METHODS & TOOLS BRIEFS

Weather on the Ground: Improving Rainfall Data with In-Situ Sensors

50x2030
DATA-SMART AGRICULTURE

JUNE 2026

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BACKGROUND

Accurate measurement of rainfall is essential for understanding agricultural productivity and climate risks, yet many data sources often fail to capture weather conditions at the scale that farmers experience. This brief draws on a field study in Uganda that tests whether low-cost, in-situ weather sensors can complement existing data by improving the measurement of local rainfall patterns and enabling more reliable analysis of the relationship between weather and agricultural outcomes.

KEY POINTS

- **Rainfall drives smallholder risk, but it is often mismeasured:** Sparse ground networks and reliance on satellite rainfall products can miss the local extremes and within-season dynamics that matter most for crops, livelihoods, and early warning systems.

- **Low-cost sensors can provide high-quality ground-level data:** In Uganda, in-situ sensors closely matched professional weather stations and significantly outperformed satellite products in capturing rainfall variability and extremes.

- **Measurement choices can change policy conclusions:** Using different rainfall data sources can lead to very different—and sometimes misleading—results in weather-yield analysis, underscoring the importance of improving measurement before drawing policy conclusions.

- **A hybrid approach can be a practical path forward:** Satellite data remain indispensable for their broad coverage and historical records, but they can benefit from local ground truth via denser local ground observations. Further testing across tools and contexts will be key to inform scaling.

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WHY HYPERLOCAL WEATHER DATA MATTERS

Across rainfed smallholder systems, the way rainfall falls within a season — its timing, intermittency, and extremes — can matter as much as seasonal totals for yields and livelihoods. As climate risks intensify, the credibility and usefulness of agricultural statistics depend on whether weather inputs capture the dynamics that farmers actually experience on their fields.

In many low-income settings, rainfall is frequently mismeasured. Ground station networks are sparse, unevenly distributed, and costly to maintain and equipment failures and budget constraints can lead to prolonged data gaps and discontinuities in the historical record. As a result, analysts and operational systems often rely on remotely sensed precipitation products. These products are valuable: they provide consistent coverage and, in many cases, long historical records. But they come with important limitations. Because they represent averages over grid cells — often several kilometers — they tend to miss intense, localized rainfall events, smooth out short-duration heavy precipitation, and misalign rainfall timing at the scale of a farmer's field. A growing body of research has begun to document these limitations systematically (Michler et al., 2022; Josephson et al., 2025).

For efforts to strengthen agricultural data systems and support evidence-based policy in low-income countries, this is not an abstract concern. If the weather inputs feeding into yield models, shock diagnostics, and targeting decisions are noisy or biased, then downstream analyses can point to the wrong places, the wrong timing, and the wrong interventions.

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A NEW POSSIBLE APPROACH: DENSIFYING OBSERVATIONS AT LOWER COST

Uganda's national meteorological network, operated by the Department of Meteorological Services (DMS), provides essential data but faces constraints common to many national systems: sparse geographic coverage, high maintenance costs, and the difficulty of replacing faulty equipment in a timely manner — all of which can lead to data gaps and discontinuities in the historical record.

The Uganda Climate, Land Area, and Soil Study (CLASS) tested whether lower-cost, rapidly deployable commercial in-situ sensors[1] could complement conventional networks, improve survey-linked analysis, and strengthen the evidence base for climate-smart agricultural policy.

In August 2023, the project deployed 80 sensors across five districts in Eastern and Northern Uganda: Buyende, Kamuli, Kaliro, Apac, and Dokolo. Five devices were co-located with professional DMS meteorological stations to allow direct validation of sensor readings, while the remaining 75 were installed at host farms within enumeration areas where an agricultural household survey was also conducted. The distribution of these sensors followed the random selection of survey enumeration areas, ensuring balanced geographic coverage across districts and a direct link with the household survey design (Figure 1). Within each selected area, site placement was guided by several practical criteria to ensure correct functioning and safeguarding of the devices (e.g., atmospheric exposure free from obstructions, adequate connectivity for data transmission, physical security, and the willingness of host farmers and local institutions to accommodate and help maintain the equipment).

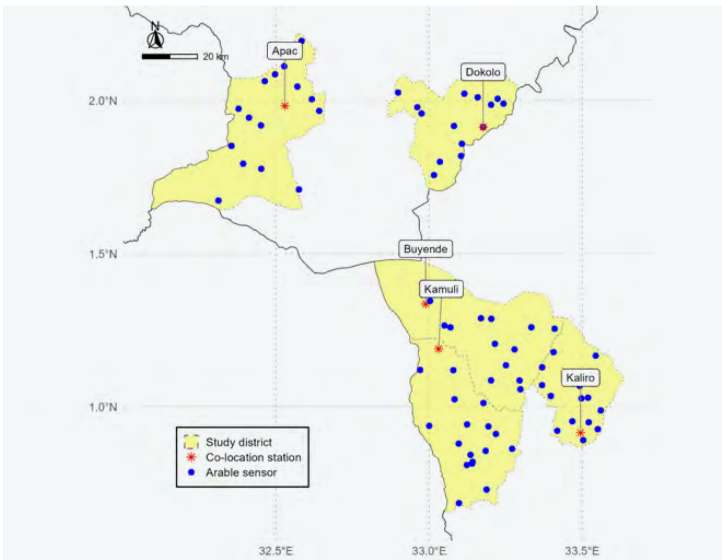


FIGURE 1 — Sensor deployment across the five study districts in Uganda, showing locations of in-situ sensors and distinguishing co-located validation sites from EA-level sites. Source: Paolantonio et al., 2026 (forthcoming).

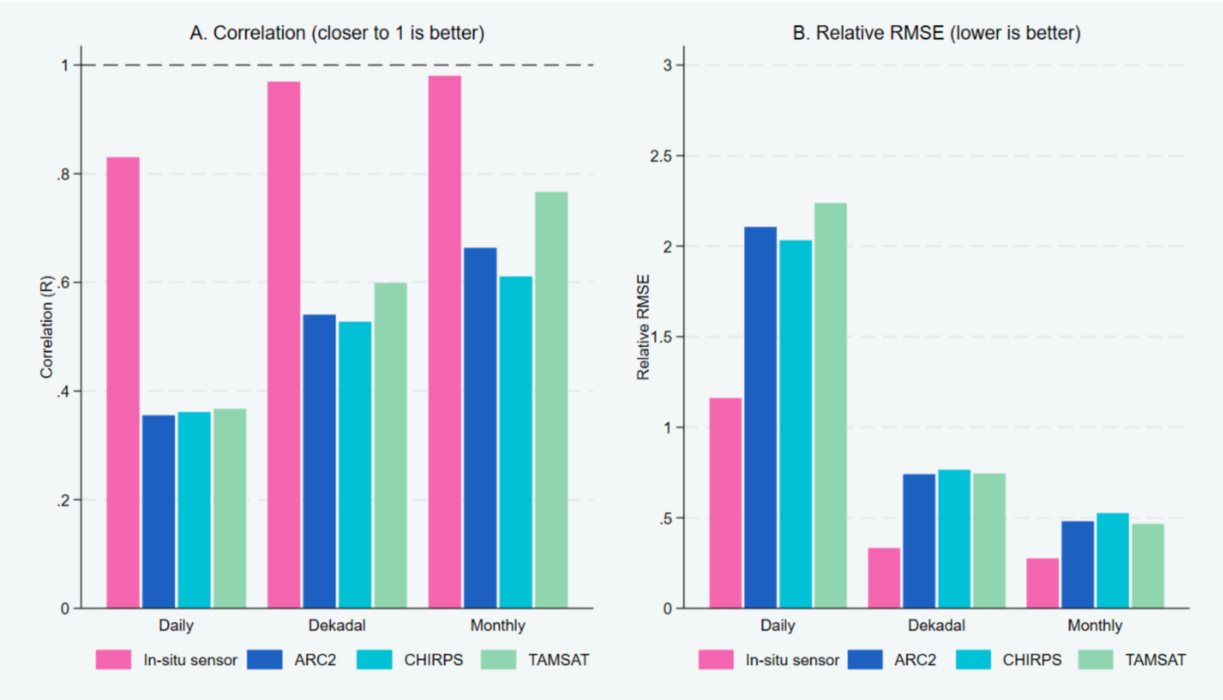
1 In this study, the Arable Mark 2 sensor was used. At roughly USD 900 per unit at the time of the study, the Arable Mark 2 was approximately 25 times cheaper than a professional automatic weather station of the type used by the Uganda DMS, making it realistic to contemplate deploying sensors in the kind of dense configurations that sparse professional networks cannot support. Mention of this specific product does not constitute an endorsement; other comparable low-cost sensors and solutions are available and warrant testing in similar contexts.

WHAT THE EVIDENCE SHOWS: SENSORS PERFORM, SATELLITES SMOOTH

56% of heavy rainfall events were correctly detected by the sensor

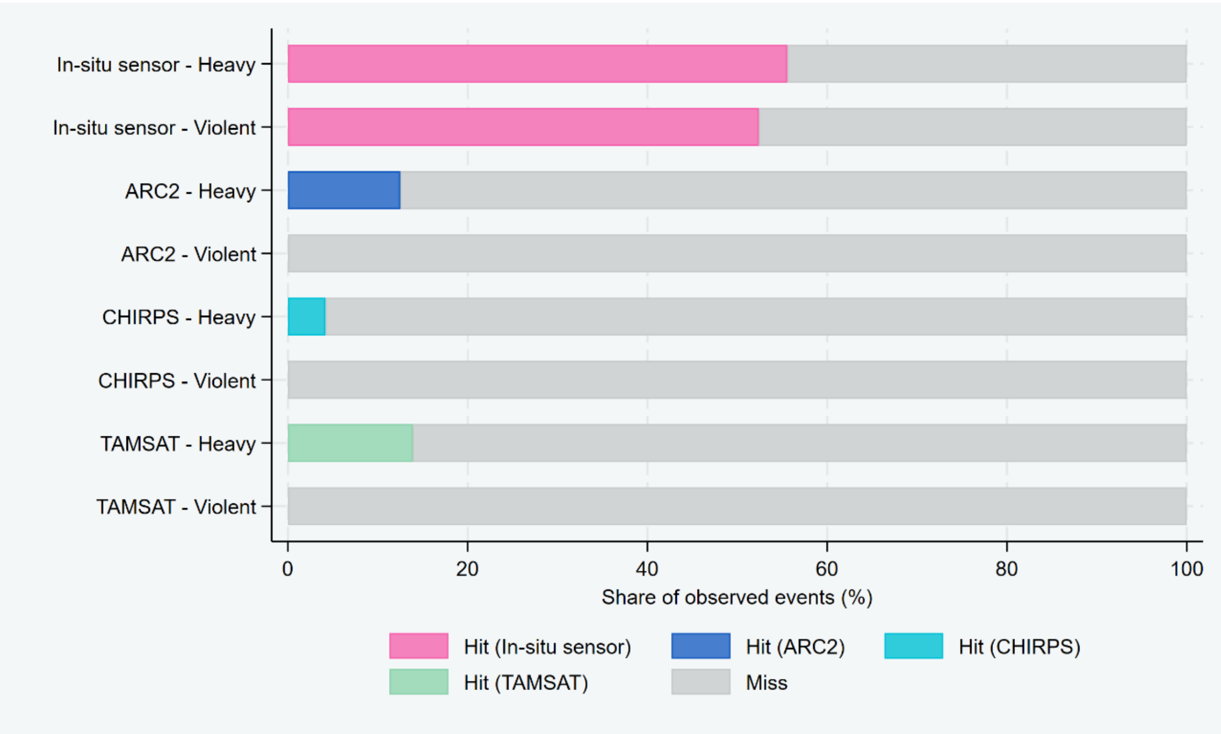
Across multiple metrics and time scales, sensor rainfall measurements closely matched readings from professional DMS stations. Correlation exceeded 0.8 at the daily level, and 0.9 at dekadal and monthly resolutions respectively, with relative Root Mean Square Error (rRMSE) values well below those of any satellite product at all temporal scales (Figure 2). Critically, the sensor correctly detected around 56% of heavy rainfall events and over 50% of violent events — compared to detection rates of 5–14% for heavy events and 0% for violent events across all three satellite products (Figure 3). This is an important proof of concept: lower-cost commercial devices can provide ground-truth-quality rainfall inputs for climate analytics and official statistics in areas where station networks are thin.

FIGURE 2 — Rainfall measurement performance by data source and temporal resolution. The figure shows the values of two performance metrics — correlation coefficient (R) and relative root mean square error (rRMSE) — for the commercial in-situ sensor deployed in the study and three satellite-based gridded products (ARC2, CHIRPS v2, TAMSAT), each evaluated against readings from professional meteorological stations over the period 1 September 2023 – 30 June 2024. Metrics are shown separately for three temporal resolutions (daily, dekadal, and monthly) and averaged across four co-location sites in Uganda. Higher correlation and lower rRMSE values indicate closer agreement with the professional station benchmark. Produced based on Figure 4 in Paolantonio et al., 2026 (forthcoming).



The contrast with satellite-based gridded products was stark, particularly for the indicators that matter most for climate-risk analysis. ARC2, CHIRPS v2, and TAMSAT showed systematically higher errors and lower correlation at all resolutions (Figure 2) and failed entirely to detect violent rainfall events while missing most of heavy ones (Figure 3). Where the field-level sensors recorded intense rainfall, satellite products often registered only moderate or light rainfall or missed the event altogether. This matters because it is precisely these extremes — heavy rains and prolonged dry spells — that are most relevant for crop stress, early warning, and applications such as agricultural insurance. A data system that smooths them out risks systematically underestimating the exposure of farmers to weather shocks.

FIGURE 3 — Detection of heavy and violent rainfall events by data source. The figure shows the share of observed heavy (20–39.9 mm/day) and violent (≥40 mm/day) rainfall events correctly detected (hits) or missed by the commercial in-situ sensor deployed in the study and three satellite-based gridded products (ARC2, CHIRPS v2, TAMSAT), over the period 1 September 2023 – 30 June 2024. Each bar represents the percentage of total observed events in that intensity category that were either detected (colored segment) or missed (gray segment) by each product, relative to the professional meteorological station benchmark. Values are aggregated across four co-location sites in Uganda. A hit is recorded when both the evaluated product and the benchmark agree that rainfall falls within the same intensity category on a given day. Produced based on Figure 5 in Paolantonio et al., 2026 (forthcoming).



WHEN MEASUREMENT CHOICES CHANGE POLICY CONCLUSIONS

Photo via World Bank.

Perhaps the most consequential finding from the Uganda study concerns the role of measurement quality in statistical inference: the choice of rainfall data source does not just affect the precision of estimates: it can change conclusions entirely about the relationship between rainfall and yields.

The study estimated the relationship between seasonal rainfall indicators and maize yields at the plot level, using each data source in turn. When plot-level outcomes were linked to in-situ sensor data, statistically significant associations were rare across the preferred model specification: at most 1 out of 20 rainfall variables tested produced a significant coefficient, and that result was consistent with agronomic expectations (Figure 4). When the same analysis was run using satellite products, apparent significance was far more common — up to 10 significant variables for CHIRPS v2 and 8 for TAMSAT. Agronomic consistency did not follow: ARC2 produced zero agronomically consistent results out of 4 significant ones, CHIRPS v2 only 1 out of 10, and TAMSAT 3 out of 8 (Figure 4). Results varied in magnitude, direction, and significance across satellite products and model specifications, and were frequently difficult to reconcile with what agronomic knowledge would predict.

The interpretation is sobering: some apparently significant weather-yield relationships found in studies using satellite data may partly reflect measurement noise rather than genuine agronomic signals. This is worth keeping in mind when interpreting findings from contexts where ground-level rainfall data is sparse. This underscores the value of investing in better measurement before drawing strong policy conclusions.

The null results produced by the field-level sensor data are themselves informative. The 2023 growing season in Uganda was unusually wet — influenced by El Niño conditions — which likely compressed the variation in rainfall-driven crop stress that would normally generate detectable yield responses. A well-measured null result in a low-stress season carries a useful message: the rainfall indicators tested may not have been the primary drivers of yield variation in that period. This is a more actionable finding than a spurious significant result pointing in an unpredictable direction.

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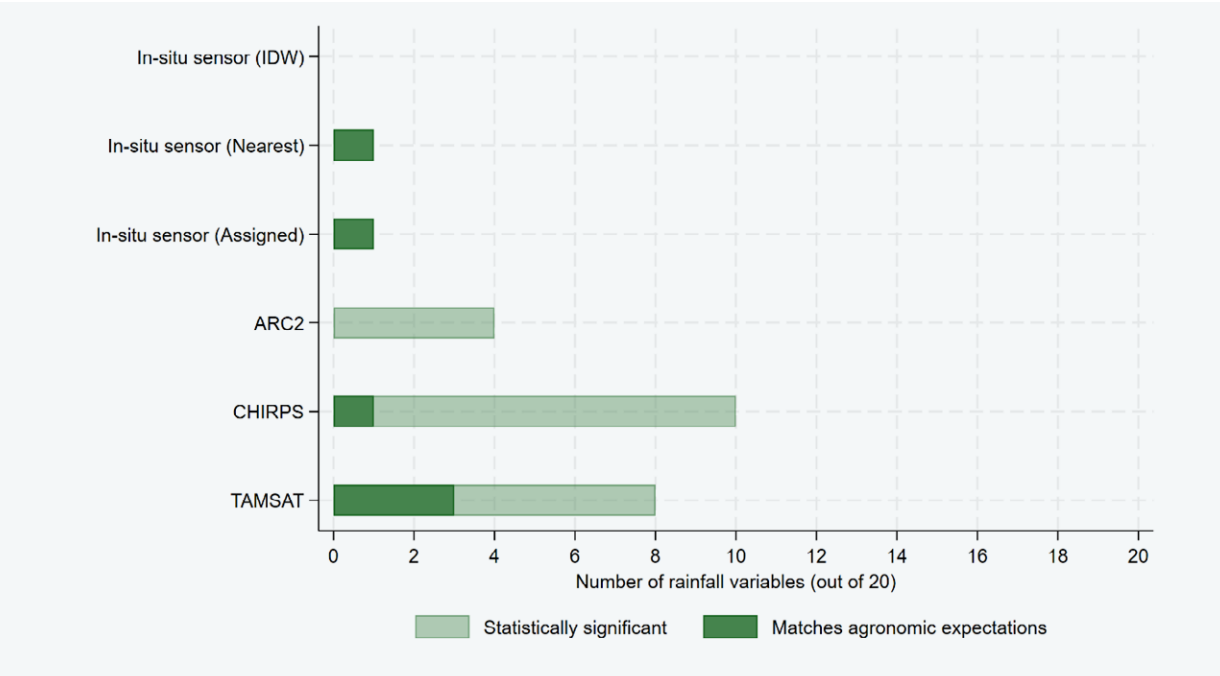
FIGURE 4 — Statistical significance and agronomic consistency of rainfall-yield associations by data source. The figure shows, for each rainfall data source, the number of rainfall variables (out of 20 tested) that produce a statistically significant coefficient in plot-level maize yield regressions (lighter bar), and among those, how many are significant in a direction consistent with agronomic expectations (solid bar). For the in-situ sensor data three version are shown, reflecting different approaches to matching sensor readings to plot-level data: "Assigned" assigns data from the sensor installed within the enumeration area where the household is located; "Nearest" matches each plot to the geographically closest sensor; "IDW" applies inverse distance weighting to interpolate rainfall values from multiple nearby sensors, with closer devices receiving greater weight. Satellite-based gridded products (ARC2, CHIRPS v2, TAMSAT) are matched to plots using their geographic coordinates. Results are based on plot-level maize yield regressions for the 2023 growing season. Results are from the preferred model specification; see Paolantonio et al., 2026 (forthcoming) for full specification results. Produced based on Figure 8 in Paolantonio et al., 2026 (forthcoming).



OPERATIONAL LESSONS: WHAT IT TAKES TO IMPLEMENT SUCCESSFULLY

These findings on measurement quality and statistical inference are only as credible as the data collection process that underpins them. The Uganda pilot generated early observations on what field deployment involves in practice. These should be read as reflections from a first test rather than established best practice, and many are specific to the technology used in this study.

Plan for real-world disruptions and invest in data management from the start. Data gaps are likely over the deployment period. The pilot experienced sensor failures, transmission interruptions, and other issues that left gaps in the data. A functioning data pipeline should be in place before data collection begins and cover aspects such as data ingestion and storage, routine quality checks, documentation of missingness and any imputation rules used for analysis.

Allow sufficient time for deployment and align with the survey and agricultural calendar. Installation may take longer than expected due, for example, to logistical constraints and the onboarding of local teams. In this pilot, delays caused some devices to miss early planting dates, requiring imputation for early-season data. Pre-deployment connectivity checks, routine monitoring, and clear troubleshooting protocols can help minimize unplanned data loss.

Community engagement and caretaker presence matter. Sustained operation depend on trust and local ownership. Early engagement with community leaders, clear communication about the purpose of the devices, and the assignment of local caretakers for routine inspection and safeguarding were important enabling factors that should be budgeted for from the start.

Partner with national meteorological services. Early engagement brings local expertise, institutional buy-in, and opportunities for validation and data sharing as well as longer-term sustainability. In Uganda, co-locating sensors with DMS stations was essential for validating the technology and offers a pathway to building local technical capacity with new weather observation technologies.

A DIRECTION WORTH EXPLORING FURTHER

The evidence from Uganda does not argue for replacing satellites with ground sensors — nor does a single pilot provide sufficient basis for broad prescriptions. What it does suggest is that a hybrid approach, combining the broad coverage of satellite products with the precision of local ground observations, is worth exploring further. Figure 5 offers one way of visualizing how these complementary data sources could be organized.

> The evidence from Uganda suggests a hybrid approach: combining the broad coverage of satellite products with the precision of local ground observations

Satellite products remain indispensable for their geographic reach and long historical records, but this pilot indicates they may benefit from local ground truth — particularly for detecting extremes and producing more credible estimates of weather–yield relationships. Low-cost commercial in-situ sensors represent one possible tool for this, though additional testing and comparative evidence across tools, densification approaches, and contexts would be valuable before drawing conclusions about what works best and where. Some potentially promising directions suggested by this pilot include:

- Deploying low-cost commercial sensors alongside agricultural surveys to enable better-measured analysis of weather impacts on agricultural and socioeconomic outcomes in data-sparse settings.

- Using sensor data to assess and, where appropriate, correct biases in satellite products for specific locations and seasons.

- Exploring how improved local rainfall data could strengthen early warning systems, particularly for extreme events that satellite products tend to miss.

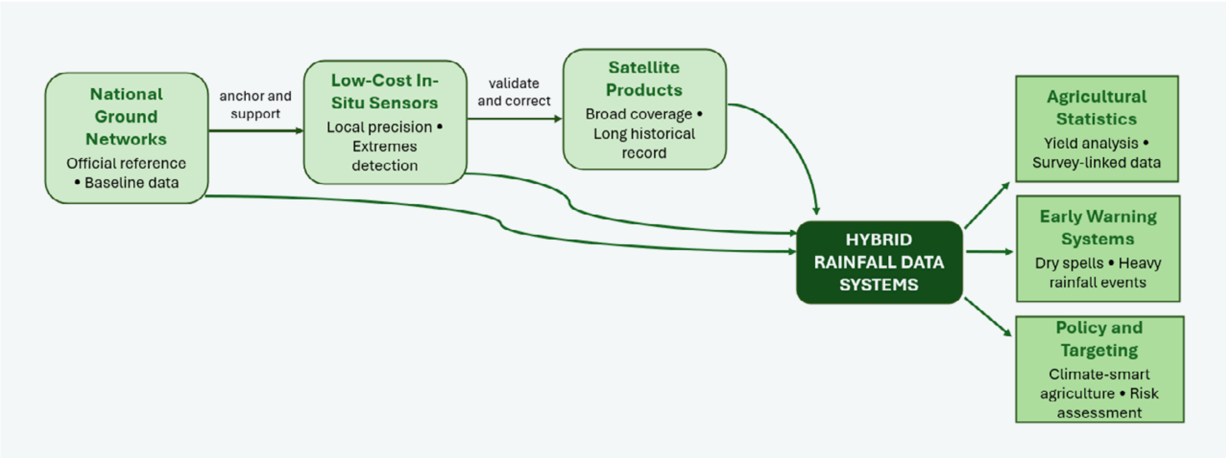


FIGURE 5 — A hybrid approach to rainfall data for agricultural analysis. Low-cost in-situ sensors and national ground networks complement satellite products by providing local precision and enabling validation and bias correction. Together, these data sources can support more credible agricultural statistics, early warning systems, and policy decisions. Note: this schematic reflects a possible direction suggested by the Uganda pilot rather than an established operational framework.

At a fraction of the cost of professional automatic weather stations, low-cost commercial in-situ sensors offer an attractive entry point for densifying ground observations. Whether this cost advantage is justified relative to alternative approaches is a question that deserves further investigation, as is the long-term field performance of these products under varying conditions. What the Uganda experience does confirm is that the cost of relying exclusively on noisy rainfall data is not trivial: it can lead to measurement artifacts that masquerade as policyrelevant findings.

Learn more:

The findings in this brief are drawn from the following outputs of the Uganda Climate, Land Area, and Soil Study (CLASS) under the 50x2030 Initiative:

- Weather or Not: Low-Cost In-Situ Sensors to Strengthen Climate-Smart Agricultural Data and Decisions (Paolantonio et al. 2026, *forthcoming*).
- 50x2030 Technical Note on Using In-Situ Sensors for Weather Monitoring and Data Collection. (*forthcoming*)

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