SPARC

Supporting Pastoralism and Agriculture in Recurrent and Protracted Crises

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SUPPORTING PASTORALISTS THROUGH AFRISCOUT STEWARD AND REGEN: APPENDICES

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About SPARC

Climate change, armed conflict, environmental fragility and weak governance and the impact these have on natural resource-based livelihoods are among the key drivers of both crisis and poverty for communities in some of the world's most vulnerable and conflict-affected countries.

Supporting Pastoralism and Agriculture in Recurrent and Protracted Crises (SPARC) aims to generate evidence and address knowledge gaps to build the resilience of millions of pastoralists, agro-pastoralists and farmers in these communities in sub-Saharan Africa and the Middle East.

We strive to create impact by using research and evidence to develop knowledge that improves how the UK Foreign, Commonwealth and Development Office (FCDO), donors, non-governmental organisations, local and national governments and civil society can empower these communities in the context of climate change.

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ACRONYMS

AIPW	augmented inverse probability weighting
AMP	adaptive multi-paddock
ANCOVA	analysis of covariance
AS	AfriScout
ATE	average treatment effect
cRCT	cluster randomised control trial
FGD	focus group discussion
IE	impact evaluation
ITT	intent-to-treat
KII	key informant interview
M&E	monitoring and evaluation
MD	Mahalanobis distance
NDVI	Normalised Difference Vegetation Index
OLS	ordinary least squares
RGU	regenerative grazing unit
SMA	standardised month anomaly
SPARC	Supporting Pastoralism and Agriculture in Recurrent and Protracted Crises

APPENDIX A. AFRISCOUT Steward AND AFRISCOUT Regen MODELS AND INTERVENTIONS: EXECUTIVE SUMMARY

This appendix describes AfriScout (AS) Steward and AS Regen and the interventions evaluated in the study. For the purpose of this research, the intervention associated with AS Steward was only implemented in Kenya, while the intervention associated with AS Regen was only implemented in Ethiopia. Both interventions are information-based, paired with support from Field Agents. However, there are differences in the information provided, how it is delivered and the support delivered by Field Agents. These differences are discussed in the next subsections.

Both AS Steward and AS Regen are successors to the initial AS prototype, developed in 2013 by Project Concern International (now Global Communities). This prototype provided pastoralists with **paper maps of traditional grazing areas, overlaid with remotely sensed data derived from the Normalised Difference Vegetation Index (NDVI)**. NDVI is a measure of the density of vegetation in an area. These satellite-powered maps were distributed every ten days as paper printouts through local government and community networks. The AS prototype was rolled out in Ethiopia and Tanzania.

A three-year study of the AS prototype conducted by Fordham University (Machado et al., 2020) showed positive results in terms of map accuracy, uptake and outcomes for herds but some limitations of the paper-based distribution system. In particular, the use of the maps decreased over time, due to challenges with the distribution of hard copies which resulted in only one map for at least 100 households. Distribution also faced frequent delays.

Building from the findings and limitations of the paper-based prototype, AS was remodelled as a smartphone app, making it possible for pastoralists to access the maps from their own pockets. The AS Steward app has undergone two iterations: AS Steward, which disseminates pure information and can be considered the direct successor to the initial AS prototype; and AS Regen, which disseminates both information and hands-on grazing planning advice. While a mobile app exists for AS Steward, a mobile app for AS Regen is currently under development.

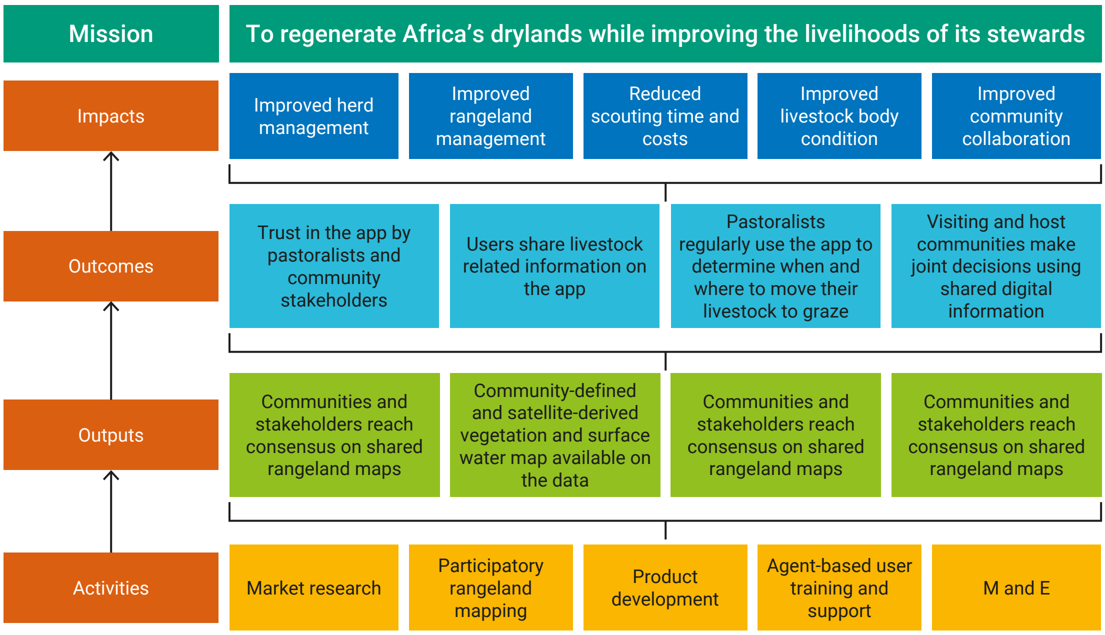
Theory of change, and description of AS Steward and AS Regen

Figure A.1 illustrates the theory of change for AS Steward and Figure A.2 for AS Regen. Leaving aside the details of each model presented in these figures, AS's theory of change is based on two key mechanisms: 1) the ability of AS information – and in the case of AS Regen, advice – to affect pastoralists' decision-making; and 2) the ability of new decision-making practices to bring about positive outcomes for rangelands, herd conditions and pastoralists' well-being.

As a livelihood, pastoralism is particularly vulnerable to climate change and adverse weather events. This threatens the food security of pastoralist communities. AS interventions seek to improve the livelihoods and resilience of these communities by providing information and targeted advice on migration, grazing patterns and rangeland management.

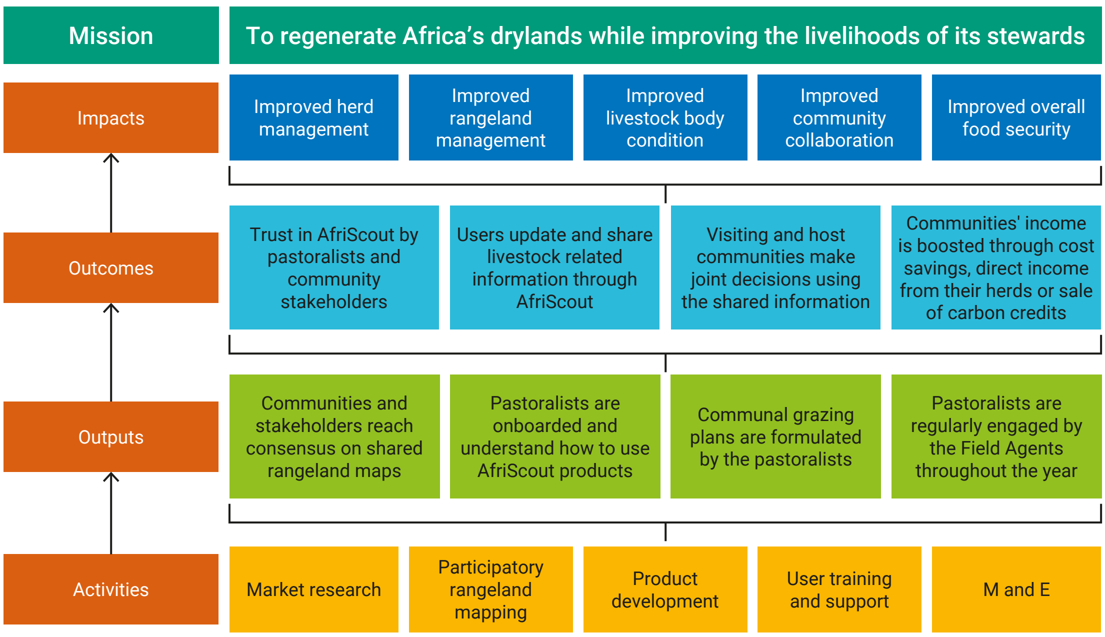
The following subsections detail the differences between AS Steward and AS Regen, as well as the information provided by the interventions and their operations on the ground. As discussed in the main SPARC Technical Report, the impact evaluation (IE) looked at the causal effects of AS Steward in Kenya and AS Regen in Ethiopia.

FIGURE A.1. AS Steward THEORY OF CHANGE



Source: Authors' own.

FIGURE A.2. AS Regen THEORY OF CHANGE



Source: Authors' own.

AS Steward (Kenya)

AS Steward provides satellite data on vegetation conditions, as well as ground-sourced alerts within a given community-defined grazing area. Individuals and groups determine how best to use that information to make better decisions for their herd and the grasslands they rely on. AS Steward does not seek to provide advice; rather, it provides real-time information that pastoralists can integrate into their decision-making around grazing, migration and other aspects of herd and rangeland management (such as the decision to vaccinate or sell livestock and conflict avoidance).

The app presents near real-time rangeland conditions, updated every ten days, based on NDVI data. It displays current vegetation conditions and surface water within a subscriber's traditional grazing areas. AS and Hoefsloot Spatial Solutions collaborate to create the maps, using satellite data, that are easy to interpret and useful for pastoralists. The maps incorporate NDVI data from the Meteostat satellite Second Generation SEVIRI instrument and the Sentinel-1 and Sentinel-2 satellites. In areas that receive Field Agent support, AS Field Agents provide guidance on ways to differentiate between grass, shrubs and invasive species (which show up as green on maps). For example, pastoralists can identify areas that are consistently green throughout the seasons (which are more likely to be shrubs or invasive species) by comparing the latest maps with previous versions. The AS team used human-centred methods throughout AS Steward's design process, starting with paper-based maps and evolving into the mobile app.

The app's main features include:

- **Localised grazing maps:** Each community is linked with a local grazing map that represents their customary rangelands. While this masks conditions in areas outside accepted traditional grazing lands, it significantly expands the user's field of vision within their grazing areas.
- **Current vegetation conditions:** Vegetation cover is represented with intuitive colour variations and updated every ten days.
- **Surface water detection:** Surface water that is at least 10 metres in diameter is detected and represented.
- **Peer-to-peer grazing alerts:** Users can share geolocated alerts on their maps to notify others in the area about predators, restricted grazing, conflicts and other information important for migration decision-making.
- **Migration distance calculation:** The app can calculate the distance between any two points on the map. Users can select points by tapping on the map.
- **Terrain view:** Terrain view allows users to see land contours like hills, mountains and valleys.
- **Historical maps:** The app shows a scrolling gallery of maps for the previous 12 months for that area, so users can see how vegetation cover changes.

All of these features have been optimised for low-price smartphone devices in low-connectivity environments. The app can work entirely offline and only requires connectivity once every ten days to automatically update the maps and peer-to-peer alerts. AS Steward was designed for populations with low levels of literacy, with a heavy focus on iconography. Additionally, users can change the language settings to one of six East African languages.

Figure A.3 shows a screenshot of the mapped area of Isiolo in Kenya. Areas in dark green are locations where the NDVI values are higher, and hence the vegetation conditions are better. Areas in brown show locations with low NDVI values, hence worse vegetation conditions. Grazing areas are displayed in red.

As well as being able to check the NDVI data in a given area, users can use terrain view to see changes in topography and calculate distances between locations. This enables them to better plan migration routes (see Figure A.4). The app also stores vegetation map updates from previous months, enabling subscribers to analyse seasonal changes in their local grazing areas.

The AS Steward app also integrates crowd-sourced indigenous knowledge; users can add geolocated 'Alerts' to the maps to flag instances and locations of disease, conflicts, water shortage, predators, restricted grazing and other hazards (Figure A.5).

The app is free to download via the Google PlayStore or a scannable QR code, and it is available to pastoralists in Kenya, Tanzania and Ethiopia. There are currently over 48,000 user accounts across all three countries (approximately 27,000 in Kenya; 14,000 in Ethiopia; 7,000 in Tanzania).

FIGURE A.3. SCREENSHOT OF THE AS Regen THEORY OF CHANGE

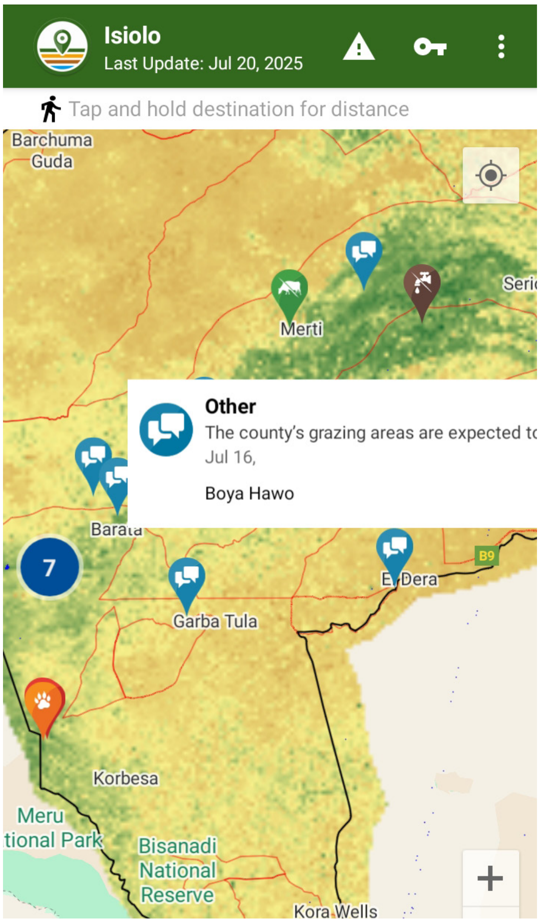


FIGURE A.4. SCREENSHOT OF THE AS Steward MOBILE APP TERRAIN VIEW

Photo credits: AfriScout.

FIGURE A.5. SCREENSHOT OF THE AS Steward MOBILE APP TERRAIN VIEW

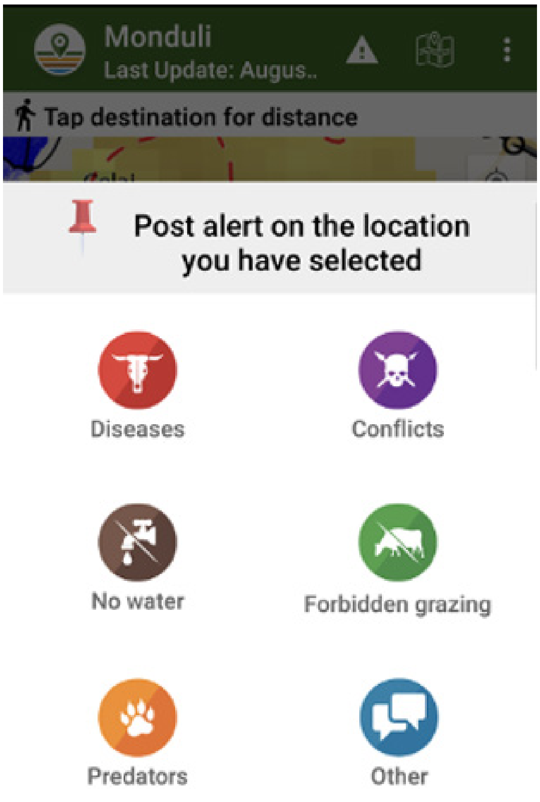


Photo credit: AfriScout.

AS Regen is an intensive, localised grazing module developed to provide hands-on grazing planning at a community level. It follows an adaptive multi-paddock (AMP) grazing approach. Under AS Regen, smaller regenerative grazing units (RGUs) are defined within communities (or clusters of communities) with direct stewardship responsibilities. Project-defined RGU boundaries closely align with suitable administrative structures such as *kebeles* (wards) and sub-*kebeles*. Each RGU is led by a management committee that, with the help of Field Agents, is responsible for creating community grazing maps and grazing plans, and for implementing them during the season. AMP grazing divides a rangeland into virtual paddocks, the aim of which is to increase the intensity and frequency of herd movement within rangelands in a practice more generally known as rotational grazing. AS Regen adapted traditional AMP to a much larger, landscape-level application. There are no physical fences around paddocks and many hundreds of people and thousands of animals are required to work in unison.

AS Regen (Ethiopia)

Global Communities is currently developing an app (in the beta-testing stage) to support AS Regen. The app will have two versions, tailored to the main intended users of AS Regen: RGU committee members and Field Agents. The first version will show the specific RGU's rangeland map and grazing plan map, with current active paddocks and upcoming movements. It may be possible to request other maps if migration to those areas is necessary. The Field Agent version will include RGU plans, updates and a monitoring component to record the number of livestock in each paddock. Unlike AS Steward, vegetation data is not currently included in the beta version of the AS Regen app, though Global Communities intends to work with partners to integrate vegetation information in the future.

Global Communities is also exploring the possibility of being able to facilitate RGUs to sell carbon credits through their activities, as an extra source of income.

Interventions evaluated

AS Steward

The AS Steward app can be downloaded for free, therefore it is accessible to both the treatment and control group. Consequently, the treatment intervention was defined as promotion of the app, along with the active engagement and training provided by Field Agents in the treatment clusters. It was considered relevant to provide structured training, in part because literacy and technological skill levels in pastoral communities are quite low compared to other parts of the country. Additionally, a detailed introduction and explanation of the AS Steward app is often required for pastoralists to understand and use it properly. Pastoral communities have also retained in-person interaction, which they trust more, especially when a new product/idea is being introduced to them. Novel interventions are often better welcomed when pastoralists see a familiar face explaining a product/idea in their local/traditional language. Previous internal studies also show that Field Agent support has resulted in faster and easier understanding of the app with more prolonged usage than other types of engagement.

Field Agents, who are recruited from the same communities, have specific responsibilities in treatment areas. They:

- actively recruit households in treatment clusters
- provide download and onboarding support as required to users (one-time only)
- regularly follow up with users, either in-person or via phone/SMS (bi-weekly)
- send targeted and scheduled engagement activities through the AS Hub Customer Engagement team, including push notifications, promotions and SMS nudges (bi-weekly)
- set targets for user enrolment and engagement in treatment clusters (monthly)
- review and approve crowd-sourced alerts before they are published on the app (ongoing).

Because the AS Steward app was launched in 2018, some study areas (both treatment and control) had already received some exposure before the start of the intervention. Results from the baseline survey (Causal Design, 2023) show that 12.8% of respondents in Kenya had used the app, and 90% to 97% of those individuals had already received some sort of training. However, this prior training differed from that provided to treatment clusters and described above. Since its launch in 2018, AS has promoted the download and use of the AS Steward app through a network of Field Agents. These agents have:

- marketed and promoted AS in their 'territory' (typically an entire mapped area, e.g., a region in Kenya)
- supported pastoralists in downloading the app
- provided initial onboarding/training in use of the app (this has not been formal training, nor has it been supported by a training manual or curriculum)
- provided ongoing engagement by troubleshooting problems or challenges.

Training provided through the treatment intervention was more intense and structured than previous app training. Field Agents helped users download the app and get acquainted with it, and they also engaged users and provided regular support throughout the length of the study.

AS Regen

Because AS Regen is not available as an app currently, only households located in treatment areas could experience any benefits from the intervention. As such, the evaluation of AS Regen looks at the provision of training and additional support, and more generally the impact of the AS Regen model.

As with AS Steward, Field Agents are critical in implementing AS Regen. Field Agents are given additional guidance and training to enable them to conduct multi-day community-level trainings on AS, regenerative grazing, carbon sequestration, community mapping, creating virtual paddocks and developing community grazing plans. Field Agents provide regular ongoing training, monitoring and support, and they collect data on herd movements regularly.

AS Regen is implemented in three key steps:

1. **Pre-launch:** Field Agents introduce the concept of regenerative grazing and establish RGU management structures.

    a. Field Agents conduct initial awareness-raising with leaders and community members about topics such as rotational grazing and rangeland management. A particular exercise used at this stage is the 'three circle' demonstration to show water retention in different types of soil (dry, with rain and with manure).

    b. After initial awareness-raising and community buy-in is obtained, Field Agents establish RGU committees. RGUs are formal committees with structured bylaws and enforcement powers. They typically comprise eight members who are appointees from both traditional and official leadership. Formal appointees include the *kebele* chair, *kebele* manager, a government extension agent and, in some cases, a women's or youth representative. Informal appointees include community members in traditional leadership roles, such as rangeland representatives, herd managers and water managers.

2. **Launch:** Field Agents lead community-led mapping exercises and develop RGU plans.

    a. Community-led mapping is an inclusive process to map out rangelands and community resources, and to decide how to divide these into paddocks. Community-led mapping is intended to be conducted deliberately to include the perspectives and participation of all community members, including women and youth.

    b. Based on findings from the community-led mapping, RGU committees develop initial regenerative grazing plans with the support of Field Agents. Grazing plans are then shared with the wider community in community meetings, to gather inputs from other households. Plans are revised based on this feedback.

    c. Once finalised, grazing plans are disseminated to the wider community in a multi-step process that involves various levels of leadership. Plan information is shared with cluster leaders, who then pass information to group or village leaders. These leaders pass information on to household heads, who share plan details with other household members, including herders and shepherds. Plans and rangeland maps are also documented and copies are shared with Field Agents and Global Communities, as well as being posted at *kebele* offices.

3. **Implementation and monitoring:** RGU committee members implement grazing plans. Ongoing adjustments are made as necessary, with support and monitoring from Field Agents.

    a. RGU committees are responsible for ensuring community members' adherence to the plan (mainly that people are using the right paddock and 'resting' paddocks are not being grazed). In cases of non-adherence, RGU committees undertake awareness-raising efforts with these households or even enforce financial penalties in accordance with RGU committee bylaws.

b. RGU committees meet regularly (typically monthly) and make adjustments to plans as needed, such as in response to changing weather conditions.

c. Field Agents conduct monitoring activities on a seasonal and monthly basis to confirm the status of pasture in paddocks. Data is sent to Global Communities.

Compared to AS Steward, AS Regen is supported much more intensively and therefore the intervention is very different. Field Agents are recruited from and embedded within two or three RGUs. An RGU closely aligns with suitable administrative boundaries and structures (e.g., a *kebele*, sub-*kebele*, sub-location, etc.). Under AS Regen, Field Agents are responsible for:

- administrative set-up, including facilitation and documentation of key activities such as community-led mapping, formation of a management committee, signing of bylaws and community agreements (one-time only)
- delivering the 'Village Instruction Series', which are trainings on climate change, carbon and regenerative practices (one-time only)
- initiating and providing ongoing management and support for RGUs to establish and adhere to seasonal grazing plans (monthly)
- ongoing monitoring and evaluation support, including collecting GPS points; documenting observations on the ground through photos, ground descriptions and grass measurements; and reporting on each RGU's number of animals per paddock (monthly)
- collecting seasonal data to set baselines and document changes (quarterly, at the start and end of the season).

To date, all Regen activities have been implemented and overseen by Field Agents without a dedicated mobile app. Grazing plans are implemented through the RGU management committee who determines and communicates with herders when it is time to move a herd from one paddock to another. However, the AS Steward app has also been available in Ethiopia in both treatment and control areas during the study period, although Field Agents do not provide any support related to this app. Because of this parallel access to both models, the study asked questions related to AS Steward among herders in Ethiopia.

AS Regen was implemented in three cohorts during the study period: Cohort 1 was launched in October–November 2022; Cohort 2 was launched in March–May 2023; and Cohort 3 was launched in March–May 2024.

Primary and secondary research questions

The overall goal of the IE was to identify the **attributable outcomes of AS use on pastoralist decision-making and the impact on rangeland conditions and herd conditions**. Table A.1 sets out specific primary and secondary research questions. The primary research questions were designed to elucidate the impact of AS, primarily on rangelands, herd conditions and grazing for AS Regen, and primarily on herd conditions and migration-related variables for AS Steward. Secondary research questions addressed the auxiliary outcomes of AS and investigated causal pathways.

The anticipated outcomes and goals of AS Steward and AS Regen were similar, but it is important to reiterate that, for each country, all research questions focused on either AS Steward (in Kenya) or AS Regen (in Ethiopia). In other words, in Kenya, all research questions focused on the *information services provided through AS Steward*, while all research questions in Ethiopia focused on *the grazing planning support provided through AS Regen*.

Furthermore, though all research questions were relevant for both models, some questions were pertinent to either AS Regen or AS Steward, or they manifested differently under the two. Table A.1 notes some of these intervention-specific nuances.

TABLE A.1. RESEARCH QUESTIONS

Research question	Notes
Primary research questions	
1. Does AS influence pastoralists' decision-making and behaviours around migration, grazing patterns and rangeland management?	AS Steward focuses on behaviours and decision-making; AS Regen focuses on grazing plans and adherence to the plan
2. What are the impacts of AS on rangeland conditions?[1]	Impact on rangeland conditions is more of a direct outcome for AS Regen than for AS Steward
3. What are the impacts of AS on herd conditions?	Applies to both AS Regen and AS Steward
Secondary research questions	
4. What are the specific features of AS used and what value do they provide?	This is only measured for AS Steward; AS Regen's app is under development
5. How do pastoralists integrate AS into their decision-making?	
6. How does AS affect collective decision-making, information sharing, cooperation and collaboration among pastoralist groups?	Effects anticipated to be higher for AS Regen than AS Steward
7. Does AS impact perceptions of rangeland management capacity for pastoralists?	Effects anticipated to be higher for AS Regen than AS Steward
8. Does AS reduce the expense and risks of scouting for pastoralists?	More relevant to AS Steward
9. Does AS impact the perceived prevalence of conflict for pastoralists?[2]	Both models anticipated addressing conflict indirectly by focusing on cooperation/ collaboration; AS Steward also addresses conflict more directly through pure conflict avoidance
10. What are the impacts of AS on pastoralist well-being?	
11. Does AS impact pastoralists' perceptions of their own well-being?	
12. How does AS affect human–wildlife encounters and wildlife conservation efforts?	More relevant to AS Steward than AS Regen

Source: Authors' own.

1 Findings for this question are largely based on perception, and where possible were triangulated with NDVI data. Based on the geolocation of the homestead and areas of migration, the evaluation examined the average vegetation conditions in those areas. The accuracy of the information for the areas of migration depends on the degree to which pastoralists can identify the specific areas where they migrated.

2 Given the difficulty of ascertaining comprehensive, objective information about the prevalence of conflict in pastoralist areas, findings for this research question relied on perception indicators. A robust set of quantitative and qualitative perception measures were used. The specific measures were discussed and agreed during the survey design phase.

Research questions were answered through a combination of qualitative and quantitative methods (see Research methodology section of the main report and Appendix C and Appendix D for more details). The qualitative findings are not as generalisable as findings from the quantitative survey, but they nonetheless provided additional triangulation, extra detail and validation for the quantitative findings, as well as revealing potential mechanisms driving the results. Table A.2 presents a mapping of methods and data sources that were used to answer each research question.

TABLE A.2. MAPPING OF RESEARCH QUESTIONS, METHODS AND DATA SOURCES

Research question	Impact evaluation (survey)	Qualitative inquiry (focus groups and interviews)	AS data (Google Analytics, CommCare, NDVI)[3]
Primary research questions			
1. Does AS affect pastoralists' behaviours and decision-making around migration, grazing patterns and rangeland management?	*		
2. What are the impacts of AS on rangeland conditions?[4]	*		*
3. What are the impacts of AS on herd conditions?	*		
Secondary research questions			
4. What are the specific features of AS used and what value do they provide?	*	*	
5. Does AS impact perceptions of rangeland management capacity for pastoralists?	*	*	
6. How do pastoralists integrate AS into their decision-making?		*	
7. How does AS affect collective decision-making, information sharing, cooperation and collaboration among pastoralist groups?		*	
8. Does AS reduce the expense and risks of scouting for pastoralists?	*		
9. Does AS impact the perceived prevalence of conflict for pastoralists?[5]		*	
10. What are the impacts of AS on pastoralist well-being?	*		
11. Does AS impact pastoralists' perceptions of their own well-being?		*	
12. How does AS affect human–wildlife encounters and wildlife conservation efforts?	*	*	

Note: * Denotes source to be used primarily.
Source: Authors' own.

3 The evaluation utilises data from the AS dashboard (collected through Google Analytics), AS CommCare data and NDVI data.

4 Findings for this question rely largely on perception, triangulated with NDVI data where possible. Based on the geolocation of the homestead and areas of migration, the evaluation examined the average vegetation conditions in those areas. The accuracy of the information for the areas of migration depends on the degree to which pastoralists can identify the specific areas where they migrated.

5 Given the difficulty of ascertaining comprehensive, objective information about the prevalence of conflict in pastoralist areas, findings from this research question also rely on perception indicators.

APPENDIX B. BASELINE AND ENDLINE QUANTITATIVE DATA COLLECTION ACTIVITIES, AND ENDLINE QUALITATIVE DATA COLLECTION ACTIVITIES

Baseline data collection

Sampling strategy

The sampling strategy for the IE consisted of first selecting a set of clusters and then selecting a set of households within those clusters.

Clusters

To select the 351 community clusters, the AS team identified areas where they are most likely to introduce or expand operations in the immediate future. The following criteria were used to select *kebeles*/sub-locations:

1. Areas with good security
2. Areas with good network connections
3. People have access to smartphones (i.e., 10 or more households with smartphones within the area)
4. Areas have a good relationship with Global Communities, its partners or the AS project specifically.

Kebeles/sub-locations that met all or most criteria were selected. In Kenya, we eliminated areas where other stakeholders are undertaking similar work (e.g., Northern Rangelands Trust conservancies in Isiolo and areas that are implementing the Kenya Resilient Arid Lands Partnership for Integrated Development Plus programme (RAPID+).

Household selection

In *kebeles*/sub-locations included in the study, households that met the following criteria were randomly selected:

1. Households own livestock
2. Households are permanent residents of the community
3. Households migrate some animals for pasture throughout the year

4. Households own a smartphone
5. The person answering the survey is the main decision-maker in the household for matters related to livestock, grazing and migration.

It was not possible for all households to satisfy all five criteria. Table B.1 shows the two criteria not satisfied by all households. While all households in Kenya had access to a smartphone, this was not the case in Ethiopia. In 10 *kebeles* enumerators could not find any household that owned a smartphone, and they found 40 households where at least one person had access to a smartphone.[6] In treatment *kebeles* where at least one person had access to a smartphone, we expected to observe high spillovers from households owning smartphones to households without access. To account for the fact that not all households had smartphones at baseline, ownership of smartphones was included as a covariate at endline.

Around 98% of respondents were the main decision-makers in the household for matters related to livestock, grazing and migration. In 2% of households it was not possible to interview the decision-maker, mainly because he/she had migrated in search of pasture. To reduce this share for endline, enumerators planned more time for the surveys, to increase the likelihood that the decision-maker was present.

TABLE B.1. SELECTION CRITERIA NOT SATISFIED BY ALL HOUSEHOLDS

Country	Kenya	Ethiopia	Total
Percentage of households owning a smartphone	100%	84.42%	92.21%
Percentage of respondents who are the main decision-maker in the household for matters related to livestock, grazing and migration	98.63%	97.66%	98.12%

Source: Authors' own.

Field preparation

The AS team led all phases of survey data collection and they digitised the survey using the CommCare platform. Enumerator training in Kenya was conducted on 8 February 2023 and the pilot was conducted on 9 and 10 February. In Ethiopia, training was conducted on 18 February 2023 and the pilot took place between 19 and 21 February. Pilot testing was conducted at LMD and Kambi Turkana sub-locations in Isiolo County for Kenya and at Lagasure (Somali Moyale), Besheda (Hammer), Dharito (Borena) and Hawbarre (Dhelasuftu) for Ethiopia. For data collection in Kenya, 21 enumerators and 5 supervisors were deployed and each supervisor was assigned one county. In Ethiopia, 36 enumerators and 7 supervisors were deployed, with each supervisor assigned 2 *woredas* (counties), except in South Omo where they were assigned one *woreda* and jointly supported the remaining *woreda*. To ensure quality data, a series of activities were performed both during and after data collection.

Data collection

Data collection activities in Kenya took place from 10 February to 10 March 2023. In this country, 1,752 households in 175 sub-locations were interviewed. Data collection activities in Ethiopia took place from 19 February to 6 March. In this country, 1,753 households in 176 *kebeles* were interviewed (Table B.2).

6 In these *kebeles*, an average of 65% of households interviewed had access to a smartphone.

TABLE B.2. BASELINE SURVEY CHARACTERISTICS

Country	Number of counties/ *woredas*	Number of sub-locations/*kebeles*	Number of households
Kenya	5	175	1,752
Ethiopia	12	176	1,753

Source: Authors' own.

The field team experienced challenges accessing some *kebeles* in Ethiopia. As soon as an issue was reported by the field team, AS communicated with Causal Design, who determined adequate replacement clusters. For each *kebele* with issues, AS provided a set of possible replacements located in a similar *woreda* and Causal Design randomly selected one. In one case (Melkahalu), a specific *kebele* was used because all remaining *kebeles* in the *woreda* had security issues. Table B.3 lists the seven *kebeles* with issues and the replacements used. All seven had security issues.

TABLE B.3. CLUSTER REPLACEMENT CASES

Initial *kebeles* (*woredas*)	Replacement *kebeles*	Reason for replacement
Galgalo Dimtu (Moyale)	Hallu Huloko	Insecurity
Nanaw (Moyale)	Chamuki	Insecurity
Batalu (Buna)	Ajawa	Insecurity
Murale (Hammer)	Minogeltu	Insecurity
Aegude (Hammer)	Gembela	Insecurity
Kulema (Hammer)	Area Keysa	Insecurity
Melkahalu (Kalu)	Matagefersa	Insecurity

Source: Authors' own.

During post-data collection quality checks, 42 pairs and 3 triplets were found to have the same phone numbers. Some of these cases were exact duplicates and therefore only one observation was kept per pair/triplet. For all other duplicates, the AS team manually inspected the data and determined which observations should be kept. It is important to mention that it is possible for two households to have the same phone number. This happens because family ties in the pastoral community usually extend past the nuclear family. Additionally, many households are polygamous – the man usually owns the phone even though it might be used by more than wife.

Causal Design performed a series of quality control activities before, after and during data collection (see Table B.4. below).

TABLE B.4. QUALITY ASSURANCE ACTIVITIES

Before data collection
▪ Supported the development of a paper version of the survey tool. ▪ Assisted with bench-testing the digitised survey tool and provided feedback to AS. ▪ Reviewed enumerator training manuals.
During data collection
▪ Ran regular high-frequency checks and provided feedback to AS on adjustments to the tool.
After data collection
▪ Cleaned the data provided by AS.

Source: Authors' own.

Endline data collection

Sample frame

At endline, the objective was to sample the same households as at baseline. However, it was not possible to revisit all of the baseline sub-locations in Kenya or the selected *kebeles* in Ethiopia. Table B.5 lists all baseline clusters not surveyed or with issues at endline, the replacement cluster and the issue encountered. In the case of Kenya, it was not possible to access four control sub-locations. For these, the AS team provided a set of potential replacement sub-locations in the same mapped area as the inaccessible ones and Causal Design randomly selected the replacement. In the case of Ethiopia, there were issues with six of the *kebeles* initially selected. In four of these no replacement was used for various reasons: in Delgimure there was a treatment *kebele* and no replacement was available; in Galaba and K Gumata there were control *kebeles* belonging to the same quadruplet, and hence no control *kebele* within the same quadruplet was available; the other three *kebeles* in the same quadruplet as Bonkori were surveyed.

TABLE B.5. SUB-LOCATIONS/*KEBELES* REPLACED IN KENYA AND ETHIOPIA (MAPPED AREA IN PARENTHESES)

Baseline clusters not surveyed/with issues	Replacement clusters	Reason for replacement
Kenya (AS Steward)		
Elraya (Moyale)	Iladu (Moyale)	Security issues
Qilta (Moyale)	Odda (Moyale)	Security issues
Mary (Moyale)	Kinisa (Moyale)	Security issues
Jebder (Wajir North West)	Bute (Wajir North West)	Baseline households migrated outside and were not traceable
Ethiopia (AS Regen)		
Delgimure (Dassenach)		Area had issues. Data was collected but excluded from the analysis
Galaba (Gomole)		Security issues. Not replaced
K Gumata (Gomole)		Security issues. Not replaced
Nini (Somali Moyale)	Arsame (Filtu)	Households were interviewed but there were multiple issues
Gondroba (Hammer)	Assile (Hammer)	Active conflicts prevented the team from entering Gondroba
Bonkori (Hudet)		*Kebele* was supposed to be a control area, but the area was merged with Roko (a treatment area) and therefore received treatment. Not replaced

Source: Authors' own.

Even in areas that could be surveyed, it was not always possible to revisit all of the baseline households. Where baseline households could not be found, or no one was present with knowledge of the household's livestock and migration activities, new households were surveyed from the same areas. These new households were selected in the same way as those selected at baseline, with the addition of one screening question: Had the household been living in the area since January 2022? The number of replacement households (including those in replacement sub-locations in Kenya) and the total number of households interviewed at endline is presented in Table B.6.

TABLE B.6. NUMBER OF HOUSEHOLDS INTERVIEWED AT ENDLINE IN EACH SITE, DIFFERENTIATING BETWEEN REPLACEMENT AND BASELINE HOUSEHOLDS

	Replacement households	Baseline households	Total
Kenya (AS Steward)			
Treatment	72	808	880
Control	120	754	874
Ethiopia (AS Regen)			
Treatment	7	643	650
Control	17	653	670

Source: Authors' own.

Field preparation and data collection

The AS team led all phases of survey data collection and digitised the survey using the CommCare platform (see Table B.7. below for characteristics of the endline survey). AS also led three-day enumerator training in Kenya and Ethiopia: day 1 focused on understanding the objective of the data collection exercise and reviewing the paper version of the survey tool; day 2 focused on reviewing the survey tool on CommCare and conducting in-house data collection exercises; and day 3 for pilot interviews and data entry testing. Training was held in Isiolo in Kenya and in Yabello in Ethiopia.

Data collection activities took place during January–March 2025. Quantitative enumerator training was conducted in Kenya on 27 January 2025 and the pilot was conducted on 28 January. In Ethiopia, training was conducted on 19 February and the pilot took place on 20 February. Pilot testing was conducted at LMD and Kambiodha sub-locations for Kenya and at Dida for Ethiopia. For data collection activities, 22 enumerators and 5 supervisors were deployed in Kenya, with each supervisor assigned one county. In Ethiopia, 35 enumerators and 5 supervisors were deployed, with each supervisor assigned two *woredas*, except in South Omo where they were assigned one *woreda* and jointly supported the remaining one.

TABLE B.7. ENDLINE SURVEY CHARACTERISTICS

Country	Number of counties/ *woredas*	Number of sub-locations/*kebeles*	Number of households
Kenya	5	172	1,754
Ethiopia	12	129	1,320

Source: Authors' own.

Endline qualitative inquiry

Study sites

Qualitative data collection utilised a purposive sampling approach, though the number of sites and site selection criteria varied slightly between Kenya and Ethiopia. As the qualitative inquiry aimed to provide further details on how and why AS interventions contribute to outcomes, community-level data was collected only from treatment clusters.

In Kenya, one treatment cluster (sub-location) was selected in each of the five mapped areas for qualitative data collection. Clusters were selected purposively based on:

- **Gender balance:** Clusters were selected where both men and women were surveyed at baseline to ensure both male and female perspectives were captured.
- **Intensity of implementation:** Clusters were selected with high (or medium, where high was not possible) levels of implementation, based on Global Communities monitoring data. This ensured that respondents had meaningful reflections and learnings about AS implementation. High implementation was determined as the ideal level, with monthly in-person visits by Field Agents; medium implementation was defined as average implementation, with bi-monthly in-person visits and users mostly engaged through phone calls and SMS.
- **Accessibility/security:** Only areas that were deemed accessible and secure (based on inputs on ground conditions from Global Communities) were selected to ensure the safety of the data collection team.

In Kenya, the number of sites was exhaustive, covering all five mapped areas. Table B.8 lists the sub-locations where data was collected.

TABLE B.8. QUALITATIVE DATA STUDY SITES IN KENYA

Mapped area	Cluster/ sub-location	No. of female AS users surveyed at baseline	No. of male AS users surveyed at baseline	Intensity of implementation
Garissa South	Burburis	8	2	High
Isiolo	Malkadaka	5	7	High
Moyale	Butiye	5	5	Medium
North Horr	North Horr	6	5	High
Wajir North West	Masalale	5	4	Medium

Source: Authors' own.

Similarly, in Ethiopia, one treatment cluster (*kebele*) was selected per mapped area for qualitative data collection. Clusters were selected purposively based on:

- **Gender balance:** Clusters were selected where both men and women were surveyed at baseline to ensure male and female perspectives were captured. Some *kebeles* were also purposively selected as they had female Field Agents.
- **Cohort or launch date:** Given AS Regen's staggered implementation across mapped areas, Causal Design selected clusters where AS Regen's implementation had been ongoing for as long as possible (Cohort 1 launched in October–November 2022 and Cohort 2 in March–May 2023). This ensured some degree of consistency across data collection sites, and it maximised efficiency and possible learnings from the qualitative data.
- **Accessibility/security:** Only areas that were deemed accessible and secure (based on inputs from Global Communities) were selected to ensure the safety of the data collection team.

It was not possible to visit all mapped areas in Ethiopia exhaustively. All *kebeles* in one mapped area (Dekhaftsu) were inaccessible during the study due to insecurity; implementation was still at early stages in four others (Dassenach, Gnangatom, Hudet and Malbe), which limited the likelihood of outcomes and the ability of qualitative data to substantiate outcomes. Table B.9 lists the qualitative sample in Ethiopia, covering seven mapped areas.

TABLE B.9. QUALITATIVE DATA STUDY SITES IN ETHIOPIA

Zone	Mapped area	Cluster/ *kebele*	No. of female baseline survey respondents	No. of male baseline survey respondents	Launch period/ cohort	Gender of field agent
Borena	Wayama	Mormora	5	5	Mar/Apr/May 2023	Female
Borena	Golbo	Maddo	3	7	Mar/Apr/May 2023	Male
Dawa	Somali Moyale	Lagsure	11	9	Mar/Apr/May 2023	Female
East Borena	Dirre	Qawa	4	6	Oct/Nov 2022	Male
East Borena	Gomole	Gadda	4	6	Mar/Apr/May 2023	Male
Liben	Filtu	Lantuweri	3	7	Mar/Apr/May 2023	Male
South Omo	Hammer	Zeldeketa	1	9	Mar/Apr/May 2023	Male

Source: Authors' own.

Respondents

Given that different stakeholders were involved in the two AS models, respondents varied for each country. Respondents in each location were purposively selected based on their role in AS's implementation chain. This included AS implementers, specifically Field Agents in both countries, and both formal and informal RGU management committee members in Ethiopia, specifically the *Kebele* Chair (formal appointee) and Rangeland Representative (informal appointee). Pastoralist community members were also interviewed (specifically both male and female household decision-makers in both countries), and app users and herders in Kenya and Ethiopia, respectively. During data collection it was found that respondents' roles on the ground overlap, with particular overlaps between household decision-makers and RGU members in Ethiopia, and app users in Kenya. This may explain the similarities in responses across different respondent types.

Efforts were made to include perspectives from both genders by holding separate focus group discussions (FGDs) for male and female community members in each respondent category. However, it was not possible to obtain an even representation across both genders for implementers, because the majority of Field Agents in Ethiopia and all Field Agents in Kenya are male. Similarly, *Kebele* Chairs and Rangeland Representatives, who were selected to provide insights as leaders of RGU management committees, are also predominantly male.

Table B.10 gives a full list of the interviews conducted by respondent and gender. Table B.11 and Table B.12 give detailed information by country, including how stakeholders are defined and the total number of respondents reached through interviews.

TABLE B.10. QUALITATIVE DATA COLLECTION BY COUNTRY AND RESPONDENT TYPE

Type	Respondent	No. of interviews conducted	
		Kenya (Steward)	Ethiopia (Regen)
FGD	Field Agents	1 (all male)	7 (5 male, 2 female)
FGD	Household decision-makers	10 (5 male, 5 female)	N/A
FGD	App users	10 (5 male, 5 female)	N/A
FGD	Herders	N/A	14 (7 male, 7 female)
KII	RGU committee members	N/A	14 (all male)
Total		21	35

Source: Authors' own.

TABLE B.11. QUALITATIVE INQUIRY RESPONDENTS FOR KENYA

Type	Respondent	No. of interviews	No. of respondents reached	Definition/notes
FGD	Field Agents	1	5 (all male)	Exhaustive – Field Agents from all mapped areas included in the IE. The FGD with Field Agents was conducted by Causal Design during the in-person training for Field Agents in Isiolo in January 2025.
FGD	App users	10	36 (18 male, 18 female)	Those who have direct access to the app. Sample from across mapped areas, disaggregated by gender (for a total of two in each mapped area).
FGD	Household decision-makers	10	55 (28 male, 27 female)	Defined as those who predominantly make decisions around household livestock (such as when or where to graze, migration, vaccinations, etc.). Sample from across mapped areas, disaggregated by gender (for a total of two in each mapped area).
Total		21	96 (51 male, 45 female)	

Source: Authors' own.

TABLE B.12. QUALITATIVE INQUIRY RESPONDENTS FOR ETHIOPIA

Type	Respondent	No. of interviews	No. of respondents reached	Definition/notes
KII	Field Agents	7	7 (5 male, 2 female)	Includes Field Agents in all possible mapped areas based on cohort and security.
FGD	Herders	14	117 (58 male, 59 female)	People who utilise AS information, either directly through accessing the app or secondary knowledge. Sample from across mapped areas, disaggregated by gender (for a total of two in each mapped area).
FGD	Household decision-makers	14	118 (59 male, 59 female)	Those who predominantly make decisions around household livestock (such as when or where to graze, migration, vaccinations, etc.). Sample from across mapped areas, disaggregated by gender (for a total of two in each mapped area).

Type	Respondent	No. of interviews	No. of respondents reached	Definition/notes
KII	RGU committee members; *Kebele* Chairs	7	7 (all male)	Sample from across mapped areas (one per mapped area).
KII	RGU management committee; rangeland representative	7	7 (all male)	Sample from across mapped areas (one per mapped area).
Total		49	256 (136 male, 120 female)	

Source: Authors' own.

Data collection

Qualitative data collection was conducted and managed by Causal Design and AS. Causal Design developed qualitative data collection tools, tailored to different respondent types and the AS Steward/Regen interventions. Tools were semi-structured in nature, with special care taken in their design to sequence questions to facilitate the flow of conversation, to avoid leading, to elicit objective and detailed responses, and to create opportunities for validation. Tools were translated by Global Communities teams into local languages for deployment, namely Amharic, Afaan Oromo and Somali.

Field data collection was conducted by AS Field Agents in Kenya and by members of Global Communities' Zonal Officers and monitoring and evaluation (M&E) team in Ethiopia. Causal Design conducted the FGD with Field Agents in Kenya directly, during the in-person qualitative data collection training.

Causal Design led three-day in-person training for qualitative enumerators in Isiolo, Kenya, and in Yabelo, Ethiopia, in January and February 2025, alongside the quantitative survey training. The training included a thorough review of the research objectives and data collection tools to ensure the intent of questions was well understood in the context of the overall research. Necessary revisions to data collection tools were made with enumerators' input during the training. This was to ensure that questions were clear, appropriate and would yield relevant data, as well as confirming that translations were accurate. The training also included an overview of qualitative research fundamentals, interview techniques, research ethics, fieldwork logistics and data entry (particularly, a training-of-trainers module for transcribers/translators who would be assisting with data entry, given that it was not possible for transcribers/translators to attend the qualitative enumerator training). The final day of qualitative training included pilot interviews and subsequent debriefs.

Interviews were audio recorded with respondents' consent, and data was transcribed and translated by locally hired transcribers/translators. Data was entered into standardised data entry forms, which included the full English-language interview transcripts as well as demographic and administrative data. Causal Design reviewed all data entry forms to provide enumerators with feedback on interview technique and data entry, as well as to request clarifications and additional details as necessary to maximise data quality, clarity and comprehensiveness.

APPENDIX C. RESEARCH METHODOLOGY

Construction of quadruplets

To balance treatment and control clusters, we used a stratified randomisation approach combined with matched quadruplets. The evaluation used two strata: (i) country, and (ii) county (Kenya) or *woreda* (Ethiopia). Among counties and *woredas*, this study selected sub-locations (Kenya) and *kebeles* (Ethiopia) and used these as 'clusters'. In total, 175 sub-locations in five counties in Kenya were surveyed at baseline, and 176 *kebeles* across 12 *woredas* in Ethiopia were surveyed. Ten households in each sub-location or *kebele* were sampled at baseline for inclusion in the study.

Once the strata (country and county/*woreda*) were determined, we constructed quadruple matches. Since there are many different outcomes of interest, we used the set of variables (closely related with the main outcomes of the study) presented in Table C.1 to construct a Mahalanobis distance[7] (MD) between clusters within a strata. Pairs of clusters with the smallest MD were matched, and then matched pairs of pairs were constructed using the mean of the covariates for each pair.

TABLE C.1. VARIABLES USED TO CONSTRUCT THE MAHALANOBIS DISTANCE

Variables	
Household has a smartphone	Respondent is the main decision-maker
Share of animals in good or moderate condition	AS as an important migration source
Number of unsuccessful migrations	Duration of last migration (nights away from home)
State of pasture in migration area is graze or transition	Half or more of the animals migrated
Half or more of the animals lost during migration	Community has a shared grazing plan

Source: Authors' own.

Regression specifications

This section provides additional details on the quantitative methods used to estimate the impacts of the AS interventions. In the main report, we describe the use of a cluster-level randomised control trial (cRCT) for the AS Regen intervention in Ethiopia and a quasi-experimental approach for the AS Steward intervention in Kenya. This section describes the specific regression models used for the AS Regen intervention. Appendix D discusses in depth the contamination issues in Kenya and the approach followed to address this.

Cluster-level RCTs are used widely for causal inference because the random assignment of communities to treatment or control groups ensures that any observed differences in

7 The MD is a method to find a subset of control units similar to treated units. The MD can be thought of as a scale-free Euclidean distance. Two clusters with the same covariate values will have an MD of 0. The more different the covariate values are, the larger the MD between the two clusters.

outcomes can be attributed to an intervention. To ensure a balanced comparison, we used a stratified randomisation approach combined with matched quadruplets. This involved grouping communities into quadruplets based on similar characteristics at baseline (using an MD measure), then randomly assigning two communities from each quadruplet to the treatment group and two to the control group. This method ensured that the treatment and control groups were statistically similar, on average, from the outset (Causal Design, 2023).

To estimate the intervention's impact, we used an intent-to-treat (ITT) analysis. This method measures the effect of simply being assigned to a treatment area, regardless of whether every household fully participated. Because of the high level of compliance in Ethiopia (98% of treatment area respondents reported that their community followed a shared grazing plan), the ITT estimates are very similar to the average treatment effect (ATE), which measures the impact of actually receiving the intervention.

To calculate the difference in outcomes, we employed ordinary least squares (OLS) for continuous variables and linear probability models for binary outcomes. When baseline data was available, we utilised an analysis of covariance (ANCOVA) model, as this method is known to produce more precise estimates in RCTs (McKenzie, 2012). The main regression specification is presented below, and all results refer to this model. All variables were analysed at the household level, with standard errors clustered at the quadruplet match level to account for potential correlation among households within the same cluster (Abadie et al., 2023).

Model 1: Main model

(Equation C.1) $$y_{EL,i} = \beta_0 + \boldsymbol{\beta_1}\cdot \mathrm{Treatment}_i + \beta_2\cdot y_{BL,i} + \beta_3\cdot \mathrm{MissingBaseline}_i + \beta_4\cdot y_{BL,i}\cdot \mathrm{Treatment}_i + \beta_5\cdot \mathrm{MissingBaseline}_i\cdot \mathrm{Treatment}_i + \theta_1\cdot X_{BL,i} + \theta_2\cdot \mathrm{MissingX}_i + \theta_3\cdot X_{BL,i}\cdot \mathrm{Treatment} + \theta_4\cdot \mathrm{MissingX}_i\cdot \mathrm{Treatment}_i + \delta_{quad,i} + \epsilon$$

Equation C.1 regresses the outcome variable at endline ($y_{EL,i}$) on the treatment variable ($\mathrm{Treatment}_i$), a set of fixed effects associated with the quadruple match (δ_{quad}), the baseline value of the outcome of interest ($y_{BL,i}$), and a set of covariates expected to correlate with the outcome variables ($X_{BL,i}$). The value of the treatment variable is equal to one if household i is located in a treatment area and zero otherwise. The quadruplet match variables are a set of binary variables that take the value of 1 if the household is located in a cluster that belongs to the quadruplet and 0 otherwise. **The main coefficient of interest is β_1, which measures the impact of being located in an area that received treatment compared to an area that did not receive the treatment.**

Following Zhao and Ding (2024), we do not exclude observations that do not have baseline values (e.g., replacement households), but instead account for the missing values by including a binary variable (e.g., $\mathrm{MissingBaseline}_i$). Whenever the baseline value of an outcome is missing for a household, the value of the missing variable is equal to 1 (0 otherwise), and the value of $y_{BL,i}/X_{BL,i}$ is equal to 0. Additionally, both the baseline variable and the missing indicators are centred on the sample mean of the variable.

In addition to the main specification presented above, we consider three more specifications. The first additional specification (model 2) is a basic regression model where the outcome variable at endline ($y_{EL,i}$) is regressed on the treatment variable ($\mathrm{Treatment}_i$) and a set of fixed effects associated with the quadruple match (δ_{quad}). The value of the treatment variable is equal to one if household i is located in a treatment area and zero otherwise. The quadruplet match variables are a set of binary variables that take the value of 1 if the household is located in a cluster that belongs to the quadruplet and 0 otherwise. For example, if the household is located in a cluster that is part of the quadruplet A, then $\delta_{A,i}$ would be equal to 1, and the quadruplet match variables for all the other quadruplets would be equal to 0. As in the main model, the main coefficient of interest is β_1, which measures the impact of being located in an area that received treatment compared to an area that did not receive the treatment.

Model 2: Basic model

$$\text{(Equation C.2) } y_{EL,i} = \beta_0 + \beta_1 \cdot \text{Treatment}_i + \delta_{quad,i} + \epsilon_i$$

The second additional specification (model 3) includes the baseline value of the outcome of interest ($y_{BL,i}$) as an additional control whenever that variable was collected at baseline. Following Zhao and Ding (2024), we do not exclude observations that do not have baseline values (e.g., replacement households), but instead account for the missing values by including a binary variable (MissingBaseline_i). Whenever the baseline value of an outcome is missing for a household, the value of the MissingBaseline is equal to 1 (0 otherwise) and the value of $y_{BL,i}$ is equal to 0. Additionally, both the baseline variable and the MissingBaseline variables are centred on the sample mean of the variable,[8] and are interacted with the treatment variable.

Model 3: ANCOVA model

$$\text{(Equation C.3) } y_{EL,i} = \beta_0 + \beta_1 \cdot \text{Treatment}_i + \beta_2 \cdot y_{BL,i} + \beta_3 \cdot \text{MissingBaseline}_i + \beta_4 \cdot y_{BL,i} \cdot \text{Treatment}_i + \beta_5 \cdot \text{MissingBaseline}_i \cdot \text{Treatment}_i + \delta_{quad,i} + \epsilon_i$$

The last model is very similar to the main specification used, and adds a set of covariates (demeaned and interacted with the treatment variable) expected to correlate with the outcome variables, as additional control variables. Table C.2 shows the variables included as covariates. Except for the NDVI variables around the household's home,[9] all the other variables were measured at baseline, thus ensuring that they are not correlated with the treatment status. The only difference between the main specification and model 4 is the NDVI variable; in the case of Ethiopia the main specification includes the average NDVI during the rainy season before the start of the intervention (June–August 2022), while model 4 includes the average NDVI during the dry season before the start of the intervention (December 2022 – February 2023). The results for the main specification and model 4 are very similar, since the NDVI values during the rainy and dry season are highly correlated.

Model 4: ANCOVA model with covariates

$$\text{(Equation C.4) } y_{EL,i} = \beta_0 + \beta_1 \cdot \text{Treatment}_i + \beta_2 \cdot y_{BL,i} + \beta_3 \cdot \text{MissingBaseline}_i + \beta_4 \cdot y_{BL,i} \cdot \text{Treatment}_i + \beta_5 \cdot \text{MissingBaseline}_i \cdot \text{Treatment}_i + \theta_1 \cdot X_{BL,i} + \theta_2 \cdot \text{MissingX}_i + \theta_3 \cdot X_{BL,i} \cdot \text{Treatment}_i + \theta_4 \cdot \text{MissingX}_i \cdot \text{Treatment}_i + \delta_{quad,i} + \epsilon_i$$

8 In all the equations we use the notation that whenever we reference a variable different than Treatment_i or $\delta_{quad,i}$, that variable was previously demeaned. Otherwise we would need to explicitly include the demeaning process (x_i - mean(x_i)), thus increasing the length of the equation.

9 To compute this variable we averaged the NDVI values in a radius of 10 km around the GPS coordinates of the household. We are aware that this is only a proxy of the vegetation conditions where a household keeps its herd when not on migration. We also ran regressions looking at smaller (5 km) or larger (20 km) radiuses, obtaining similar results. Besides changing the radiuses, it is not possible to construct a more accurate variable without knowing with more precision where each household keeps its herd.

TABLE C.2. COVARIATES

Variables	
Respondent’s gender	Respondent’s age
Household size	Household’s main livelihood is pastoralism
At least one person in the household has smartphone	Respondent does not have any schooling
Household owns cattle	Household owns camel
Household owns sheep or goats	NDVI around the household’s home in rainy season
NDVI around the household’s home in dry season	NDVI around the household’s home before the last migration

Source: Authors’ own.

Qualitative data analysis

The qualitative data was analysed using ATLAS.ti computer-assisted qualitative data analysis software. This followed a content analysis approach, allowing for in-depth exploration of the data. Coding was both deductive and inductive, whereby an initial codebook was drafted based on research questions, primary and secondary indicators, and known key themes, with further codes and subcodes added as they emerged from the data. The finalised codebooks (by country), at the point of saturation, were applied to the whole dataset. Once all the data was coded, we leveraged ATLAS.ti’s analytical tools (including code-document comparison, code distribution and code-co-occurrences) to systematically examine data, identify patterns and triangulate findings.

APPENDIX D. CONTAMINATION AND SPILLOVER ISSUES IN KENYA

The problem

The cRCT in Kenya was designed to ensure that the assignment to treatment within mapped areas was determined randomly. This approach ensures that treatment and control households are similar, which guarantees that the changes observed at the endline between treatment and cluster households are due to the intervention and not to pre-intervention differences. The success of this design hinges on appropriate implementation of the intervention (i.e., providing the intervention only in treatment areas), and on household compliance to the treatment assignment (e.g., a household assigned to a control area not seeking to obtain the treatment). The endline survey included the following questions to check this was the case. It is important to remember that the treatment is specifically the provision of training on use of the app and not access to the app, which is free for everyone.

- Have you used the AS mobile app?
- Did you receive training or orientation on how to use the AS mobile app?
- Have you been contacted by an AS Field Agent in the last three months?

Table D.1 presents the number of households who answered positively these questions, disaggregated by mapped area and treatment assignment. Looking at the numbers for the whole study area, we observe: (i) less than perfect implementation in treatment areas, (ii) a high level of contamination (i.e., control households receiving the treatment), and (iii) a high correlation between answers to the three questions. Overall, 72% of households in treatment areas stated they had received training and 73% stated they were contacted by an AS Field Agent. More concerning for the success of the RCT design, is the fact that around 37% of control households received the training and/or were contacted by an AS Field Agent.

We also observe large variability across mapped areas. While an area like Isiolo shows high levels of implementation (87% of treatment households received the training) and low levels of contamination (less than 4% of control households received the training), implementation in treatment areas like Wahir North West was extremely low (less than 15% received training), and more control households than treatment households received the training. These results are similar when we look at the level of the ward or the quadruplets, and are highly detrimental to the validity of the RCT design.

TABLE D.1. NUMBER OF HOUSEHOLDS WHO HAD USED THE APP, RECEIVED TRAINING AND/OR WERE CONTACTED BY AS FIELD AGENTS, BY MAPPED AREA AND TREATMENT STATUS

		Treatment assignment	AS app usage	AS training	Field Agent support
Garissa South	Control	145	97	91	92
	Treatment	140	139	138	138
Isiolo	Control	299	12	11	11
	Treatment	284	260	248	259
Moyale	Control	150	141	140	139
	Treatment	154	153	152	151
North Horr	Control	100	64	51	61
	Treatment	120	86	74	79
Wahir North West	Control	180	37	36	17
	Treatment	182	31	27	18
Total	Control	874	351	329	320
	Treatment	880	669	639	645

Upon observing these problematic results, we discussed them with the AS team to understand the drivers. AS contacted Field Agents and reviewed M&E data, concluding that control areas received training or support from AS Field Agents only in a few isolated cases. This was corroborated by information from Google Analytics showing app activity among treatment and control households. Cellphone numbers collected during the baseline or endline surveys were matched with cellphone numbers from Google Analytics for the period January 2023–February 2025. Summary statistics are presented in Table D.2. Contrary to what has been discussed above, the Google Analytics data shows a high level of implementation (close to 80% of treatment households show app activity) and a very low level of contamination (around 6% of control households show app activity). Notwithstanding some differences at the mapped area level, the numbers from Google Analytics suggest implementation of the intervention was relatively successful.

TABLE D.2. SUMMARY STATISTICS ON AVERAGE APP USAGE BY TREATMENT STATUS AND MAPPED AREA

		No. of households	% of households showing app activity	No. of app activities	No. of times map downloaded	No. of times app was accessed
Garissa South	Control	145	3%	0.71	0.09	0.61
	Treatment	141	66%	2.78	0.45	2.31
Isiolo	Control	323	4%	0.6	0.06	0.5
	Treatment	292	90%	2.36	0.26	2.02
Moyale	Control	210	17%	0.36	0.06	0.3
	Treatment	194	81%	1.26	0.22	1.03

		No. of households	% of households showing app activity	No. of app activities	No. of times map downloaded	No. of times app was accessed
North Horr	Control	107	8%	1.39	0.11	1.28
	Treatment	126	60%	1.9	0.29	1.59
Wahir North West	Control	204	0%	NA	NA	NA
	Treatment	202	87%	0.45	0.06	0.38
Total	Control	989	6.1%	0.58	0.07	0.5
	Treatment	955	80%	1.7	0.24	1.43

The discrepancy between self-reported survey data (Table D.1) and actual app usage data from Google Analytics (Table D.2) is likely related to **significant information spillovers** within mobile pastoralist communities, which influenced how survey questions were interpreted by respondents. Given these pervasive spillovers, when asked if they used the AS mobile app, households may not have necessarily interpreted this as physically using the app themselves, but rather as utilising the outputs or information derived from the app (e.g., where to migrate or other relevant advice). Similarly, conversations with other pastoralists who had directly used the app or received formal training might have been interpreted by some control households as 'receiving training' or 'being contacted by an AS Field Agent'. This broader interpretation is highly plausible, given the inherent mobility and interconnectedness of pastoralist communities, where information – especially concerning vital resources like pasture and water – spreads rapidly through social networks.

This widespread sharing of information means control households likely used the information provided by AS to complement their traditional sources of knowledge. Qualitative respondents consistently reported utilising AS alongside other traditional information sources, highlighting the app's value particularly for its accuracy and its ability to verify other information sources. Across locations, app users and household decision-makers reported sharing app information widely with a range of actors, predominantly family members and relatives, and other community members, as well as friends and neighbours. Reasons for this extensive information sharing include for coordination purposes and ensuring that others, including non-app users, could also benefit from the app information. This extensive and informal diffusion of information would explain the low recorded app activity via Google Analytics in control areas, despite these groups potentially benefiting indirectly from the intervention. Further details on information sharing are presented in the next subsection.

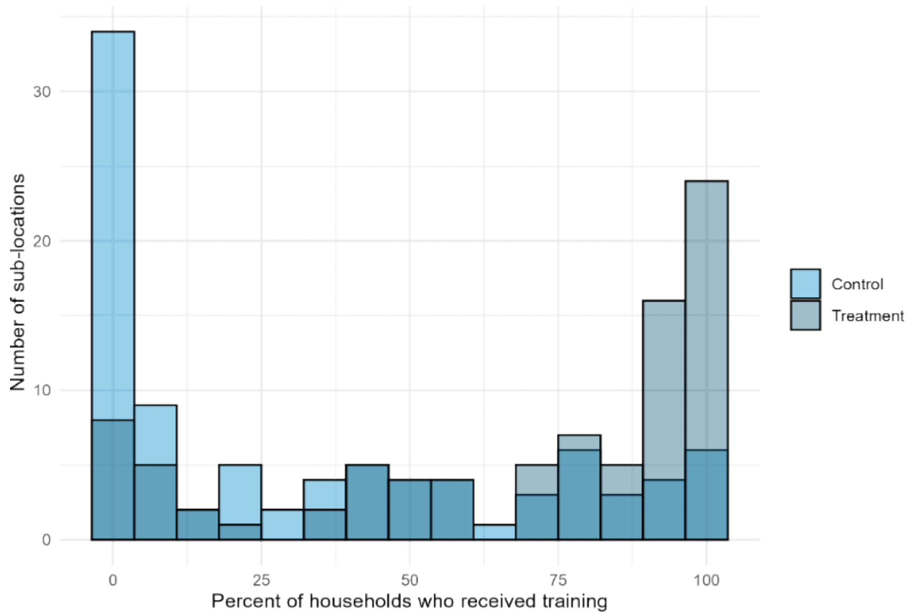
Ultimately, even though control households did not receive the intervention (i.e., training) directly, the large spillovers prevent a simple comparison between treatment and control households. An alternative strategy to partially alleviate some of these issues is presented in the last subsection in this Appendix D.

Study of spillovers

Here we further explore and provide additional evidence on spillover effects.

Figure D.1 shows the percentage of households who received AS training. In an ideal RCT, most households in treatment sub-locations would receive training and most households in control sub-locations would not. Even though we observe a larger number of control sub-locations to the left of the histogram (bars are taller) and a larger number of treatment sub-locations to the right, the figure shows many control sub-locations with a high percentage of households that received AS training. It also shows many treatment sub-locations where a low percentage of treatment households stated they received AS training.

FIGURE D.1. PERCENTAGE OF HOUSEHOLDS RECEIVING AS TRAINING AT SUB-LOCATION LEVEL



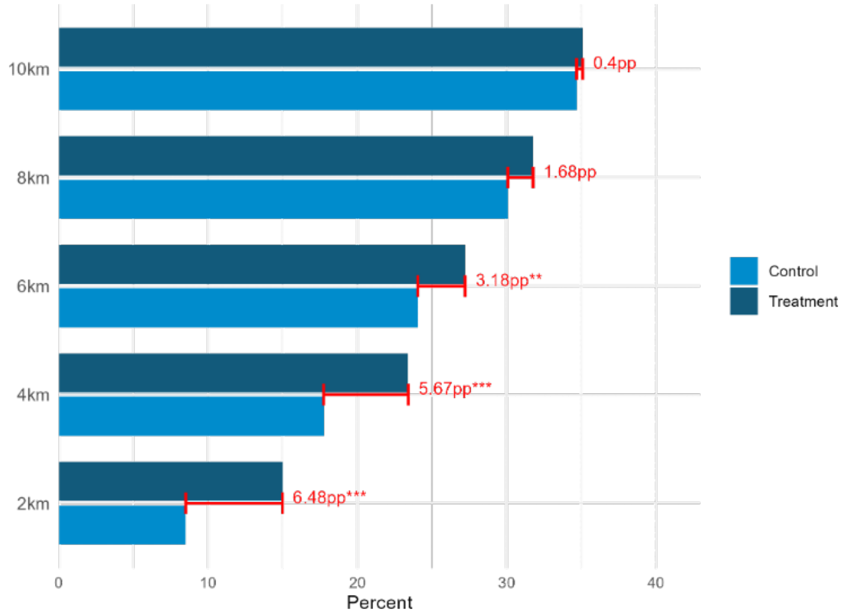
Source: Authors' own.

Given the large number of control households receiving AS training, the next step in our analysis was to understand if receiving training is associated with being closer to treatment households who received training, since this would strengthen the argument that spillover effects are prevalent in the study. We constructed exposure measures as follows: for each household in our dataset, we drew a circle of given radiuses and counted the number of treatment households receiving AS training who were inside that circle.[10,11] Figure D.2 shows the average number of treatment households that received AS training for different radiuses. As expected, treatment households have more treatment households around them who received AS training. Nonetheless, control households have, on average, close to nine treatment households who received training in a radius of 2 km and 15 households in a radius of 4 km.

10 We constructed alternative exposure measures using the number of treatment households who used the AS app or who said they were contacted by a Field Agent over the past three months. Because the results are very similar, we do not present them here.

11 An alternative approach would be to include any household (either treatment or control) who received AS training. We decided not to use this approach since our objective was to look at the first round of information sharing (e.g., a treatment household who received training from an AS Field Agent sharing information).

FIGURE D.2. NUMBER OF TREATMENT HOUSEHOLDS WHO RECEIVED TRAINING



Source: Authors' own.

To explore if control households exposed to more treatment households were more likely to have used AS or to have received training, we ran the regression specified in equation D.1. Here, ASvar corresponds to different variables related with AS, and the exposure variable is the number of treatment households who received AS training in a radius of 2 km.[12]

(Equation D.1) $ASvar_{EL,i} = \beta_0 + \beta_1 \cdot Exposure_i + \beta_2 \cdot ASvar_{BL,i} + \beta_3 \cdot MissingBaseline_i + \epsilon_i$

Table D.3 presents the results of these regressions, as well as the mean levels of the variables for the households with the lowest exposure measures (bottom half) and highest exposure measures (upper half). Households in the bottom-half group had, on average, 0 treatment households receiving training in a vicinity of 2 km, compared with 17 households from the upper-half group. We observe large differences when we look at the AS-related variables. For example, one additional treatment household in a radius of 2 km increases the likelihood of having used AS by 0.71 percentage points. This means that a control household with 10 treatment households receiving training in a 2 km radius is 7.1 percentage points more likely to have received AS training.

TABLE D.3. IMPACT OF NUMBER OF TREATMENT HOUSEHOLDS RECEIVING TRAINING ON DIFFERENT AS-RELATED VARIABLES (CONTROL HOUSEHOLDS ONLY)

	Bottom half		Upper half			
Outcome	Mean	N	Mean	N	Treat. effect	P-value
Exposure measure: Number of treatment households who received AS training in a radius of 2 km						
Percent of pastoralist households that received some training or orientation on using AS	28.76%	452	47.15%	422	0.67**	0.036
Percent of pastoralist households contacted by an AS Field Agent in the last three months	28.76%	452	45.02%	422	0.92***	0.004

12 To account for spatial correlation we used conley standard errors.

	Bottom half		Upper half			
Outcome	Mean	N	Mean	N	Treat. effect	P-value
Percent of pastoralist households that used AS	31.41%	452	49.52%	422	0.71**	0.027
Percent of pastoralist households for whom AS is an important source of migration information	24.55%	452	45.49%	422	0.73**	0.05
Percent of pastoralist households that had heard of AS	53.76%	452	67.29%	422	0.58*	0.099
Average number of treatment households who received training in a radius of 2 km	0	452	17.61	422	NA	NA

Source: Authors' own.

These results are evidence of the presence of information spillovers. Nonetheless, given that the variables are self-reported and that implementation of the intervention varied at the mapped area level, the evidence is only suggestive.

To further study the potential presence of spillovers, the FGDs included conversations related to the flow of information. **Qualitative interviews corroborate the finding that sharing of AS information is widespread among pastoralist communities**. Respondents in FGDs for app users and also household decision-makers reported sharing app information with a range of actors, predominantly family members and relatives, and other community members, as well as friends and neighbours. This reflects a strong culture and practice of sharing information, which can boost AS's broader impact through spillover to other communities, even when not specifically targeted by programme implementers. Additionally, respondents noted that communication with other communities had increased since using the app. In particular, the availability of AS information led to increasingly proactive coordination efforts with other communities. Respondents recalled scheduling access to particular areas and water sources based on app information, communicating more with others and making joint migration plans.

A major reason for sharing information with others is to coordinate movements and make collective decisions. Some respondents noted sharing information with family members, friends and other community members in order to facilitate collective decision-making around grazing decisions and animal health. A male app user from Garissa South explained, *'I mostly share with my relatives who also have livestock. Since we often migrate together, we need to be aligned in our decisions.'* In some cases, sharing information was also seen as a way to prevent congestion among those who graze in similar areas. A male app user from Wajir explained, *'Sharing pasture information prevents overcrowding. If one area is too full, others can find alternative grazing spots.'*

Another reason for sharing information is to ensure that others, including non-app users, can also benefit from app information and make informed decisions. Pastoralists recalled sharing information with others to avoid them making unnecessary movements, as well as sharing warnings about hazards, allowing others to take precautions and appropriate actions. A male app user from Wajir stated, *'AfriScout allows us to warn others about disease outbreaks, helping prevent the spread of livestock illnesses between communities'*. A few specifically noted sharing information with non-app users, such as people who do not have smartphones or do not check the app regularly, in order to share the benefits of the app. A female app user from Garissa explained, *'We rely on each other in times of crisis, so sharing information from AfriScout strengthens community ties. If I see a disease outbreak alert, I immediately inform those who might not have access to the app.'*

Because of the potential presence of spillovers, all the results in the findings section compare households who said they received AS training with households who said they did not receive AS training. The estimated effects cannot be considered definitive causal effects, despite the additional strategies employed to mitigate potential biases (i.e., augmented inverse probability weighting and causal forests).

Methodology to address spillovers

As discussed above, the high level of spillover between treatment and control groups compromised the cRCT design in Kenya, making it potentially misleading to directly compare groups based solely on randomised assignment. To account for these complexities, we used a multifaceted approach in our analytical strategy – we focused on measuring exposure, confirming spillovers and employing robust causal inference methods.

To better understand the extent and patterns of information spillovers, we first constructed measures of household exposure to the intervention. We utilised the precise geolocalisation of all surveyed households to determine, for any given household i, the number of treatment households within a specific radius that reported receiving training or actively using the AS Steward app. These exposure measures were designed to vary at the household level, providing a granular view of intervention intensity in the geographical vicinity of each household. We then ran preliminary regressions, incorporating these exposure measures as explanatory variables. These analyses aimed to determine if control households situated closer to treatment households were indeed more likely to self-report app usage or receipt of training, thereby empirically confirming the high level of information spillovers suggested by the qualitative data.

Our primary identification strategy shifted, given that the original treatment assignment from the RCT was not a perfectly accurate measure of a household's exposure to AS's positive impacts (whether directly through training or indirectly via information spillovers). Instead of comparing randomised treatment and control groups directly, we opted to compare households who *self-reported* having received training against those who *self-reported* having not received training. This approach takes into account the reality of information diffusion but introduces a potential for self-selection bias. Households who reported receiving training (especially in control areas) might possess unobserved characteristics, – such as higher motivation or existing social capital – which could independently influence outcomes. Therefore, while this strategy allows for an evaluation closer to the 'treatment received', it cannot provide an accurate measure of the causal effect akin to an ideal RCT.

We employed two strategies to enhance the comparability of these self-reported groups and increase the reliability of our estimates. First, the analysis excluded households in Moyale, where over 95% of all households (across both randomised treatment and control arms) stated they received training, which made meaningful comparison impossible due to near-universal exposure. Second, we applied an augmented inverse probability weighting (AIPW) approach (Kang and Schafer, 2007; Hoffmann, 2024). AIPW is a 'doubly robust' estimation method, meaning it provides consistent estimates of the treatment effect if either the model for the outcome or the model for the propensity score (the probability of receiving treatment given observed covariates) is correctly specified.

AIPW is built upon propensity scores, which are estimated probabilities that a household received training (the treatment) given their observed baseline characteristics. We constructed the propensity scores by running a logistic regression model, where the outcome is the binary variable indicating training receipt (yes/no), and the predictors are a comprehensive set of pre-intervention household attributes.[13] The core idea behind propensity score methods is to re-weight the observed data. This re-weighting effectively creates a synthetic population where the distributions of observed baseline characteristics are balanced between the 'trained' and 'untrained' groups, as if training had been randomly assigned. This process directly addresses confounding by observed variables, thereby making the groups more comparable and reducing bias in the estimated treatment effect. AIPW extends this by being a 'doubly robust' estimation method. This means it can provide consistent (reliable) estimates of the treatment effect if *either* the model for the outcome (how covariates affect the outcome) *or* the model for the propensity score (how covariates affect the probability of training receipt) is correctly specified. This approach offers an advantage by providing a safeguard against potential misspecification of one of the models and increasing confidence in the resulting estimates. To further enhance balance and satisfy the overlap assumption necessary for robust estimation, we 'trimmed the edges' of the propensity score distribution, retaining only observations with propensity scores within the range of 0.1 to 0.9.[14] This ensures that comparisons are made only among households that had a realistic chance of being in either the trained or untrained group, focusing the analysis on areas of substantial covariate overlap.

Finally, to provide a flexible and non-parametric estimation of potential outcomes and improve precision, we also utilised causal forests, a machine learning approach pioneered by Athey and Wager (2019). Causal forests are particularly advantageous due to their ability to handle complex, non-linear relationships and high-dimensional data without requiring strong pre-specified assumptions about the functional form of these relationships. This leads to more precise estimates. This method works by building an ensemble of decision trees, similar to a random forest. Each 'tree' in the forest recursively partitions the data into smaller, more homogeneous groups based on the provided covariates. However, unlike standard random forests that predict outcomes, causal forests are specifically designed to estimate causal effects. They achieve this by structuring the trees to identify subgroups where the effect of training is similar, effectively creating local randomised experiments. The final estimate for each household is then derived by averaging the predictions from many such trees, providing a robust and data-adaptive way to estimate potential outcomes and, consequently, the average treatment effect with high accuracy. This approach was implemented using the grf R package. By combining these advanced econometric techniques with machine learning, we aim to provide the most credible and comprehensive insights into the impact of the AS mobile app, particularly in the presence of real-world implementation complexities and information spillovers.

However, despite our extensive efforts to mitigate bias through the use of exposure measures, sample trimming and advanced methods like AIPW and causal forests, our estimates cannot be considered definitive causal effects. A primary reason for this lies in the inherent nature of our revised identification strategy: comparing households who *self-reported* having received training against those who *self-reported* having not received training. While AIPW is very good at balancing observed baseline characteristics

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13 We used the following baseline variables: gender, livestock sales as the main income source, AS is an important source of migration information, value of herd, overall herd condition over the past year improved, areas where household migrated had water availability, the pasture in the areas where households migrated was either graze or transition state, sizes of the herd for each of the three animals, and the NDVI in a 10 km radius of the household. We also included ward fixed effects, due to the large variability of the training variable across mapped areas and at a more granular level across wards.

14 Crump et al. (2009: 187) study the optimal subsamples to estimate the average treatment effect more precisely and find that 'a good approximation to the optimal rule is provided by the simple rule of thumb to discard all units with estimated propensity scores outside the range [0.1,0.9]'.

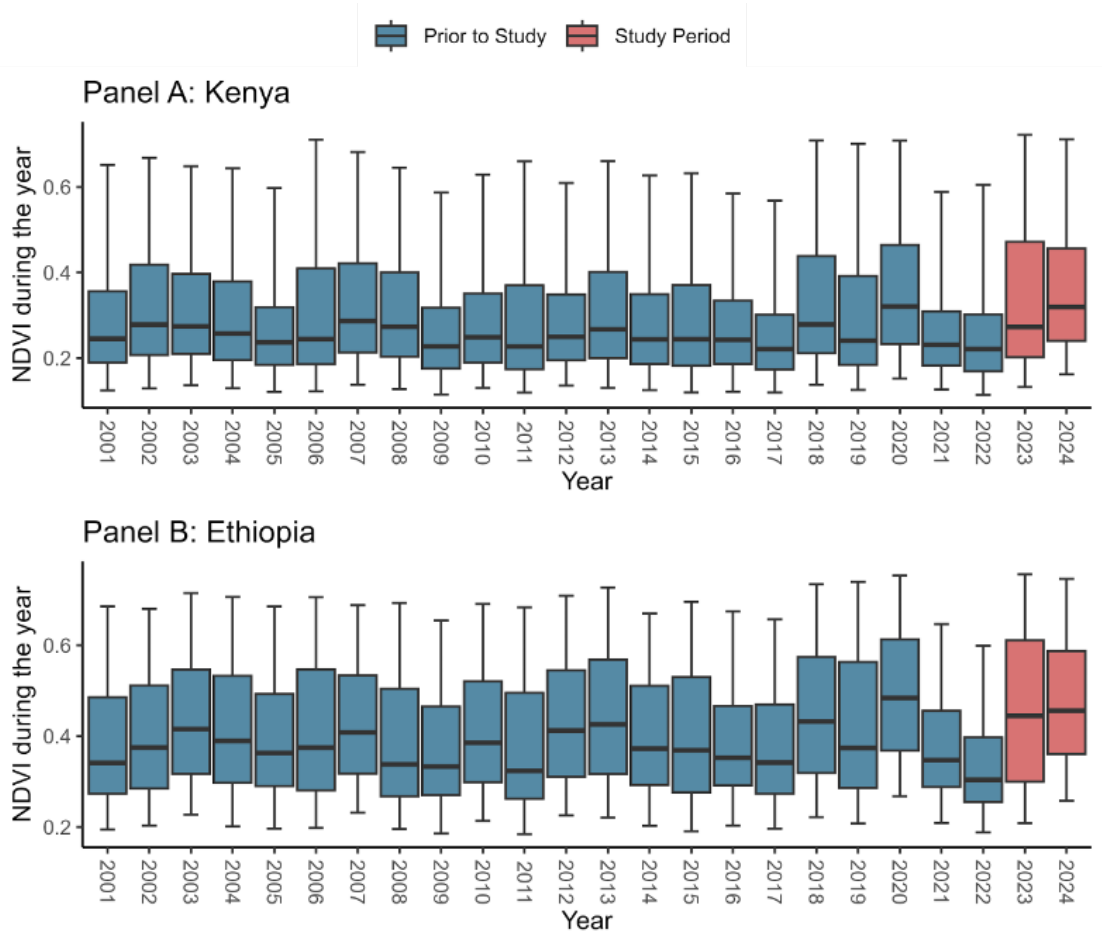
between groups, it cannot account for unobserved confounding factors. It is plausible that households (especially those in control areas) who actively sought out and self-reported having received training were inherently more motivated and innovative or they possessed other unmeasurable traits that might independently influence the outcomes, thereby introducing a self-selection bias not fully addressed by conditioning on observed covariates alone. More critically, the pervasive information spillovers observed within these highly mobile and interconnected pastoralist communities pose a fundamental challenge to causal inference. Spillovers directly violate the stable unit treatment value assumption (SUTVA), a foundational assumption for most causal inference methods, including AIPW. SUTVA posits that a unit's outcome is solely determined by its own treatment status and is not affected by the treatment status of other units. When information from 'treated' households rapidly disseminates to 'control' households, the 'control' group's outcomes are no longer a pure reflection of the absence of intervention, as they are indirectly exposed to its benefits. The sheer scale of these spillovers fundamentally blurs the distinction between treated and control environments, making it very difficult for any statistical approach to fully disentangle the direct causal impact of the formal intervention from the widespread indirect effects. This underscores the inherent complexities and limitations of conducting impact evaluations in such dynamic and highly interactive social-ecological systems.

APPENDIX E. NDVI AND M&E DATA USED IN THE STUDY

NDVI data

NDVI data was used to construct outcome variables on the vegetation conditions in migration areas and around study communities. NDVI is a measure of an area's vegetation greenness captured via satellite imagery and it is widely used as an indicator of vegetation density and health (NASA Earthdata, n.d.). Its values range from -1 to 1, with higher values indicating more dense vegetation.

FIGURE E.1. YEARLY DISTRIBUTION OF NDVI VALUES IN KENYA AND ETHIOPIA MAPPED AREAS (2001–2024)



Notes: Boxplots depict the distribution of NDVI values of pixels spanning all mapped areas in each country during an entire year. The bottom of the box denotes the 25th percentile of NDVI values, the top of the box denotes the 75th percentile, the horizontal bar inside the box denotes the median, and the bottom and top whiskers denote the 5th and 95th percentiles, respectively.

Source: Authors' own.

Figure E.1 confirms a general sentiment gathered from qualitative exercises and informal conversations with AS staff: the couple of years prior to implementation of the AS interventions (2021–2022) were drought years characterised by poor vegetation, while the implementation years (2023–2024) were years with more plentiful rain, characterised by good vegetation. In both countries, median NDVI values in study areas (denoted by the horizontal bars inside the boxplots) were significantly higher during the period of study than in the two years prior, and they correspond to some of the highest median NDVI values in the past 24 years. The distances between the bottom and top of the study-period boxes, especially for 2023, are also quite large, which signals that the study-period years also had significant variability in vegetation cover across the study areas.

Causal Design followed the approach of Machado et al. (2020) when constructing rangeland condition indicators using NDVI data. Standardised month anomaly (SMA) values were constructed for the areas respondents last migrated to (in Kenya) and for areas 5 km, 10 km and 20 km around the exact location where respondents were surveyed (in Ethiopia). To do so, monthly NDVI data from 2000 to 2025 for all study areas was obtained through NASA's Earth AppEEARS data extraction tool (Didan, 2021; AppEEARS Team, 2025).[15] The data was downloaded and stored, and then the average NDVI in each area of interest was calculated for each month. Areas of interest were based on either migration areas that respondents selected as having migrated to on a physical map at the time of the survey or a radius around participants' survey locations. Therefore, for each area of interest, 300 average NDVI values were calculated: one per month for 25 years of data. Monthly SMA values were then calculated for each area by subtracting the 25-year average for a specific month from the NDVI value and dividing by the 25-year standard deviation for a specific month. For example, to calculate an area's February 2000 SMA, (1) the average NDVI among all February months in the 25-year dataset was calculated, then (2) the standard deviation of NDVI values among all February months in the 25-year dataset was calculated, and finally (3) the SMA value was calculated by subtracting the average calculated in (1) from the NDVI value for February 2000 and dividing this result by the standard deviation calculated in (2). In this example, an SMA NDVI value of 1.0 for a given area in February 2000 would mean that the area's NDVI for February 2000 was one standard deviation higher than the average value for the month of February (2000–2024) in that area.

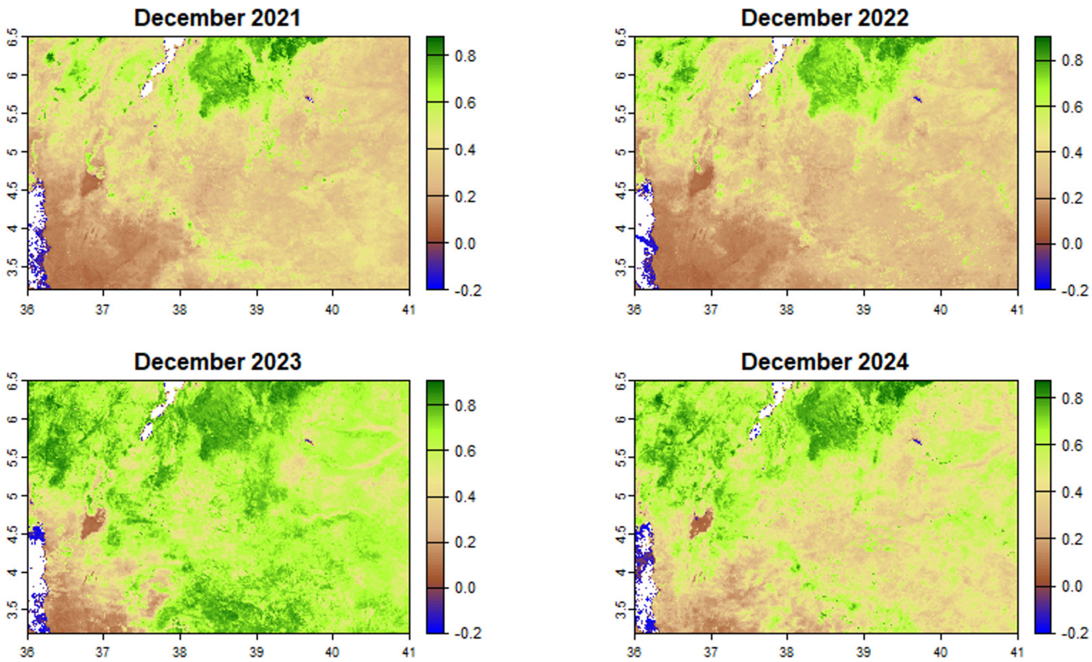
Causal Design decided to use NDVI data for the construction of these indicators to provide an objective measure of vegetation conditions that matched the data used to create the AS Steward maps (which also use NDVI data). Despite these appealing features, this approach does have some limitations, however:

- **Soil background effects:** NDVI can be influenced by soil colour and reflectance in drylands with sparse vegetation, leading to errors in results about vegetation conditions (Convention on Biological Diversity, 2009).
- **Inability to detect different plant species:** NDVI does not distinguish between plants of different species, some of which might be less suited for animal consumption than others (Lacouture et al., 2020).
- **Sensitivity to climatic conditions:** NDVI values can fluctuate based on climatic conditions, like clouds and rain, leading to errors in results about vegetation conditions (Ali et al., 2013).

15 The Causal Design team downloaded .tif files containing MODIS/Terra Vegetation Indices Monthly L3 Global 1 km SIN Grid V061.

Figure E.2 shows an example of how the NDVI data downloaded by Causal Design depicts greenness in a sample area (chosen from the Ethiopia study areas). Vegetation cover improved considerably in December 2023, compared to the prior two years, which matches the results presented above that study areas saw heavy rainfalls and higher NDVI values during the intervention years. To construct household-level NDVI indicators, Causal Design loaded the NDVI data (a map with NDVI values per pixel as shown in Figure E.2) in R, filtered the data to only include the pixels in the area of analysis (either a migration location or a radius around the household's home), and then calculated the SMA values as described above.

FIGURE E.2. SAMPLE NDVI MAPS FROM ETHIOPIA (DECEMBER 2021 – DECEMBER 2024)



Source: Authors' own.

M&E data

Global Communities shared monitoring data related to AS Steward (the mobile app) registration and usage with Causal Design, which was collected by Field Agents using CommCare and with Google Analytics functionalities for app developers. The data provided to Causal Design for analysis included:

1. **Field Agent registration data (Kenya only):** This data records the first touch-point Field Agents had with users in treatment areas, recording them in a database for future follow-up.

2. **App user monitoring and follow-up data (Kenya only):** This data is self-reported by Field Agents on how they follow up with app users in treatment areas. Field Agents record the mode of engagement (e.g., call, WhatsApp, in person) and type of engagement (e.g., help with app download, general check-in, troubleshooting).

3. **App download dashboard data (Kenya and Ethiopia):** This data records the phone numbers of all users who download the AS Steward app.

4. **Posted alerts data (Kenya and Ethiopia):** This data records all alerts posted by users and Field Agents in the mobile app (e.g., prevalence of disease or lack of water in a particular location). App users are identified by the phone number they registered with.

5. **User activity data (Kenya and Ethiopia):** This data records every use of the app in Kenya and Ethiopia, including opening the app, posting an alert and downloading a map. App users are identified by the phone number they registered with.

The data, often used in conjunction with the phone numbers provided by study participants at baseline and endline, was used to assess the extent to which:

1. pastoralists in control areas of Kenya downloaded and used the app as registered user pastoralists in Ethiopia (where the AS Steward app was available to be downloaded but was not the intervention being studied).
2. app users utilised the app's different functionalities, such as posting different alerts and downloading vegetation maps.

APPENDIX F. REGRESSION RESULTS

Here, we present robustness checks showing the treatment coefficients from primary indicators across the following regression specifications:

- Basic: Model without covariates
- ANCOVA: Model with baseline value of the outcome variable
- Rainy season covariates: Same as the main specification but including the NDVI around the household's home during the rainy season.

For each indicator and specification summarised in Table F.1. below, the first number represents the treatment coefficient (with stars associated with statistical significance). The number in parentheses represents the standard error of the coefficient and the number in square parentheses corresponds to the p-value.

TABLE F.1. PRIMARY INDICATOR REGRESSION SPECIFICATIONS (AS Regen)

Outcome	Main	Basic	ANCOVA	Rainy season covariate
Rangeland management capacities and behaviour changes				
Percent of households living in communities with a shared grazing plan	90.62*** (2.09) [0]	90.33*** (2.42) [0]	90.45*** (2.37) [0]	90.6*** (2.02) [0]
Percent of households that do something to improve the quality of the grass in their area	83.45*** (2.06) [0]	83.49*** (2.26) [0]	83.26*** (2.29) [0]	83.24** (2.1) [0]
Percent of households that feel very confident or confident that their community is able to manage rangelands and rangeland conditions	79.7*** (2.86) [0]	79.43*** (3.79) [0]	79.29*** (3.38) [0]	79.56*** (2.93) [0]
Rangeland conditions				
Percent of households that are very satisfied or satisfied with the quality of the pasture and grass in the areas they have access to for their livestock	82.68*** (2.05) [0]	81.92*** (2.73) [0]	81.9*** (2.46) [0]	82.5*** (2.17) [0]
Average NDVI in a radius of 10 km around the household's home (rainy season, June–August 2024)	0.06 (0.07) [0.36]	0.05 (0.07) [0.507]	0.05 (0.07) [0.507]	0.07 (0.07) [0.297]
Average NDVI in a radius of 10 km around the household's home (dry season, December 2024 – February 2025)	-0.01 (0.05) [0.797]	-0.03 (0.06) [0.618]	-0.03 (0.06) [0.618]	-0.00 (0.05) [0.967]

Outcome	Main	Basic	ANCOVA	Rainy season covariate
Herd conditions				
Percent of pastoralist households for whom the average herd condition improved over the last year	70.94*** (3.94) [0]	71.19*** (5.5) [0]	71.16*** (5.51) [0]	70.54*** (3.99) [0]
Percent of sheep/goats in good condition	33.8*** (3.74) [0]	33.13*** (4.92) [0]	33.32*** (4.69) [0]	33.45*** (3.74) [0]
Percent of camels in good condition	38.31*** (6) [0]	31.65*** (10.04) [0.004]	31.52*** (10.07) [0.004]	43.23*** (8) [0]
Percent of cattle in good condition	44.51*** (3.48) [0]	45.05*** (5.38) [0]	45.09*** (4.76) [0]	44.62*** (3.62) [0]
Use of AS Steward and migration-related indicators				
Percent of pastoralist households for whom AS is an important source of migration information	52.07*** (6.05) [0]	52.75*** (5.29) [0]	52.71*** (5.28) [0]	52.8*** (5.25) [0]
Number of times a household migrated to an area and found insufficient pasture	-0.25 (0.16) [0.127]	-0.19 (0.15) [0.221]	-0.18 (0.15) [0.223]	-0.2 (0.15) [0.205]
Percent of households who migrated to areas with a water source available	3.83 (3.27) [0.212]	4.49 (0.118) [2.76]	4.35 (2.72) [0.123]	4.44 (2.69) [0.112]
Percent of households who migrated to areas where the state of the pasture was transition or graze	5.89** (2.65) [0.055]	5.45** (2.21) [0.022]	5.36** (2.18) [0.021]	5** (2.19) [0.032]
Average NDVI (standardised deviation) in migration areas	-0.02 (0.05) [0.779]	0.04 (0.07) [0.565]	0.04 (0.07) [0.565]	0.01 (0.05) [0.785]
Percent of sheep/goat herd lost during migration	-0.86 (2.67) [0.736]	-1.07 (2.39) [0.659]	-1.36 (2.46) [0.585]	-1.36 (2.51) [0.593]
Percent of camel herd lost during migration	-5.46 (5.15) [0.53]	0.21 (4.38) [0.963]	0.48 (4.19) [0.91]	0.49 (5.41) [0.929]
Percent of cattle herd lost during migration	-7.06 (5.72) [0.259]	-3.06 (5.38) [0.575]	-3.22 (5.26) [0.546]	-2.51 (5.16) [0.631]

Outcome	Main	Basic	ANCOVA	Rainy season covariate
Herd conditions				
Percent of pastoralist households for whom the average herd condition improved	1.86 (2.38) [0.438]	0.81 (2.41) [0.739]	0.82 (2.43) [0.74]	0.89 (2.35) [0.707]
Percent of sheep/goats in good condition	-1.1 (2.89) [0.697]	-0.67 (2.6) [0.798]	-0.6 (2.64) [0.822]	-0.65 (2.65) [0.808]
Percent of camels in good condition	-5.46 (5.71) [0.457]	-7.7* (4.13) [0.078]	-7.59* (4.26) [0.091]	-6.9 (4.21) [0.117]
Percent of cattle in good condition	1.56 (3.21) [0.632]	-1.12 (2.94) [0.707]	-1 (2.98) [0.739]	-1.15 (3.18) [0.721]

Source: Authors' own.

APPENDIX G. KEY FINDINGS FOR SECONDARY INDICATORS

The primary indicators discussed in the main report (under the key findings and analysis in sections 4 and 5) directly address the core objectives of the AS Steward and AS Regen interventions. We also examined a range of secondary outcomes on pastoralists' livelihoods.[16]

AS Steward secondary indicators

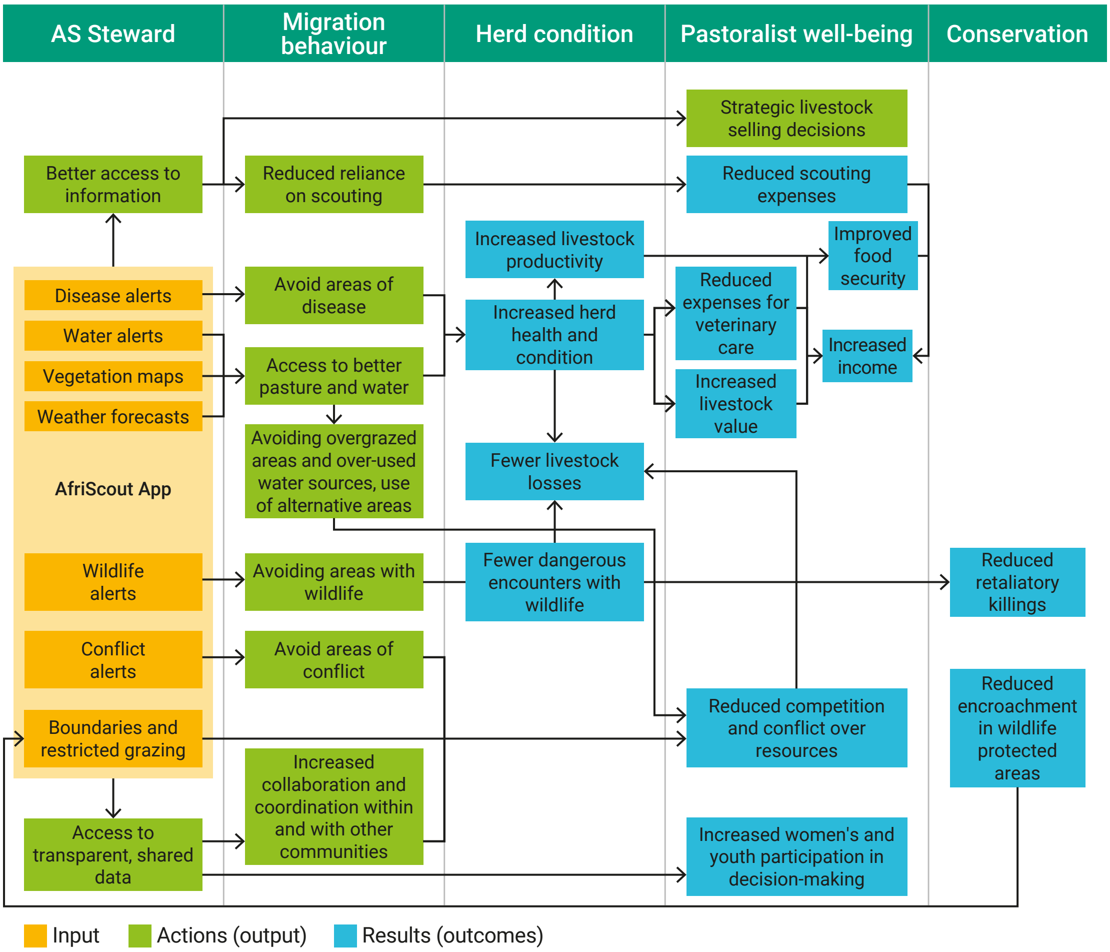
For AS Steward, we looked at a diverse set of secondary indicators, organised into seven categories:

- Migration decision-making
- Conflict
- Expenses and risks of scouting
- Rangeland conditions
- Rangeland management
- Collective decision-making
- Human–wildlife interactions.

Figure G.1 shows a simplified diagram of the causal chains and reported effects of AS Steward on secondary indicators. These are based largely on qualitative data, given that survey findings show few significant results (possibly due to issues of contamination and unusually high rainfall, as discussed earlier). Nonetheless, the overall findings of the qualitative aspect of the evaluation illustrate that AS Steward has led to a number of financial and non-financial benefits, most of which are direct and anticipated. More indirectly, the availability of information has also led to changes in decision-making and levels of coordination with other pastoralists both within and outside communities. The quantitative aspect of the evaluation allows for triangulation of these qualitative findings by comparing secondary outcomes between households who have received AS Steward training and those who have not.

16 Sections 5.2.3 and 5.3.3 in the full Impact Evaluation Report (Causal Design, 2025) present quantitative and qualitative evidence of the impact of AS Steward and AS Regen on secondary indicators.

FIGURE G.1. EFFECTS OF AS Steward ON SECONDARY INDICATORS



Source: Authors' own.

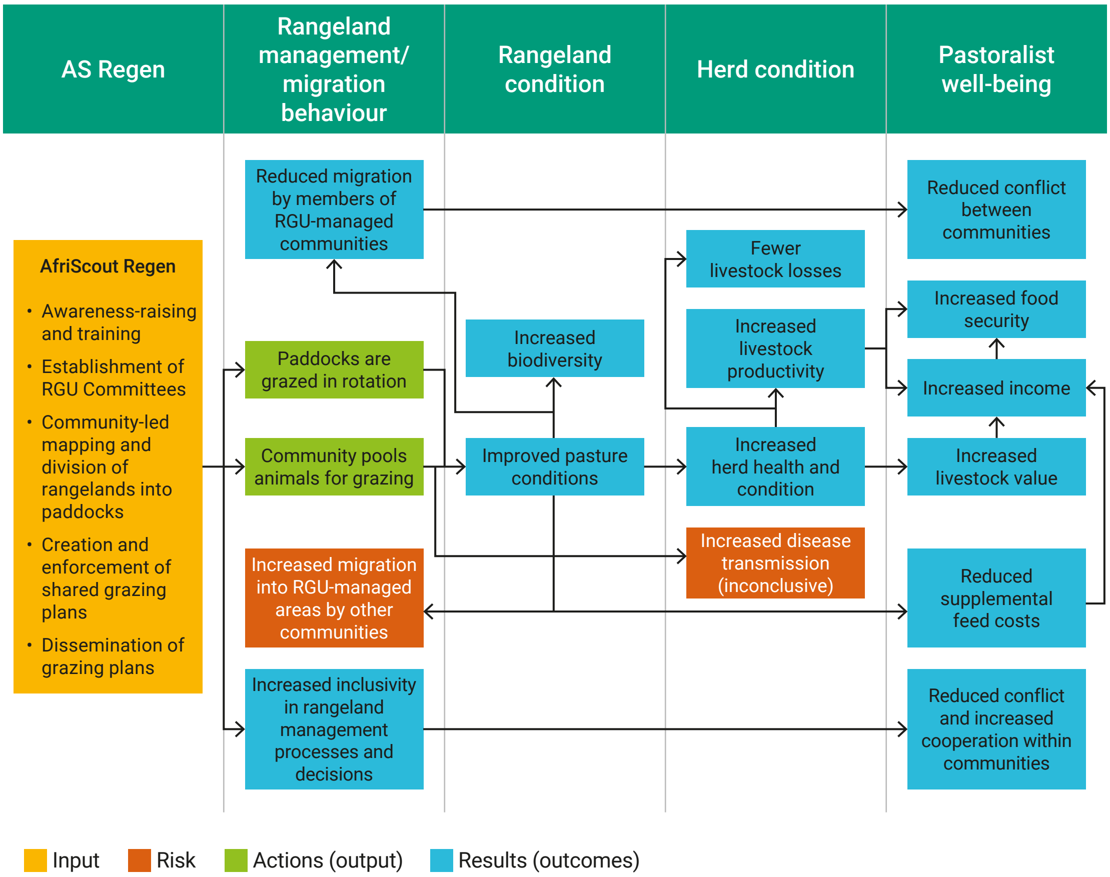
AS Regen secondary indicators

For AS Regen, we looked at a diverse set of secondary indicators, organised into four categories:

- Conflict
- Human–wildlife encounters and conservation
- Migration
- Expenses and risks of scouting.

Figure G.2 shows a simplified diagram of the causal chains and observed impacts of AS Regen on secondary indicators, based on both qualitative and quantitative data. The findings related to well-being and conflict are largely directly attributable to the intervention's design, given its focus on improved resource management, and community governance and coordination, and the impacts these have on pasture and herd conditions. In contrast, some of the observed effects on human–wildlife encounters and conservation, migration and the use of scouts are largely considered beneficial side-effects, emerging indirectly from changes in grazing patterns, resource availability and community dynamics fostered by AS Regen.

FIGURE G.2. EFFECTS OF AS Regen ON SECONDARY INDICATORS



Source: Authors' own.

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