CGIAR SUSTAINABLE FARMING

Crop failure on smallholder farms in Sub-Saharan Africa: What can farm survey data tell us?

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Authors:

Jordan Chamberlin[a], Bisrat Haile Gebrekidan[b] , Santiago López-Ridaura[c] Deo-Gratias Hougni[d] & Oyakhilomen Oyinbo[c]

[a] CIMMYT-Kenya, Nairobi, Kenya
[b] CIMMYT-Ethiopia, Addis Ababa, Ethiopia
[c] CIMMYT
[d] CIMMYT-Zimbabwe, Harare, Zimbabwe

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Abstract

Although rainfed agricultural production on smallholder farms in Africa is often characterized as risky, and crop failure is frequently mentioned as a problematic production outcome, the incidence of crop failure has been poorly documented in the region. We explore the available empirical evidence for the prevalence and distribution of crop failure, using nationally representative household survey data from the region. We find that estimates of the prevalence of crop failure are very common throughout the region, with 36% of agricultural plots and 50% of households reporting some degree of crop area losses due to seasonal production shocks on average. These estimates vary considerably, however, across countries and years as well as how crop failure is defined (i.e., extent of damages and the source to which damages are attributed). Using detailed data from Zambia, we show that prevalence estimates are sensitive to measurement decisions. We also use plot-level econometric models to estimate how crop failure varies not only by location, but by farm management conditioners. However, our models provide mixed evidence on the effectiveness of widely promoted climate smart agricultural practices to mitigate against losses. We suggest avenues for further research on this topic, and potential innovations in farm survey design that may better capture crop failure.

1. Introduction

Smallholder farming in Sub-Saharan Africa (SSA) is frequently characterized as highly risky for farmers (Schlenker & Lobell 2010; Thierfelder & Wall 2011; Sonwa et al. 2017; Nyoni et al. 2024; Wollburg et al. 2024). The majority of small farmers in the region primarily engage with rainfed production and are exposed to increasingly volatile seasonal conditions, including rainfall amounts and temporal distributions, erratic temperature distributions, and a range of pests and diseases. This has motivated many calls to promote practices which lower risk and increase productive resilience, e.g. through conservation agriculture (CA) and climate smart agriculture (CSA) (Corbeels et al. 2014; FAO 2021). While many assessments of smallholder farming in SSA have explicitly made reference to the risk of crop failure as a defining characteristic of the region's production environments, few of these studies define crop failure explicitly, let alone offer any empirical evidence on the prevalence, distribution or drivers of crop failure in the region. This is an important omission because without such empirical data, policy and investment priorities risk being guided by stylized assumptions about risk rather than by evidence on where, why, and for whom crop failure actually occurs.

We address this gap through a descriptive evaluation of the incidence and distribution of crop failure as observable in existing nationally representative survey data from smallholder farming households across SSA. These data (including Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania and Uganda) were observed at different years spanning the past decade (2009-2020) and include data on 257,154 plots on 143,354 farms. We characterize the incidence of crop failure based on several alternative definitions, showing how the estimates of incidence vary by reason (i.e., associated shock) and by outcome definition. Using detailed plot-level data from Zambia collected in 2012, 2015 and 2019, we estimate the sensitivity of crop loss prevalence estimates to alternative outcome variable construction. We also use plot-level econometric models to estimate the conditioners of crop failure.

The literature we contribute to is surprisingly sparse, given the centrality of vulnerability to narratives of rainfed production on smallholder farms in SSA. A small number of studies have evaluated unharvested plot area outcomes (i.e., where the crop-specific harvest area of plots is less than the corresponding planted area) as "crop abandonment," on the basis of data limitations precluding the distinction between crops being lost due to a shock (and thus being unharvestable) versus crops not being harvested because poor performance of the crop in a portion of the plot leads farmers to commit their limited resources to other parts of the farm where returns are higher (Mulungu & Tembo 2015). Mulungu & Tembo (2015), Yenibehit et al. (2024), Chekenya et al. (2024) all take this definitional approach to evaluate the incidence and determinants of crop area losses, focusing on maize in Zambia, and using data spanning multiple years, but with limited farm and plot-level managerial controls. They concur in the finding that weather-related outcomes (e.g., excess rainfall and low temperatures early in the season) increase abandonment risk, presumably by lowering expected profitability of mid-/late-season management investments and resulting harvests. Wollburg et al. (2024), on the other hand, use similar outcome measures (the harvested-to-planted area ratio) in conjunction with the accompanying farmer-identified main reason for the difference to identify crop failure associated with climatic shocks. They use data on 120,000 agricultural fields across six countries to show that 35% of plots are affected by such shocks, with an average reduction in national crop production of 29%.

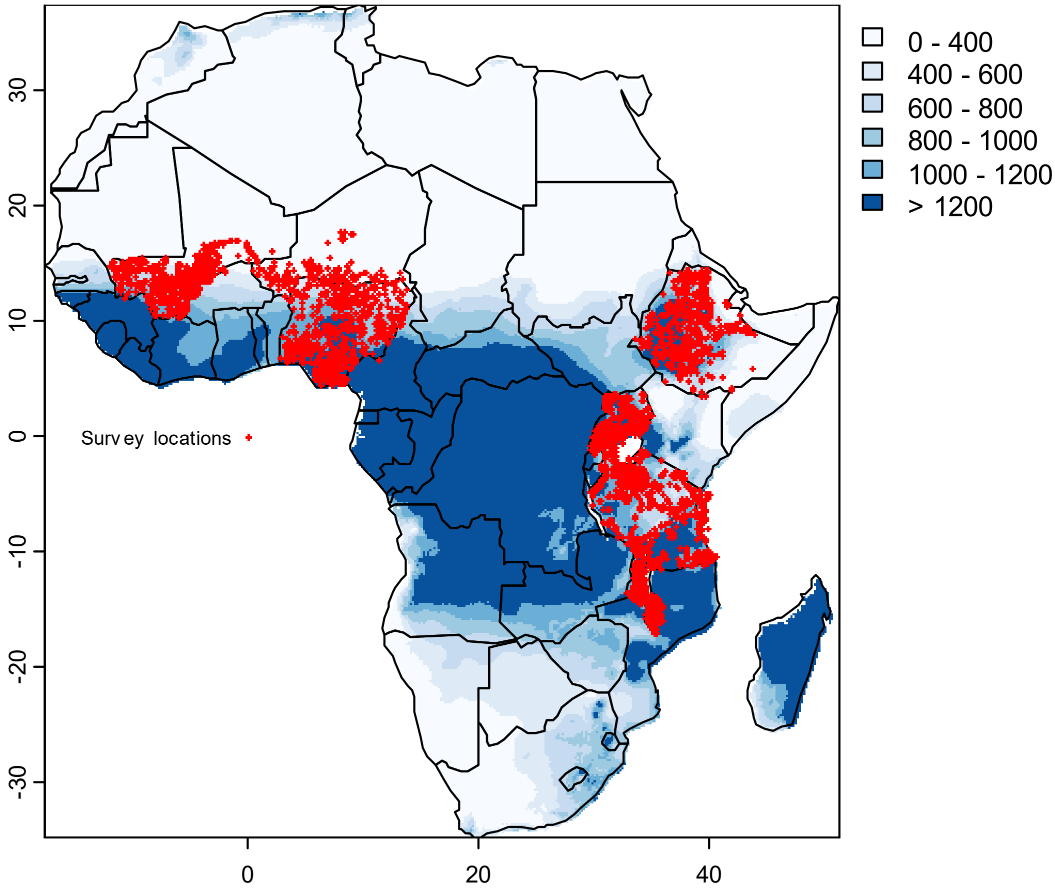
Our study builds initially on the continental-scale work of Wollburg et al. (2024), using an expanded set of countries and survey rounds from the LSMS-ISA (Bentze & Wollburg 2024). We use our updated assessment (which includes an additional ~130,000 plots) as the starting point for an updated descriptive assessment for the continent. From there, however, we use detailed plot-level data from three waves of a nationally representative farm household panel survey in Zambia to make two further contributions to the literature. First, we explore how crop failure incidence estimates vary across alternative outcome variable construction decisions. We use this analysis to offer some comments on best practices for further data collection. Secondly, we explore the role of management practices often associated with CA/CSA in mitigating crop failure outcomes.

The rest of this paper is organized as follows: we describe our data and key definitions in Section 2, after which we outline our analytical approaches in more detail in Section 3. Section 4 presents evidence on the incidence of plot-level crop failure for 7 countries observed at multiple periods over the last decade. We then use three waves of nationally representative panel data from Zambia to unpack crop failure: first discussing alternative possible definitions of crop failure and their implications for incidence estimates (Section 5) and then evaluating managerial and other conditioners of plot-level crop failure outcomes, using household-level econometric models (Section 6). We briefly discuss our results and their implications for additional research in the concluding remarks in Section 7.

2. Data and definitions

We use two sets of data in this analysis. The first is the most recent version of the World Bank's Harmonized Dataset on Agricultural Productivity and Welfare, which compiles comparable measures from survey data from seven countries collected under the LSMS-ISA project (Bentze & Wollburg 2024; World Bank 2025). These data (including Ethiopia, Malawi, Mali, Niger, Nigeria, Tanzania and Uganda) were observed at different years spanning the past decade (2009-2020) and include data on 257,154 plots on 143,354 farms. Survey locations are shown in Figure 1. A total of 27 different country-year datasets are included in the current version of this harmonized dataset (Table 1).

Figure 1: Survey locations of pooled LSMS-ISA data



Note: Average annual rainfall in mm shown in the background (data source: WorldClim).

Secondly, we use detailed data from the Zambian Rural Agricultural Livelihoods Survey (RALS), the country's flagship, nationally representative agricultural household survey, designed to generate high-quality microdata on smallholder farming systems, livelihoods, and rural welfare. Three waves are household panel data are included, with a total of 24,014 household observations (8,839 in 2012; 7,934 in 2015; and 7,241 in 2019) and a corresponding set of 96,833 plot-level observations.

Our primary definition of crop failure is based on the ratio of harvested to planted area for a given crop, which provides a continuous measure of the extent to which planted area ultimately contributes to harvested output. This approach captures both complete and partial crop losses and allows for consistent measurement across heterogeneous production environments. For plots containing multiple crops, harvested and planted areas are attributed to each crop in proportion to its reported area share within the plot, ensuring that intercropping and mixed-cropping systems are accurately reflected in the construction of crop-specific failure measures rather than being implicitly treated as full losses or full successes. This proportional allocation preserves total plot area, maintains comparability across farms and crops, and aligns the measurement of crop failure with farmers' actual land-use and management decisions.

In the Zambia data, for every plot with non-zero differences in planted and harvested areas, we have farmer-reported reasons for the difference (Table 4, below). In the final wave of the survey, we also have a farmer-reported response to the question “Did your household experience any droughts in any part of your fields during the [reference period] agricultural season?” We use this to compare plot-level responses to shock-associated crop area losses.

3. Analytical approach

Our multi-country descriptive work is straightforward, based on responses pooled across nationally representative sampling frames. In addition to this descriptive work, we offer an econometric evaluation of the conditioners of crop failure outcomes. For this, we report findings from our preferred model specification – a fractional probit model – which accommodates the [0,1] range of our primary outcome variable of interest (i.e., the ratio of harvested to planted area of the plot). To address potential endogeneity concerns arising from time-invariant unobserved heterogeneity at the household level, we include the Mundlak-Chamberlain device (Mundlak 1978; Chamberlain 1982), which is also sometimes referred to as the correlated random effects model (Wooldridge 2019) and which has been show to be applicable to fractional response models such as the one we implement here (Papke & Wooldridge 2008). For robustness, we also explored a number of alternative modeling approaches (including linear probability models of binary crop failure measures, and alternative ways to control for household-level fixed-effects), which give qualitatively similar results, and which we do not report here.

4. Prevalence of crop failure in SSA

Our basic measure of crop failure in the harmonized LSMS-ISA data is a binary indicator defined at the plot level to indicate any non-zero difference between planted and harvested area which is explicitly linked to a climate-related cause (drought, erratic rainfall, flooding, pests and/or disease). Plot-level prevalence of crop failure is summarized in Table 1, panel A.

Crop failure incidence varies substantially across countries and over time but is consistently non-trivial in most settings. Pooled across all observations, the average failure share is 0.36, indicating that more than one-third of planted areas fail to reach harvest. Ethiopia and Malawi exhibit persistently high incidence, with average failure shares of 0.46 and 0.54 respectively, and several years exceeding 0.5, suggesting structurally risky production environments. Tanzania also shows relatively high and stable failure rates, averaging 0.51, while Niger displays extreme volatility, with very high failure in some years (e.g., 0.94) but a lower average of 0.75 based on limited observations. In contrast, Nigeria and Uganda record markedly lower failure incidence, averaging 0.07 and 0.15 respectively, although Uganda shows a sharp decline over time from relatively high early values. Mali exhibits moderate but comparatively stable failure shares around 0.26. Aggregating across countries by year reveals pronounced interannual variation, with average failure shares ranging from a low of 0.21 in 2012 to highs above 0.40 in several years, underscoring both the spatial heterogeneity and temporal instability of crop failure risk in smallholder farming systems. (Figure 2 graphically summarizes the data from Table 1 panel A.)

Table 1 Panel B reports the number of households with one or more plots with plot failure. Here, we find similar variability across countries and years, but at much higher levels. On average, 50% of the households in the sample are reporting crop failure in any given year.

When we differentiate crop losses by the type of associated shock (Table 2 and Figure 3) a number of patterns stand out. First, drought is the most prevalent shock associated with crop loss (affecting 19% of plots), followed by erratic rainfall (10% of plots), pests (7% of plots) and flood (2.4% of plots). Secondly, the relative exposure to these different types of shocks varies strongly by mean rainfall: in arid areas, the risk of drought dwarfs other shocks as a cause of crop failure, but in relatively rainfall-abundant areas excessive and erratic timed rainfall becomes a larger concern.

Table 1: Incidence of crop failure in SSA

Panel A: Plot-level incidence

	Year												
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2019	2020	2022	*all*
Ethiopia				0.46		0.38		0.54		0.46		0.43	*0.46*
Malawi		0.43			0.51				0.69		0.60		*0.54*
Mali						0.24			0.27				*0.26*
Niger			0.94			0.49							*0.75*
Nigeria			0.07		0.08			0.05		0.10			*0.07*
Tanzania	0.60		0.57		0.51		0.43			0.44			*0.51*
Uganda		0.39	0.12	0.08		0.03		.		.	0.09		*0.15*
total	0.60	0.40	0.40	0.21	0.37	0.29	0.43	0.44	0.33	0.34	0.29	0.43	0.36

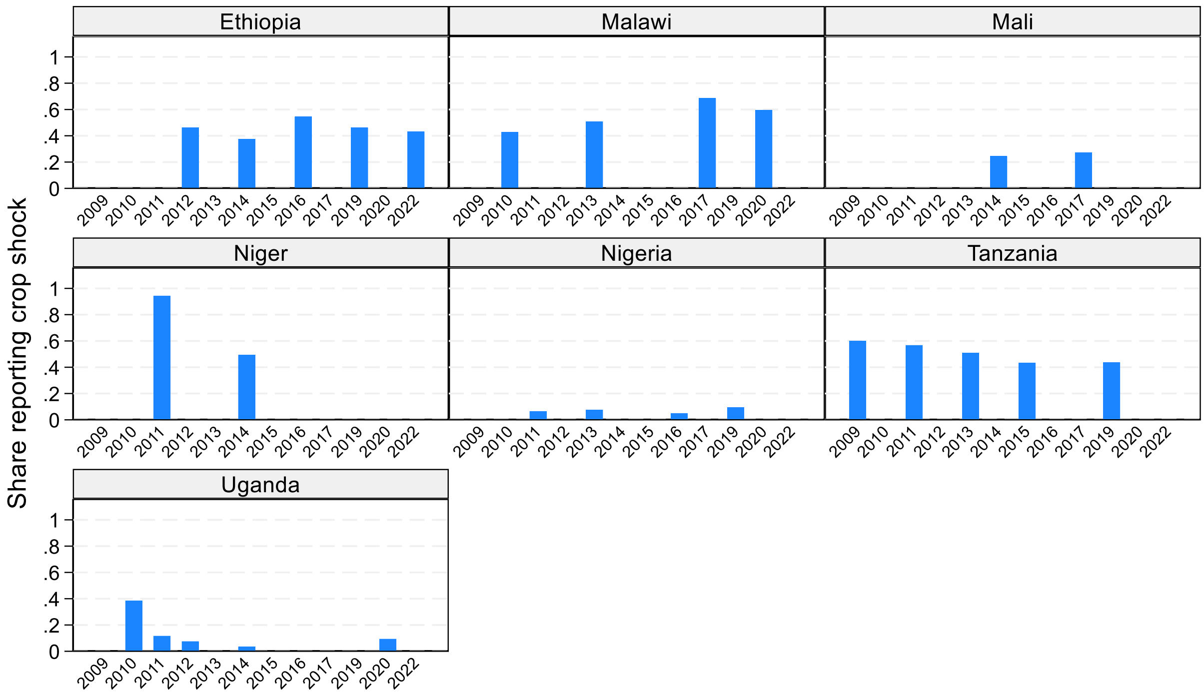
Source: LSMS-ISA Harmonized Dataset on Agricultural Productivity and Welfare

Panel B: Household-level incidence

	Year												
	2009	2010	2011	2012	2013	2014	2015	2016	2017	2019	2020	2022	*all*
Ethiopia				0.62		0.74		0.85		0.75		0.81	*0.76*
Malawi		0.60			0.62				0.79		0.75		*0.68*
Mali						0.39			0.42				*0.41*
Niger			0.96			0.60							*0.80*
Nigeria			0.08		0.10			0.08		0.16			*0.11*
Tanzania	0.76		0.74		0.66		0.57			0.55			*0.65*
Uganda		0.73	0.32	0.21		0.12		.		.	0.26		*0.32*
total	0.76	0.66	0.50	0.39	0.46	0.47	0.57	0.47	0.50	0.45	0.50	0.81	*0.50*

Source: LSMS-ISA Harmonized Dataset on Agricultural Productivity and Welfare

Figure 2: Incidence of climate-related crop failure across countries & years



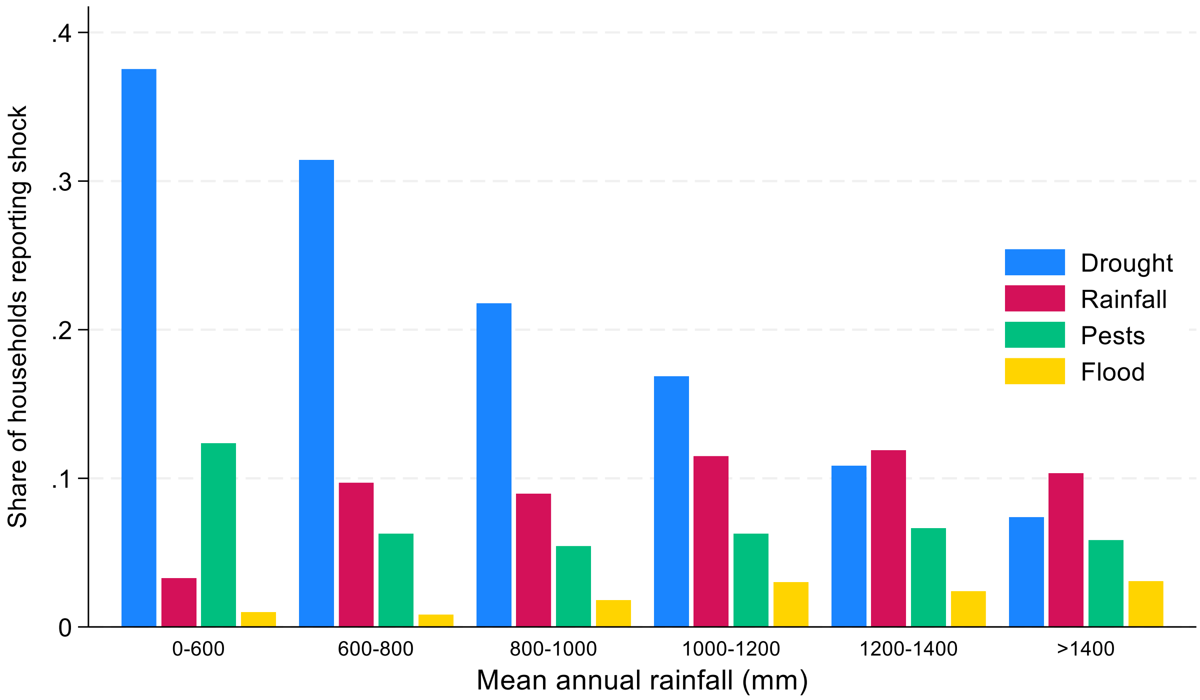
Source: LSMS-ISA Harmonized Dataset on Agricultural Productivity and Welfare

Table 2: Incidence of shock-related losses, by shock type

Rainfall category	Drought	Erratic rainfall	Pests & disease	Flood
0-600	0.375	0.033	0.124	0.010
600-800	0.314	0.097	0.063	0.008
800-1000	0.218	0.090	0.054	0.018
1000-1200	0.168	0.115	0.063	0.030
1200-1400	0.108	0.119	0.066	0.024
>1400	0.074	0.103	0.058	0.031
Total	**0.188**	**0.099**	**0.068**	**0.024**

Note: Rainfall category is average rainfall amount in mm. Sources: LSMS-ISA Harmonized Dataset on Agricultural Productivity and Welfare; WorldClim.

Figure 3: Distribution of crop failure by type of shock across annual rainfall categories



Source: LSMS-ISA Harmonized Dataset on Agricultural Productivity and Welfare

5. Alternative crop failure definitions

This section evaluates the sensitivity of estimates of the incidence of crop failure to alternative definitions, using a more detailed analysis of data from the Zambia data. To begin with, we may note that nominal reasons for crop loss may be difficult to discretely map into categories of policy interest. For example, among responses provided by Zambian farmers regarding the primary cause of crop area loss (Table 4), some are clearly attributable to drought (e.g., "wilting due to drought" or "failed germination due to drought"). Other responses, however, are more ambiguous and may reflect interacting mechanisms. In particular, a reason such as "soils generally bad" may correspond to underlying soil constraints—such as low water-holding capacity or poor structure—that amplify crop vulnerability during dry spells, rather than representing a cause that is independent of climatic stress. As a result, farmer-reported causes may conflate proximate symptoms with deeper biophysical drivers, complicating straightforward attribution to single policy-relevant categories.

Table 3: Distribution of responses to question: what was the main reason for crop area losses on this plot?

% of responses	*Main reason for crop area reduction*	*drought*	*pests*	*flood/rain*	*mgt*	*other*
4%	water logging			x		
41%	wilting due to drought	x				
7%	animal/bird destruction		x			
2%	field not weeded, weeded late				x	
7%	pests and diseases		x			
<1%	fire					x
5%	floods, heavy rain			x		
7%	soils generally bad					x
12%	lack of fertilizer				x	
1%	lack management experience				x	
<1%	received bad agronomic advice				x	
1%	insufficient labor				x	
2%	failed germination due to drought	x				
1%	failed germination due to bad seed					x
1%	low productivity due to bad seed					x
5%	planted late				x	
3%	eaten fresh					
<1%	witch weed / striga		x			
1%	do not know					x
<1%	not enough seed				x	
<1%	reduced harvest due to crop mixture				x	

Note: Table shows reasons provided to explain why plot area harvested was less than area planted. The percentage of responses shown in first column is taken from the 2019 survey round. The right-most 5 columns show how these reasons were aggregated in subsequent tables in this paper.

Table 4: Incidence of plot area losses by main reason

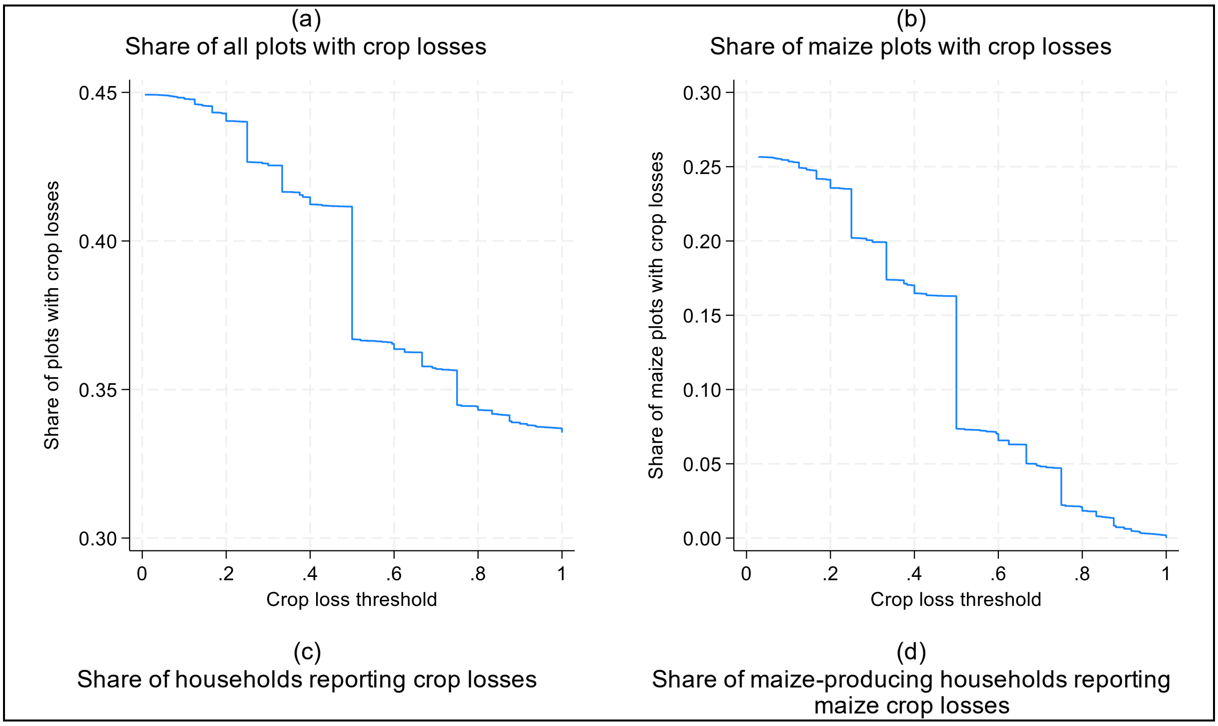
	drought	**flood/rains**	**pest/disease**	**management**	**other**	**any**
2012	3.6%	2.0%	2.6%	10.1%	3.6%	22.0%
2015	4.6%	1.1%	1.8%	4.1%	1.7%	13.5%
2019	6.9%	1.4%	2.3%	3.6%	1.4%	15.6%
total	5.0%	1.5%	2.2%	6.0%	2.3%	17.1%

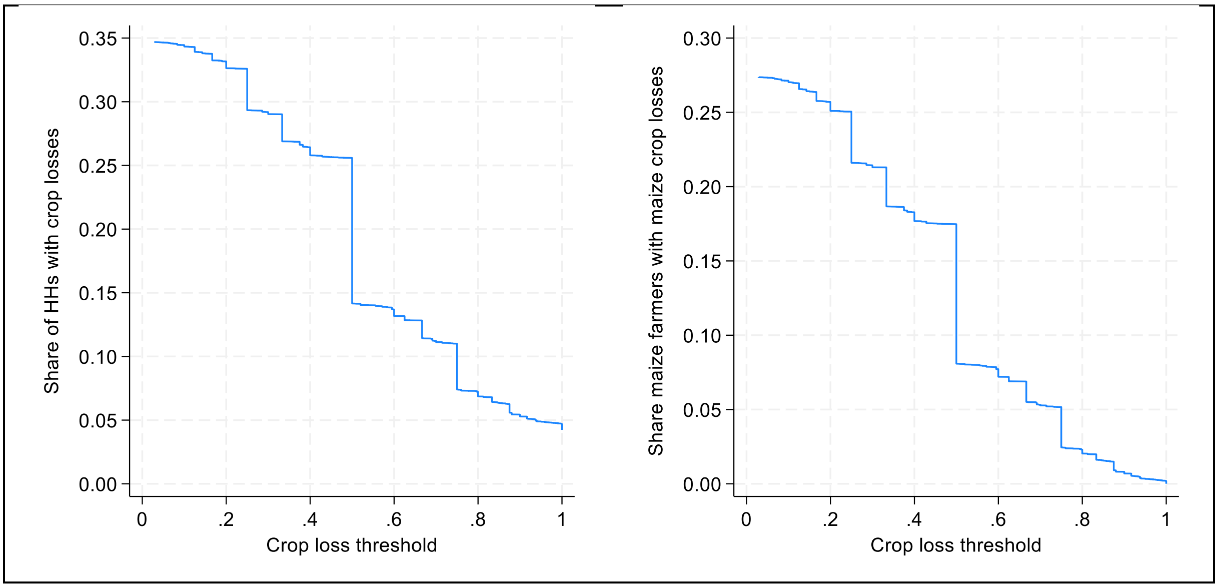
Note: Table shows the percentage of agricultural plots experiencing losses (defined as a non-zero difference between area planted and area harvested), according to the main reason for the loss, according to survey respondents. Source: Zambia Rural Agricultural Livelihoods Survey (RALS)

Figure 4 shows how the incidence of crop losses at plot and household levels varies as a function of the severity of losses. The key takeway is that a large share of households experience limited losses, while a much smaller share of households experience catastrophic losses (i.e., at or near complete loss of planted crop). For example, while 35% of households experience some crop losses (on any of their crops), only 10% of households experience crop losses of 75 or more percent on any given crop (panel C). Similarly, while 27% of maize producers report maize crop losses, only 5% of such households experience maize crop losses of 75 or more percent (panel D).

In the 2019 round of the Zambia survey, respondents were asked if they had suffered any production losses due to drought. 41% of the sample indicated that they had experienced such losses. This is much higher than the 10% of households reporting crop-area losses that they explicitly attributed to drought. Some of this discrepancy may be related to the imperfect mapping of crop-loss reasons discussed above. However, the 41% of households reporting drought losses is also higher than the 30% of households with crop-area losses ascribed to any reason. While the likelihood of reporting drought-related production losses does increase with the severity of crop-area losses ascribed to drought (Figure 5), the discrepancy in shares suggests that crop-area losses may not be the only way to measure crop failure or production losses associated with climatic shocks.

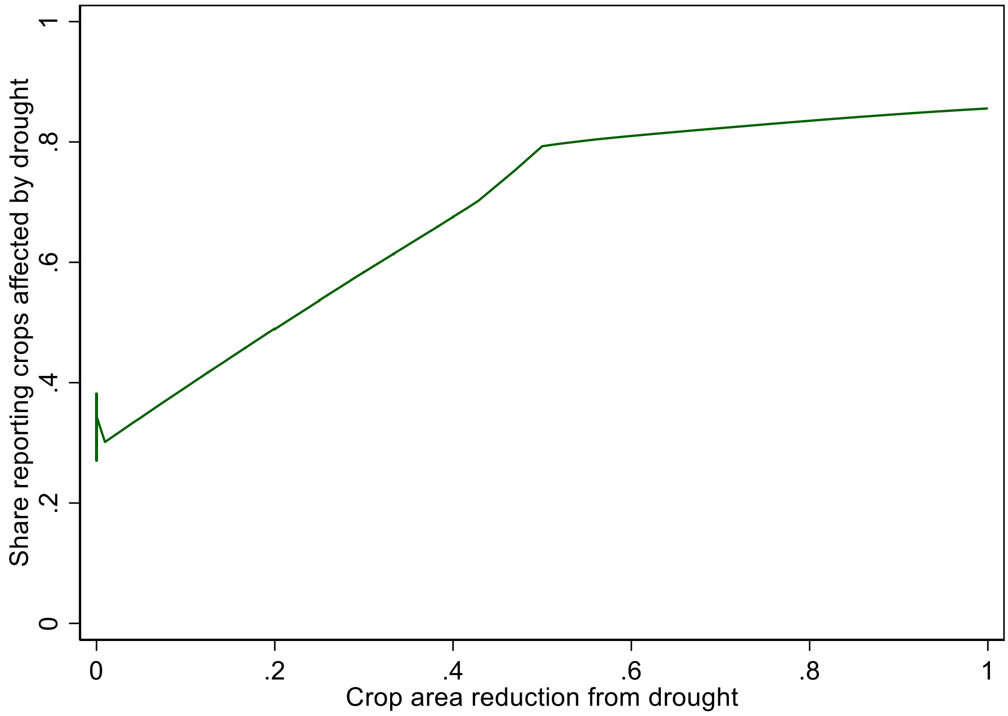
Figure 4: Incidence of crop losses at plot & household levels





Note: Graphs indicate the share reporting losses by the severity of loss (with shares ranging from .001 to 1), attributed to any cause. Source: Zambia Rural Agricultural Livelihoods Survey (RALS)

Figure 5: Correspondence between self-reported farm-level crop losses due to drought and incidence of crop-area reductions with drought as main cause



6. Drivers of crop failure

CA and CSA practices are often advocated as adaptation measures to climatic volatility, with presumed increases in resilience and reductions in the probability of crop failure in the face of climate-related shocks. To evaluate this, we estimate a number of plot-level models of the conditional correlates of crop failure, measured as a continuous share (where 0 indicates no losses, and 1 indicates complete failure). We report average partial effects (APEs) from these models in Table 6. Four different specifications are shown, differing in their dependent variables: crop area reductions for any reason and for all crops (column 1); crop area reductions from drought only, for all crops (column 2); crop area reductions for any reason, only for maize (column 3); crop area reductions from drought only, only for maize (column 4).

A number of observations stand out from these results. First, larger plots are more prone to crop failure, which may reflect greater internal heterogeneity of land quality characteristics, and/or may reflect that larger plots are more likely to be found in extensive systems and landscapes which are more likely to have marginal production endowments. Second, of the practices associated with CA and CSA, only a few practices show clear risk reductions. APE estimates for intercropping are consistently negative (indicating that adoption is associated with lower crop area loss intensities), but not significantly so for drought-specific losses. Rotations (defined as having a cereal grain following a legume in a subsequent cropping season, or vice versa) is negatively associated with crop failure intensity for the pooled crop model (column 1), but not for either of the maize models (columns 3 and 4) where the coefficient estimate is positive and statistically significant. This result is hard to make sense of in agronomic terms, but may reflect preferential rotation in lower quality soils to target maize productivity improvements through nitrogen fixation (which would indicate model inconsistency). Zero tillage is negatively associated with crop failure intensity but only at a statistically significant level for maize (column 3). Residue retention has no significant effects in any of the models.

The positive APE estimate for manure is surprising and hard to interpret agronomically. A positive association between manure use and crop failure may reflect selection and context rather than a causal agronomic effect (which again raises concerns about consistency of our model). In many smallholder systems, manure is applied primarily on poorer or more marginal plots, or by households facing liquidity constraints that limit access to mineral fertilizer, so manure use may proxy for underlying soil degradation and structural vulnerability. In addition, the quality and quantity of manure applied are often highly variable and frequently below levels required to improve nutrient availability or soil water-holding capacity; in some cases, poorly decomposed manure may even induce short-run nutrient immobilization, weakening crops during early growth stages and increasing sensitivity to rainfall stress. Finally, manure use may represent an ex ante response to anticipated risk, with farmers substituting manure for mineral fertilizer in seasons or locations they already perceive as risky, thereby reinforcing a positive correlation between manure application and subsequent crop failure even in the absence of a direct negative effect of manure itself.

With respect to purchased inputs (fertilizer and improved seed), we find that nitrogen (N) application rates are associated with higher crop failure intensity – a non-intuitive result that is at odds with Mulungu & Tembo's (2015) findings for Zambia. One possible explanation may derive from nitrogen's tendency to amplify climate sensitivity. N fertilization stimulates rapid vegetative growth, increases leaf area, and raises water demand. Under conditions of rainfall shortfalls, intra-seasonal dry spells, or heat stress, this higher transpiration demand can accelerate soil moisture depletion, making N-responsive crops more vulnerable to drought-induced wilting or incomplete grain filling. In addition, N uptake and yield response are highly contingent on adequate and well-timed moisture; when rains fail or are poorly distributed, applied N is more likely to remain unused or be lost, resulting in low returns and, in extreme cases, crop failure or abandonment. This “risk-amplifying” role of N is well documented in rainfed systems where moisture is the primary limiting factor.

We find that potassium (K) supply, is negatively associated with crop failure intensity. Potassium plays a protective, stress-buffering role: it is central to stomatal regulation, osmotic adjustment, and enzyme activation, all of which enhance plant tolerance to drought and heat stress. Adequate K nutrition improves water-use efficiency, strengthens root systems, and increases resistance to lodging and certain pests and diseases, thereby reducing the likelihood that climatic shocks translate into irreversible crop damage. In this sense, K acts less as a yield accelerator and more as a resilience input, lowering the probability that climatic stress leads to crop failure.

Third, the contrasting associations may reflect farmer behavior and targeting. Nitrogen is often applied more heavily on larger or more marginal plots in anticipation of good seasons, increasing exposure when conditions deteriorate, whereas K use—where it occurs—is more likely to be applied on better-managed or higher-potential fields, reinforcing its negative association with failure. Moreover, K deficiencies are widespread but under-recognized in many smallholder systems; where K is applied, it may correct a binding constraint that materially improves stress tolerance.

Finally, we see that improved seed is negatively related with crop failure intensity. While we do not know the specific variety being used, many improved varieties have mean-preserving, variance-reducing yield characteristics, such as Drought Tolerant Maize (DTM). This finding thus aligns with other research on DTM impacts (e.g., Simtowe et al. 2019).

Table 5: Marginal effects from fractional probit models of crop loss

	(1) Crop area reduction for any reason (all crops)	(2) Crop area reduction from drought (all crops)	(3) Crop area reduction for any reason (maize)	(4) Crop area reduction from drought (maize)
plot size (ha)	0.018***	0.003***	0.016***	0.001
	(0.002)	(0.001)	(0.002)	(0.001)
intercropped=1	-0.022***	-0.001	-0.051***	-0.002
	(0.005)	(0.003)	(0.007)	(0.005)
rotation=1	-0.011***	-0.001	0.048***	0.021**
	(0.003)	(0.002)	(0.012)	(0.009)
zero till=1	-0.012	-0.007	-0.031**	-0.004
	(0.008)	(0.005)	(0.013)	(0.009)
residue=1	0.001	0.001	0.001	-0.000
	(0.002)	(0.001)	(0.004)	(0.002)
manure=1	0.024***	0.011***	0.002	0.006
	(0.005)	(0.003)	(0.007)	(0.004)
irrigated=1	-0.006	-0.003	0.019	0.002
	(0.014)	(0.006)	(0.025)	(0.012)
weedings (#)	-0.002	0.000	-0.005	-0.001
	(0.002)	(0.001)	(0.003)	(0.002)
N (log kg)	0.012***	0.003**	-0.002	0.000
	(0.002)	(0.001)	(0.003)	(0.002)
P (log kg)	0.006	0.003	0.007	0.005
	(0.005)	(0.002)	(0.008)	(0.004)
K (log kg)	-0.032***	-0.008***	-0.035***	-0.010**
	(0.006)	(0.002)	(0.009)	(0.004)
imp. maize seed =1			-0.010*	-0.007**
			(0.005)	(0.003)
female mgr=1	0.006	0.005**	0.011	0.010*
	(0.004)	(0.002)	(0.009)	(0.006)
Rainfall (log mm)	-0.082***	-0.041***	-0.066***	-0.058***
	(0.008)	(0.004)	(0.014)	(0.008)
Rainfall variability	0.077***	0.043***	0.094***	0.051***

	(1) Crop area reduction for any reason (all crops)	(2) Crop area reduction from drought (all crops)	(3) Crop area reduction for any reason (maize)	(4) Crop area reduction from drought (maize)
	(0.009)	(0.005)	(0.016)	(0.009)
Crop dummies	Yes	Yes	No	No
Mundlak-Chamberlain device	Yes	Yes	Yes	Yes
Observations	56,579	56,579	25,109	25,109
R-squared	0.0426	0.0515	0.0489	0.0544

Cluster robust standard errors shown in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01. The dependent variable in each model is the share of crop area lost to shocks, with differing shocks and crops shown in each specification. All models estimated on three waves of panel data with fractional probit models. The Mundlak- Chamberlain device denotes the inclusion of time-averages of household characteristics to control for unobserved heterogeneity at the household level. Rainfall refers to the long-term average rainfall for the growing season. Rainfall variability is the long-term average coefficient of variation of dekadal rainfall observations within a growing season. Improved maize seed is only used as a control in the maize models.

7. Conclusions

This report has shown that smallholder farmers in SSA face very high rates of crop failure. Nationally representative survey data indicate that 36% of plots and 50% of households experience crop failure (defined as harvested area being less than the planted area) on average in any given year. However, these patterns vary considerably across geography, by type of associated shock.

When we unpack the definition of crop failure to account for intensity (i.e., share of crop area losses), we find that while marginal losses are very common, more intensive crop failure outcomes are much more restricted. Future work could usefully attempt to disentangle crop failure outcomes through alternative measurement strategies, possibly asking households to identify the extent of damages in more explicit ways in survey questionnaires. Triangulation across multiple crop loss indicators may give more robust measures of crop failure at plot and household levels in survey-based analyses.

Our work on identifying the managerial shifters of crop failure risk is tentative. We find some support for the risk-reducing effects of crop management practices associated with Conservation Agriculture and Climate Smart Agriculture, such as intercropping, rotations, zero tillage and improved varietal adoption. But given the complexity of crop failure causes – and potential difficulties in correctly classifying the cause(s) of failure – more work should be done in this area. This is particularly important if we are to build a stronger evidence base for which practices, in which combinations, deliver the best resilience dividends for farmers in differing local contexts.

References

Bentze, T. P., and P. R. Wollburg. 2024. A Longitudinal Cross-Country Dataset on Agricultural Productivity and Welfare in Sub-Saharan Africa (English). Policy Research working paper; PEOPLE; LSMS Washington, D.C. : World Bank Group. http://documents.worldbank.org/curated/en/099422411182437399

Chamberlain, G., 1982. Multivariate regression models for panel data. Journal of Econometrics, 18(1), pp.5-46.

Chekenya, N.S., 2023. Climate-induced crop failure and crop abandonment: What do we know and not know? African Journal of Agricultural and Resource Economics, 18(2), pp.141-151. https://doi.org/10.53936/afjare.2023.18(2).9

Chekenya, N.S., Yenibehit, N. and Dzingirai, C., 2024. Determinants of crop abandonment by smallholder maize farmers in Zambia. Agrekon, 63(3), pp.166-180. https://doi.org/10.1080/03031853.2024.2402524

Corbeels, M., Thierfelder, C. and Rusinamhodzi, L., 2014. Conservation agriculture in sub-Saharan Africa. In Conservation agriculture (pp. 443-476). Cham: Springer International Publishing.

FAO. 2021. Climate-smart agriculture case studies 2021 – Projects from around the world. Rome. https://doi.org/10.4060/cb5359en

Mulungu, K. and Tembo, G., 2015. Effects of weather variability on crop abandonment. Sustainability, 7(3), pp.2858-2870. https://doi.org/10.3390/su7032858

Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica: journal of the Econometric Society, pp.69-85.

Nyoni, R.S., Bruelle, G., Chikowo, R. and Andrieu, N., 2024. Targeting smallholder farmers for climate information services adoption in Africa: A systematic literature review. Climate Services, 34, p.100450.

Papke, L.E. and Wooldridge, J.M., 2008. Panel data methods for fractional response variables with an application to test pass rates. Journal of Econometrics, 145(1-2), pp.121-133.

Schlenker, W., and D.B. Lobell. 2010. Robust negative impacts of climate change on African agriculture. Environmental Research Letters 2010, 5, Article 014010.

Simtowe, F., Amondo, E., Marenya, P., Sonder, K. and Erenstein, O., 2019. Impacts of drought-tolerant maize varieties on productivity, risk, and resource use: Evidence from Uganda. Land Use Policy, 88, p.104091.

Sonwa, D.J., Dieye, A., El Mzouri, E.H., Majule, A., Mugabe, F.T., Omolo, N., Wouapi, H., Obando, J. and Brooks, N., 2017. Drivers of climate risk in African agriculture. Climate and Development, 9(5), pp.383-398.

Wollburg, P., Markhof, Y., Bentze, T. and Ponzini, G., 2024. Substantial impacts of climate shocks in African smallholder agriculture. Nature sustainability, 7(11), pp.1525-1534. https://doi.org/10.1038/s41893-024-01411-w

Wooldridge, J.M., 2019. Correlated random effects models with unbalanced panels. Journal of Econometrics, 211(1), pp.137-150.

World Bank. 2025. LSMS-ISA Harmonised Panel v.2.0. https://github.com/lsms-worldbank/LSMS-ISA-harmonised-dataset-on-agricultural-productivity-and-welfare/releases/tag/v2.0

Yenibehit, N., Dzingirai, C. and Chekenya, N.S., 2024. Risk factors in crop abandonment decisions: Evidence from Zambia. African Journal of Agricultural & Resource Economics, 19(2). https://doi.org/10.53936/afjare.2024.19(2).8

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sfp.cgiar.org sfp@cgiar.org @CgiarFarming

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