean season food insecurity using FEWS NET Food Security Outlook with IPC data
- Consistency with other remote sensing data sources

Based on this correlation analysis, the government selected three risk models as the best fit for consideration in the design of a primary trigger for the scalable mechanism. These are outlined in table 1 using rainfall as an example in their descriptions.

Table 1. Best-Performing Risk Models	
Risk model	**Description**
Dry spells during the start of the season	Total rainfall conditions over three consecutive dekads during the first eight dekads (of the rainy season) are calculated as a percentage of the normal weather conditions for the same period; if the result is less than the trigger level, the index is triggered.
Dry spells throughout the season	Total rainfall conditions over three consecutive dekads during the entire season are calculated as a percentage of the normal weather conditions for the same period; if the result is less than the trigger level, the index is triggered.
Many small dry spells throughout the season	The total number of dry 10-day periods is calculated as a percentage of the normal number of dry 10-day periods in a season; if the result is more than the trigger level, the index is triggered.

Source: World Bank

Photographs from WBG mission to Malawi for the Social Support for Resilient Livelihoods Project.

5. Three Options for Triggering Mechanisms

Using the results from the screening of available data and drought risk models, three options for a triggering mechanism was developed and presented to the GoM. The three options were designed to illustrate key structural advantages and disadvantages of different potential triggers. The options centered on Blantyre, Ntcheu, and Thyolo, the districts selected by the government for an initial phase of implementation of the scalable mechanism. These districts were selected based on drought risk, food insecurity conditions, SCTP systems readiness, and complementarity to other shock-response interventions. To make the triggers easier to understand and monitor, the options were modeled with the same index structures in all three districts, allowing for variations in trigger thresholds to make them more effective at the district level. The three options are summarized below; details are provided in table 2.

Option 1:

Early-season dry spells with a food security secondary trigger.
This binary rainfall trigger is based on early season performance, triggers early, and is backed up by FEWS NET IPC for the secondary trigger.

Option 2:

Double remote sensing rainfall trigger.
This binary trigger uses two remote sensing rainfall triggers to provide mid-season and end-of-season triggers for scale-up.

Option 3:

Stepwise drought trigger with evidence review.
This trigger uses a two-step payout structure that allows smaller and more frequent payouts for moderate droughts, backed by an evidence review.

For the satellite-based models, the government requested modeled options with trigger thresholds at a one-in-three-year drought in each district. This frequency was selected because it allowed the scale-up to respond to droughts that worsen conditions observed annually, and because it was frequent enough to see a demonstration effect during the duration of the project. To get to this frequency in all districts, trigger levels were varied to consider each district's local climatology and historical rainfall patterns.

Table 2. Characteristics of the Three Trigger Options

	Option 1 Early-season dry spells with a food security secondary trigger	Option 2 Double remote sensing rainfall trigger	Option 3 Stepwise drought trigger with evidence review
Primary Trigger			
Data source	TAMSAT	TAMSAT	TAMSAT
Risk model	Low rainfall over 30 days (three consecutive dekads) over first half of season, i.e., between November 1 and January 31 (dry spells during start of season)	Low rainfall over 30 days (three consecutive dekads) over first half of season, i.e., between November 1 and January 31 (dry spells during start of season)	Dry spells over three consecutive 10-day periods between November 1 and April 10 (dry spells throughout the season)
Timing (by when final index value is known)	Fixed (by the first week of February)	Fixed (by the first week of February)	Fixed (April 15)
Payout structure	Binary	Binary	Stepwise (two steps)
Trigger thresholds	50–60% of normal rainfall levels over the same 30-day periods	45–55% of normal rainfall levels over the same 30-day periods[a]	Step 1: 45% of normal rainfall levels over the same 30-day periods; results in 50 percent payouts Step 2: 30% of normal rainfall levels over the same 30-day time period; results in 100 percent payouts
Secondary Trigger			
Data source	FEWS NET*	ARC2*	Multiple
Risk model	Current IPC	Dry spells over three consecutive 10-day periods between November and April 10 (dry spells throughout the season)	Convergence of evidence
Timing (by when final index value is known)	March	Fixed (April 15)	Fixed (April 15)
Payout structure	Binary	Binary	Binary
Trigger thresholds	IPC3+	10–15% of normal rainfall levels over the same 30-day periods	Consensus and recommendation

Source: World Bank.
* ARC2 = African Rainfall Climatology 2; FEWS NET = Famine Early Warning Systems Network; TAMSAT = Tropical Applications of Meteorology using SATellite data and ground-based observations.
a. Because the early-season index correlated better with food insecurity than the full-season index, it is given more weight through more lenient trigger thresholds.

All options present advantages and disadvantages, with some specific to the initial districts of interest, as outlined in table 3. After evaluating these, the GoM decided to combine options 2 and 3 in the final trigger design, which is described in the next section.

Table 3. Summary of the Main Advantages and Disadvantages of Each Option

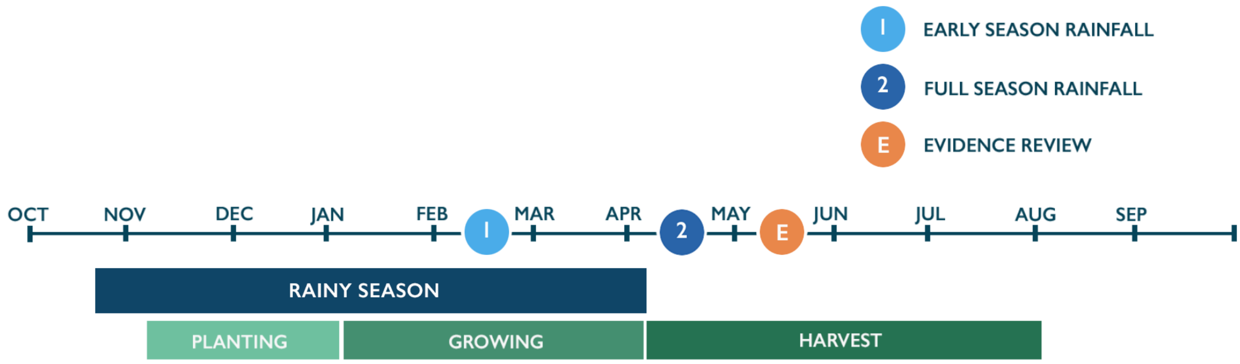
	Advantages	Disadvantages
Option 1: Early-season dry spells with a food security secondary trigger	• Option offers quick payouts for early dry spells, enabling a quick response to a failed start to the season. • Option combines a satellite-based index for the quick triggering of early dry spells with food security data for the secondary trigger; this can help manage basis risk scenarios. • The binary payout structure is easy to understand and monitor.	• Satellite index coverage ends on January 31. Hence, a late dry spell is not covered under the satellite index. • The secondary index may capture nondrought perils. Also, using an IPC3 trigger means that the secondary trigger occurs very infrequently. • Binary payout structure is highly sensitive to small changes in the trigger levels.
Option 2: Double remote sensing rainfall trigger	• Option covers early dry spells, enabling earlier scale-up, but complements this with full-season coverage. • Option reduces basis risk by using multiple sources of satellite data. • Both primary and secondary indexes are more objective and timelier than indexes based on IPC data.	• Using two satellite-based rainfall indexes creates a risk of not capturing some drought events (for instance, those related to vegetation stress or soil moisture), which may have been missed by certain types of satellite data in general. • Trigger levels for the early-season index become stricter due to the inclusion of the full-season index. Hence, the basis risk for the primary index can be higher than for option 1. • Monitoring two satellite-based indexes can be operationally more complex, especially when the two data sets provide contradictory information.
Option 3: Stepwise drought trigger with evidence review	• A stepwise structure can reduce basis risk by allowing a more lenient first step in the trigger, with a lower cost of a positive basis risk event. • Stepwise structure is preferred by the insurance market and could reduce the cost of an insurance product linked to the index. • Evidence review can better capture ground conditions.	• Implementing a two-step scale-up and explaining it to beneficiaries is more complicated. • Option can result in more "false positives," i.e., can trigger payouts when they are not needed/expected if the resultant trigger levels become too lenient. • Evidence review can be subjective and politicized.

Source: World Bank.
Note: IPC = Integrated Phase Classification.

6. Trigger Mechanism Adopted

The GoM used the inputs and options prepared through the technical assistance program to define the trigger for the scalability mechanism. The mechanism adopted was in line with option 2, which includes an objective, modelable primary trigger structure that utilizes two indexes, one based on TAMSAT covering the first half of the season (referred to as the early-season index) and another using ARC2 data covering the full season (full-season index). If the primary trigger thresholds are met in a specific district, this automatically triggers an SCTP scale-up in that district at the end of the agricultural season. In line with option 3, a secondary, complementary trigger or fail-safe was defined using an evidence review process to assess whether drought conditions are being experienced on the ground. The secondary trigger is reviewed only in cases where the primary trigger thresholds are not met but evidence on the ground suggests there might be drought conditions. The evidence review is completed by the end of the agricultural season in May. The timeline for monitoring the triggers is presented in figure 2. The payout structure of the scalability mechanism in each district is binary, i.e., if a trigger is breached in a given district, the scale-up will be operationalized in full in that district. This structure is initially desired for simplicity and ease of administration and communication but could evolve over time.

Figure 2. Timeline for Monitoring Triggers



Source: Government of Malawi, "Social Support for Resilient Livelihoods: Scalable Handbook," 2023, http://www.nlgfc.gov.mw/index.php/the-star/documents/file/135-scalable-handbook-updated-january2023

The mechanism is designed so that by mid-May, the GoM knows whether the SCTP will be scaled up and in which districts. The primary and secondary triggers are monitored during the rainfall season, covering the months from November to April. By early February, GoM can determine whether a scale-up has been triggered by the early-season index, and by mid-April whether a scale-up has been triggered by the full-season index. The expectation is that the scalable mechanism will trigger in a district if either the early-season or full-season drought index threshold is met. During the month of April, the evidence review sources are consulted, and all information is compiled into a report. By mid-May, a task force formed by government officials from different ministries meets and agrees on whether the evidence review supports a scale-up.

The drought index risk model behind the primary trigger structure performed well in predicting food insecurity (see figure 3; further details are in annex D). In addition, the primary trigger met reinsurance industry standards. The risk model was validated by a team of technical experts, including actuaries, and provided reliable and robust outputs when calibrated against historical satellite, yield, and food security data. This is important given that the primary trigger will be linked to a parametric risk transfer product covering part of the costs of scaling up the SCTP in response to drought. The secondary trigger based on the evidence review will not be part of the risk transfer product. The scale-ups triggered by the evidence review are covered by a contingency financing window.

Figure 3: Primary Trigger Performance Compared to MVAC- Affected Population, by District

Source: Tetra Tech.
Note: Years correspond to Malawi Vulnerability Assessment Committee (MVAC) assessment years. The triggers correspond to the period prior to the assessment. The 2010 MVAC is therefore mapped to the 2009/10 rainy season; this allows comparison of MVAC needs and the trigger status for the preceding production season. MVAC data for 2020 were not available at the time of the assessment.

The GoM finalized the design of the scalability mechanism in 2021, setting the rules for monitoring and implementing the mechanism in the SCTP Scalable Handbook. The handbook includes pre-agreed rules for (i) when to scale up for drought (trigger thresholds as shown in annex D), (ii) where to scale up, (iii) which households to cover, and (iv) what level of payment to provide. Table 4 provides details on the scalable mechanism parameters that were pre-defined by the GoM. The rationale behind the selected levels is also documented in the Scalable Handbook. GoM has also constructed a financing plan to fund the SCTP scale-ups that combines a risk transfer instrument and contingency financing.

Table 4. Pre-defined SCTP Scalable Mechanism Parameters

Parameter	Level selected
Rural household coverage	17% in each of the selected districts
Transfer amount per household per month	MK 25,000 (~US$24)[a]
Duration of transfers	3 months
Historical frequency of scale-up	1-in-3-year return period

Source: Government of Malawi.
[a] Based on exchange rate as of December 2022 of MK 1,026 per US$1.

Photographs from WBG mission to Malawi for the Social Support for Resilient Livelihoods Project.

7. Scalable Mechanism in Action and Forward Look

The SCTP scalable mechanism was implemented for the first time during the 2021/22 rainfall season. That rainfall season was characterized by an unprecedented late onset that resulted in failed planting in several parts of Malawi. On top of that, livelihoods were affected by three cyclones—Ana, Dumako, and Gombe—and by macroeconomic factors related to the Russia-Ukraine conflict.

Based on the 2021/22 season conditions, the government scaled up the SCTP in the three districts—Blantyre, Ntcheu, and Thyolo. The lack of rainfall at the beginning of the season was well captured by the primary trigger. Scale-up was triggered in Ntcheu based on the agreed early-season index, and both Thyolo and Blantyre came very close to reaching the trigger threshold as well. Based on the near-miss situation in these two districts, and considering the worsening food insecurity conditions shown by the secondary trigger evidence review, the government also decided to scale up the SCTP in Blantyre and Thyolo. As a result of the scale-up in the three districts, GoM is providing assistance to around 74,000 households and helping to protect the livelihoods of the poor and vulnerable. The government has drawn down US$6.3 million from the contingency financing window to cover the costs of scaling up the SCTP this year in the three districts. An insurance product will be used to cover part of the costs of SCTP scale-ups for the 2023/24 and 2024/25 season.

The World Bank program will continue to provide technical assistance to support the GoM's efforts to further build a scalable or adaptive social protection system. For the 2022/23 season, the government expanded the scalable mechanism to three additional districts—Chiradzulu, Karonga, and Nkhotakota. This will increase the number of rural households being covered from 74,000 to around 116,000. The long-term vision would be to move toward a national mechanism that responds to a broader range of climate risks and incorporates a range of financing sources, to be leveraged by development partners as well as government.

The technical assistance provided in Malawi for the design of the mechanism serves as a good example of how the World Bank and technical partners can assist in implementing adaptive safety nets in other countries. In summary, the following steps can be taken to kick-start the design of a scalable mechanism:

1. Understand the linkages between livelihoods, food insecurity, and shocks in the country or region of interest.
2. Assess potential satellite data sources that could be used as the basis for designing objective and early mechanism triggers in the country or regions of interest.
3. Assess availability of food security, yield, price, and other data sets in the country and regions of interest that could serve for correlation analysis and as the basis for a fail-safe trigger.
4. Assess the readiness of delivery systems to allow for social safety net program scale-ups.
5. Discuss government's, donors', and strategic partners' commitment to investing in delivery systems that can support social safety net scale-ups, and their interest in setting up a dedicated working group to design and implement a scalable mechanism.

Annex A: Remote Sensing Data Sources Analyzed

This section presents the review of satellite data sources and drought indexes to be used for the primary trigger design for SCTP in Malawi. Fifteen satellite data sources were considered for the initial short-listing as the basis for the primary index.

Table A.1. Review of Satellite Data Sources

Product	Indicator	Description of data
OCO-2 SIF*	Chlorophyll fluorescence	Maintained by NASA. Chlorophyll fluorescence measurements have been shown to predict vegetation stress in the US. The utility of fluorescence measurements for drought assessments in Africa is yet to be evaluated.
MOD16 ET*	Evapotranspiration	Maintained by NASA. Generally considered to be inaccurate (< 60% accuracy at the global level); the geostationary satellite only measures ET at the same time of day.
ECOSTRESS*	Evapotranspiration	Maintained by NASA and embedded in the International Space Station. Initial analysis has suggested that ECOSTRESS ET data are highly accurate and can detect changes in ET over the course of the day, providing a more realistic overview of how vegetation responds to heat stress and drought.
GRACE-FO*	Groundwater	Maintained by NASA. The predecessor mission, GRACE, was shown to do a good job of measuring changes in groundwater availability. Spatial and temporal resolutions allow for interannual analysis only over large areas.
TRMM/GPM*	Rainfall	Joint mission between JAXA, NASA, and other space agencies. The constellation of satellites ensures regular data even if one of the satellites loses operational capacity.
ARC2*	Rainfall	Developed by NOAA, combining infrared measurements from the EUMETSAT network and quality-controlled Global Telecommunication System (GTS) weather station data. ARC2 data slightly underestimate rainfall levels, possibly due to the delay in obtaining daily weather station measurements.
RFE*	Rainfall	Developed by NOAA, using an interpolation method to combine Meteosat and GTS data. All satellite data are first combined using the maximum likelihood estimation method, then GTS station data are used to remove bias.
TAMSAT*	Rainfall	TAMSAT was developed by the University of Reading in 1977 and has been available from January 1983 to the present. Multiple versions of TAMSAT are available; version 3.1 is the latest version. The data are available on a daily, pentadal, and decadal frequency, with a high degree of accuracy at the pentadal and decadal time steps.

CHIRPS*	**Rainfall**	CHIRPS data form a 35+ year quasi-global rainfall data set. Spanning 50°S–50°N (and all longitudes) and ranging from 1981 to near present, CHIRPS incorporates CHPclim, 0.05° resolution satellite imagery, and in situ station data to create gridded rainfall time series for trend analysis and seasonal drought monitoring.
SMAP*	**Soil moisture**	Maintained by NASA. Previous studies have shown good correlation between SMAP soil moisture and drought intensity, especially in arid and semiarid areas.
SMOS*	**Soil moisture**	Maintained by ESA. Previous studies have shown good correlation of SMOS soil moisture with drought intensity, especially in arid and semiarid areas. Accuracy is slightly lower (~66%) than for SMAP (~75–80%).
MOD13 NDVI*	**Vegetation index**	Maintained by NASA. Crop monitoring with optical satellite images can be hampered by persistent cloud cover, though special techniques, such as profile smoothing or data fusion, may offer a solution.
Landsat NDVI*	**Vegetation index**	Maintained by NASA. Crop monitoring with optical satellite images can be hampered by persistent cloud cover, though special techniques, such as profile smoothing or data fusion, may offer a solution. Lower spatial resolution but higher temporal resolution than MODIS.
AVHRR NDVI*	**Vegetation index**	Maintained by USGS. Crop monitoring with optical satellite images can be hampered by persistent cloud cover, though special techniques, such as profile smoothing or data fusion, may offer a solution to overcome this problem.
SPOT-VGT*	**Vegetation index**	Maintained by VITO, a private Belgian company. Data older than three months are free of charge. Provides NDVI (normalized difference vegetation index).

Source: World Bank compilation.
*ARC2 = African Rainfall Climatology; CHIRPS = Climate Hazards Group InfraRed Precipitation with Station; ESA = European Space Agency; ET = evapotranspiration; EUMETSAT = European Organization for the Exploitation of Meteorological Satellites; JAXA = Japan Aerospace Exploration Agency; MODIS = Moderate Resolution Imaging Spectroradiometer; NOAA = National Oceanic and Atmospheric Administration; SMAP = Soil Moisture Active Passive; SMOS = Soil Moisture and Ocean Salinity; TAMSAT = Tropical Applications of Meteorology using SATellite data and ground-based observations; USGS = US Geological Survey.

These data sources were short-listed based on six features. Table A.2 summarizes the key features of these six data sets.

Table A.2. Key Features for Satellite Data Sources Based on Criteria

Satellite data source	Indicator	Historical availability	Temporal resolution	Data latency	Spatial resolution	Prior application for index insurance	Continuity
TAMSAT	Rainfall	1983+	Daily, 5-day, 10-day	< 24 hrs	4 km	Yes	Yes
CHIRPS	Rainfall	1981+	Daily, 5-day, 10-day	< 24 hrs	5.5 km	Yes	Yes
ARC2	Rainfall	1960+	1 day	< 24 hrs	10 km	Yes	Yes
Landsat NDVI	Vegetation index	1998+	1 day	< 24 hrs	1 km	Yes	Yes
MOD13 NDVI	Vegetation index	1984+	16 days	16 days	30 m	Yes	Yes
MOD16 ET	Evapotranspiration	2000+	8 days	< 24 hrs	500 m	Yes	Yes
RFE	Rainfall	2001+	10 days	10 days	8 km	Yes	Yes
ECOS-TRESS	Evapotranspiration	2018+	3–5 days	< 24 hrs	70 m	No	Yes
SPOT-VGT	Vegetation index	1998+	10 days	10 days	1 km	Yes	Yes
SMAP	Soil moisture	2015+	50 hours	< 24 hrs	36 km	No	Yes
SMOS	Soil moisture	2009+	3–5 days	< 24 hrs	35–50 km	No	Yes
TRMM/ GPM	Rainfall	1997+	3 hours	< 24 hrs	30 km	Yes	Yes, but some changes in the time series due to change of data source
AVHRR NDVI	Vegetation index	1999+	16 days	16 days	250 m	Yes	Yes
OCO-2 SIF	Chlorophyll fluorescence	2014+	16 days	16 days	2 km	No	No fallback option available
GRACE-FO	Groundwater	2018+	1 month	1 month	300 km	No	No fallback option available

Source: World Bank compilation.

Annex B: Food Insecurity Sources Analyzed

Table B.1 identifies and classifies the main possible food security indicators that could be used for scaling up social protection in Malawi.

Table B.1 Review of Food Security Indicators and Data

Indicator	Indicator type	Possible sources	Comments
MVAC IPC Assessment (medium-term projection)	Leading/composite food security outcome severity indicator/3- to 6-month forecast	MVAC*	Assessment normally released in July/August (but has been delayed in the past); includes food insecurity severity, population in IPC phase, and projection of needs.
FEWS NET Food Security Outlook (current)	Composite food security outcome severity indicator	FEWS NET*	Provided in July, October, and March each year, covering 4-month period.
FEWS NET Food Security Outlook (medium-term projection)	Leading/composite food security outcome severity indicator/3- to 6-month forecast	FEWS NET*	Provided in July, October, and March each year, forecasting ~6 months in the future.
CRW Global IPC Trigger	Leading/composite indicator derived from FEWS NET Outlooks and population data	World Bank*	Calculated in July, October, and March.
Household Economy Analysis (scenario and post-harvest)	Leading indicator	MVAC *	Provides annual household food balance disaggregated by livelihood zone and wealth group using LIAS; analysis normally conducted in May/June using MVAC Annual Assessment data.
Crop production	Leading or trailing depending on context	MoA/MVAC *	Key leading indicator for subsequent lean season (April/May informs next October–March period). A failed harvest can also lead to an extended hunger season, and other earlier indicators of crop production exist (e.g., from remote sensing).
Food prices	Leading or trailing depending on context	FEWS NET and WFP mVAM; MoA also collects price data*	Food prices are especially important for market-dependent households and during seasons when households are more market-dependent. Abnormal early increases in prices are often leading indicators; high seasonal prices are trailing. AMIS data for maize prices are available monthly since 2005 but data are patchy over both time and geography. Price data for maize and pulses are available on a weekly basis for the period December 2015 to November 2020 for over 50 markets from mVAM; this data set is more complete than the AMIS data and enables a more thorough analysis.
Labor rates/ availability	Leading indicator	MVAC Annual Assessment*	Labor is the major source of income for many food insecure households in addition to own production. Labor availability and rates have a major impact on food access.

SAFEX futures prices	Leading indicator	SAFEX*	SAFEX maize futures prices are used in the region as an early indicator of potential maize price increases and product availability (especially for white maize, which is preferred in Malawi).
Food Consumption Score (FCS)	Leading or trailing depending on context	MVAC Annual Assessment; mVAM; CRS in some districts*	Food consumption score is normally a trailing indicator as it measures recent consumption. However, unseasonal deterioration in FCS may be a leading indicator at the early onset of a food crisis.
Coping Strategies Index (CSI and rCSI)	Leading indicator (pre-crisis)	MVAC Annual Assessment*	Designed as a pre-crisis early warning indicator and quick measure of the extent of food insecurity. Reduced CSI commonly collected. Full CSI provides greater context specificity and ability to understand shifts in reversable/irreversible coping.
Household Hunger Scale	Trailing, but can be leading if adequate baseline		Measures level of hunger experiences in previous 4 weeks. Changes can signify a worsening food security situation.
Household Dietary Diversity Score (HHDD)	Trailing, but can be leading if adequate baseline		Shows changes in the number of foods consumed and can show changes as food insecurity worsens. Child dietary diversity may be a good early warning indicator for wasting.
Wasting (GAM, SAM, MUAC)	Trailing indicator (Normally measured using SMART surveys)		Wasting is a very late sign of food insecurity and stress. Also, baseline wasting rates in Malawi are low (~3–4%). MUAC has been shown to be a good predictor of increased under-5 mortality.
Mortality (CDR, U5DR)	Trailing indicator (Normally measured using SMART surveys)		Mortality (under-5 and crude) are late indicators.
Pest and disease surveillance	Hazard indicator		Pests and disease affect crop and livestock production, which in turn affects household food security.

Source: World Bank compilation.
*AMIS= Agricultural Market Information System ; CSI = Coping Strategy Index; CDR = Crude Death Rate; CRS = Catholic Relief Services; CRW = Crisis Response Window; FCS = Food Consumption Score; FEWS NET = Famine Early Warning Systems Network; GAM = Global Acute Malnutrition; IPC = Integrated Phase Classification; LIAS = Livelihoods Impact Analysis Spreadsheet; MoA = Ministry of Agriculture; MUAC = mid-upper arm circumference; MVAC = Malawi Vulnerability Assessment Committee; mVAM = mobile Vulnerability Analysis and Mapping; SAFEX = South Africa Futures Exchange; SAM = Severe Acute Malnutrition; SMART = Standardized Monitoring and Assessment of Relief and Transition; U5DR = under-five death rate; WFP = World Food Programme

Annex C: Drought-Related Indexes Modeled

Based on the lessons learned from various drought-related risk models, eight different indexes were modeled for Malawi. These drought indexes have been used for weather index insurance products in Malawi (and similar countries in the region) in the last eight years. The indexes are summarized in table C.1 using soil moisture as the illustrative remote sensing data set for indexes 1–7. Indexes 8 and 9 are based on crop yields and stress models.

The team modeled a ninth index based on district-level yield data. Overall, correlations to food security scores were high for the yield index. However, the yield index was not evaluated in further detail because of several drawbacks, including the time it takes to obtain yield data, a potential conflict of interest (given that the source of the yield data is the GoM), and subjectivity in yield assessments.

Table C.1 Risk Models

No.	Index	Description
1.	Seasonal average	The simple average soil moisture (SM) value over the entire duration of the season (November 21 of year N to April 30 of year N + 1 is calculated as a percentage of the normal average SM value for the season; if the result is below the trigger level, the index is triggered.
2.	Number of dry dekads	The total number of dry dekads (below SM value of 3, for example) is calculated as a percentage of the normal number of dry dekads in a season; if the result is more than the trigger level, the index is triggered.
3.	Number of consecutive dry dekads	The total number of consecutive dry dekads (below SM value of 3, for example) is calculated as a percentage of the normal number of consecutive dry dekads in a season; if the result is more than the trigger level, the index is triggered.
4.	Number of consecutive wet dekads	The total number of consecutive wet dekads (above SM value of 10, for example) is calculated as a percentage of the normal number of consecutive wet dekads in a season; if the result is less than the trigger level, the index is triggered.
5.	Moving average for a number of consecutive dekads over the entire season	The moving average SM over three consecutive dekads during the entire season is calculated as a percentage of the normal moving average for the same period; if the result is less than the trigger level, the index is triggered.
6.	Moving average for a number of consecutive dekads over the first eight dekads	The moving average SM over three consecutive dekads during the first eight dekads of the season is calculated as a percentage of the normal moving average for the same period; if the result is less than the trigger level, the index is triggered.
7.	Moving average for a number of consecutive dekads over the last eight dekads	The moving average SM over three consecutive dekads during the last eight dekads of the season is calculated as a percentage of the normal moving average for the same period; if the result is less than the trigger level, the index is triggered.
8.	Simple crop stress index	The yield deviations were simulated based on typical four phases for maize and crop stress factors for each phase. This index simulates the yield deviations based on a crop stress model, based on key factors and is similar to the approach taken with the Water Requirement Satisfaction Index (WRSI).
9.	Yield index, based on local maize	A simple district-level yield index was assessed, based on district- and region-level data (for 2015/16, 2017/18, and 2018/19).

Source: World Bank compilation.

Annex D: Trigger Thresholds and Historical Performance

Table D.1 sets out the GoM's baseline proposal for trigger thresholds based on rainfall as a percentage of historical average rainfall over the same time periods. The baseline thresholds have been selected to broadly align with a return period of one in three years. More weight is given to the early season index in the form of more lenient trigger thresholds, as this index correlated best with food insecurity.

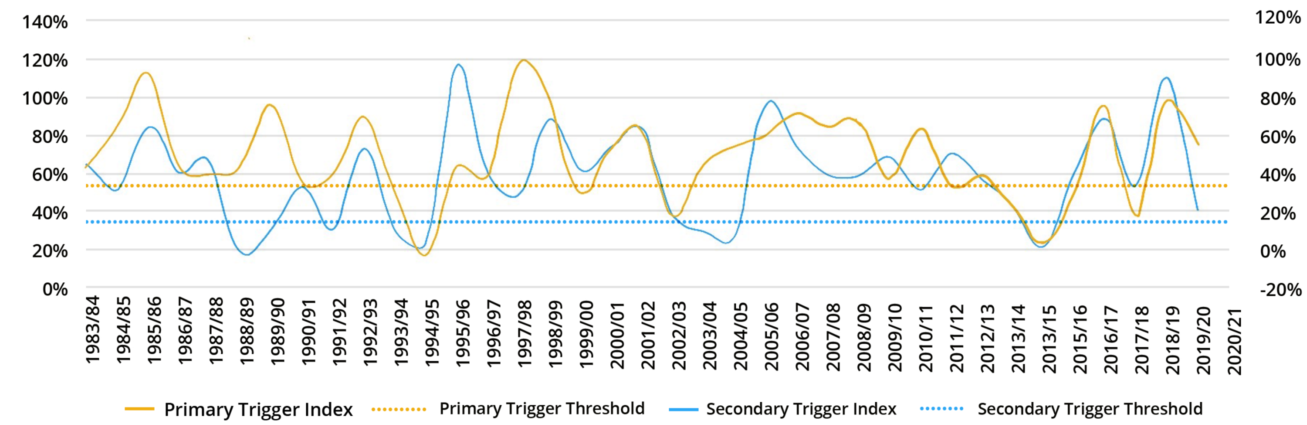
Table D.1. Baseline Trigger Thresholds

District	Early-season drought index	Full-season drought index
Blantyre	45%	10%
Ntcheu	55%	15%
Thyolo	45%	10%
Chiradzulu	45%	15%
Nkhotakota	50%	25%
Karonga	45%	25%

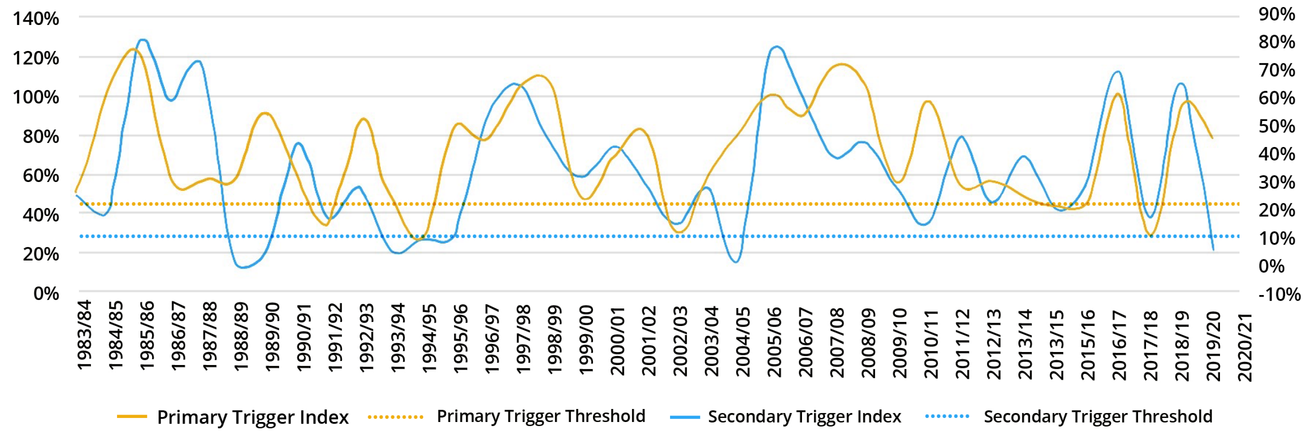
Source: World Bank.

Figure D.1. Early-Season and Full-Season Triggers: Historical Performance, 1981–2020

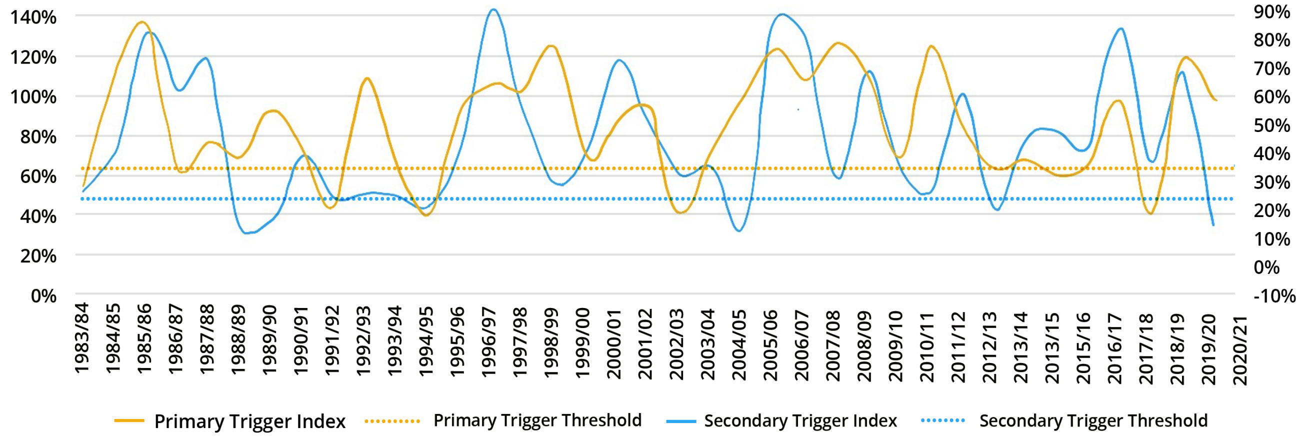
a. Ntcheu



b. Blantyre



c. Thyolo



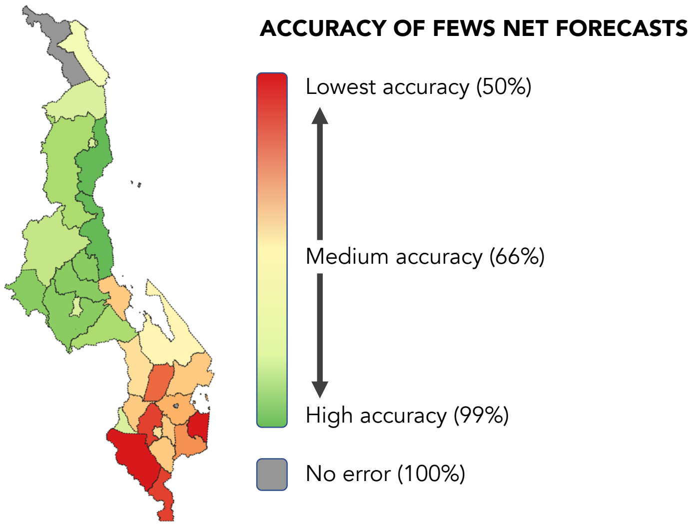
Source: Tetra Tech.
Note: In these graphs, the index triggers if the index value is below the dotted trigger threshold lines.

Photographs from WBG mission to Malawi for the Social Support for Resilient Livelihoods Project.

Annex E: Assessment of FEWS NET IPC accuracy in Malawi

The analysis for trigger design included an assessment of IPC accuracy in Malawi. Tetra Tech compared IPC projections at the district level against the same period's evaluation of current food security.. Overall, IPC forecasts tend to be more accurate in the northern parts of the country and less accurate in the southern districts (figure E.1). In general, IPC forecasts tend to overestimate food insecurity (as shown by the green areas in figure E.2); but there are periods during which food insecurity is underestimated (orange areas in figure E.2). Given the low accuracy of FEWS NET projections in Malawi's southern districts, FEWS NET projections were not used as part of the scalable mechanism trigger design.

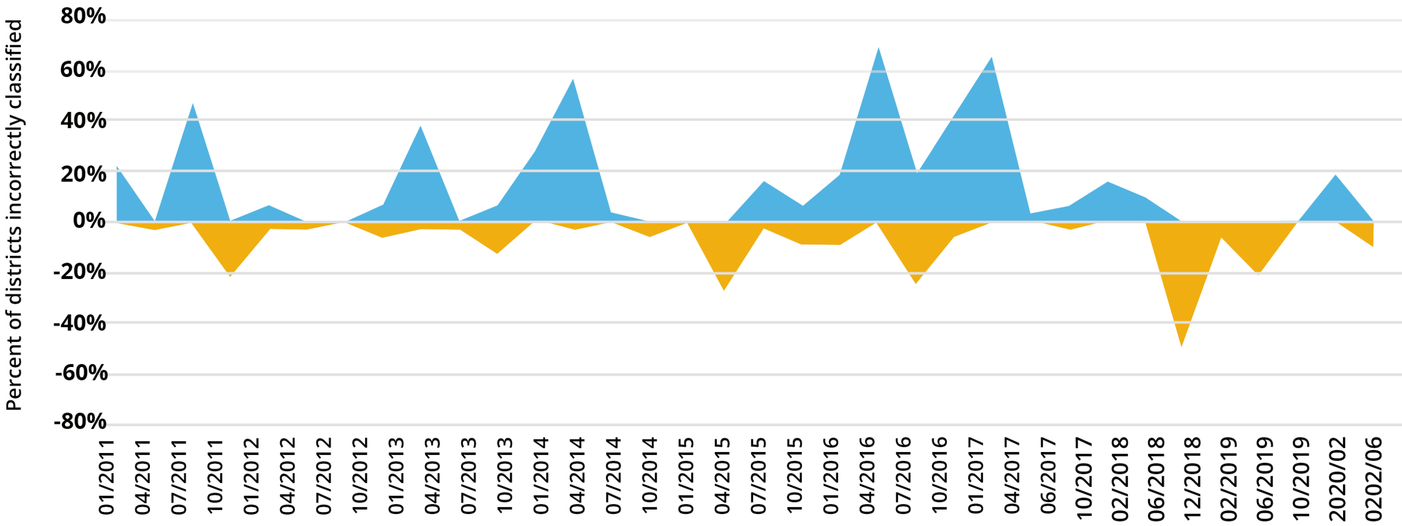
Figure E.1. Overview of Accuracy Rates of IPC Projections in Malawi



Source: Tetra Tech.

Note: FEWS NET = Famine Early Warning Systems Network; IPC = Integrated Phase Classification.

Figure E.2. IPC Accuracy Rate by Forecast Period



Source: Tetra Tech.
Note: FEWS NET = Famine Early Warning Systems Network; IPC = Integrated Phase Classification.

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