50x2030
DATA-SMART AGRICULTURE

MEASURING DISASTER-RELATED CROP PRODUCTION LOSSES USING SURVEY MICRO-DATA:

A REVIEW OF APPROACHES, EVIDENCE, AND SURVEY DESIGN CONSIDERATIONS

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AUGUST 2026

Acknowledgements

This document is a product of the 50x2030 Initiative to Close the Agricultural Data Gap and was developed by Giulia Ponzini and Philip R. Wollburg of the World Bank's Living Standards Measurement Study (LSMS) team. Valuable comments and inputs were received from Sydney Gourlay of the LSMS team and from Franck Cachia, Piero Conforti, and Adama Lo of FAO. This document draws heavily from previous methodological work conducted by the LSMS team, in particular Markhof, Ponzini and Wollburg (2022) and Wollburg, Markhof, Bentze and Ponzini (2024a, 2024b), as well as from the FAO methodology for damage and loss assessment in agriculture and other existing guidance.

The 50x2030 Initiative to Close the Agricultural Data Gap is a multi-agency effort aimed at supporting 50 low- and lower-middle-income countries to produce fundamental agricultural and rural data through the use of integrated agricultural and rural surveys. For more on the Initiative, please visit www.50x2030.org.

1. Introduction

The incidence of large-scale natural disasters and the related global costs are growing. In 2024, the total number of natural hazard-related disasters recorded was higher than the annual average for the preceding twenty years. Direct economic costs associated with these events totaled around USD 242 billion, with storms and floods contributing most to both the number of people affected and the economic losses (CRED, 2025). When cascading ecosystem costs and other social costs—including impacts on health and education—are factored in, the United Nations Office for Disaster Risk Reduction (UNDRR) estimates that the annual average cost for the period 1970 to 2023 rises to approximately USD 2.3 trillion, or 2% of global GDP (UNDRR, 2025). The frequency and intensity of environmental disasters are expected to accelerate as global warming progresses (Otto et al., 2023; Newman & Noy 2023; Clarke et al., 2022).

Growing recognition of these mounting impacts has elevated disaster-induced damages and losses on the international policy agenda, with measurement enshrined in Sustainable Development Goal 1.5.2 and the Sendai Framework.

Agriculture remains the primary livelihood for a substantial portion of the global population. In low-income countries, rural households depend directly on crop production for both income and food security. The agricultural sector is the predominant employer of adults, especially through primary agricultural production. According to FAO estimates, approximately 1.23 billion people are employed in agrifood systems globally, with 3.83 billion people worldwide living in households linked to agrifood systems-based livelihoods (Davis et al 2023). Understanding agricultural losses from disasters is essential for three reasons. First, when disasters strike agricultural systems, the impacts extend far beyond immediate economic losses—they threaten household consumption, nutritional outcomes, and long-term development trajectories. Second, agricultural damages disproportionately affect the poorest and most marginalized populations who have the least capacity to absorb shocks and recover from losses. Third, systematic measurement of these losses enables evidence-based policies that build resilience among vulnerable populations, enhance understanding of disaster risks (Sendai priority 1) and strengthen risk governance (Sendai priority 2).

Despite this critical need, current approaches to measuring disaster impacts have significant limitations. The Emergency Events Database (EM-DAT) of the Centre for Research on the Epidemiology of Disasters (CRED) serves as the primary global inventory[1]. While EM-DAT provides valuable global-scale tracking of major disasters, these aggregate statistics are less well-suited to capture the differential impacts on different population groups, especially poor and vulnerable people.

Moreover, disaster inventories systematically miss smaller, more frequent events that do not meet 'disaster' thresholds (e.g., 100+ people affected or emergency declaration required). Recent research comparing survey microdata with EM-DAT records reveals this

[1] The EM-DAT database is compiled from various sources, including United Nations, governmental and non-governmental agencies, insurance companies, research institutes, and the press.

measurement gap: survey estimates exceed EM-DAT by US$5.1 billion in damages and identify more than four times the number of affected people (Wollburg et al, 2024b).

While large catastrophic events dominate headlines, smaller and slow-onset disasters collectively cause enormous damage that is systematically undercounted. According to a UNDRR analysis, small and medium localized disasters caused 68% of all economic losses between 2005 and 2017 (UNDRR, 2021).

Critically, these impacts fall disproportionately on vulnerable populations. Recent analysis from six African countries reveals that 35% of agricultural plots experience crop losses each season, with affected farmers losing 53% of their potential harvest on average. Women-managed plots are more likely to experience losses and suffer larger losses when affected. Similarly, the poorest households are more likely to experience losses and lose more of their harvest when affected (Wollburg et al, 2024b).

Survey microdata can help address these measurement gaps by capturing disaster impacts through direct measurement at the farm level. By collecting information at the plot or household level, surveys can detect small and localized events that escape detection in macro-level statistics while revealing the heterogeneity of impacts across different contexts. Importantly, through representative sampling strategies, surveys can explicitly cover poor and marginalized populations whose experiences might otherwise remain invisible in conventional loss measurement systems. When linked to household characteristics, this granular data facilitates deeper analysis of vulnerability patterns and informs targeted resilience-building interventions.[2]

Moreover, survey microdata can play a valuable complementary role alongside remote sensing and satellite-based approaches, addressing blind spots that each method cannot resolve alone. Remote sensing provides broad spatial coverage and objective, continuous monitoring of crop conditions, but its resolution remains insufficient to capture the small and irregular plot sizes typical of smallholder farming systems in low- and middle-income countries, and it is unable to detect non-meteorological sources of crop losses such as pests and diseases that may account for a substantial share of total damage. Survey data, collected at the plot-crop level, can fill precisely these gaps.[3]

This note reviews existing survey methods for integrating disaster loss measurement into agricultural household surveys, synthesizing evidence from three analytical papers (Markhof, Ponzini & Wollburg, 2022; Wollburg et al., 2024a, 2024b) into practical

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[2] Disasters are rare events, and their impacts may remain underrepresented in household and agricultural survey data collected on an annual cycle. Survey design can mitigate this: a wider reference period, or event-triggered deployment of a loss module, increases the likelihood that an event falls within the observation window, though at the cost of longer recall. Further methodological work is needed before a firm recommendation on reference period and deployment can be made. Even so, where an event does fall within the observation window, survey microdata remains the only source that captures the distribution of impacts across households and their relationship to pre-existing vulnerability.

[3] High-quality survey data can be used to train and validate remote-sensing algorithms, providing the ground-truth observations needed to improve the accuracy of satellite-derived yield estimates in smallholder contexts. Conversely, geospatial data on rainfall intensity and other environmental variables can be linked to plot-level survey records to cross-validate farmer self-reports of shock exposure and help disentangle variation due to genuine differences in disaster impact from variation attributable to differences in farmers' perceptions — a distinction that survey data alone cannot resolve.

guidance. The underlying analysis is documented in full in the source papers. It is designed for National Statistical Offices, survey practitioners, and data analysts working to improve agricultural data systems. Although a comprehensive assessment of losses in the agricultural sector would include crops, livestock, fisheries, apiculture, aquaculture, and forest sectors as well as associated facilities and infrastructure, this note focuses specifically on measuring pre-harvest crop production losses. It should be noted that the note does not prescribe a single best-practice protocol for doing so. The state of the evidence does not yet support any prescriptions to be recommended as a universal standard. Rather, the note equips practitioners with the conceptual framework and empirical evidence needed to make informed survey design choices — presenting the strengths, limitations, and practical recommendations for each approach — and identifies the methodological research investments that will be required before a definitive best-practice module can be responsibly prescribed.

The note is organized as follows. Section 2 establishes a conceptual framework for understanding and defining disaster-related crop losses. Section 3 presents four practical approaches to quantifying these losses, accompanied by implementation guidance for each method. Section 4 addresses the methodological challenges of attributing losses to specific disaster types. Section 5 synthesizes key empirical findings on disaster impacts and explores their policy implications. Section 6 reviews survey requirements for pre-harvest crop loss measurements. Finally, section 7 sets out a future methods research agenda, identifying the methodological investments that will be required before a definitive best-practice module for pre-harvest crop loss measurement can be prescribed.

2. Conceptual framework and definition of technical terms

This guidance note builds upon the methodology for damages and losses computation in agriculture developed by Conforti, Markova and Tochkov (2020) for the FAO, and provides evidence-based survey design guidance to support the integration of damage and loss-related questions into household surveys, ensuring that the resulting data can be used by analysts to compute losses following the FAO methodology.

The FAO methodology represents the current available approach for measuring damages and losses in agriculture through household surveys. It complements previously developed disaster impact assessment frameworks, including the United Nations Economic Commission for Latin America and the Caribbean (UN ECLAC, 2003) methodology and the multi-agency Post Disaster Needs Assessment (PDNA) methodology (European Union, UN Development Group and World Bank, 2013).

It provides a standardized framework for quantifying disaster-related damages and losses across the entire agricultural sector[4]. Within the crop sub-sector, the methodology distinguishes between annual and perennial crops, as well as between damage (such as

[4] The FAO methodology covers livestock, forestry, aquaculture, fishery, and crops. Damages and Losses (Crops) = Annual crop production damage + Perennial crop production damage + Annual crop production Loss + Perennial crop production loss + Crop assets damage.

destruction of stored inputs or harvested crops) and loss (such as reductions in crop yields).[5]

While the FAO methodology encompasses this broader range of damage and loss categories across all agricultural sub-sectors, this guidance note focuses specifically on *annual crop production* losses – the sub-sector of greatest relevance to the smallholder farming households discussed in the introduction – allowing for targeted guidance on measuring yield reductions in annual cropping systems using household survey data.[6]

Box 1. Extending the framework to livestock and other agricultural losses

The methodology reviewed in this guidance note focuses on pre-harvest crop production losses — the domain for which the most developed survey-based measurement framework currently exists. Yet crop losses represent only one component of total agricultural disaster impact. When livestock losses are added to crop production losses, the scale of the problem becomes considerably larger: recent disaster statistics suggest that over the last 30 years an estimated USD 3.8 trillion worth of crops and livestock production has been lost due to disaster events, corresponding to an average loss of USD 123 billion per year, or 5 percent of annual global agricultural GDP (FAO, 2023). Livestock is a particularly important component of this aggregate figure: the sector supports the livelihoods of around 1.3 billion people globally and accounts for approximately 40 percent of the world's agricultural GDP (FAO, 2025), with nearly 1 billion smallholder livestock producers in developing countries depending on it for between 2 and 33 percent of their household income (FAO, 2018). Around 500 million pastoralists rely on livestock herding as their primary source of food, income, and wealth (World Bank, 2024). Disasters — including droughts, floods, and disease outbreaks — cause substantial livestock losses each year, yet these remain largely invisible in global disaster statistics for the same reasons that crop losses are undercounted: they disproportionately affect poor, uninsured households in contexts where reporting infrastructure is weak.

The 50x2030 survey framework already contains a number of questions that can be used to estimate livestock production losses, including data on the number of animals lost or dead due to extreme events, as well as questions aimed at identifying damage and losses of livestock-related assets caused by disasters. This provides a useful starting point. However, for a more comprehensive picture of livestock-related losses,

[5] The FAO methodology ultimately expresses damages and losses in monetary terms. The physical quantity estimates obtained through the survey approaches reviewed in this note are therefore an intermediate output: to feed a full damage and loss assessment as proposed in the FAO framework they must subsequently be valued, typically at farm-gate producer prices. This note does not address valuation, which raises separate issues — notably the choice of reference price in post-disaster markets, where prices may themselves be affected by the event.

[6] The note also restricts attention to quantitative losses, that is, reductions in the physical quantity harvested. Disasters may in addition cause qualitative losses — for example aflatoxin contamination following flooding or elevated humidity, commercial downgrading, or reduced nutritional content — which represent a real economic loss even where the crop is harvested. Such losses may originate before harvest but typically become apparent only afterwards, and are not captured by the approaches reviewed here. Estimates produced following this guidance should therefore be understood as a lower bound on total crop production impact.

the instruments would need to be expanded to cover several metrics that are a part of the FAO methodology. These include the pre-disaster value of stored animal products — milk, eggs, hides — held in stock at the time of the shock, and the pre-disaster value of stored inputs such as feed and veterinary supplies that were destroyed. Furthermore, assessing the economic value of livestock mortality requires information on the weight and body condition of the animals at the time of death — data that are rarely collected in household surveys but that are essential for converting animal counts into credible monetary loss estimates. A priority for future methodological research in this area is therefore the development and validation of practical survey-based approaches to livestock valuation at the time of a shock, including the feasibility of collecting animal weight proxies or body condition scores as part of standard agricultural survey modules. More broadly, extending the integrated loss measurement framework developed for crops to the livestock sub-sector — covering mortality, production losses, and asset damage in a comparable and systematic way — represents an important frontier for the agricultural disaster measurement agenda.

2.1 Understanding the Two Main Types of Crop Losses

When assessing disaster-related crop production losses, it is essential to recognize that they do not always manifest in the same way. In practice, two distinct types of loss can occur — often simultaneously — and a complete assessment must account for both.

The first type concerns what can be termed **planted area losses**, or losses at the extensive margin. These arise when a portion of the planted area is so severely damaged that no harvest is possible from it at all. A flood that inundates the lower-lying sections of a field is a typical example: the farmer may successfully harvest from the remaining area, but the destroyed portion contributes nothing to total production. In household surveys, this type of loss is often measured as the reduction in harvested area relative to planted area, expressed either as a percentage or in absolute terms (e.g., hectares).

The second type relates to **plant productivity losses**, or losses at the intensive margin. In this case, crops are harvested across the full planted area, but the plants themselves have been affected in ways that reduce their output below what would normally be expected. Drought stress, for instance, may affect grain development across an entire maize plot without preventing harvest: all plants are harvested, yet each produces smaller cobs with fewer grains than they would have under undisturbed conditions. This type of loss is measured as the percentage reduction in the productivity of harvested crops compared to a damage-free baseline.

These two types of loss are not mutually exclusive, and evidence from plot-level survey data collected across Sub-Saharan Africa illustrates clearly why both should be captured. The analysis draws on the Living Standards Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA), covering nearly 20,000 plots across more than 8,000 farms in Ethiopia and Malawi over multiple survey rounds between 2010 and 2020, with a focus on maize and sorghum as the principal staple crops. Yield regressions run on this data confirm that measures of planted area loss and plant productivity loss each independently explain variation in crop yields — that is, they are not simply proxying for the same underlying phenomenon but genuinely capture distinct dimensions of disaster impact (Markhof, Ponzini & Wollburg, 2022). The same study also flags, however, that while the two loss types are conceptually distinct, farmers may not perceive the corresponding survey questions as such — raising a risk that responses to the area and damage questions may partially overlap in practice, leading to double-counting if the questions are not carefully differentiated in wording and enumerator training.

The practical implication is straightforward: any assessment methodology that captures only one of these dimensions will systematically underestimate total disaster impact. A framework that records only area losses will miss the productivity losses sustained by crops that were harvested but underperformed; one that focuses only on yield reductions will overlook the complete loss of production from destroyed portions of fields. On the other hand, if the distinction between the two concepts is not handled accurately in the questions eliciting area and productivity loss information, there is a risk of overlap between the two components — leading to double-counting and overestimation of total losses. A well-designed assessment must therefore not only capture both dimensions but also ensure that they are measured on clearly distinct and non-overlapping portions of the plot.

2.2 The Counterfactual Challenge: Estimating What Would Have Been Harvested

At the heart of any crop loss assessment lies a fundamental measurement challenge: by definition, when a disaster occurs, the harvest that would have been achieved in its absence is never observed. This unobserved quantity —the "attainable yield" — is the key unknown that any loss assessment methodology must somehow approximate. Losses, whether of the area or productivity type discussed above, are ultimately calculated as the difference between this attainable yield and what was actually harvested. Without a credible estimate of the former, the latter is uninterpretable as a measure of disaster impact.

This challenge is more demanding than it may initially appear. The attainable yield is not the theoretical maximum a crop could produce under optimal conditions (this is the *potential yield*), but rather the yield that would have been realistically achieved on a given plot, by a given farmer, with the inputs and management practices deployed, had the disaster not occurred. It is therefore plot-specific and season-specific, varying with soil quality, input intensity, crop variety, and a host of other factors that differ considerably even within the same farm.

This counterfactual challenge also complicates the way in which surveys elicit information about plant productivity losses from respondents, and the respondents' ability to provide such information.

3. Attainable Harvest for Loss Quantification

As discussed above, the key challenge in measuring crop production losses is the estimation of the attainable harvest — the yield that would have been achieved in the absence of the disaster, which is, by definition, unobserved when a loss occurs. Losses are defined as the difference between this unobserved attainable harvest and the realized harvest, which is measured. This section reviews the four tested survey-based approaches to addressing this fundamental estimation problem. These four approaches do so in two distinct ways. Approaches 1 and 2 estimate the attainable yield implicitly — by asking farmers or enumerators to report the extent of area and productivity losses directly, from which the attainable yield can be recovered. Approaches 3 and 4, by contrast, estimate the attainable yield directly — using past yields, yields from unaffected plots, or pre-planting harvest expectations as an explicit counterfactual benchmark against which the realized harvest is compared. Despite this methodological difference, all four approaches are oriented toward the same objective: producing an estimate of what the farmer would have harvested in the absence of the disaster and quantify losses as its difference to the realized harvest.

None of these approaches can be considered definitive, and the evidence reviewed here indicates that each carries distinct sources of error. Nonetheless, the land area and crop damage approach can form the backbone of a crop loss module, since it is asked at the plot-crop level, is straightforward to administer within existing questionnaires, and scales without additional fieldwork. The remaining three are best used to complement it rather than to replace it. Expert assessments provide a check on the direction and magnitude of self-report bias. Past harvests or yields from comparable unaffected plots offer the means of estimating losses where the main approach cannot be applied — on fully destroyed plots, where the attainable yield can be inferred from comparable plots with at most partial losses — and can serve as an input to model-based prediction of attainable yields. Farmers' post-planting harvest expectations provide a coarser but independent proxy, most useful for full losses and for confirming the presence of large losses. Used together, these approaches allow the core estimate to be cross-checked and extended to cases it cannot cover on its own, provided the analyst remains aware of the limitations of each. Each is discussed in turn below and summarized in Table 1.

Table 1. Approaches to Estimating the Attainable Yield for Pre-Harvest Crop Loss Measurement: Data Requirements, Strengths, Weaknesses, and Recommendations

Approach	**How it estimates attainable yield**	**Proxy question**	**Strengths**	**Weaknesses**	**Recommendations**
1. Land area and crop damage	Scales up realized yield based on reported area lost and damage percentage	Approximately what percent of [PLOT] planted with [CROP] was harvested? What is the percentage of damage on [CROP]?	• Simple and scalable: can be administered to large samples with minimal additional cost or survey time. • Plot-specific: captures losses at a highly disaggregated level, accounting for within-farm heterogeneity. • Captures both loss types: when combined, the two questions on harvested area share and crop damage jointly capture both planted area losses and plant productivity losses. • Good ordinal signal: reliably identifies which plots, areas, and seasons experienced relatively higher losses, even if absolute figures are imprecise.	• Prone to satisficing and rounding errors • Farmers struggle with percentage estimation • Potential overlap between area and productivity questions • May overestimate in high-salience disaster years • May underestimate small losses in normal years • In case of full losses, attainable yield is undefined and needs to be imputed.	• Provide visual aids for percentage estimation • Clearly differentiate planted area losses from productivity losses OR merge both proxies in a single question
2. Expert assessments	Trained enumerator assessment of losses	What percentage of the potential maize harvest was lost due to damage on [PLOT]?	• Independent cross-check: provides a second, independent perspective on losses that is not subject to the same psychological biases as farmer self-reports. • Lower susceptibility to salience bias: enumerators are less likely to overreact to the emotional or psychological salience of a disaster event. • Benchmarking tool: even where enumerator assessments are imperfect, comparing them to farmer reports helps identify systematic patterns of over- or underreporting that can inform data quality checks. • Directly observable: enumerators base their assessment on physical observation of the plot, grounding the estimate in something tangible rather than recall alone.	• Not definitively more accurate than farmer reports • Enumerators also make errors and use subjective judgment (cannot be considered a "gold standard") • Requires extensive training and calibration • Requires direct assessment and cannot be implemented on a recall basis (the enumerator can observe but does not know otherwise.	• Use for adjusting/calibrating farmer-reported loss rates • Use strategically for validation sub-samples in combination with crop-cutting • Invest in standardized training with visual guides and calibration exercises • Acknowledge limitations rather than treating as gold standard

Approach	How it estimates attainable yield	Proxy question	Strengths	Weaknesses	Recommendations
3. Past harvest data or unaffected districts	Attainable yield based on past yield or unaffected districts	Past yield realizations or yields from similar but unaffected plots	Conceptually straightforward	• Requires high-frequency panel data (currently unavailable in most contexts) • Past yields may be themselves disaster-affected (downward bias) • Household mobility • Plot boundaries and crop choices change over time • Intertemporal differences in plot management decisions. • Large inter-farm yield heterogeneity even within same area • Spatial approach requires strong comparability assumptions	• Use past yield data or data from unaffected similar plots in combination with rich survey data and external source data to estimate attainable yields using econometric or machine learning models. • Use matching techniques to address comparability issues by constructing a comparison group of unaffected plots that are as similar as possible to the affected plots on observable characteristics.
4. Post-planting expectations	Attainable yield based on farmers' post-planting expectations	How much of [CROP] do you expect to harvest during the main rainy season?	• Plot- and crop-specific: expectations are formed after input and management decisions have been made, making them implicitly sensitive to the specific conditions of each plot — something that cross-plot or past-data approaches cannot fully replicate. • Low additional cost: requires only one extra question at the post-planting visit, making it easy and inexpensive to incorporate into two-visit survey designs. • Reasonable loss incidence signal: over-expectation rates broadly align with loss incidence estimates from other proxies, suggesting the approach captures the occurrence of significant losses reasonably well • Internally consistent: when both expectations and realizations are self-reported, the two measures share a similar underlying mental model, producing a consistent internal signal of loss occurrence.	• Farmers are endogenous to past shock experience and future shocks expectations. • Systematic over expectation in both self-reported expected and realized harvest. Expectations themselves are disaster-affected (endogenous) • Misses pre-survey losses (e.g., early-season flooding) which are already taken into account in the self-reported expectations. • Unit conversion challenges between visits • Cannot attribute losses to causes without additional questions • "Black box" expectation formation process	• Use as complementary approach alongside area/damage questions • Combine with Approach 1 questions (area/damage) for attribution • Include questions about re-planting and early losses

3.1 Land Area and Crop Damage Approach

The first approach estimates the attainable yield implicitly by directly eliciting information on the two components of crop loss from survey respondents: planted area losses, characterized by a reduction in harvested area relative to planted area, and plant productivity losses, which occur when a disaster only partially affects the crop, reducing yield on the harvested area without destroying it entirely. In this approach the attainable yield is scaled up from the realized yield by using the information on the reported area lost and damage percentage. Specifically, the harvested area and realized yield on that harvested area are obtained using the percentage share of planted area that was harvested, then the attainable yield is recovered from the realized yield by accounting for plant productivity losses through the reported percentage of damage on the harvested crop. The compound loss estimate consists of two additive components: (a) **planted area losses** — the production foregone on the fully destroyed portion of the plot, where no harvest was possible — and (b) **plant productivity losses** — the yield reduction on the harvested but damaged portion, where crops were collected but at below-attainable levels. The questions used to elicit this information from survey respondents are:

- **For planted area losses**: *"Approximately what percent of [PLOT] planted with [CROP] was harvested?"* [7]

- **For plant productivity losses**: *"What is the percentage of damage on [CROP]?"*

Box 2 describes the steps needed to compute the compound loss estimate in partially affected plots under the assumption that attainable yield is uniform across the plot.

Box 2. Computing the Compound Loss Estimate

Required variables:

Y^r Observed (realized) total production in kg
ha^c GPS-measured total planted plot area
s Share of planted area that was harvested (from survey question: "Approx. what % of [PLOT] planted with [CROP] was harvested?")
d Percentage of damage on the crop (from survey question: "What is the % of damage on [CROP]?")

Computation steps:

Step 1 — Derive the estimated attainable yield per hectare:
$y^c = (Y^r / (ha^c \times s)) \times (1 / (1 - d))$

[7] This question assumes that harvest has been completed on the plot at the time of the interview. If fieldwork is organized in a way that the post-harvest visit may coincide with ongoing harvest activity, it would be important to add a question to parse out the area where harvest has already been completed from the area where it has not, to avoid incorrectly recording unharvested area as lost.

Step 2 — Planted Area Loss (Part A):
Part A = y^c × (ha^c − ha^c × s)
= y^c × ha^c × (1 − s)

Step 3 — Plant Productivity Loss (Part B):
Part B = (y^c − Y^r_per_ha) × ha^c × s
where Y^r_per_ha = Yr / (ha^c × s)

Step 4 — Total Loss:
L= Part A + Part B

When a plot experiences a total crop failure — that is, when, in Box 2, the share of planted area harvested equals zero (s = 0) or the damage share equals one (d = 1) — the attainable yield becomes undefined. This is because the formula relies on an observed realized harvest (Y^r) to back-calculate the attainable yield, and no such observation exists when the crop has been destroyed in full. In these cases, the attainable yield must be imputed. Two possible methods to estimate the attainable yield are proposed in Box 3.

Box 3. Imputing the Attainable Yield for Plots with Total Crop Failure

Option 1: Imputation from Similar Plots

The first approach estimates the attainable yield by drawing on observed yields from comparable plots that did **not** experience a complete loss in the same season. The underlying assumption is that, had the fully destroyed plot not been affected, it would have achieved a yield like those of plots with analogous characteristics. Losses are then estimated applying the mean or median attainable yield of similar plots to the total area with full crop failure.[8]

This approach is straightforward to implement and computationally simple. However, its reliability depends heavily on the availability of a sufficient number of genuinely comparable plots with partial or no losses in the same geographic area and season.

Option 2: Gaussian Regression Imputation

The second approach uses a regression model to **predict** the attainable yield for fully destroyed plots based on their observed characteristics.[9] This method is more

[8] Other approaches use higher percentiles (e.g. 75th or 90th) in each locality assuming that could be a reasonable yield attained by farmers in normal conditions in a given locality and for a given technology. The estimate is sensitive to the choice of statistic used to summarize the comparator distribution — mean, median, or an upper percentile — which scales the loss directly and has no purely statistical justification. Differently from the median, which is a robust measure, higher percentiles are additionally exposed to measurement error in the upper tail where yields are self-reported. The statistic used should be stated explicitly, and ideally results reported for more than one.

[9] This method is proposed in Wollburg, P. R., Markhof, Y. V., Bentze, T. P., & Ponzini, G. (2024). *The impacts of disasters on African agriculture: New evidence from micro-data*. World Bank Policy Research Working Paper No. 10660. World Bank.

demanding analytically but produces a statistically principled estimate that accounts for the multidimensional nature of yield variation. The attainable yield is predicted using the following covariates:

- **Input variables**: plot area, total labor per hectare, fertilizer quantity (organic and inorganic), seed quantity, and use of improved seed varieties.
- **Plot characteristics**: elevation, soil fertility index, irrigation status, and intercropping dummy.
- **Plot manager characteristics**: gender, age, and education level.
- **Household characteristics**: asset index and urban/rural classification.
- **Crop and location fixed effects**: to control for systematic differences across crop types and geographic zones.

The model is estimated on plots **without full losses**, where the attainable yield can be observed or recovered using Equation 2. The fitted model is then used to predict the attainable yield for fully destroyed plots. To account for estimation uncertainty, it is recommended to **generate multiple imputations** (e.g., 100 draws) from the predictive distribution and use their mean as the final imputed value.

Both methods are valid and non-exclusive — in contexts with sufficient data, practitioners may wish to apply both and assess the sensitivity of their loss estimates to the choice of imputation method. In seasons with widespread disaster exposure, the pool of reference plots with partial or no losses may itself be limited, making both imputation approaches less reliable. In such cases, supplementary data sources — such as yield estimates from unaffected neighboring districts, historical yield trends, or remote-sensing-based productivity indices — should be considered to cross-validate imputed values.

The primary strength of the Land Area and Crop Damage Approach lies in its simplicity and scalability. It requires no additional data sources beyond the farmer's own recall at the post-harvest visit, making it straightforward to integrate into existing agricultural survey modules at minimal additional cost. When the two questions on harvested area share and crop damage are used together, they jointly capture both types of losses — planted area losses and plant productivity losses — providing a compound picture of the damage sustained. Crucially, empirical evidence shows that even where absolute figures are imprecise, the approach reliably identifies which plots, areas, and seasons experienced relatively higher losses, making it a solid ordinal signal for targeting and prioritization purposes (Markhof, Ponzini & Wollburg, 2022).

A critical limitation of the land area and crop damage approach is that the two survey questions — the share of planted area harvested (s) and the percentage of crop damage (d) — capture **farmers' perceptions** of losses rather than objectively measured quantities. Evidence from the LSMS-ISA data reveals several systematic patterns that survey practitioners should be aware of when interpreting results. First, estimating losses on a percentage scale is a cognitively demanding task as farmers lack an intuitive benchmark for formulating percentages. Farmers show a strong tendency to round their responses to psychologically convenient values such as 10%, 25%, or 50%, with a particularly conspicuous spike at 50% that is consistent with **satisficing** — the use of mental shortcuts to arrive at a plausible-sounding answer rather than investing effort in a precise estimate (Markhof, Ponzini & Wollburg, 2022). Second, recall bias is a well-documented source of measurement error in agricultural surveys more broadly, and in this context is likely compounded by the salience effect. Data reveals an asymmetric relationship between shock severity and reporting accuracy: in years with severe, salient disasters, farmers tend to **overreport losses**, while in quieter agricultural seasons, small losses are more likely to go unnoticed or be **underreported.**[10] Third, comparison with enumerators' assessments from the Uganda Methodological Experiment on Measuring Maize Productivity, Variety, and Soil Fertility (MAPS) experiment reinforces these concerns: enumerators reported average crop damage of 21%, compared to 34% reported by farmers for the same plots — a statistically significant gap that points to systematic overestimation on the intensive margin (Markhof, Ponzini & Wollburg, 2022).

What this means practically is that the method performs well at capturing **ordinal differences** in losses — that is, distinguishing relatively more affected plots, seasons, or geographic areas from less affected ones — but is less reliable for **cardinal precision**, meaning the exact percentage figures should not necessarily be taken at face value. Loss estimates derived from this approach are therefore best interpreted as **approximations of relative magnitude** rather than precise measurements of absolute losses. This makes the method particularly valuable as a targeting and prioritization tool — for identifying severely affected areas, flagging anomalous seasons, or comparing loss patterns across regions — while cautioning against its uncritical use in contexts requiring high-precision monetary valuations of crop damage, such as insurance payouts or legal compensation assessments.

Key takeaway for survey practitioners: The land area and crop damage approach is promising but imperfect. Farmers struggle with percentage estimation, rounding, and salience bias—particularly overreporting losses in severe shock years. Both questions may also suffer from measurement overlap, meaning the combined estimate can be inflated despite each measure independently explaining yield variation. To improve reliability, use visually-aided formats and either clearly differentiate the two loss types through careful question phrasing, or consolidate them into a single question anchored to farmers' expected harvest. Both approaches reduce satisficing and measurement error.

3.2 Enumerator Assessments of Area and Productivity Losses.

The second approach follows the same implicit logic as Approach 1 — estimating the attainable yield by recovering it from reported area and productivity loss information — but replaces the farmer as the source of that information with an independent

[10] This salience effect is strikingly illustrated by the Ethiopian drought year of 2015/16, in which the loss-to-harvest ratio for maize reached 1.44 — a value that is mathematically implausible under normal conditions and strongly suggestive of inflated farmer reports in response to the heightened psychological salience of the drought. In contrast, the same ratio stood at a more plausible 0.94 in the comparatively normal 2018/19 season (Markhof, Ponzini & Wollburg, 2022).

enumerator assessment. Rather than relying on farmer recall and perception, the enumerator visits the plot at or near harvest time and forms an independent judgment on the share of planted area that was not harvested and the degree of damage on the harvested crop. The attainable yield is then recovered from the realized yield in exactly the same way as in Approach 1, using the enumerator's assessments of area loss and damage percentage in place of the farmer's self-reports.

This approach may be implemented in two ways either alongside or instead of farmer reports. The recommended approach for the enumerator assessment is a **double reporting approach**, in which both the farmer and a trained enumerator independently provide their assessment of losses on the same plot. The farmer supplies their own loss estimate as usual, while the enumerator conducts a separate, independent assessment based on a crop cut or structured visual inspection of the plot. The two estimates are then compared, with discrepancies flagged for further investigation or resolved through a reconciliation protocol. This approach preserves the farmer's perspective — which may carry valuable contextual information about the causes and timing of losses — while simultaneously generating an independent check on its accuracy, helping to identify and correct for the systematic overreporting.

The key strength of enumerator assessments is that they provide an independent, observationally grounded perspective on losses that is not subject to the same psychological biases as farmer self-reports. Because enumerators base their assessment on direct physical inspection of the plot rather than recall or perception, they are less susceptible to the salience-driven overreaction that inflates farmer reports in years with severe adverse climate events.

Despite the value of an independent observational perspective, enumerators' assessments come with two important limitations that survey practitioners should be aware of before incorporating them into an agricultural survey.

Incorporating enumerator assessments into a survey module introduces an operational complication that does not arise with farmer self-reports alone. For an enumerator to conduct a meaningful visual assessment of crop losses, the plot must be visited while physical evidence of the damage is still present — ideally before or during harvest, when the effects of disasters on standing crops remain observable. This requirement creates a tension with the standard two-visit survey structure: either an additional interim visit must be scheduled specifically for the enumerator assessment, adding cost and logistical complexity to the fieldwork, or the post-harvest visit must be brought backward to a point in the agricultural cycle that may be suboptimal for collecting other agronomic metrics — such as self-reported harvest quantities, which can only be accurately reported once harvest is fully complete. Survey planners should weigh this trade-off carefully when deciding whether and how to incorporate enumerator assessments, and should consider whether a targeted sub-sample approach — conducting assessments on a subset of plots rather than the full sample — might offer a cost-effective middle ground.

Beyond the operational challenge, enumerator assessments cannot themselves be considered a reliable objective benchmark for measuring crop losses. Enumerators assess losses through visual judgment rather than direct, objective measurement, and evidence from the Uganda MAPS experiment shows systematic divergence from farmer reports — enumerators reporting average losses of 21% compared to 34% reported by farmers for the same plots — that far exceeds what would be expected from normal differences in human judgment (Markhof, Ponzini & Wollburg, 2022). Crucially, without an independent external standard or validated ground truth, there is currently no way to determine which estimate is more accurate. That said, this does not mean the two estimates are equivalent in their analytical properties. Enumerators, unlike farmers, are physically present on the plot during or shortly after harvest: they can count plants, observe the proportion of damaged cobs or grain, and mentally reconstruct the relationship between what was planted and what was harvested in a way that is grounded in direct observation rather than retrospective recall. This process — though still involving judgment — may in some respects be less susceptible to the salience-driven overreaction and recall bias that inflate farmer reports in severe shock years, and represents a direction for future methodological research into whether structured enumerator protocols can be designed to better exploit this observational advantage. For now, both farmer self-reports and enumerator assessments remain imperfect proxies that capture overlapping but distinct information. Enumerator assessments are most valuable when used as a cross-check on farmer data to identify systematic patterns of bias and as a data quality diagnostic tool, rather than as a definitive measure of losses in their own right. More research is needed to establish whether and under what conditions structured enumerator observation protocols — potentially combined with crop cut data on a validation sub-sample — can move closer to a reliable objective benchmark for intensive-margin loss reporting. Box 4 discusses how crop cutting data can be used for loss measurement purposes and outlines a research agenda for developing this approach further.

Key takeaway for survey practitioners:

Use enumerator assessments as a check on farmer self-reports, rather than as a standalone replacement — the two sources capture overlapping but not identical information, and their value lies precisely in the comparison between them. Flag severe shock years as contexts where farmer and enumerator assessments are most likely to diverge, with farmers systematically inflating their loss estimates. Where resources allow, enumerator assessments are most cost-effective when deployed on a validation sub-sample alongside crop cuts, rather than across the full survey sample. Future survey design should explore whether structured training protocols and standardized visual comparison tools can reduce the gap between farmer and enumerator assessments and move closer to an objective benchmark for intensive-margin loss reporting.

Box 4. Crop Cutting as a Tool for Loss Measurement

Crop cutting — the physical harvest and weighing of a randomly demarcated subplot within an agricultural plot — is widely considered the closest available approximation to an objective measure of crop yield and is already implemented as an optional module within the 50x2030 survey framework (50x2030 Initiative, 2025). Its standard application is to improve the accuracy of crop production and yield estimates by replacing error-prone farmer self-reports with direct physical measurement. However, the data collected as part of a standard crop cutting exercise also carry useful information for disaster-related crop loss measurement that is not fully exploited.

The 50x2030 crop cutting protocol already collects, as complementary data points within the subplot, the **number of maize plants planted**, the **number of plants harvested**, the **number of plants damaged**, and the **number of plants pre-harvested** by the household prior to the enumerator's visit. Together these counts provide a direct, observationally grounded basis for distinguishing between planted area losses — where plants were fully destroyed and did not contribute to harvest — and plant productivity losses — where plants were harvested but produced less than their undamaged potential. The ratio of fully destroyed plants to total plants in the subplot, combined with the harvested weight from the remaining plants, can in principle be used to estimate the **planted area loss** component of the compound loss estimate described in Section 3.1 — that is, the production foregone from plants that were completely destroyed and contributed nothing to harvest. This offers a more objective, count-based alternative to the farmer's self-reported share of planted area harvested that underlies Approach 1. However, the **plant productivity loss** component — the yield reduction on plants that were harvested but partially damaged — cannot be recovered from standard crop cut data alone, as it would require knowing by how much damaged but harvested plants underperformed relative to their undamaged potential. Going further, a more precise disaggregation of both loss types could in principle be achieved by extending the standard crop cutting data collection to record separately the number and weight of **partially damaged plants** — those that were harvested but visibly affected — and **fully destroyed plants** — those that could not be harvested at all. This distinction maps directly onto the two-component loss formula set out in this guidance note and would allow plant productivity losses and planted area losses to be estimated independently from observed plant counts and weights, rather than inferred from farmer perceptions. Implementing this extension within the existing 50x2030 crop cutting protocol would require only a modest addition to the subplot data collection form and enumerator training materials. However, whether plant-count-based loss estimates derived in this way are sufficiently accurate and comparable to other proxies remains an open methodological question that warrants dedicated field testing and validation before this approach can be recommended for routine use.

For guidance on implementing crop cutting within the 50x2030 survey framework, including subplot demarcation protocols, sampling design, and fieldwork organization, readers are referred to the companion **50x2030 Technical Note on Crop Cutting** (50x2030 Initiative, 2025), available at www.50x2030.org.

3.3 Past Harvest Data or Data from Similar but Unaffected Plots

This approach estimates the attainable yield — what a farmer would have harvested in the absence of a disaster — by drawing on yield information that already exists, either from the same plot in previous seasons or from comparable plots in unaffected areas in the current season.[11] The underlying logic is straightforward: if a reliable estimate of what a plot normally produces can be established, any shortfall relative to that benchmark in a disaster-affected season can be attributed to the shock (Markhof, Ponzini & Wollburg, 2022).

The principal advantage of this approach is that it draws on observed yield data on non-damaged plots rather than on loss perceptions or expectations, reducing reliance on subjective farmer judgment (although these measures are self-reported). Where panel data are available, using yields from the same plot over time holds soil quality and other plot characteristics broadly constant, reducing the confounding that arises from comparing different plots with different growing conditions. Similarly, yields from comparable unaffected plots or districts can provide a reasonable external reference point for what the affected area might have produced in the absence of a shock, particularly for regional or national-level loss assessments.

Notwithstanding, both variants of this approach face significant practical and conceptual limitations that practitioners should be aware of.

For past yield data, the most fundamental problem is data availability. Obtaining a robust multi-year yield trend requires high-frequency annual panel data at the plot level — a type of data that is exceedingly rare in most LSMS-type surveys, which typically operate on two-to-three-year cycles. Beyond availability, there is a deeper conceptual issue. Past yield observations are likely to provide a downward-biased estimate of the attainable harvest, because harvest losses occur frequently (55-65% of plots in Markhof et al. 2022 the sample). Any past harvest data is therefore likely to carry over the effect of past shocks into the current-season loss estimate. Using the maximum historical yield as a workaround can also be problematic: beyond the risk of simply picking out outliers driven by measurement error rather than genuine peak performance, an abnormally good year may reflect growing conditions — rainfall, temperature, input availability — that are no longer representative of the current season, meaning that the historical maximum may not reflect the attainable yield under current conditions either.

As for the unaffected-plot variant discussed below, for this approach to be operational, the analyst must first be able to identify which plots were affected by a disaster and which can be considered unaffected ones. In both cases the reliability of this classification depends on the quality of farmer-reported attribution — discussed in detail in Section 4 — and misclassification of affected plots as unaffected, or vice versa, will introduce bias into the loss estimates derived from this approach.

[11] Methods for estimating the attainable yield from comparable plots are set out in Box 3.

For yields from unaffected plots, the key challenge is ensuring genuine comparability. The accuracy of this method crucially depends on the degree to which factors other than disaster impact are constant between disaster-affected and "control" plots. This may not be the case, as the literature suggests the presence of large inter-farm differences in yields due to idiosyncratic shocks but also measurement error, varying input intensities, and soil quality. Notably, yields vary considerably even within the same farm among pure-stand plots without losses. This indicates that soil quality, management, and idiosyncratic conditions vary sharply across small areas, making it **nearly impossible to identify truly 'comparable' control plots**—even neighboring plots in the same district may differ substantially in attainable yield

One approach to addressing this comparability challenge is **matching**, which identifies a set of control plots that are as similar as possible to the affected plots on observable characteristics, rather than relying on the assumption that all unaffected plots in a given area are broadly equivalent. By pairing each disaster-affected plot with unaffected plots matched on key observable characteristics — such as input intensity, plot size, soil quality, intercropping status, and plot management practices — practitioners can reduce the confounding that arises from simple district-level comparisons.

Past yield data and unaffected plot yields as inputs to predictive models: Despite their limitations as standalone benchmarks, past yield data and yields from similar unaffected plots can serve as valuable inputs to econometric or machine learning models for predicting attainable yields. Using rich survey data as provided by the LSMS-ISA, it is possible to account for multiple confounding factors—such as soil quality, input use, crop management practices, and idiosyncratic plot conditions—and predict attainable yields by combining past yield data, data from several similar but unaffected plots, and planting season crop management decisions. This modelling approach leverages the complementary strengths of each data source while reducing reliance on any single flawed estimate.

However, in the absence of such sophisticated modelling, practitioners should treat estimates derived from the simple past yield or unaffected plot approach as at best **indicative of relative magnitude rather than reliable measurements**.

Key takeaway for survey practitioners: This approach is **not recommended as a primary measurement method** in most contexts. Past yield data suffer from downward bias (carried-over shocks), require rare high-frequency panel data, and comparability of unaffected plots is undermined by intra-farm heterogeneity. Best reserved for imputation models or sensitivity analysis where rich panel data exist, not as a standalone strategy.

3.4 Farmers' Post-Planting Harvest Expectations

This approach uses farmers' own harvest expectations — collected at the post-planting visit before the harvest occurs — as a proxy for the attainable yield. The underlying rationale is that at planting time, most crop management decisions, input use, and plot preparation have already been made. A farmer's expected harvest at this stage therefore implicitly reflects all these factors, potentially providing a more plot-specific and context-sensitive benchmark for the attainable yield than either past data or yields from other plots (Markhof, Ponzini & Wollburg, 2022). The survey question used in this approach is:

"How much [CROP] do you expect to harvest from [PLOT] during the [main agricultural season]?"

This question is asked at the post-planting visit and compared to realized production collected at the post-harvest visit.

The distinctive strength of this approach is its sensitivity to plot- and farmer-level heterogeneity. Because expectations are formed after the main input and management decisions for the season have already been taken, they implicitly reflect the specific conditions of each plot — including differences in input intensity, intercropping arrangements, and soil management — in a way that cross-plot comparisons or historical averages cannot easily replicate. It is also a low-cost addition to any two-visit survey design, requiring only a single additional question at the post-planting visit. Where both expectations and harvest realizations are collected as self-reports, the two measures share a broadly consistent internal logic, making the expectation gap a reasonable signal of whether a significant loss occurred (Markhof, Ponzini & Wollburg, 2022).

Despite its appeal, the approach faces several important limitations that practitioners should consider carefully:

Endogeneity of expectations. Farmers may adjust expectations according to the amount of information they have, such as accurate weather forecasts, or considering recent shock exposure. This will inevitably contaminate the expected harvest as an unbiased estimate of the attainable harvest without shocks.

Planting-season losses are missed. Alternatively, farmers who have already experienced early-season damage may downwardly adjust their expectations, leading to an underestimate of the attainable yield and therefore an underestimate of total losses.

Coarse measurement for small losses. The difference between expected and realized harvest may be too coarse of an estimate of crop losses for small losses. Crops that perform unexpectedly well can, by this definition, not record a loss if realized harvest outperformed expected harvest, even if some minor damage occurred.

Unexplained expectation formation. Markhof, Ponzini, & Wollburg (2022) show that neither a set of respondent characteristics nor past shock exposure or other factors potentially associated with the process of forming an expected harvest estimate are significant predictors of the expectation gap across crops and countries, leaving a sizeable behavioral "black box" that makes it difficult to systematically correct for bias in expectations.

Key takeaway for survey practitioners:
Despite these limitations, farmers' post-planting expectations remain a practically useful and relatively low-cost complement to other loss proxies, particularly in surveys that already feature a two-visit structure. Farmers' self-reported harvest expectations

generally prove fair, albeit likely endogenous, proxies of the attainable harvest, and align relatively well with harvest realizations if both rely on the same underlying mental model. Practitioners should treat the expectation gap as an indicative signal of loss occurrence and relative magnitude rather than a precise estimate, and use it alongside — rather than instead of — other approaches. Surveys not currently collecting post-planting expectations should consider adding this question, given its low cost and the additional triangulation it enables. For the full technical analysis, readers are referred to Markhof, Ponzini & Wollburg (2022).

3.5 Main takeaways

No single approach reviewed in this section can be considered definitive for measuring pre-harvest crop production losses at the plot level. Each carries known limitations that affect both its precision and its comparability across contexts, and none has been validated against a reliable objective benchmark. That said, the limitations of the four approaches are different in nature — what one tends to miss or distort, another may capture more reliably — which means that using multiple approaches in combination and comparing their outputs can increase confidence in the resulting estimates, even if it cannot guarantee accuracy. The land area and crop damage approach could form the backbone of any crop loss module given its scalability and ease of implementation, but its known limitations — particularly the risk of overreporting in severe shock years and the possible difficulty farmers face in accurately differentiating between the two types of losses — mean it should not be used in isolation. Enumerator assessments would add a valuable independent layer of verification but require significant investment in enumerator training and calibration to be meaningful. Post-planting expectations offer a low-cost, plot-specific complement that is easy to incorporate into any two-visit survey design, while past yield data and yields from unaffected plots are best reserved for cross-validation or contexts where richer panel data are available.

4. Challenges with Attributing Losses to Disasters

Beyond quantifying how much was lost, accurately establishing *which* disaster caused those losses is an equally important challenge. This section discusses how loss attribution is currently approached in household surveys, the main limitations of each approach, and how future survey design could improve on existing practice.

Multitopic household surveys such as the LSMS-ISA, and agricultural surveys such as the 50x2030 Initiative's Farm Income, Labor, and Productivity (ILP) questionnaire, offer several survey-based proxies for shock attribution, operating at different levels of aggregation — plot, household, and community — with some important differences in sensitivity and scope(Markhof, Ponzini & Wollburg, 2022). Concretely, four types of questions are used for loss attribution:

- **Plot-crop level questions** ask farmers directly about the cause of their losses, either in relation to area losses (*"Why was the area harvested less than the area planted?"*) or crop damage (*"What was the main cause of the damage on [CROP]?"*). These are the most disaggregated and sensitive measures available, asked specifically in relation to crop losses during the agricultural season of interest.

- **Household-level questions** ask whether the household was affected by a specific shock — such as drought — in the last 12 months. These are broader in scope and not tied to a specific plot or crop.
- **Community-level questions** ask a congregation of knowledgeable community members to describe the most significant adverse events in the last two to three years. This provides a coarser, area-level signal of shock occurrence.

In addition to these self-reported sources, surveys can be complemented by geospatial data — such as modelled rainfall estimates — to provide an externally verifiable anchor for shock identification. Comparing 12-month total rainfall against long-term averages, for instance, allows practitioners to identify areas exposed to below-normal precipitation without relying solely on farmer recall[12]. Comparing self-reported shock exposure to these external benchmarks allows practitioners to assess how well farmer perceptions align with measured conditions on the ground, and to flag cases where the two sources diverge significantly.

Main Issues with Each Approach

Plot-level self-reports are the most granular and contextually relevant attribution tool, but carry an important limitation: they cannot discern idiosyncrasy due to differences in farmers' perceptions from idiosyncrasy in shock reports due to actual differences in highly localized loss occurrence (Markhof, Ponzini & Wollburg, 2022). In other words, when two neighboring farmers attribute their losses to different causes, it is impossible to tell whether this reflects genuinely different experiences or simply different interpretations of the same event. Agreement between farmers on the same shock within the same enumeration area is generally limited, but improves substantially in severe shock suggesting that the salience and intensity of the disaster plays a role for the consistency with which farmers record losses and attribute them to the same shock (Markhof, Ponzini & Wollburg, 2022). This is further corroborated when self-reports are compared against geospatial rainfall data: across years, farmers report either a notably higher or a notably lower incidence of drought exposure than the rainfall-based drought indicator, with the two measures aligning closely only during severe, and diverging considerably in more normal seasons. This points to a non-negligible share of the variation in farmers' shock reports being driven by differences in perception rather than differences in actual exposure (Markhof, Ponzini & Wollburg, 2022).

Household and community-level shock reports provide a broader signal but introduce additional noise. They are not directly tied to a specific plot or season, use different reference periods, and may reflect welfare impacts more broadly rather than strictly agricultural losses. Household and community reports may relate to a loss of consumption rather than necessarily an agricultural or meteorological event, and have the drawback of not defining shocks in relation to a clear benchmark, leaving room for

[12] While drought is the most prevalent shock in the study region, it is not the only one present. Floods, irregular rains, pests, and crop diseases also feature in the data, and index-based approaches can in principle be extended to capture other meteorological shocks where appropriate geospatial products are available

endogeneity in responses — for example, hardship being rationalized ex-post by reporting a drought (Sohnesen, 2020).

Geospatial data offer the ability to link survey data with additional sources of information, available over long periods of time and across great spatial expanses, but they come with their own limitation: they operate at a spatial resolution that may still be too coarse to capture the highly localized variation in shock impact that occurs at the plot level.

The overarching conclusion is that it is difficult to confidently attribute losses to specific disasters based on self-reports alone, and that no existing single data source — whether self-reported or index-based — provides a fully reliable attribution measure across all shock types and intensities.

How to Improve Future Household Surveys

Routinely linking survey data to gridded geospatial products would help distinguish genuine shock exposure from perceptual noise and would allow practitioners to flag cases where self-reports diverge substantially from measured conditions for follow-up investigation. As the range of available geospatial products expands, this approach can be progressively extended beyond rainfall to other shock types including flood extent mapping and vegetation stress indices.

Future surveys should also consider **triangulating across all available attribution proxies** — plot-level, household-level, and community-level — rather than relying on any single question. The different shock proxies point in similar directions but vary in the shock incidence they suggest and are imperfectly correlated (Markhof, Ponzini & Wollburg, 2022). Combining them systematically would improve confidence in loss attribution and help identify unreliable observations.

Diaries and mixed-mode data collection for within-season tracking. Some planting-season losses are effectively invisible to post-harvest surveys because farmers adjust their expectations and behavior before the harvest visit, and attribution noise is compounded when farmers recall events from several months earlier. Two complementary approaches could help. **Farmer diaries** — simple structured booklets in which farmers record significant events on their plots as they occur during the season — would capture shock occurrence in near-real time, before memory fades and before farmers rationalize losses ex-post. However, their practical adoption in most survey programs faces significant challenges. Literacy requirements limit their applicability in contexts where a substantial share of smallholder farmers have limited or no formal education. Compliance is difficult to ensure and monitor without frequent enumerator contact, which largely offsets the cost advantages over more intensive data collection approaches. And the quality of entries tends to deteriorate over time without active supervision. Alternatively, **mixed-mode data collection using phone surveys** — short, targeted check-ins deployed between the post-planting and post-harvest visits — could achieve a similar effect at lower cost and with wider reach, leveraging the growing mobile phone penetration in smallholder farming communities. However, caution is warranted before recommending this approach for routine implementation. Evidence from a large-scale survey mode experiment in rural Nigeria, conducted as part of the 50×2030 initiative, shows that phone surveys generate consistent and economically meaningful differences relative to in-person interviews across a wide range of outcomes including shocks, with responses differing by 17–18 percent at the median (Markhof et al, 2026). Additionally, data from the same mixed-mode study in Nigeria point to reportedly higher use of labor and non-labor agricultural inputs when using mixed-mode approaches relative to the traditional recall approach (Contreras et al., *forthcoming*).

5. And So, What? Understanding the Impact and Implications of Crop Losses

Despite all these measures being imperfect alone, they are still relevant. Survey microdata reveals a picture of crop losses that is both more severe and more nuanced than what aggregate disaster statistics would suggest. Drawing on harmonized plot-level data from over 120,000 agricultural fields across six African countries between 2008 and 2019, Wollburg et al. (2024a, 2024b) show that crop losses due to adverse climatic events are not exceptional events but a routine feature of smallholder agriculture — affecting around 35% of plots in any given season and reducing national crop production by 29% on average, with peaks as high as 81% in Niger in 2011.

Losses are not evenly distributed. The microdata reveals substantial heterogeneity in who bears the burden of crop losses. Plots managed by women are more frequently affected and suffer larger losses than those managed by men — a gap partly explained by women farming smaller and lower-elevation plots, with differential access to inputs and land playing a further role. Poorer households are also disproportionately exposed: those in the wealthiest decile are about 4.3 percentage points less likely to record a crop loss and lose about 6.6 percentage points less of their harvest when they are affected. Losses have also become more common over time, with the estimated likelihood of a plot incurring a loss increasing by close to 10 percentage points over the 11-year period studied. This temporal trend appears driven by a higher prevalence of smaller, more frequent shocks rather than increasingly severe individual events.

Farmers face multiple shocks simultaneously. A further insight from the microdata is that crop losses rarely stem from a single source. Multiple shocks are recorded in every country and year covered, and in some cases several shocks affect the same farm in a single agricultural season — ranging from 1.5% of farms in Tanzania in 2014 to 21% in Ethiopia in 2018–2019. Drought is the most common shock, recorded on an estimated 19–22% of plots, but irregular rains, floods, and pests also contribute substantially and their relative prevalence varies considerably across countries, regions, and years. Floods, while less frequent, cause disproportionately large damage — reducing crop production on affected plots by 62% on average. This diversity and co-occurrence of shocks has important implications for both measurement and policy: survey instruments need to be designed to capture multiple loss causes simultaneously, and resilience-building interventions cannot focus on a single hazard type.

Smaller and less visible events matter most. One of the most policy-relevant findings is that the aggregate burden of crop losses is driven largely by events that never appear in global disaster databases. Wollburg et al. (2024b) show that the microdata document damages from droughts and floods worth USD 5.1 billion more than what is recorded in EM-DAT across the same countries and years, affecting between 145 and 170 million people — more than four times the number reported in macro statistics. These discrepancies are not primarily explained by large, well-documented disasters being undercounted. Rather, they stem from a large number of smaller, more localized adverse events that are widespread and economically significant at the household level but fall below the minimum thresholds for inclusion in disaster inventories. Importantly, these are the very events that disproportionately affect poor, rural smallholders whose losses are uninsured and rarely captured by sources that disaster inventories rely on.

Microdata and macro-data are complementary, not competing. The findings do not imply that macro-level disaster inventories such as EM-DAT are without value — they provide broad, continuous, global coverage that microdata cannot match. Rather, the two sources capture different aspects of disaster impacts and are strongest in different contexts. Macro-data perform well for large, salient events that trigger international media coverage and formal emergency declarations; microdata are better suited to capturing the cumulative burden of frequent, small, and localized shocks that affect poor and marginalized populations. As Wollburg et al. (2024b) conclude, improving microdata systems — through more flexible and higher-frequency data collection, greater harmonization of survey instruments, and systematic integration of geospatial data — is essential to ensure that the full extent of climate-related crop losses is visible in the data that inform policy on disaster risk reduction, food security, and the loss-and-damage agenda.

6. Survey Requirements for Crop Loss Measurement

Despite the methodological challenges documented in this guidance note and the open research questions that remain, the evidence reviewed makes clear that survey microdata are indispensable for understanding the true scale, distribution, and drivers of disaster-related crop losses — precisely because they capture what aggregate statistics cannot: the frequent, localized, and often small adverse events that collectively impose the heaviest burden on the poorest and most vulnerable farming households. While more methodological research is needed before a definitive best-practice module for damages and losses measurement can be prescribed, the body of evidence reviewed here is already sufficient to inform concrete improvements to existing survey designs.

For measuring crop production losses through household surveys, this guidance note has reviewed four approaches, each with distinct strengths and limitations that practitioners should be fully aware of before designing a survey or interpreting results. No single approach can be considered best practice in isolation: the land area and crop damage approach is scalable and easy to implement but prone to satisficing and perceptual bias; enumerator assessments provide an independent observational check but are operationally demanding and cannot themselves be considered a gold standard; post-planting harvest expectations are plot-specific and low-cost but endogenous to past shock experience; and past yield or unaffected plot data offer an objective reference point but are rarely available at the frequency and granularity required. Crucially, the limitations of each approach are different in nature, which means that where one tends to fail, another may perform better — and it is precisely this complementarity that makes combining them valuable.

Practitioners are therefore encouraged to use these proxies as complementary lenses on the same underlying phenomenon — each capturing a different dimension of what was lost and why — and treat convergence across approaches as a signal of confidence and divergence as a prompt for scrutiny. The same logic applies to loss attribution: plot-level, household-level, and community-level shock questions each capture a different signal, and no single source alone is sufficient to confidently attribute losses to specific disaster types. Understanding the strengths and limitations of each tool reviewed in this note is not merely a technical exercise — it is the foundation for designing surveys that produce credible, policy-relevant estimates of disaster-related crop losses. The survey design requirements and suggested enhancements for each approach, summarized in Table 2, translate this understanding into practical guidance for 50x2030 and similar survey programs.

Integrating crop loss measurement into agricultural household surveys requires a set of structural and content conditions to be in place. These are discussed below.

6.1 Visit Structure

Measuring crop losses using the approaches reviewed in this document ideally requires a minimum of two visits per agricultural season. The post-planting harvest expectation question (Approach 4) is best collected before harvest-season shocks materialize, so that expectations reflect the farmer's genuine anticipation of yield rather than an assessment already influenced by damage that has occurred. The area and damage loss quantification questions (Approach 1) and cause-of-loss attribution questions must be collected after harvest is complete. However, it is important to note that Approach 1 — the core loss quantification module — can be implemented in a single post-harvest visit, without any post-planting data collection. This is a relevant consideration for the 50×2030 country surveys, and other national agricultural surveys, that operate on a single-visit schedule: while a single-visit design precludes the use of post-planting harvest expectations (Approach 4) as a triangulation tool, it does not prevent the collection of the planted area loss and plant productivity loss questions, which remain fully feasible and are the minimum requirement for any crop loss measurement effort.

Where enumerator assessments (Approach 2) are incorporated into survey implementation, an additional operational consideration arises regarding visit timing. For an enumerator assessment to be meaningful, the plot must be visited while physical evidence of crop losses is still observable — ideally at or shortly before harvest, when damaged and destroyed plants remain visible in the field. This requirement can be met by scheduling an **additional interim visit** at harvest time specifically for the enumerator

Table 2. Survey Design Requirements and Suggested Enhancements for Crop Loss Measurement and Attribution

Survey design element	Approach	Minimum requirement	Suggested enhancement
LOSS QUANTIFICATION			
Planted area loss question	Land area & crop damage (Approach 1)	*"Approx. what % of [PLOT] planted with [CROP] was harvested?"* — asked at post-harvest visit, per crop per plot	Visual aid (pictogram scale) to anchor percentage responses; clearly differentiate from productivity question in enumerator training
Plant productivity loss question	Land area & crop damage (Approach 1)	*"What is the % of damage on [CROP]?"* — asked at post-harvest visit, per crop per plot; trust post-harvest over post-planting reports	Clearly differentiate from area questions or consider merging into a single anchored loss question to reduce overlap and satisficing
Full-loss imputation variables	Land area & crop damage (Approach 1)	Plot area, labor inputs (family and hired), fertilizer and seed values, agricultural asset index, plot dummies (irrigation, intercropping, ownership), plot manager gender, household size, livestock ownership, electricity access, urban/rural classification, elevation, topographic wetness index, distance to road and population center	Apply 100-draw multiple imputations and cross-validate imputed values against yields from similar plots with partial losses in the same season
Post-planting harvest expectation	Post-planting expectations (Approach 4)	*" How much [CROP] do you expect to harvest from [PLOT] during the [REFERENCE AGRICULTURAL SEASON], assuming no weather, pest, or other types of damage?*— asked at post-planting visit, per crop per plot	Add priming question anchoring expectation to a shock-free scenario; flag cases where expectations already reflect early-season damage
Enumerator assessment	Expert assessments (Approach 2)	Structured visual inspection protocol with standardized training across field teams; inter-rater reliability checks during fieldwork	Crop condition comparator (progressive damage photographs) as enumerator calibration tool; double-reporting sub-sample for quality validation alongside crop cuts

Survey design element	Approach	Minimum requirement	Suggested enhancement
Past yield / unaffected plots	Past harvest data (Approach 3)	Collect consistent plot-level yield data across survey rounds to build time series; flag rounds affected by shocks to avoid downward bias in baseline	Annual data collection cycles; econometric or machine learning models to predict attainable yield controlling for input intensity, soil quality and plot management
LOSS ATTRIBUTION			
Plot-level attribution question	Attribution — minimum	*"Why was the area harvested less than the area planted?"* and *"What was the main cause of damage on [CROP]?"* — per crop per plot; allow up to two reasons; comprehensive shock list covering drought, irregular rains, floods, pests, crop disease, hail and wildfire	Shock identification visual card shown to farmer at attribution question to standardize interpretation across respondents
Household-level attribution question	Attribution — complementary	*"Was your household affected by [SHOCK] in the last 12 months?"* — for all key shock types	Cross-tabulate with plot-level reports to flag inconsistencies; use as corroborating signal rather than primary attribution source
Community-level attribution question	Attribution — complementary	Congregation-based module on the most significant adverse events in the last two to three years	Compare plot and household reports to identify systematic divergence; use as area-level contextualization of plot-level findings
Geospatial linkage	Attribution — complementary	GPS coordinates disseminated at enumeration area level (offset to protect anonymity); routine linkage to freely available rainfall products	Plot-level GPS coordinates; privacy-conserving geolocation protocols for public data release; extend linkage beyond rainfall to flood extent mapping and vegetation stress indices as products become available

assessment; **anticipating the post-harvest visit** to coincide more closely with the harvest period, is not recommended.

6.2 Level of Data Collection

Loss measurements must be conducted at the **plot-crop level**. The area harvested, the percentage of crop damage, the realized harvest quantity, and the cause of loss must be recorded separately for each crop on each plot. Farm- or household-level aggregates are insufficient for computing the compound loss estimate and cannot support the plot-specific imputation of full losses.

For reliable attribution of losses to specific disaster types, plot-level cause-of-loss questions are the minimum requirement. Household-level shock reports and community-level event information provide complementary corroborating signals that improve confidence in attribution and help identify unreliable observations.

6.3 Complementary Data Points

For plots with complete crop failure, attainable yield cannot be directly observed and must be estimated through imputation. Several approaches are available, as discussed in Section 3.1, ranging from simple imputation from similar plots to regression-based methods. Where a regression imputation approach is used — which is among the more robust options available — a specific set of covariates is required: plot area, non-hired and hired labor inputs, fertilizer and seed values, an agricultural asset index, plot-level management dummies (irrigation, intercropping, ownership, pesticide use), gender of the plot manager, household size, livestock ownership, electricity access, urban/rural classification, elevation, topographic wetness index, and distances to the closest population center and road. Ensuring these variables are collected in the same dataset as the loss questions therefore significantly expands the analytical options available to practitioners when dealing with full-loss plots.

6.4 Plot Area Measurement

Plot area is a critical variable in crop loss assessment. In the compound loss formula, it serves as the denominator for yield calculations and the scalar for converting per-hectare loss estimates into absolute production losses. More specifically, the planted plot area is needed to derive the attainable yield from the realized harvest and to compute both planted area losses and plant productivity losses as described in Section 3.1. An inaccurate area measure therefore propagates directly into the loss estimate, regardless of how carefully the other variables are collected.[13]

For this reason, plot area should be measured objectively using GPS-based devices rather than relying on farmer self-reports. Farmer-reported plot areas are known to be systematically biased — with evidence suggesting that farmers can underestimate the smallest plots by more than 300% (Carletto et al., 2017) — and reliance on self-reported estimates would introduce measurement error directly into the loss calculation. GPS-based area measurement provides a cost-effective and largely unbiased alternative and is already standard practice across all household-sector 50x2030 instruments, making it a readily available enabling condition for crop loss measurement in surveys operating within that framework.

6.5 GPS Coordinates

Beyond plot area measurement, the collection of GPS coordinates adds significant analytical value specifically for disaster-related crop loss measurement. Linking survey data to gridded geospatial data products enables the use of objectively measured environmental conditions as an alternative source for shock identification, not influenced by household characteristics or behaviors, and allows practitioners to cross-validate farmer attribution reports, flag cases where self-reports diverge substantially from measured conditions, and disentangle genuine differences in disaster impact from perceptual noise — a distinction that survey data alone cannot resolve. Although plot-level GPS coordinates are valuable for the data producer and owner, in practice only household coordinates aggregated to an offset enumeration area location can typically be publicly disclosed. Michler, Josephson, Kilic & Murray (2021) find no discernible effect of different coordinate obfuscation methods on estimates of the relationship between weather and agricultural production, concluding that publicly available remote sensing weather products are currently too coarse in resolution for obfuscation to make a substantial difference in which grid cell a household falls in, and that gauge-and-satellite merged products perform consistently well across a wide variety of settings. This suggests that meaningful geospatial linkage for shock attribution may remain feasible

[13] This point is worth nuancing in light of evidence from Abay, Abate, Barrett & Bernard (2019), who show that yield estimates can exhibit greater error when only the denominator — plot area — is measured objectively while the numerator — harvest quantity — continues to rely on farmer self-report, compared to settings where both components are measured consistently. Whether the same dynamic applies to loss estimation under Approach 1 is an open question: in this approach the realized yield, itself derived from a self-reported harvest quantity and a GPS-measured plot area, serves as the basis from which the attainable yield is recovered through the compound loss formula. An asymmetric error profile between numerator and denominator could therefore propagate into the attainable yield estimate and ultimately into the loss figure. This suggests that, where resources allow, using crop cut data for the realized yield — rather than farmer self-reports — would reduce this source of asymmetric error and produce a more internally consistent basis for recovering the attainable yield. This is an additional argument for the crop cutting methodological study proposed in Section 7.

even under standard data disclosure constraints — though this inference extends beyond the scope of the paper, which focuses on yield estimation rather than shock attribution specifically.

Box 5 below summarizes the current coverage of the minimum requirements identified in this section against the standard 50×2030 instruments, indicating which are already in place, which represent priority additions, and where gaps remain for future expansion.

Box 3. Integrating Crop Loss Measurement into 50×2030 Surveys: Current Coverage and Gaps

The 50×2030 survey system is well positioned to support disaster-related crop loss measurement. Most of the structural prerequisites identified in this guidance note are already embedded in the standard instruments, meaning that adding comprehensive crop loss measurement is largely a matter of targeted additions rather than a redesign. The table below summarizes current coverage against the minimum requirements identified in this note.

On the enabling side, data are already collected at the parcel-plot-crop level across, GPS-based plot area measurement and coordinates are standard practice, and the majority of variables required for full-loss imputation are available. The planted area loss question — capturing the share of planted area that was harvested — is already present in the post-harvest crop roster. Additionally, the Non-Farm Income and Living Standards (ILS-HH) questionnaire's shocks and coping section provides a natural home for household-level shock attribution with only targeted expansion of the shock type list required.

Importantly, while the two-visit structure is the standard 50×2030 baseline, many country implementations operate on a single-visit schedule. This does not preclude crop loss measurement: the planted area loss question and, once added, the plant productivity loss question can both be collected at the post-harvest visit alone. The post-planting harvest expectation question is the only element that strictly requires a two-visit structure.

The most important gap is the plant productivity loss question, which captures yield reduction on the harvested but damaged portion of the plot and is not yet part of the standard instruments. Its addition must be carefully sequenced relative to the existing planted area question — with the damage percentage question explicitly anchored to the harvested area — to ensure the two loss components are measured on distinct and non-overlapping portions of the plot and do not risk double-counting.

Requirement	Currently in 50×2030?	Instrument[14]	Notes
Plot-crop level data collection	✓ Yes	CORE, ILP, PME, MEA	Standard parcel-plot-crop structure
GPS-based plot area measurement	✓ Yes	CORE, ILP, PME, MEA	Required denominator for compound loss formula
GPS coordinates for geospatial linkage	✓ Yes	CORE, ILP, PME, MEA	Enables linkage to geospatial products
Variables for full-loss imputation	✓ Largely yes	CORE, ILP, PME, MEA	Larger set of variables available in ILP and PME
Planted area loss question	✓ Yes	CORE, ILP, PME, MEA post-harvest crop roster	Share of planted area harvested; already collected
Household-level shock attribution	✓ Partial	ILS-HH shocks and coping	Present but requires expansion of shock type list
Two-visit structure	✓ Yes (recommended); single-visit feasible for Approach 1	CORE, ILP, PME, MEA	Many country implementations operate on single-visit schedule; planted area and productivity loss questions collectible at post-harvest only; Approach 4 requires two visits
Plant productivity loss question	✗ Not yet	—	Priority addition; must be anchored to harvested area to avoid overlap with planted area question; feasible in single-visit surveys
Post-planting harvest expectation question	✗ Not yet	—	Requires two-visit structure
Community-level shock information	✗ Not yet	—	No community module in any standard instrument

[14] For details on the 50x2030 questionnaires, visit: www.50x2030.org/resources/survey-instruments. Design documentation is found in 50x2030 Initiative (2024).

7. Discussion – Future Methods Research

The measurement of disaster-related crop losses through survey microdata has advanced considerably through the work reviewed in this guidance note, but a number of important methodological gaps remain. The priorities identified below are organized from most to least innovative, distinguishing where possible between directions explicitly identified in past work and extensions proposed here. The first two priorities — geospatial data integration and image-based AI approaches — are considered the most promising frontiers and are discussed in greater depth accordingly.

Integrating geospatial data for shock attribution and loss imputation. The evidence reviewed in this guidance note consistently points to geospatial data integration as the single most promising avenue for improving both shock attribution and attainable yield estimation, and one that can be pursued with data infrastructure that already exists. Markhof, Ponzini & Wollburg (2022) show that farmer self-reports of drought exposure align with rainfall-based indices primarily in years with severe, widespread events and diverge considerably in more normal seasons — with a non-negligible share of the variation in self-reports driven by differences in perception rather than actual exposure. Wollburg, Markhof, Bentze & Ponzini (2024b) call explicitly for greater integration of survey and geospatial data, noting that too few surveys currently capture and disseminate plot-level geolocations, and that where they do, deliberate imprecision introduced for privacy reasons can hamper analyses. Future research should assess the value-added of systematically linking plot-level survey records to high-resolution geospatial products — including rainfall indices, flood extent maps, and vegetation stress indices — for cross-validating farmer attribution reports, flagging unreliable observations, and constructing objective shock exposure indicators that do not rely on farmer recall. As the range of available geospatial products expands and their spatial resolution improves, this approach can be progressively extended beyond rainfall to other shock types.

Beyond attribution, geospatial and remote-sensing data hold significant untapped potential as inputs into **econometric or machine learning models for predicting attainable yields on disaster-affected plots** — complementing or replacing the simpler imputation approaches reviewed in Section 3.1. Future research should develop and validate predictive models that combine plot-level survey covariates — input use, management practices, soil characteristics, crop variety — with geospatial environmental variables to produce plot-specific attainable yield estimates, and should systematically assess which configurations produce the most accurate out-of-sample predictions across different shock types, crop systems, and contexts. Realizing the full potential of geospatial integration requires both methodological investment and data governance progress, including the development of privacy-conserving mechanisms that allow access to true plot geolocations for research purposes while protecting respondent confidentiality.

Image-based AI and multimodal models for loss measurement. A second high-priority and largely untested frontier is the use of field photographs and multimodal AI systems — artificial intelligence models capable of processing both images and text simultaneously — for crop loss attribution and quantification. During a survey visit, enumerators could be asked to photograph the plot or a sample of plants within the subplot, capturing visible evidence of crop damage — discoloration, lodging, pest infestation, incomplete cob development — at the time of observation. These images could then be processed using computer vision models trained to identify and classify crop damage types and estimate their severity, providing an independent, image-based signal that could be compared against both farmer self-reports and enumerator assessments. For attribution, image-based classification of damage symptoms — distinguishing, for example, the visual signatures of drought stress from those of pest damage or waterlogging — could reduce reliance on farmers' subjective interpretation of shock type, which the evidence reviewed in this note identifies as a significant source of attribution noise. For quantification, models trained on labelled crop cut data could in principle predict the share of damaged or destroyed plants from plot photographs, offering a scalable approach to loss estimation that goes beyond what percentage-scale recall questions can achieve. Critically, the crop cutting context provides the ideal setting for developing and validating this line of research: plot photographs collected during crop cut visits alongside objective yield measurements and plant counts would provide the labelled training data needed to develop, train, and evaluate image-based loss models against an objective benchmark. While this approach remains largely untested in smallholder crop loss measurement in low-income settings, the rapid advancement of multimodal AI capabilities and the growing availability of labelled agricultural imagery make it a genuinely promising venue for methodological experimentation, and one that deserves dedicated investment in pilot studies.

Establishing an objective benchmark for crop loss measurement. Farmer self-reports and enumerator assessments diverge in ways that cannot be fully explained, and neither can be confidently proclaimed accurate without an independent benchmark. Crop cut data is the closest available approximation, but its potential for loss measurement has not yet been systematically exploited. A dedicated crop cutting methodological study — designed to collect crop cut yields alongside farmer self-reports, enumerator assessments, plant count data, and plot photographs on the same plots — would help address several of the open questions identified in this guidance note simultaneously, and would provide the foundational labelled dataset needed to develop and validate both the geospatial integration and image-based AI approaches described above. Future methodological research should use this kind of integrated design to assess the accuracy of different loss proxies across a range of shock types, severities, and farming contexts, and to explore whether extending the standard crop cutting protocol to record separately the number and weight of partially damaged and fully destroyed plants allows reliable estimation of both planted area losses and plant productivity losses.

High-frequency and within-season mixed mode data collection for shock attribution and quantification. A recurring limitation in loss attribution is that post-harvest surveys ask farmers to recall the timing, type, and severity of shocks that may have occurred weeks or months earlier. Future research should evaluate the feasibility and value-added of higher-frequency, within-season data collection — through lightweight phone survey modules— specifically designed to capture shock occurrence close to the time of the event, before memory fades and before farmers rationalize losses ex-post. Beyond improving attribution accuracy, within-season data collection would also improve the precision of loss quantification by capturing eventual replanting of damaged areas—information that is currently lost in the annual survey cycle.

Developing and testing visual and structured survey instruments. As picture-based diagnostic across all plots could not be scalable, near-term improvements to the accuracy of self-reported loss estimates can be pursued through redesigned survey instruments that reduce the cognitive demands of loss estimation. Future research should develop and field-test concrete survey innovations — including pictogram-based loss scales, crop condition comparator photographs, shock identification cards, and seasonal calendar aids for attribution questions — and evaluate their effect on the reliability and accuracy of self-reported loss estimates through controlled survey experiments.

Improving the accuracy of post-planting harvest expectations and farmer-reported counterfactuals. Markhof, Ponzini & Wollburg (2022) identify farmers' post-planting harvest expectations as a promising but imperfect proxy for attainable yield, noting that the factors underlying expectation formation remain a largely unexplained behavioral black box, and call for quasi-experimental research designs to better understand how expectations can be elicited more accurately. A related and potentially more promising approach — not yet systematically tested in the literature — is to ask farmers directly at the post-harvest visit how much they believe they would have harvested had the shock they reported not occurred. Because it is asked after harvest — when the farmer has full knowledge of what actually happened and can reason directly about the shock's impact — this counterfactual question may produce a more grounded estimate of the attainable yield than post-planting expectations formed under uncertainty. Whether farmers can form reliable counterfactual judgments of this kind remains an open question that warrants dedicated methodological testing, ideally through a survey experiment collecting this question alongside post-planting expectations, area and damage reports, and crop cut data on the same plots.

Extending the analysis to perennial crops and non-crop agricultural losses. The methodology and findings reviewed in this guidance note apply primarily to annual crops. Perennial crops introduce additional complexity due to the possible cumulation of shocks across seasons. Similarly, livestock losses, damage to agricultural assets, and storage losses are important components of total agricultural disaster impact that the current framework does not cover. Extending the methodology to these domains is an important priority for future work.

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