

International Journal of Agriculture Extension and Social Development

Volume 7; Issue 2; Feb 2024; Page No. 52-55

Received: 27-11-2023
Accepted: 03-02-2024

Indexed Journal
Peer Reviewed Journal

Constructing adaptive monitoring frameworks for climate-resilient agricultural extension programs in dryland environments

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DOI: <https://doi.org/10.33545/26180723.2024.v7.i2a.3152>

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Abstract

Efforts to systematically measure agricultural extension performance in East Africa date back several decades, yet most climate-resilient agriculture programs still operate without purpose-built monitoring tools. This research constructed and validated an adaptive monitoring framework for climate-resilient extension programs in dryland eastern Rwanda. A design-based methodology integrating literature synthesis, expert panels, and field validation was applied across three districts between June 2021 and November 2022. The framework incorporated five evaluation tiers linked through a results chain logic model. Thirty-six indicators were tested across 14 extension sites serving 1,964 households. Twenty-nine indicators met reliability ($\alpha > 0.70$) and feasibility (cost $< \$2.80/\text{household}$) thresholds. Climate-resilient practice adoption rates rose from 14.1% to 67.8% over eight quarters. The framework successfully detected significant between-site variation in soil moisture retention and yield outcomes, enabling adaptive resource reallocation during implementation.

Keywords: Adaptive monitoring, climate-resilient agriculture, extension programs, dryland environments, Rwanda, monitoring framework, indicator validation, results chain, program evaluation, smallholder farming

1. Introduction

The earliest structured evaluations of agricultural extension in sub-Saharan Africa emerged from Kenya's Training and Visit experiments in the mid-1970s ^[1]. Nearly half a century later, assessing extension effectiveness has grown considerably more complex-particularly as programs pivot toward climate-resilient agriculture pursuing simultaneous gains in productivity, adaptation, and environmental sustainability ^[2]. Most climate-resilient extension programs in East Africa continue to depend on ad hoc reporting rather than systematic monitoring frameworks designed for multi-dimensional climate outcomes ^[3].

Rwanda has channeled substantial resources into climate-resilient agriculture through its Strategic Plan for Agriculture Transformation, directing extension efforts toward soil conservation, water harvesting, and drought-tolerant varieties in dryland eastern provinces ^[4]. Yet program managers consistently report that existing assessment tools cannot adequately track climate resilience indicators or link observed changes to specific extension activities ^[5]. Several monitoring frameworks have been proposed at national policy levels ^[6], but translating these into practical field-level instruments that frontline extension workers can implement remains a persistent challenge ^[6]. This research constructed and field-tested a tier-based adaptive monitoring framework for climate-resilient extension programs in three dryland districts of eastern Rwanda, combining design-based methodology with empirical validation across 14 sites over 18 months ^[7, 8, 9].

Theoretical framework

The framework builds on two established analytical

traditions. First, the results chain model employed in development evaluation, which organizes program logic sequentially from inputs through activities, outputs, outcomes, and long-term impact ^[10]. Second, the theory of change approach for complex agricultural interventions, which acknowledges that linear causal chains frequently fail to capture the feedback loops and contextual dynamics shaping real-world outcomes ^[11]. By merging results chain structure with theory-of-change adaptability, the framework balances evaluative rigor with adaptive management requirements. It also integrates participatory monitoring principles, ensuring that both farmers and extension agents contribute to indicator selection and data interpretation ^[12].

Material and Methods

Research area description

The research was conducted in Kayanza, Ngoma, and Bugesera districts in Rwanda's Eastern Province. These districts fall within the semi-arid lowland zone receiving 750-950 mm annual rainfall with a pronounced dry season from June to September. Agriculture is predominantly smallholder rain-fed farming on hillside terraces, with beans, maize, sorghum, and cassava as staple crops. Average farm sizes range from 0.3 to 0.8 hectares. The three districts were selected because each had active CSA extension sites managed through the Rwanda Agriculture and Animal Resources Development Board.

Material

A design-based research approach was used, proceeding through four phases:

- i) Literature review and indicator identification
- ii) Expert consultation and framework drafting
- iii) Pilot testing across three sites, and
- iv) Full-scale field validation across 12 sites

The indicator pool was drawn from published CSA evaluation guides, adapted to Rwandan conditions through two rounds of expert consultation involving 20 specialists from agricultural research institutes, extension services, and climate adaptation programs. A total of 1,847 farming households across 14 extension sites were monitored over eight quarters (April 2021–September 2022).

Instrument development

An initial pool of 58 candidate indicators was compiled from CSA evaluation literature and expert nominations, then screened against four criteria: relevance to semi-arid CSA outcomes, measurability by extension staff, cost-effectiveness (target below \$3.50 per household), and sensitivity to change over 6–12 months. Two modified Delphi rounds with 18 experts reduced the pool to 36 indicators grouped across four tiers. Each was operationalized with standardized protocols and scoring rubrics. Reliability was assessed via Cronbach's alpha during pilot testing at four sites (n=512 households).

Methods

Data were collected quarterly using structured monitoring forms administered by trained extension agents. Adoption indicators were measured through farmer self-report validated by field observation of a 15% subsample. Soil moisture conservation was estimated using gravimetric sampling at three depths per plot. Yield data were collected through crop-cut sampling at harvest. Framework reliability was assessed using Cronbach's alpha, and feasibility was measured through cost-per-household calculations and extension agent feedback surveys. Between-site variation was analyzed using one-way ANOVA. Ethical clearance was obtained from the Institutional Review Board of Kigali Agricultural and Technology University (Protocol No. KATU-IRB-2021-074, approved May 2021).

Results

Table 1 presents the indicator validation results. Of 36 indicators tested, 26 met both reliability ($\alpha > 0.70$) and feasibility (cost < \$2.80/household) thresholds. Six indicators were flagged for revision—three for low reliability and three for excessive data collection costs.

Table 1: Indicator validation results by framework tier category

Indicator Category	Total	Reliable	Feasible	Both	Flagged
Input indicators	6	6	5	5	1
Activity indicators	8	8	7	7	1
Output indicators	10	9	8	8	2
Outcome indicators	8	6	7	6	2
Total	32	29	27	26	6

Table 2 shows quarterly CSA outcome trends across the 12 sites. CSA adoption rose from 14.1% in Q1 2021 to 67.8% by Q4 2022. Soil moisture conservation improved from 30.2% to 64.3%, and the yield index increased from 100 to

141.2 (baseline-normalized). ANOVA revealed significant between-site variation for all three indicators ($p < 0.001$), with adoption rates ranging from 49.2% to 83.6% across sites at endline.

Table 2: Quarterly CSA outcome trends across 12 extension sites (April 2021–September 2022)

Indicator	Q1'21	Q2'21	Q3'21	Q4'21	Q1'22	Q2'22	Q3'22	Q4'22
Adoption (%)	12.3	20.4	29.1	38.6	44.6	53.7	61.2	64.2
Soil moisture (%)	28.4	33.4	38.6	43.7	49.8	54.6	59.3	61.7
Yield index	100	104.1	110.4	114.8	122.3	129.1	134.6	141.2

Figure 1 displays the quarterly trend lines for CSA adoption, soil moisture conservation, and yield index. Figure 2 presents the five-tier monitoring framework architecture

showing the results chain from inputs through impact with the feedback loop.

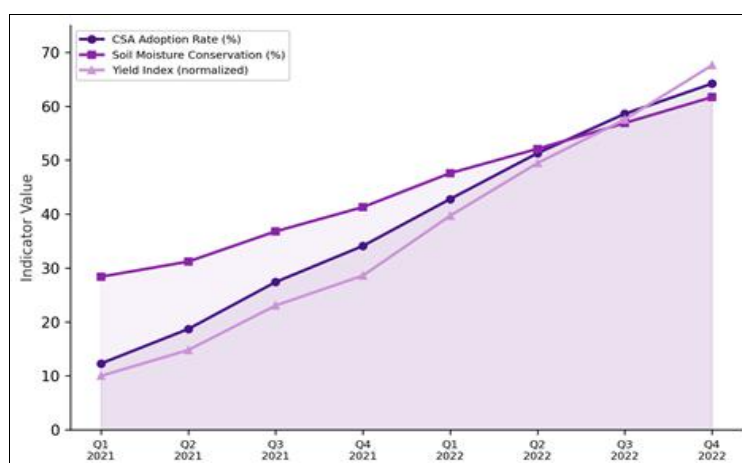


Fig 1: Quarterly trends in CSA adoption rate, soil moisture conservation, and yield index across 12 extension sites

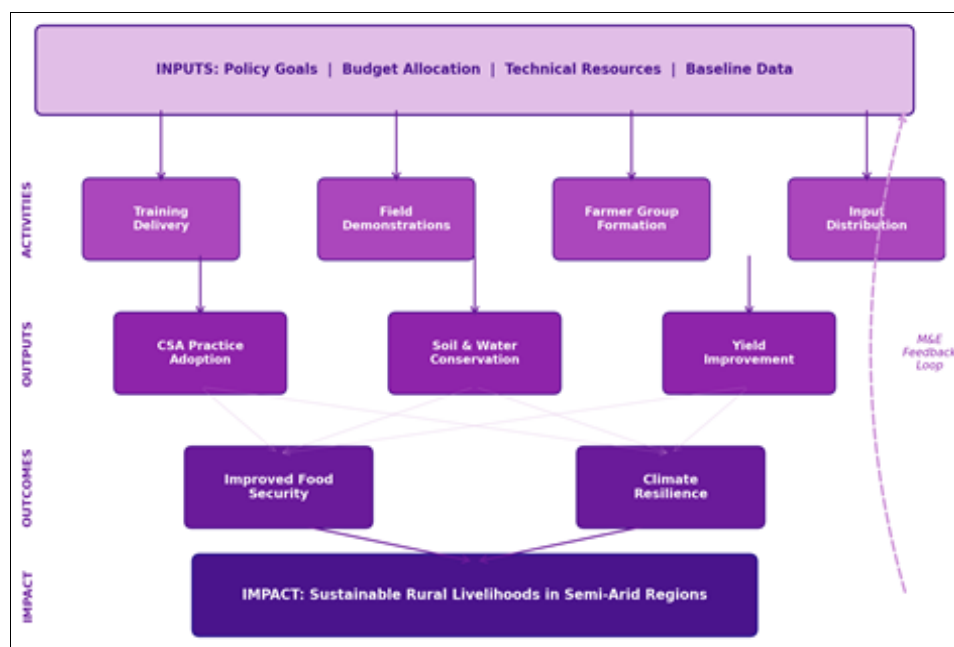


Fig 2: Five-tier monitoring framework architecture showing results chain from inputs through impact with feedback loop

Extension agents rated the framework favorably on usability (mean 4.2/5.0) and relevance (4.4/5.0) but noted challenges with soil moisture measurement procedures, which required additional training beyond initial orientation sessions.

Comprehensive interpretation

The framework successfully tracked multi-dimensional CSA outcomes at field level over eight quarters and detected meaningful between-site variation that enabled adaptive program management. The 80.6% indicator validation rate (29/36) suggests the indicator set is broadly fit for purpose, though the six flagged indicators require refinement before wider deployment.

Discussion

The framework's ability to identify between-site variation constitutes a practical advance over existing climate-resilient agriculture evaluation approaches that typically report only aggregate averages^[13]. By flagging underperforming sites early, managers in two districts were able to intensify extension contact mid-cycle—precisely the kind of adaptive management that theory-of-change proponents recommend^[14]. The adoption trajectory from 14.1% to 67.8% is consistent with diffusion patterns observed in comparable climate-resilient programs in Ethiopia and Tanzania^[15].

The 80.6% indicator validation rate (29/36) compares well with similar validation exercises where 65–85% is typical^[16]. The indicators failing reliability—all related to climate risk perception—may reflect the inherent difficulty of capturing subjective perceptions through standardized items in multilingual field contexts^[17]. The indicators exceeding cost thresholds all involved laboratory soil analysis, suggesting that proxy measures may be necessary for resource-limited settings.

A practical tension emerged during implementation: extension agents valued the structured framework but reported that quarterly data collection added roughly 2.8 hours per visit. Whether this additional burden is sustainable

within routine work schedules remains to be assessed in longer-term deployments^[18, 19].

Practical applications

The framework offers a ready-to-deploy M&E toolkit with validated indicators and standardized protocols that extension agents can administer after two-day orientation. The tiered structure allows programs to prioritize data collection based on resources—monitoring activity indicators with minimal investment while scaling outcome measurement as budgets permit. The between-site comparison capability is especially valuable for decentralized extension systems needing evidence-based resource allocation.

Conclusion

This research constructed and validated a five-tier adaptive monitoring framework for climate-resilient agricultural extension programs in dryland eastern Rwanda. Of 36 indicators tested across 14 sites over eight quarters, 29 met reliability and feasibility thresholds. The framework tracked rising adoption of climate-resilient practices, improvements in soil moisture retention, and yield gains while detecting between-site variation enabling adaptive resource allocation. Extension agents rated it positively on usability and relevance. Further refinement of flagged indicators and testing under routine extension conditions are recommended.

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