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Seeds for recovery: The long-term impacts of a complex agricultural intervention on welfare, behaviour and stability in Syria (SEEDS)

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About this research project paper

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Abstract

There is **scarce evidence** on whether and how assistance in humanitarian emergencies and conflict settings impacts household well-being and behaviour. Conducting rigorous impact evaluations in such settings poses multiple challenges in design and data collection.

In SEEDS, we evaluate the impact of a complex large-scale multi-arm agricultural intervention on productivity, food security, and resilience in the context of an on-going humanitarian crisis in **Syria**. Specifically, we identify the causal impacts of agricultural asset transfers over various time horizons (the short-, medium-, and long-run), and across different conditions and subgroups (gender and conflict intensity) at the household-level. We evaluate the effectiveness of irrigation rehabilitation separately at the community-level.

We use and combine **various data sources**, including a unique survey panel dataset collected over a period of four years from multiple governorates in Syria, satellite remote-sensing data, and publicly available violent conflict incidence and weather data.

Our **findings** from using cutting-edge machine and deep learning approaches together with innovative balancing and analytical methods can be summarised as follows:

For average treatment effects at the household-level, we find that the provision of agricultural asset support leads to **significant improvements in food security** in the short- and long-term, three years after the intervention. The positive and significant effect on food security is driven mainly by the increased consumption of healthy food items such as vegetables.

In the long-run, livestock support reduces the use of **harmful coping strategies** households employ to deal with food shortages. Interestingly, we find that households who received vegetable kits are not just less likely to sell their productive assets in the long-term but also are less likely to marry off their young daughters or send their children to work. Overall, we find that both agricultural and livestock asset support is key to improving households' resilience in the long-term.

The **irrigation rehabilitation interventions** at the community-level positively affected agricultural productivity compared to the pre-intervention and pre-conflict periods. However, these effects were only significantly pronounced in the spring season.

As for the heterogeneity analysis, we find that **female-headed households** benefit remarkably more in terms of food security in the medium-term compared to male-headed families. Moreover, households residing in areas that are moderately affected by **violent conflict** show stronger food security improvements compared to households from peaceful or conflict-intense settings.

Overall, we draw **three overarching lessons** from our findings in SEEDS: First, agricultural support in protracted conflict settings effectively improves the long-term welfare and resilience of vulnerable households. In fact, the presence of an ongoing humanitarian operation acts as a social safety net if circumstances deteriorate suddenly. Second, not all interventions are equally effective, and not all households equally benefit, underscoring the need to design and implement inclusive context-specific interventions with detailed targeting. Third, methodologically, using multiple remote data sources and machine learning methods help overcome challenges in conducting rigorous impact evaluations in hard-to-reach humanitarian emergency settings.

1. Introduction

Objectives of the project

SEEDS has three overarching objectives:

First, to improve our understanding of the short-, medium-, and long-term welfare and behavioural impacts of complex agricultural interventions in protracted humanitarian crises *(empirical research objective)*. Specifically, we address the following four cross-cutting research questions:

- RQ1. What are the separate and overall effects of the various agricultural interventions on food security, nutrition and resilience? How do the impacts differ by type of support over time?
- RQ2: Are the impacts sustained three years after the end of the programme?
- RQ3: How does exposure to violence and weather shocks affect and interact with programme impacts and pathways?
- RQ4: How do impacts and pathways vary by subgroups of the population including by gender?

Second, to adapt existing approaches and test novel approaches for conducting rigorous impact evaluations of complex interventions in these settings *(methodological research objective)*. Specifically, we address the following two methodological questions:

- MQ1: How can satellite data and modern computational techniques be used to improve the data available for impact evaluations in crisis settings for both outcome measures and contextual factors?
- MQ2: How can modern computational and statistical techniques such as machine learning be used to improve the evaluation of impact causality, pathways, heterogeneity, evolution over time?

Third, to draw attention to and inform about the opportunities for impact evaluations of complex interventions in crisis settings and the lessons learnt from evidence of a specific complex intervention (*Learning and communication objective)*. Specifically, we address the following two learning questions:

- LQ1: Can research and policy adapt their tools to ensure significant and effective learning in conflict-affected and humanitarian settings?
- LQ2: What alternative designs, methods, data and measurements can be used to overcome challenges in conducting impact evaluation in conflict-affected and humanitarian settings?

Contribution to the literature

Conflict, agriculture and food insecurity. In 2022, 193 million people worldwide were classified as food insecure. Of these, 72% live in conflict-affected countries or territories (FSIN, 2022). Together with economic distress and weather extremes, violent conflict remains one of the main drivers of food insecurity in the world (FAO et al., 2022). When affected simultaneously by multiple shocks such as conflict, economic crisis and weather extremes at once, 94% of households are unable to afford healthy food (FAO et al., 2021). The strong relationship between violent conflict and food insecurity is well established in the literature (Brück et al., 2019a; Kaila & Azad, 2023; Martin-Shields & Stojetz, 2019). Conflict shapes multiple aspects of food production and consumption, and consequently impacts nutrition and health (Shemyakina, 2022; Rudolfsen, 2020). For example, armed conflict has shown to negatively affect farm production where lack of inputs such as seeds, fertilisers, and tools becomes more prevalent (Baliki et al., 2022a; Lin et al., 2022). Moreover, the inability to access land and other natural resources can further negatively impact agricultural production (Jaafar et al., 2015). For example, Arias et al (2019) found that exposure to violent conflict can lead to an increase in risk aversion, which results in a reduction in agricultural investment, impacting economic output and productivity in the long-run. In another study, Appau et al. (2021) find that a 10% increase in bombing in Vietnam decreases agricultural productivity by 3%. Armed actors also use agricultural production and cropland cultivation as means of sustenance (Eklund, 2017; Jaafar & Woertz, 2016). As wars end, agriculture is one of the first key coping strategies households use, but rural markets and institutions often struggle to function without external support (Arias et al., 2019; Bozzoli and Brück, 2009).

Impact evaluations in conflict and humanitarian settings. Puri et al. (2017) write that “there is a dearth of theory-based, reliable evidence causally linking interventions to relevant outcomes” in the humanitarian sector (though notable recent exceptions are cited above) (p. 519). The lack of rigorous evidence is partly based on a lack of data due to security and ethical concerns (Idriss, 2019), but also due to practical challenges for both implementers and researchers. As Puri et al. (2017) write, "these challenges can be overcome without compromising the ethical standards and principles that ought to guide humanitarian action and social science research practice" (p. 520). In the absence of high-quality panel data, important knowledge gaps concerning these methodological topics include causal inference; impact pathways; combining multi-disciplinary approaches; accounting for context; remote monitoring; and external validity. If these challenges can be overcome, the scope for learning is huge and improvements in efficiency can be up to 50% (Alda and Cuesta, 2019).

Impact of aid in humanitarian settings. Evidence on the impact and effectiveness of humanitarian and development support in conflict-affected settings is also increasing in the past years, but has mainly focuses on the impacts of cash or food transfers (Altındag & O'Connell, 2023; Bedoya et al., 2019; Kurdi, 2021; Schwab, 2019; Salti et al., 2022; Tranchent et al., 2019; Tusiime et al., 2013) rather than on complex agricultural interventions (Brück & d'Errico, 2019). Moreover, impacts on welfare and behaviour are often assumed rather than tested and quantified, and systematic learning for programme design and modalities is rare (Martin-Shields & Stojetz, 2019; Brück et al., 2019b). We are aware of only a handful of studies of food security interventions based on credible counterfactuals in conflict-affected settings, none of them from Syria (Aurino et al., 2019; Brück et al., 2019c; Ecker et al., 2019; Schwab 2019; Tranchant et al., 2019; Vallet et al., 2021). How and if a complex agricultural intervention improves food and nutritional security, and how it strengthens the resilience of households against recurring shocks remains broadly understudied.

The impact of the war in Syria. There is an extensive literature on the drivers, forms and impacts of the war in Syria and other conflict-affected countries in the region (see, e.g., Jaafar et al., 2016) and on the interventions to alleviate both the war and its adverse socio-economic impacts (e.g. Verwimp et al., 2019). Existing studies focus mostly on Syrian refugees (or on others affected by the war) than on Syrians residing in or returning to Syria. There are also a number of rigorous impact evaluations conducted, mostly about interventions for Syrian refugees in Lebanon (e.g., Altındağ & O'Connell, 2023; De Hoop et al., 2018; Salti et al, 2022). However, we are not aware of a single impact evaluation having taken place in Syria since the start of the war (or, indeed, before), using rigorous methods for causal identification and accounting for the specific Syrian context.

From agriculture to nutrition and health. Zooming out of conflict and crises setting, there is a significant body of literature that studies the theoretical and empirical links between agriculture and nutrition, yet strong causal evidence of the effectiveness of targeted agricultural intervention on production and consumption in developing settings remains inconclusive (Ruel et al., 2018). A number of studies show that agricultural interventions improve diet diversity and quality and thus micronutrient status (Baliki et al., 2022b; 2019; Mary et al., 2020; Rutherford et al., 2016; Schreinemachers et al., 2020). Interventions that incorporate multiple aspects of nutrition education and health such as improvement in WASH practices, health access, and the provision of fortified products along with the agricultural intervention may be more effective than agricultural interventions alone, especially for improving nutrition and long-term health (Doocy et al., 2019). There is a number of systematic reviews of nutrition-sensitive agricultural interventions have burgeoned in the past decade (Bizikova et al., 2020; Haby et al., 2016; Masset et al., 2012; Poulsen et al., 2015; Sharma et al., 2021; Webb and Kennedy, 2014; Wordofa & Sassi 2020). However, none focus on conflict-affected or humanitarian settings.

To address this gap, we conducted a systematic review under SEEDS on the impacts of agricultural interventions on food security and nutrition in populations affected by humanitarian crises. In the paper, we review different types of nutrition-sensitive agricultural interventions, including biofortification, homestead food production, livestock and dairy, agricultural extension, irrigation, aquaculture, and value chain programs. More specifically, we reviewed the existing published and grey literature, identified key systematic reviews, and screened references focusing on populations affected by humanitarian crises. Moreover, we use the search strategy of the most recent review (Ruel et al., 2018) and update the search strategy by adding conflict-related search terms.

Our results showed that out of 12,621 articles from which 12,440 articles were identified through search databases, 88 articles from ReliefWeb and Google Scholar, and 93 articles from 3ie, 179 articles were screened for full-text review. After reading carefully, 172 articles were further excluded because they did not meet the eligibility criteria. Only seven articles were included in the final stage. Out of these, three were conducted in post-conflict, three in protracted humanitarian crises and one is post-natural disaster. Findings have shown that agricultural extension, homestead food production, and livestock support were the main agricultural interventions used in conflict and humanitarian crises settings. Most of these studies show that agricultural intervention improved household food security and resilience. Some studies have shown the positive impact of the intervention on children's minimum dietary diversity, minimum meal frequency and acceptable diet targets. However, this improvement did not necessarily translate into better child nutrition (underweight and stunting), mainly due to the lack of precision in estimating birth dates to assess anthropometric data. A few studies have also shown a positive impact of the program on agriculture production techniques, agricultural inputs, adoption of several marketing strategies and the use of financial services.

Based on the literature and the systematic review, we see at least three remaining knowledge and research gaps in this sub-field.

1. It remains unclear when and under what conditions or contexts, which policy or intervention mix should be applied.
2. The pathways through which agricultural intervention influences welfare and behavioural outcomes in humanitarian settings are not fully understood.
3. The long-term impacts of agricultural interventions in emergency settings are not yet well-researched, nor the sustainability of the impact beyond the programme's specific period.

SEEDS makes four broad contributions:

First, SEEDS is the one of the first studies to analytically examine the long-term impacts of a complex agricultural intervention on welfare and behaviour in a protracted crisis setting, tracking households over four years through a panel household survey. The research papers under SEEDS provided novel evidence on the short- and long-term impacts of separate and combined programme impacts on food security, nutrition, resilience, and productivity, as well as across multiple local conditions and vulnerable subgroups.

Second, we open the black box on how complex interventions in crisis settings work by mapping out how impact pathways may be relevant at different points in time after the end of the intervention and how these impacts are heterogeneous across different groups and levels of violent conflict. The results show clearly who benefits most (and who does not) from these interventions, which is crucial to fine-tune future programmes to maximise benefits for Syrians (and other war-affected populations) beyond this project.

Third, we leverage the longitudinal nature of the study to test how households react and cope with recurring multiple shocks such as conflict, drought, and macroeconomic recession, and how programme impacts strengthen the response of vulnerable small-holder farmers to these shocks.

Finally, we will test if and how, methodologically, rigorous learning can take place in challenging security and humanitarian settings, strengthening the role of evidence-based policymaking and programming in the humanitarian sector, and highlighting to academics and practitioners the feasibility and importance of undertaking research in challenging environments.

Policy relevance

In the past three years, the world has witnessed a significant increase in the number of global crises, including covid-19, hyperinflation, and the war in Ukraine, which are hampering efforts to achieve zero hunger. Today more than ever, there is an urgent need to better understand how governments, donors, implementing agencies and academia can collectively work together to develop pro-poor policies that achieve multiple interrelated SDGs (Yavuz et al., 2022). These challenges are particularly manifested in war-affected, post-conflict, fragile and insecure settings, where there is a need to transition from unsustainable emergency support to development-oriented and inclusive policies.

Generating stronger rigorous evidence to address these challenges is gaining attention in academic, practitioner and donor circles. Two recent global reports on food insecurity (the State of Food Security and Nutrition in the World by FAO, IFAD, UNICEF, WFP and WHO and the Global Report on Food Crises by FAO, WFP and IFPRI) call for information and analysis, strategic programming, high-level policy uptake, advocacy and coordination in preventing food crises and boosting recovery in conflict-affected settings (FAO et al., 2022; FSIN, 2022). Moreover, FAO stresses that today the food and agriculture-related SDG monitoring still lacks comprehensive data (FAO, 2022). FAO Directors-General Qu Dongyu highlighted in his speech in 2022 at the United Nations High-Level Political Forum on Sustainable Development (HLPF) the importance of science and research in understanding the role agriculture plays in their action against food insecurity. UNICEF highlights that stakeholders particularly agree on the importance of evidence from crisis settings and that donors are willing to provide more resources into high-quality research in crisis settings (Bakrania et al., 2021).

SEEDS addresses these policy gaps by generating rigorous new insights on the long-term impacts of complex agricultural interventions in protracted crises. The study is one of the first to causally assess the long-term impacts and pathways in Syria, providing novel evidence that can be highly relevant to other countries, and benefiting stakeholders working on recovery and reconstruction in war-affected settings. In terms of Syria-specific policies, we provide recommendations on how better to design and implement complex agricultural interventions. More specifically, the project benefits practitioners and policymakers working on recovery and reconstruction in war-affected settings by breaking down the impacts and mechanisms of programming, and how these vary across context, who they particularly benefit, and how sustainable the benefits are. The answers generated and disseminated in our project feed directly into the current policy debates around fighting food insecurity and hunger.

Innovation and relevance to CEDIL

Innovation. SEEDS uses novel and multiple data sources in combination with innovative methods. First, the panel survey dataset provides unique multidimensional and longitudinal data from treatment and control groups in Syria. It tracks the same households over four waves until three years after the end of programme implementation, which facilitated novel analysis of the evolution of effects over time, including medium- and long-run estimation. Moreover, we use high resolution satellite data to examine the impact of the intervention at the village levels. Second, the overarching innovative methodology in SEEDS builds on: 1) Using modern machine learning and deep learning techniques to produce the geo- and time-coded data and predictions from the satellite information; 2) Spatially and temporally matching contextual data with household survey data from the interventions to be evaluated to facilitate analyses of how contextual variation affects the intervention impacts; 3) Using and testing various matching and balancing techniques including entropy balancing to overcome challenges in design (changes in treatment assignment) and data (attrition) and finally 4) applying cutting-edge honest causal forests to assess heterogeneity of treatment effects.

Relevance to CEDIL. The programme in Syria is an important case study of a complex intervention in a protracted humanitarian crisis, meeting CEDIL's definition of complex interventions as follows: We study two intervention packages delivering a) agricultural assets to households and b) rehabilitation of agricultural infrastructure to communities. SEEDS tests impacts of the packages over various time horizons (the short-, medium-, and long-run), at multiple levels (household and community), and across different conditions (gender and conflict intensity). Our novel findings from a complex and challenging context which are disseminated through six research papers, two evidence briefs, and multiple capacity building and policy workshops, are relevant to CEDIL's research and policy goals.

2. The intervention

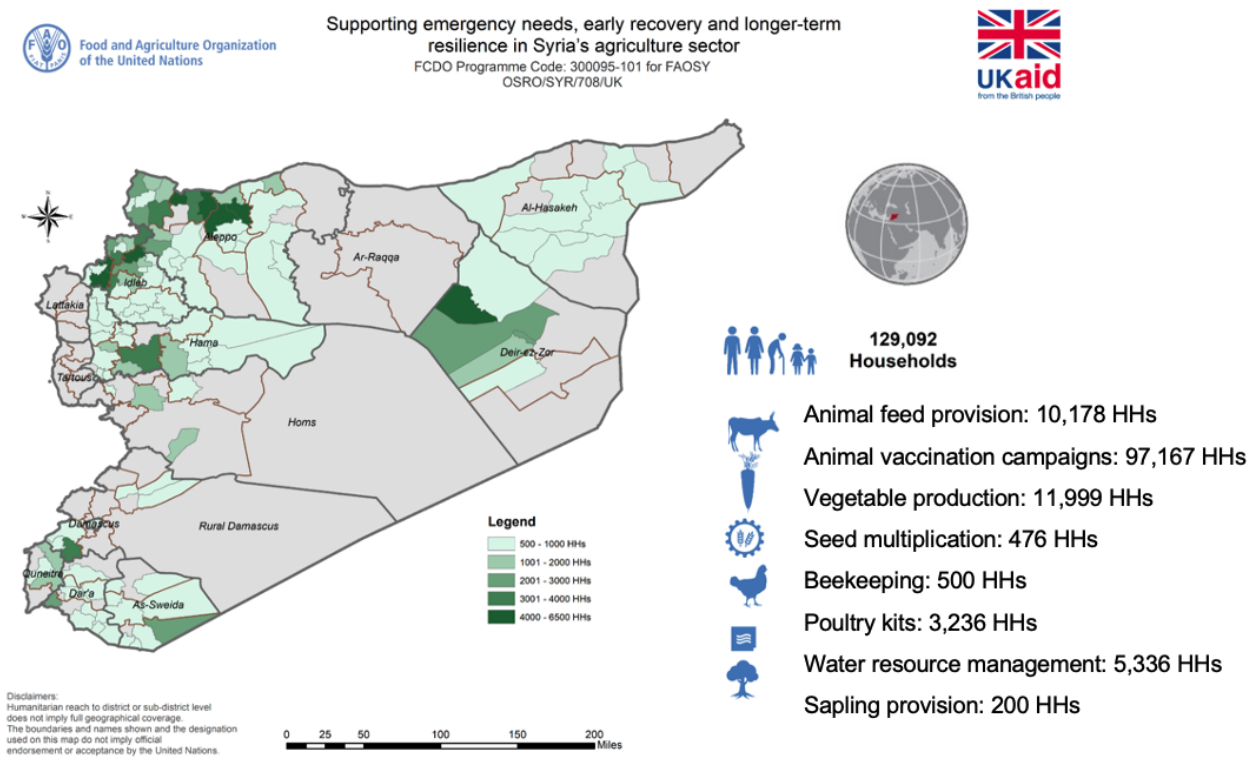
Context and activities

We study a multi-arm intervention implemented by the Food and Agriculture Organisation of the United Nations (FAO) in one of the most challenging contexts in the world – contemporary wartime Syria. In addition to protracted violent conflict, Syria is plagued by macroeconomic instability and extreme weather shocks, which are the main drivers of food insecurity in the country (FSIN, 2022). In 2022, 12 million people in Syria were threatened by food insecurity (WFP, 2022) and 14.6 million people were in need of food and livelihood assistance in 2022 (OCHA Syria, n.d.). Since the start of violent conflict in 2011, the level of food insecurity has increased (FSIN, 2022). Moreover, Syria's recurrent episodes of drought severely affected the agriculture sector and the access to drinking water (ibid). Additionally, the country is plagued by an economic crisis reinforced by high unemployment rates, inflation and the financial crisis in neighbouring Lebanon, which blocks large amounts of Syrian funds (ibid). The crises of the past years in Syria have put the lives and livelihoods of a large part of the population at risk, significantly transformed and weakened the entire agricultural sector, and created an urgent need to support agricultural activity and markets.

FAO in Syria provided (and continues providing) critically important programmes to support vast rural populations and the agricultural sector in Syria, with the aim to establish an entry point for long-term reforms of agricultural markets and institutions. We studied two intervention packages in the context of the "Supporting Emergency Needs, Early recovery, and Longer-term Resilience in Syria's Agriculture Sector" programme funded by the Foreign, Commonwealth and Development Office (FCDO), which delivered multiple components at both the village and household levels. We studied the impacts of two overarching support packages at the core of these interventions: 1) the direct transfer of agricultural assets to households; and 2) investments and rehabilitation in local infrastructure.

The implementation period of this programme was from mid-2018 until the end of 2020, delivering support in several Governorates. The programme targeted vulnerable rural farmers mainly focusing on households headed by women, unemployed young men susceptible to the appeal of armed groups, and small-scale farmers and herders who lost their productive assets and/or lacked access to inputs. Figure 1 visualises the implementation area and gives an overview of the intervention packages and the number of beneficiaries for each package. The intervention arms relevant for our studies include: (i) animal vaccination campaigns combined with salt licks, (ii) vegetable seeds kits, (iii) beekeeping and (iv) poultry support, (v) vegetable seedlings, and (vi) the rehabilitation of damaged irrigation systems to increase access to irrigated lands and enhance water use efficiency for small farmers. All types of asset transfers arms were distributed once to beneficiary households, who did not did not receive additional support from FAO. A detailed description of the intervention arms is provided in Annex A1.

Figure 1. FAO's emergency and recovery support in Syria



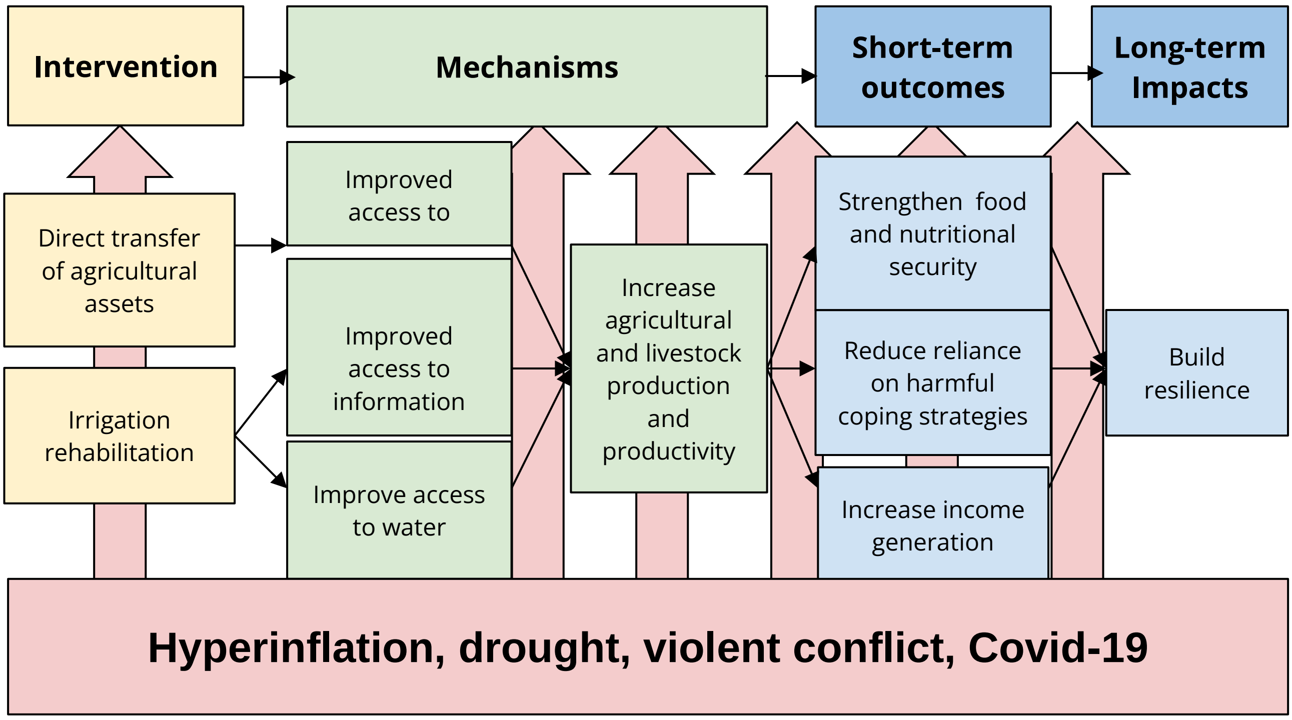
Notes. Figure provided by FAO (2022).

The distribution of the vegetable kits started in mid 2018 and lasted until mid 2019, poultry and beekeeping kits were distributed between early 2019 and March 2020. The vegetable seedlings and the animal vaccination campaign were carried out in the course of 2020. All preceding intervention packages were distributed on the household-level. The irrigation activities were implemented at the village-level in the governorates of Deir-Ez-Zor in 2020.

Theory of change

The overall programme targeted both small-holder farmers and the agricultural sector in Syria at large, with a view to increase access to agricultural assets and to recover the rural agricultural sector. More specifically, the starting point of the intervention was that crisis-affected small-scale farmers faced significant constraints in accessing agricultural inputs and sufficient water to their land, which limited localised food production. To alleviate these constraints, the intervention provided direct agricultural inputs to households for crop, vegetable, and livestock production, and improved access to information and technologies for irrigation and water resource management. Figure 2 displays the theory of the change of the programme, highlighting the relationship of the two intervention packages to the short-term and long-term impacts, as well as the mechanisms through which these relationships take place. Moreover, the theory of change underscores the importance of shocks (red arrows) in directly and indirectly influencing and shaping the implementation of the interventions, the pathways through which they operate, and the outcomes they achieve.

Figure 2: Diagram of the intervention's theory of change



More specifically, we hypothesise that the programme achieves its outcomes as follows:

The direct asset transfer should immediately increase farmers' access to agricultural input including high-quality seeds, tools, and livestock feed. In turn, the increased accessibility was intended to have two positive impacts in the short-run. First, it increases livestock and crop production at the household level, which is crucial for establishing and maintaining the supply of sufficient as well as nutritious food. Second, it contributes to higher agricultural productivity and yields. In the short- and medium-term these agricultural mechanisms should strengthen food access and consumption, diversify opportunities for income generation, reduce reliance on harmful coping strategies, relax budget constraints and reduce the need to take out loans. Improvements in these economic and nutrition well-being indicators will in the long-term, improve nutritional and food security further and strengthen the resilience of households against shocks.

The rehabilitation of irrigation systems was at the community-level and was expected to unlock similar pathways. In the first instance, the package increased access to water supply among farmers, which should immediately boost production levels, especially in drought years. In the medium-term, these improvements should increase agricultural productivity and decrease vulnerability to weather shocks. As for the asset transfer, theory predicts downstream improvement in nutrition, health and related well-being outcomes, and builds household resilience against shocks.

In summary:

1. In the short-term: Receiving both irrigation (access to water) and asset transfer (access to inputs) increases agricultural and livestock production and productivity levels.
2. In the medium-term: Asset transfers increase food security, opportunities for income generation, liquidity and independence from loans and credit to purchase inputs and foods, and reduces reliance on harmful coping strategies.
3. In the long-term: in interaction, the interventions increase nutritional and food security and strengthen resilience to income and weather shocks.

Outcomes

First, we assessed the impact of agricultural support on the use of agricultural inputs, production, and productivity.

- **Agricultural inputs** were assessed based on whether the household used any of the following in the past 12 months: seeds/seedling, pesticide, organic fertiliser, inorganic fertiliser, or hired labour.
- **Agricultural production** was assessed based on whether the household produced one or more of the five major annual food crops (irrigated and rainfed wheat, barley, tomato, eggplant, and cucumber) over the most previous season.
- **Productivity:** Agricultural yield for each of the food crops (t/ha) was calculated based on the harvest quantity and the area planted.

Second, we complement the assessment of agricultural productivity by measuring vegetation indices derived from satellite imagery such as the **normalised difference vegetation index (NDVI).** These indices are effective in quantifying and evaluating vegetation cover and vegetation vigour. The NFVI is calculated as follows:

$$NDVI = \frac{NIR-R}{NIR+R}$$

where NIR and R are the near infrared and red reflectance, respectively. NDVI values range from -1 to 1, with negative values corresponding to water bodies, and values below 0.25 corresponding to bare soil surfaces or remains of harvested cereals. NDVI values between 0.25 and 0.4 represent surfaces with minimum vegetation present, and values greater than 0.4 represent vegetated land. The higher NDVI values are (i.e., closer to 1.0), the stronger and healthier the vigour of the vegetation.

We analyse precipitation history and long-term trends per governorate to disentangle the impact of rainfall on agriculture production using satellite data. We compute a **rainfall ratio** for each year by which we control for precipitation using equation

$$Rainfall\ ratio = \frac{Rainfall_{year}}{Average\ rainfall_{2000-2020}}$$

Third, we measure food and nutritional security using the food consumption score (FCS) and the Household Dietary Diversity Score (HDDS):

- **FCS** captures access and consumption of various food groups. This indicator measures both the types of food groups consumed and the frequency of consumption in the past seven days. The following categories with the corresponding weights in parentheses are included: starches (2), pulses (3), vegetables (1), fruit (1), meat/fish/eggs (4), milk/dairy

(4), fats (0.5), sugar (0.5), and condiments (0). The FCS is derived from the sum of the weighted category values (WFP, 2008).

- **HDDS** is the sum of food items consumed in the previous day before the survey out of twelve food groups (Swindale & Bilinksy, 2006). All the food groups have the same weights in the HDDS, which makes the indicator more suitable for measuring diversity of diets compared to the FCS.

Fourth, we measure resilience and coping behaviours to shocks using the reduced Coping Strategy Index (rCSI) and the application of harmful livelihood coping strategies:

- **rCSI** measures household adaptive capacity based on the need to employ harmful coping strategies to deal with food shortages. These include: relying on less preferred or less expensive food, relying on help from relatives or friends, reducing the number of meals eaten a day, and limiting portion size at meals. Each strategy is weighed by their relative severity and the overall indicator takes a value between 0-35, and a higher score indicates an increase in household food insecurity (Caldwell & Maxwell, 2008).
- **Harmful livelihood coping strategies** were assessed by asking the households whether they had to sell productive or household assets, send children to work, arrange child marriages, take up credit for food, sell food obtained through food aid or sell non-food humanitarian aid in the past 30 days.

3. Data

Quantitative data and survey modules

The main source of data to assess the impact of the asset transfers in SEEDS is the household panel survey data. The data was collected by local enumerators through face-to-face interviews. In total, four waves of data were collected. Table 1 shows the timing of the data collection vis-a-vis the interventions. The baseline (wave 1) was collected before the implementation of the interventions. Wave 2 was collected in one year, after the distribution of the phase 1 interventions including vegetable kits, poultry, beekeeping and irrigation rehabilitation. Wave 3 was collected after the end of all the intervention including those distributed in Phase 2. The fourth wave was collected two years after the completion of all intervention arms (and three years after the end of distribution of the vegetable kits).

Table 1. Intervention and data collection time plan

	Phase	2018	2019				2020				2021				2022		
		Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3
Wave 1																	
Vegetable kits, drip irrigation sets and agricultural tools	1																
Poultry kit	1																
Beekeeping	1																
Irrigation rehabilitation	1																
Wave 2																	
Vegetable seedlings	2																
Livestock vaccination	2																
Wave 3																	
Wave 4																	

Notes. Irrigation rehabilitation programme not covered by survey data collection.

Data collection process. Before the start of baseline data collection (wave 1), we conducted a two-day enumerator training in Damascus. Local enumerators were identified and selected in close coordination with FAO. On the first day of the training, the survey questionnaire and design were introduced and explained, while on the second day, we piloted the questionnaire in the form of mock interviews. Participants were randomly assigned to interviewer and interviewee roles. Each team of enumerators covered one governorate, with the team members residing in their respective governorates. For each team, we selected a team leader who was responsible for overseeing the data collection process and providing support to enumerators in the field. Moreover, in each governorate, FAO's local focal expert was in contact with the team leader throughout the process, directing and coordinating the overall field-work.

The questionnaire was designed in collaboration with FAO in English and then translated to Arabic language. The wave 1 questionnaire consisted of 13 survey modules, including information on the household head; the household; land ownership and accessibility; household food sources; food security and dietary diversity; the use of harmful food-related coping strategies; the use of harmful livelihood coping strategies; access, price, availability and quality of agricultural inputs; the purchase of agricultural inputs; income from agricultural value chains; post-harvest storage and processing; access to drought early warning systems and exposure to adverse shocks. The questionnaire was approved by local authorities before the start of the data collection for each wave.

Fieldwork was built on ISDC's, AUB's and FAO's policies, including rigorous codes of conduct, ethical guidelines, security policies, data protection policies and guidelines for ensuring good scientific practices. The physical security and mental well-being of our respondents, enumerators and staff were paramount at all times. We conducted adequate security monitoring and risk assessments in accordance with FAO's guidelines for Syria before undertaking any fieldwork. Consent was obtained and adjusted to fit standards in conflict-sensitive settings (Falb et al., 2019). Participants had full control over which components of the study they participated in without affecting their beneficiary status with FAO. Most importantly, no benefits to participants were withheld, and non-beneficiaries were not misled for participating. We obtained an IRB exemption for the analysis of the household survey data from the IRB office at the American University of Beirut.

Attrition

In each wave, we followed up with all households once included in the survey. Hence, some households who we were not able to reach in intermediate, were also followed up with again in later waves. In our survey, the attrition rate was 10.7% at wave 2, 7.8% at wave 3 and 12.5% at wave 4 compared to the baseline (or the first time the households were interviewed). The attrition rates are similar in the control and treatment group. By comparing baseline household characteristics of the attrited and non-attrited households, we do not detect any strong differences (detailed attrition table displayed in Annex A2).

Remote-sensing, weather, and conflict event data

Apart from our household survey data, we use additional data sources to conduct the impact measurement and analysis:

First, we use satellite image data to measure agricultural productivity outcomes. More specifically, we use NASA's U.S. Geological Survey Landsat series of Earth Observation satellites because it provides consistent, continuous, and uninterrupted spatio-temporal images of Earth's land surface at 30-m resolution. Landsat provides optimal spatial resolution and spectral information that can efficiently monitor land use, biomass change, deforestation and evapotranspiration trends (Jaafar & Ahmad, 2020). Here, we use Landsat 5 (period of record: 2000 – 2012,), Landsat 7 (period of record: 2000 – 2022), and Landsat 8 (period of record: 2013 – 2021). We use cloud-free Landsat imagery to derive the NDVI using the near-infrared and red bands.

Second, in addition to surface reflectance data, we also use rainfall data from the Climate Hazards Group InfraRed Precipitation with Station dataset (CHIRPS). CHIRPS provides gauge-corrected global rainfall data (period of record: 1981 – present) at 0.05° resolution; it incorporates satellite imagery with in-situ station data to create gridded rainfall time series. We use the CHIRPS pentad collection available on Google Earth Engine (GEE) to derive annual rainfall for the period of interest (de Sousa et al., 2020). This also allows us to compare with the self-reported shock survey data. Figure 3 shows a snapshot of variation of the yearly rainfall by sub-districts in 2020.

Figure 3. Precipitation in year before wave 3 in mm (sub-district averages)

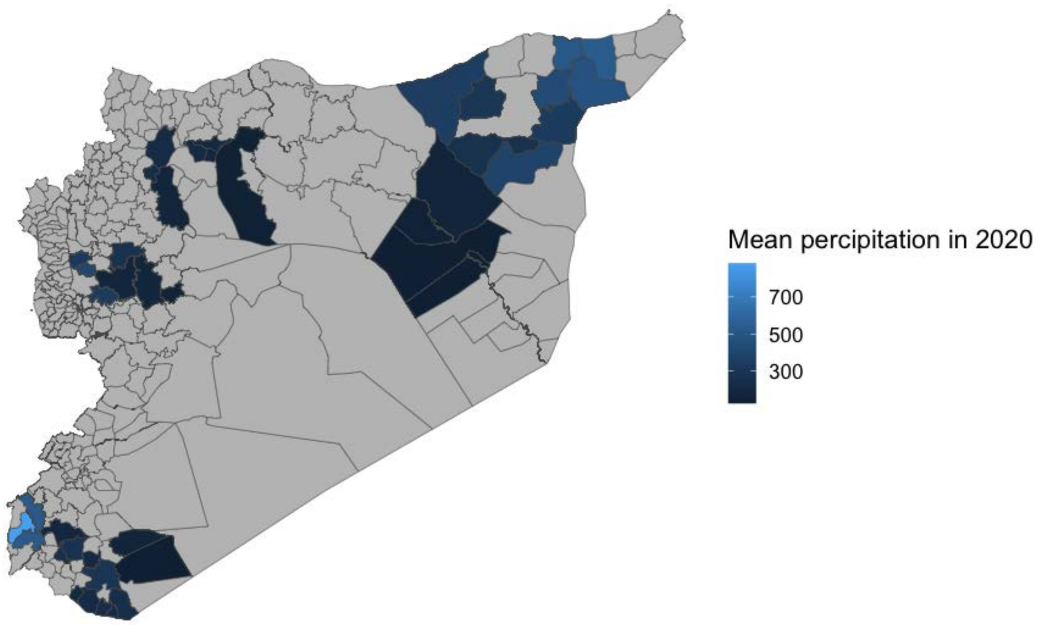
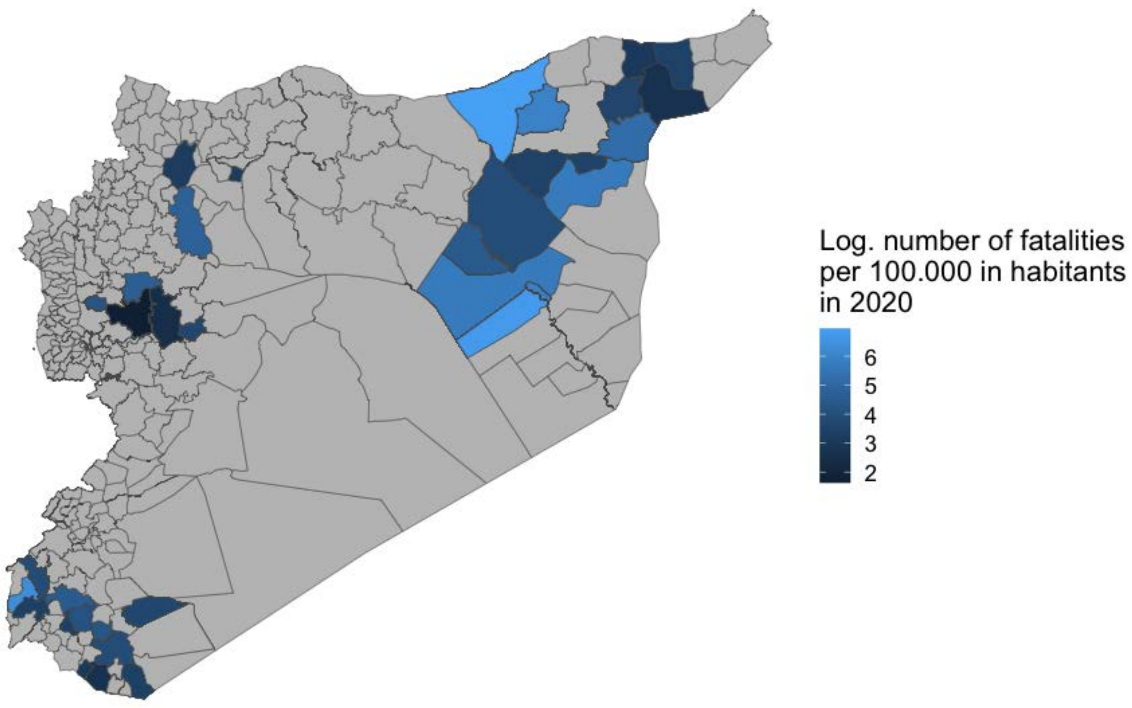


Figure 4. Number of fatalities per 100.400 inhabitants through violent events in year before wave 3 (sub-district averages)



Third, we use Armed Conflict Location and Event Data (ACLED) which provides geo- and time-coded information on conflict events. ACLED started compiling granular spatial conflict event data in Syria from 2017, which is updated on a regular basis (Raleigh, et al., 2010). We calculated the number of conflict events per month and year per sub-district per 100,000 inhabitants in the study area. We also differentiate these numbers by different conflict event types, including by violence against civilians, battles, explosions or remote violence, protests, strategic development and riots. Moreover, we calculate the number of fatalities per 100,000 inhabitants per subdistrict per month and per year. The resulting variables served as proxy measures of political stability and conflict exposure that the households level. Figure 4 displays the logarithmic variation between the different sub-districts in our study in 2020.

Finally, we merged key population data at the sub district-level with our survey data. The data were estimated by FAO for the year 2019. The dataset included population size estimates and shares including the share of the female, disabled and widowed population in every subdistrict. These numbers are used as a proxy for long-term indicators of violent conflict.

Data quality

Overall, in light of challenges of collecting data in Syria including during conflict and covid-19, the household panel survey data was of very good quality. The comparatively low 10% attrition rate for such a setting speaks clearly of the effort FAO and their data collection team has put into ensuring that we follow up with households over a period of four years. Given the circumstances, we were only able to collect data using pen and paper which leads to a larger number of human errors both during the interviews and the data entry. The data were entered using Microsoft Access, which we programmed meticulously in advance to avoid entry errors. The steady communication between the research team and FAO's team allowed us to review minor data inconsistencies and correct them, for example non-matching household IDs or enumerator-related entry errors. Like this, we developed a rich and consistent data set that was easily mergeable to other data sets through P-Codes. Moreover, through documenting the variable structure in a detailed codebook (see Annex B), we avoided misinterpretations of complex variables. On the downside, agricultural production and yield data suffered from wide-ranging measurement errors, which we were able to replace by satellite data. Lastly, we were not able to collect some of the key variables in later waves, which were removed during the approval stage by the local agencies due to their sensitivity. This implies that not all variables were available in all waves.

4. Methodology

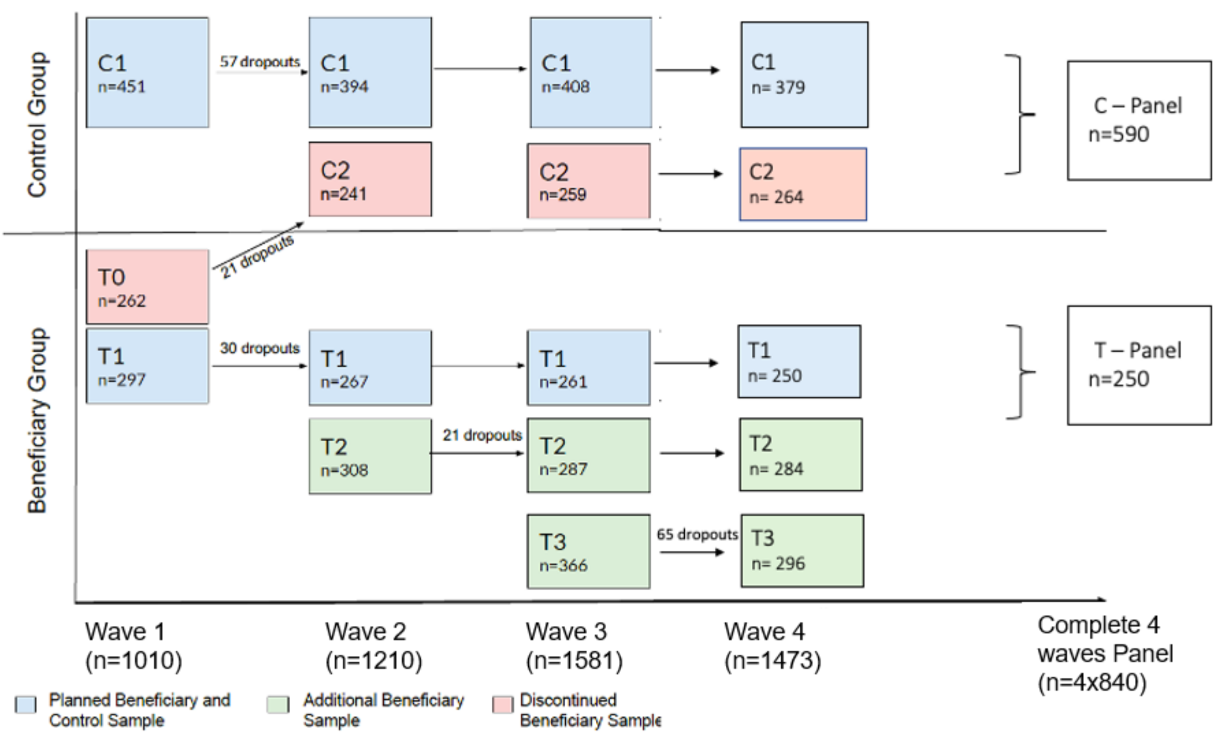
Evaluation design

We use a quasi-experimental panel design, comparing households that received any of the intervention packages (the "treatment group") with comparable households that did not receive support (the "control group"). Since the irrigation rehabilitation programme was implemented on the community-level, we compare control and treatment villages in its separate study design (more below). The "gold standard" for programme impact evaluation are experimental designs, where units of observation are randomly assigned to treatment and control groups. Yet, in protracted crisis settings, such as in Syria, randomised experiments are usually not feasible, particularly for large-scale interventions (Puri et al., 2017).

The panel feature of the design entails analysing pre-intervention data and at least one wave of post-intervention data collected from the same villages and households over up to four years. This design allowed us to estimate short-, medium-, and long-term impacts of receiving support. Following up with the same households is the ideal way to guarantee that the changes induced by the programme are accurately captured and not confused with other changes among households and villages during the implementation period. This is particularly crucial in the Syrian context where political, economic, and climatic factors are very volatile. To ensure that any changes we observe among beneficiaries between baseline and follow-up waves are the result of receiving programme activities, it is key that the control group is selected such that it is not systematically different from the treatment group, particularly in terms of location and socio-economic characteristics. At baseline, the sampling of the beneficiaries was conducted by drawing a random sample from FAO's beneficiary lists proportional to the total number of recipients across each activity, taking into account the geographic representation of the beneficiary sample. We only included beneficiary households that received only one asset transfer support. Control villages and households were selected from the same set of sub-districts.

Sampling strategy. The sampling strategy at baseline was done as follows: First, we identified the number of potential beneficiaries per sub-district and per activity. Second, we drew samples from these sub-districts proportional to the number of beneficiaries per each activity. This ensures that samples at the sub-district level are balanced. Third, we identified and randomly selected a set of villages within each targeted sub-district. Fourth, in each of the sampled beneficiary villages, the enumeration team was provided with an alphabetic list of designated beneficiaries and randomly selected every second household from this list for interviews. Whenever beneficiaries had not been identified yet, we requested that the team identify respondent households based on the eligibility criteria defined by FAO for their target groups and randomly select a sample for interviews. Finally, similar control villages were determined in the field. Enumerators were trained to select a number of non-beneficiary villages proportional to population in its governorate to ensure speedy yet effective data collection. The enumerators were informed about the selection process, and it was communicated clearly that they need to select the non-beneficiary interviewees from villages based on the same eligibility criteria for the selection of beneficiaries in the intervention villages. Eligibility criteria for the control group were vulnerable rural farmers prioritising households headed by women, unemployed young men susceptible to the appeal of armed groups, and small-scale farmers and herders who lost their productive assets and/or lacked access to inputs.

Figure 5. Study design and sample composition



Changes in treatment assignment after baseline. Figure 5 shows the structure of study design across the 4 waves. The survey sample at baseline contained 1,010 households in total, including 559 in the treatment and 451 in the control group. Unfortunately, after baseline, there was a change in the criteria of the targeting for the beekeeping and poultry interventions which implied that a significant number of the potential beneficiaries that we identified at baseline, will not receive support. Specifically, 47% of the initial treatment sample was discontinued from the treatment group after baseline (marked as change in T0 to C2 in Figure 5). This also implies that a minor share of the control households from C2 live in treatment villages.

In order to compensate for the drop in statistical power and to cover all asset transfer intervention arms in our survey, we relied on an adaptive survey design. First, we collected data from a new sample at Wave 2, where we are able to easily identify who received which type of support. We increased the sample size by 308 households (T2) across the whole of the survey to cover proportionally the number of households who received poultry and beekeeping. In Wave 3, we included an additional sample of 366 households to cover beneficiary households that received Phase 2 support, including livestock vaccination and vegetable seedling support (T3). We followed the same sampling strategy for the additional treatment households as described above. At Wave 4, we followed all the households that were interviewed in any previous wave. We collected interviews from 643 control and 830 treatment households in Wave 4.

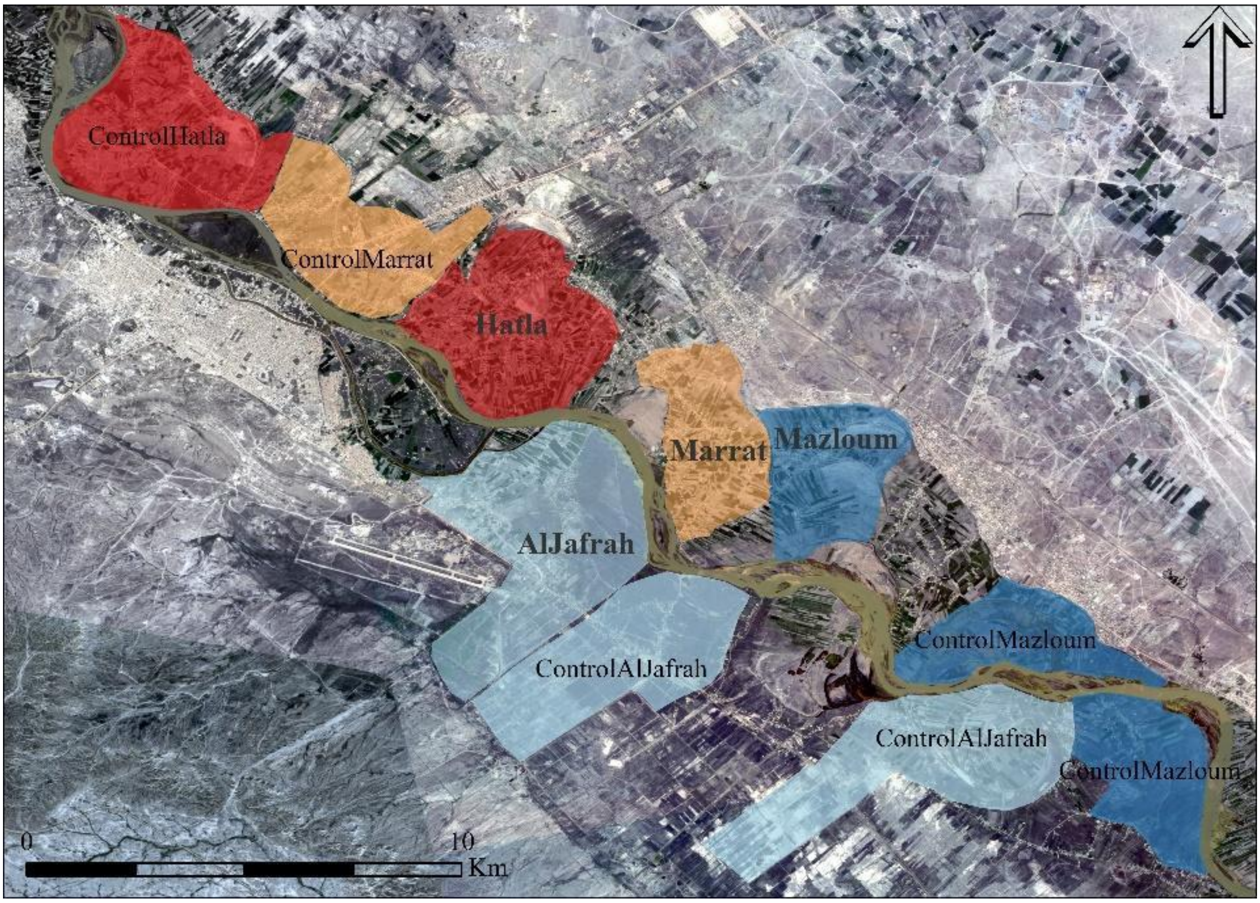
Based on this adaptive design, we have the following: (1) The data contains households who have at least two observations in the panel. Therefore, we can analyse changes in the long-term across most of the interventions. (2) We have a 4-wave complete panel data which includes 590 control and 250 treatment households (last column in Figure 5). However, given the changes in treatment assignment, the panel only contains households that received the vegetable kits intervention arm. Therefore, our full panel analysis will only measure impacts of this intervention arm.

Such an adaptive design can pose some challenges that need to be addressed. The main downside of such an approach is the absence of the baseline observations of these new households, which makes a straightforward and a rigorous assessment more challenging, yet not impossible. A second challenge is that the control group is not any more structurally similar to the treatment group, which requires us to rely more on matching and balancing techniques.

Integration of remote-sensing methods

The irrigation intervention is studied separately from the household survey as the intervention took place at the community levels and the impacts will be measured on the same level using NDVI from the satellite data. In this study design, we delineated the extent of intervention villages using high resolution imagery available on Google Earth Pro as the extent of productive agriculture areas in pre-conflict years. Using information from FAO, we were able to accurately delineate the intervention villages in Deir-Ez-Zor. Three study periods were defined: pre-conflict period (2000-2012); conflict period (2013-2018); and post-conflict period (2019-2021). The post-conflict period is also the post-intervention period for the target villages. Based on prior knowledge of the region's agriculture sector, cropping patterns, major crops cultivated there, and time series analysis of the normalised difference vegetation index (NDVI), two growing seasons were defined in Deir-Ez-Zor Governorate, by observing NDVI peaks: spring season (wheat and cereals), and summer season (sesame, cotton, and vegetables).

Figure 6. Sampling treatment and control villages using remote-sensing



To disentangle the effect of the interventions from that of other agro-ecological factors, we selected control villages based on the following: (1) areas that are heavily cultivated and irrigated from the Euphrates River, underground wells, or storage reservoirs; (2) areas that will not benefit from the intervention but are located near intervention villages; and (3) areas in the same climatic zone with similar topographic and crop type characteristics as the intervention areas. Control villages were also chosen to be statistically similar to intervention villages in terms of agricultural productivity during the pre-conflict and conflict period. The similarity between control areas and intervention areas implies that any difference in agricultural production and crop yield is due to the intervention. For every intervention village, one or two control villages were delineated, and the analysis was performed by averaging the results of the control villages and comparing them with the averaged results of the intervention villages. Moreover, the results of every intervention village were compared to the results of the corresponding control village(s). Figure 6 shows the control villages for each intervention village.

Identification strategy

Our sample shows imbalances on several household and individual characteristics between the control and the treatment group at baseline (Annex A3). To correct for those, we applied several approaches to balance and estimate the data:

First, to estimate the short-term impact of the vegetable kit provision using the full panel data, we applied a fixed effects model combined with a propensity score matching approach. The main advantage of a fixed effects estimation is that it accounts for time-fixed omitted variable bias by estimating the within-household variation. The large control group in the panel allows using greedy 1:1 nearest-neighbour propensity score matching (Baliki et al., 2022c).

Second, to assess the intervention impact of the vegetable kits in the long-run, we applied entropy balancing following Hainmueller (2012). The method increases the group comparability by perfectly balancing selected covariates through generating weights to control units. Compared to nearest-neighbour matching, this approach retains the original sample size since it does not discard non-matched observations. We combined this approach with a differences-in-differences estimation using the panel data set (Kayaoglu et al., 2023).

Third, to assess the treatment effect of the other asset transfer interventions that were not part of the complete panel (namely the provision of vegetable seedlings, the beekeeping and poultry support, and the provision of livestock vaccines and salt licks), we needed to overcome the absence of panel data across the first two waves. Due to this misrepresentation of treatment households, we estimated the additive treatment impact of all asset-transfer interventions using cross-sectional regressions at the post-endline to derive the long-run impact. Then, we estimated the change between the endline and post-endline using a differences-in-differences estimation only using panel data between the two waves. Again, we relied on entropy weighting to strengthen the rigour of the causal claims of the impact assessment (Kayaoglu et al., 2023).

Fourth, for the long-term intervention-specific analysis, we grouped the observations by livestock interventions, including the provision of beekeeping and poultry support, animal vaccines and salt licks; and agricultural interventions, including the provision of vegetable kits and vegetable seedlings. Like this, we were able to analyse sector-specific treatment effects while retaining an appropriate treatment sample size. For the intervention-group-specific evaluation, we used panel estimations including exclusively observations from Wave 3 and 4. Again, we applied difference-in-difference after entropy balancing. We complement the analysis by cross-sectional estimates from wave 4 after entropy balancing (Kayaoglu et al., 2023).

Fifth, to measure impact heterogeneity while correcting for sample imbalances, we use the honest causal forest (Athey et al., 2019). This machine learning technique recursively and iteratively partitions the observations into subgroups based on their predicted treatment effect size and a menu of covariates. Before each iteration, the data are split in halves. while one half of the data is used to define the tree structure, the other half is used to estimate. Since the tree structure is exogenous for the estimation data, this “honest” approach prevents overfitting. Averaging within-subgroup treatment effects delivers a conditional average treatment effect (CATE). The model allows the inclusion of a large number of covariates in relation to the number of observations, which enabled us to test the role of over 20 covariates in driving treatment heterogeneity. We weighed the CATE by augmented-inverse propensity weighting, which weighs the observations by overlap in key covariates, which are additionally weighted by their importance in treatment heterogeneity (Athey et al., 2019). This method is particularly adequate for non-randomized samples, like ours, because through these double robust estimators, we ensure a consistent estimation as long as either the propensity score model or the regression model is correctly specified (ibid., Glynn and Quinn, 2010). We interpreted the CATE estimate from the sample overlapping in propensity scores to maximise the degree of causal inference.

We collapsed the panel waves 1 and 3 into one cross-section to evaluate the medium-run heterogeneous impacts of receiving vegetable kits (Weiffen et al., 2022).

Finally, for analysing the satellite data, we perform k-means clustering over the intervention and control villages. Clustering relies on unsupervised machine learning because it works by grouping unlabelled objects. Here, we use the k-means clustering algorithm, which groups objects based on features in k number of clusters or groups. The k-means algorithm determines the best k centre points (cluster centroid) and assigns each object to the closest cluster centroid. Objects nearest to the cluster centroid are grouped together as one cluster. The cluster centroids are defined such that the cumulative square of the distances from each object to its closest centroid is minimised. We apply the clustering algorithm on the NDVI, NDMI, and MNDWI bands and pre-define three *clusterers*. We sort the *clusterers* using the NDMI band and obtain three classes – dry pixels, irrigated pixels, and water pixels. We perform zonal statistics to estimate the irrigated area and percent irrigated area for spring and summer seasons of years 2000 – 2021 for both intervention and control villages. We observe the distribution of irrigated areas in each village and how it changes over time. To study whether there was a significant change in agricultural production during the post intervention period (2020-201), we test the hypothesis using Wilcoxson's non-parametric test. The post-intervention NDVI, NDMI, and irrigated areas generated from the unsupervised classification were individually compared to their conflict means (2013 – 2018) to observe whether the intervention improved agricultural activity. This analysis was performed individually on both intervention and control villages (Sujud et al., 2022).

We conducted several robustness tests to validate our findings in the specific research papers including for example using different propensity score matching approaches and various model specifications. The results of the robustness tests are not displayed in this report but are available in the specific papers (Baliki et al., 2022x; Kayaoglu et al., 2023; Weiffen et al., 2022).

5. Quantitative analysis

Impact of the intervention

In this report, we present a summary of the findings from four different analyses and research articles conducted under SEEDS. We will attempt to provide an overarching narrative of the findings from the different papers. For more information please do refer to the specific research papers. First, we present the short- and medium-term impacts of the vegetable kit provision on food security and use of food-related coping strategies. The analysis uses panel data from three waves, where control households were matched to treatment households using propensity score matching (Baliki et al., 2022c). Second, we show the findings of the impact of the vegetable kits intervention in the long-run on resilience based on entropy balanced time trends and differences-in-differences estimations with kernel propensity score matching (Kayaoglu et al., 2023). Third, we present the long-term combined impacts of all intervention packages, and then separately for livestock interventions including the provision of poultry, beekeeping and livestock vaccine support, and for agricultural interventions including the provision of vegetable kits and vegetable seedlings. Here, we rely on ex-post cross-sectional comparisons and differences-in-differences estimations using the last two waves of data, both balanced using entropy technique by key observable covariates (Kayaoglu et al., 2023). Fourth, we present findings on the impact of the irrigation intervention on crop productivity at the community-level using satellite imagery and machine learning (Sujud et al., 2022). Finally, we present key drivers of heterogeneous treatment effects of the vegetable kits provision on food security using an honest causal forest algorithm (Weiffen et al., 2022).

Short- and medium-term impacts of vegetable kits on food security

We begin this section with the impacts of vegetable kits on food security in the short- and the medium-term using fixed effects estimations after nearest-neighbour propensity score matching on baseline values based on the results from Baliki et al. (2022c). Table 2 shows the overall baseline mean for FCS and rCSI in the first column and the average treatment effect (ATE) one and two years after the vegetable intervention. The mean FCS at baseline for the overall sample was 54.9, indicating an acceptable level of food consumption on average. We find that receiving vegetable kits increased the FCS on average by 8.3 points one year after the intervention and by 8.7 points two years after ($p < 0.01$). We find no significant treatment effect in rCSI in the short- and medium-term.

Table 2: The short- and medium-term impacts of vegetable support on food security indicators

	Baseline mean (SD)	1- year impact estimate (SE)		2- year impact estimate (SE)	
FCS	54.9 (17.9)	10.1*** (2.1)	8.3*** (2.1)	9.9*** (2.0)	8.7*** (2.0)
rCSI	7.8 (5.4)	-0.64 (0.6)	-0.57 (0.62)	-0.005 (0.68)	-0.05 (0.69)
# of Obs.	442	884	884	1326	1326
Controls	-	No	Yes	No	Yes
Fixed Effects	-	Yes	Yes	Yes	Yes

*Note: Baseline means include both intervention and control households. Control variables: Occupation of the household head, land and livestock ownership, water constraints, and exposure to drought (All coded as dummy variables). Matching variables for nearest-neighbour propensity score matching: the use of seeds or seedlings in the past 12 months, water constraints, agricultural land and livestock ownership, household head gender, age, occupation, education, residential status, and household size (All coded as dummy variables apart from age and household size). * =p<0.1, **=p<0.05, ***=p<0.01.*

Next, Table 3 shows the ATE of the vegetable kit intervention on the specific food groups in the short-and medium-term. Vegetable kits provision significantly increased the consumption of nutrient-rich food such as vegetables, fruits (medium-term only), meat products (short-term only), eggs (short-term only), fish (medium-term only), milk, pulses and nuts, and root tubers one and two years after the intervention. As expected, we detected a pronounced increase in the consumption of vegetables, which increased by almost 21% and 28% in the short- and medium-term, respectively ($p < 0.01$).

Table 3: Impact of vegetable intervention on the consumption of different food groups over the past seven days

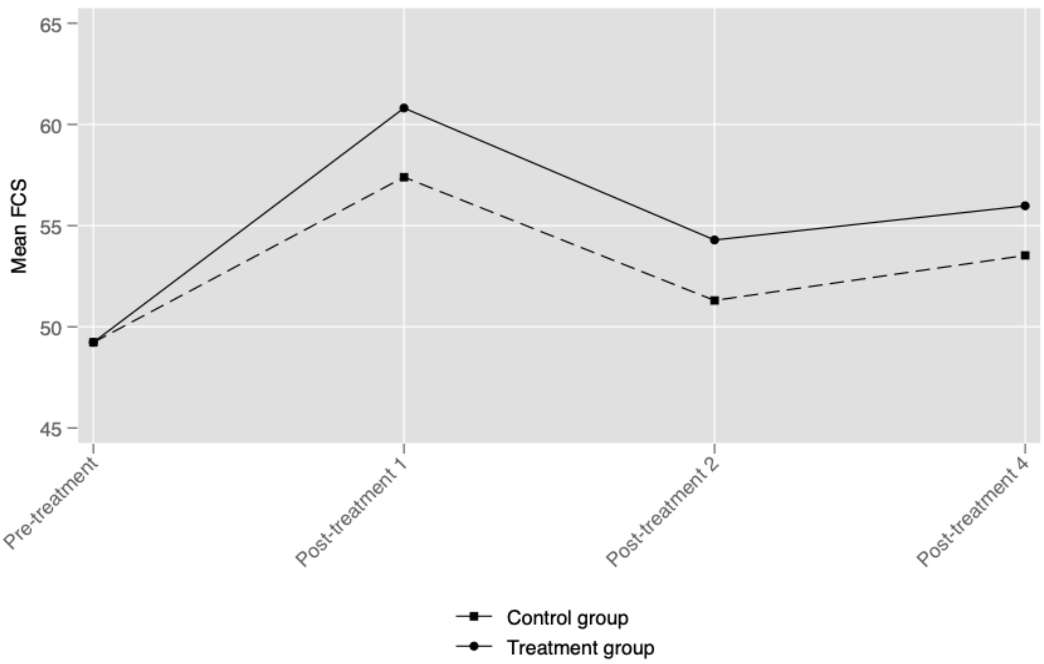
	Baseline mean (SD)	1- year impact estimate (SE)		2- year impact estimate (SE)	
Cereals	6.82 (0.86)	0.04 (0.12)	0.02 (0.12)	-0.10 (0.09)	-0.11 (0.09)
Root tubers	2.47 (1.36)	0.26 (0.16)	0.21 (0.16)	0.33*** (0.16)	0.32** (0.16)
Vegetables	3.57 (1.97)	0.77*** (0.24)	0.74*** (0.24)	1.01*** (0.23)	1.01*** (0.24)
Fruits	1.08 (1.26)	0.12 (0.15)	0.11 (0.15)	0.23* (0.14)	0.24* (0.14)
Meat & Poultry	0.72 (0.71)	0.18** (0.08)	0.15* (0.08)	0.14* (0.08)	0.14 (0.08)
Eggs	2.28 (1.84)	0.77*** (0.23)	0.63*** (0.23)	0.42** (0.21)	0.33 (0.20)
Fish	0.04 (0.22)	0.018 (0.31)	0.005 (0.03)	0.08* (0.04)	0.07* (0.04)
Pulses & Nuts	1.92 (1.29)	0.70*** (0.17)	0.60** (0.17)	0.83*** (0.18)	0.78*** (0.18)
Milk	3.15 (2.63)	0.81*** (0.29)	0.58** (0.28)	0.96*** (0.29)	0.78*** (0.29)
Oil & Fat	5.66 (1.78)	0.40* (0.20)	0.45** (0.21)	0.67*** (0.18)	0.67** (0.19)
Sugar	6.76 (1.01)	0.25 (0.19)	0.43** (0.18)	0.07 (0.23)	0.16 (0.22)
# of Obs.	442	884	884	1326	1326
Controls	-	No	Yes	No	Yes
Fixed Effects	-	Yes	Yes	Yes	Yes

*Note: Baseline means include both intervention and control households. Score range from 0 to 7, according to the number of days in the past 7 days on which the food items were consumed. Control variables: Occupation of the household head, land and livestock ownership, water constraints, and exposure to drought (All coded as dummy variables). Matching variables for nearest-neighbour propensity score matching: the use of seeds or seedlings in the past 12 months, water constraints, agricultural land and livestock ownership, household head gender, age, occupation, education, residential status, and household size (All coded as dummy variables apart from age and household size). * =p<0.1, **=p<0.05, ***=p<0.01.*

Long-term impacts of vegetable kits on food security and household resilience

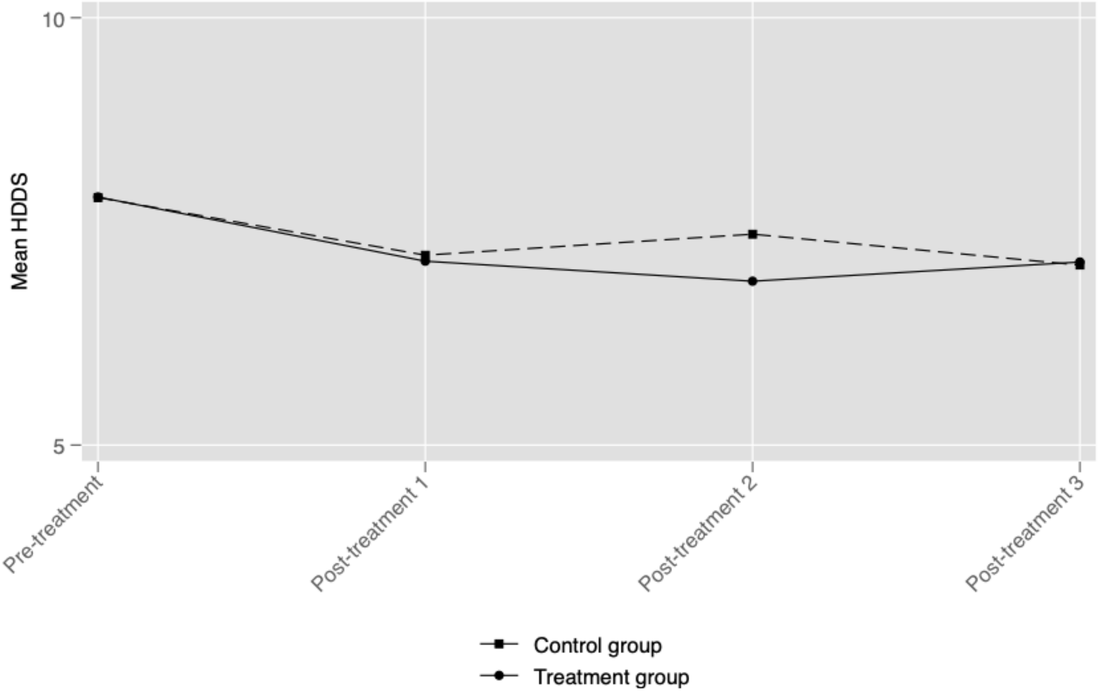
Next, we present the findings from the long-term impacts of vegetable support on food security and resilience outcomes based on the results from Kayaoglu et al. (2023) using entropy balanced time trends and differences-in-differences estimations with kernel propensity score matching. Figure 7 shows that the impact we detected in the short-term and medium-term are sustained in the long-term with an ATE of 3.54 points, which corresponds to an increase of about 7.2% compared to the FCS at baseline. Figure 8 and Figure 9 present similar trends in HDDS and rCSI. For HDDS in Figure 8, we observe that, on average, HDDS slightly decreases for the treatment group; however, the effect is marginal and is not significant. Hence, we do not find a significant treatment effect of the provision of vegetable kits on HDDS. The rCSI analysis in Figure 9 shows that the weighted number of days that households had to employ negative coping strategies to deal with food shortages has increased on average over time, but the increase in the treatment group was significantly smaller than for the control group, both in the short-run and long-run, which translates into a positive treatment effect.

Figure 7. Trends between treated and untreated groups using the entropy balancing with the pre-treatment data



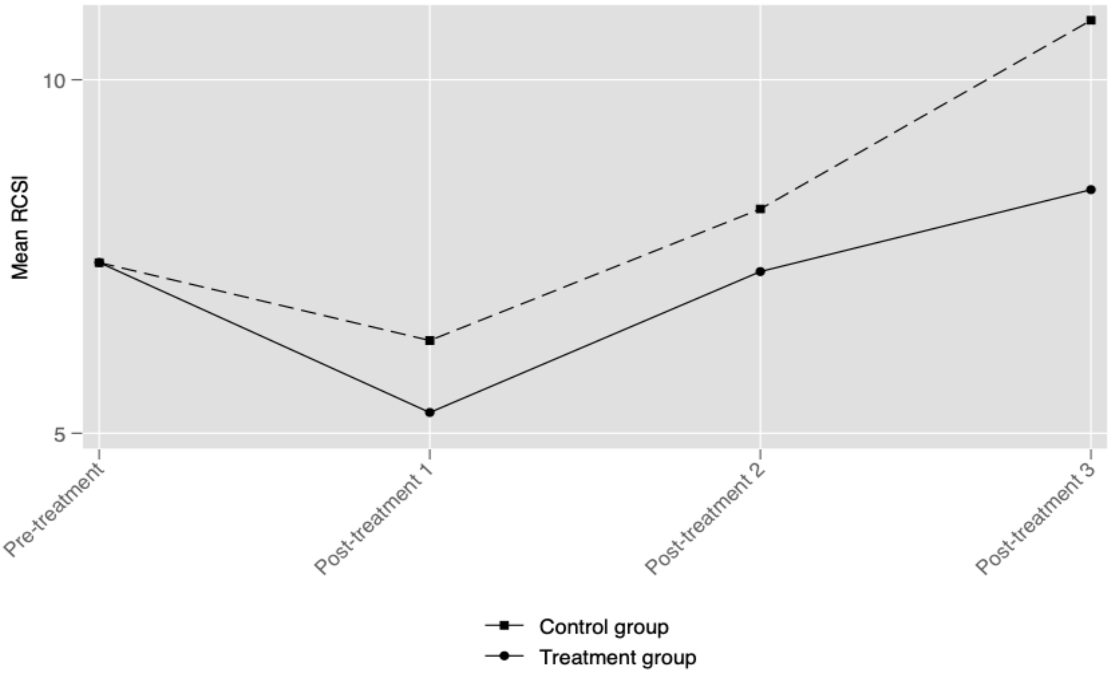
Notes: Baseline values of FCS, household head gender, age, and education and the share of income from different sources used for entropy balancing.

<u>Figure 8. HDDS trends between treated and untreated groups using the entropy balancing with the pre-treatment data</u>



Notes: Baseline values of HDDS, household head gender, age, and education and the share of income from different sources used for entropy balancing.

<u>Figure 9. rCSI trends between treated and untreated groups using the entropy balancing with the pre-treatment data</u>



Notes: Baseline values of rCSI, household head gender, age, and education and the share of income from different sources used for entropy balancing.

In addition to the long-term impact of vegetable kits intervention on food security, we also analysed if the intervention had any impact on the resilience of the treated households. Table 4 shows that the probability of applying several livelihood coping strategies, namely child labor, child marriage, the sale of food aid, the sale of humanitarian assistance, taking up credit to access food, the sale of household assets and the sale of productive assets, decreased significantly for treatment households in the long-term. Thus, our results show that short-term oriented humanitarian aid can also have long-term impacts on households' resilience, particularly in reducing the use of irreversible harmful coping strategies at the economic level, such as the sale of productive assets, and at the social level, such as child marriage which can have unpredictable negative long-term impacts.

Table 4. Long-term average treatment effect of vegetable kits intervention on household resilience

	Child labour	Child marriage	Sale of food aid	Sale of hum. assistance	Take credit to access food	Sale of HH assets	Sale of prod. assets
ATET	-0.156*** (0.056)	-0.130* (0.068)	-0.170*** (0.053)	-0.111** (0.046)	-0.172** (0.067)	-0.217*** (0.062)	-0.302*** (0.057)
Sub-district FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1156	461	1097	1023	1373	593	1304
R^2	0.340	0.380	0.17	0.24	0.31	0.400	0.140

*Notes. Kernel PSM Difference-in-difference estimations. Outcome variables are binary. Variables used in calculating kernel weights and as control variables: rCSI, household head gender, age, education, child labor, child marriage, sale of household assets, sale of productive assets, sale of food aid. * =p<0.1, **=p<0.05, ***=p<0.01. Standard errors in parentheses and clustered on the household level.*

Long-term impacts of other agricultural asset transfers on food security and household resilience

In this subsection, we present the long-term impacts of all intervention arms combined as well as intervention-specific effects for livestock and agricultural interventions. Here, we rely on ex-post cross-sectional comparisons and differences-in-differences estimations, both entropy balanced by key observable covariates (Kayaoglu et al. 2023).

Table 5. Long-term effects of agricultural and livestock package on FCS

	Cross-sectional			Diff-in-Diff		
Treatment	-2.498			4.714		
	(3.01)			(3.32)		
Agri. Treatment		10.682***			4.217	
		(3.73)			(4.89)	
Livestock Treatment			-10.995**			7.042
			(0.49)			(5.15)
Duration of treatment	Yes	Yes	Yes	Yes	Yes	Yes
Duration X treatment type	No	Yes	Yes	No	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Subdistrict FEs	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,040	736	759	1,011	730	732
R-squared	0.450	0.475	0.475	0.391	0.394	0.433

*Notes. Covariates are gender, age and education level of household heads, household size, number of shocks, income shares from different economic activities, land restriction dummy, and water constraint dummy. Entropy balancing is done for the mean and variances of age, gender and education of household heads. Cross-sectional model based on wave 4; Diff-in-Diff=Differences-in-Differences model between wave 3 and 4. *p-value<0.10, **p-value<0.05, ***p-value<0.01. Standard errors in parentheses and clustered on the household level.*

Table 5 shows that there is no significant combined treatment effect of all intervention arms on food security. However, after splitting and grouping by the intervention types, we find a positive strong average treatment effect of agricultural support of 10.7 points on the FCS. Our estimation also shows a significant negative impact of livestock support of 11 points on the FCS which explains the null-findings for the combined intervention.

Table 6 displays the long-term impacts on rCSI. Treatment households use, on average, significantly fewer food-related coping strategies to deal with food shortages, independent of the intervention arm received. When looking at the impact of agricultural and livestock interventions separately, we observed that on average, households who received the agricultural intervention, reduced their use of food-related livelihood coping strategies by 3.3 days within 30 days with respect to the severity weighting. For households that received the livestock interventions, this reduction is on average 8.7 days. In addition, we find that in the livestock treatment group, rCSI significantly decreased between the last two waves, showing that the impact is still effective 3 years after the intervention ended.

Table 6. Long-term impacts of agricultural and livestock package on the rCSI

	Cross-sectional			Diff-in-Diff		
Treatment	-2.604**			-.685		
	(1.062)			(1.346)		
Agri. Treatment		-3.267***			-2.346	
		(1.273)			(1.898)	
Livestock Treatment			-8.745***			-5.727**
			(2.048)			(2.332)
Duration of treatment	Yes	Yes	Yes	Yes	Yes	Yes
Duration X type	No	Yes	Yes	No	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Subdistrict FEs	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,060	751	772	1,060	751	772
R-squared	0.448	0.504	0.487	0.442	0.501	0.461

*Notes. Covariates are gender, age and education level of household heads, household size, number of shocks, income shares from different economic activities, land restriction dummy, and water constraint dummy. Entropy balancing is done for the mean and variances of age, gender and education of household heads. Cross-sectional model based on wave 4; Diff-in-Diff=Differences-in-Differences model between wave 3 and 4. *p-value<0.10, **p-value<0.05, ***p-value<0.01. Standard errors in parentheses and clustered on the household level.*

Table 7. Long-term impacts for relying on less preferred and less expensive food (# of days)

	CS			Diff-in-Diff		
Treatment	-4.654***			-3.255		
	(1.588)			(2.051)		
Agri. Treatment		-.588			1.305	
		(1.619)			(2.457)	
Livestock Treatment			-17.166***			-15.379***
			(2.936)			(3.654)
Duration of treatment	Yes	Yes	Yes	Yes	Yes	Yes
Duration X type	No	Yes	Yes	No	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Subdistrict FEs	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,060	751	772	1,060	751	772
R-squared	0.411	0.426	0.434	0.516	0.569	0.530

*Notes. Covariates are gender, age and education level of household heads, household size, number of shocks, income shares from different economic activities, land restriction dummy, and water constraint dummy. Entropy balancing is done for the mean and variances of age, gender and education of household heads. Cross-sectional model based on wave 4; Diff-in-Diff=Differences-in-Differences model between wave 3 and 4. *p-value<0.10, **p-value<0.05, ***p-value<0.01. Standard errors in parentheses and clustered on the household level.*

To better understand how the intervention packages influenced the food-related coping behaviour, we break down the treatment impacts for the components of rCSI in Tables 7-9, disregarding the index weighting. First, we found that livestock interventions, on average, have a significant and large impact on the days spent relying on less preferred and less expensive food (Table 7) translating into 17.17 days less on average than the control group households.

Table 8 displays the impact of intervention types on borrowing food or relying on relatives and friends for food. We find that agricultural intervention decreased the use of borrowing strategies by 4.6 days on average compared to the control group. For the livestock intervention, we did not detect a significant treatment impact.

Table 8. Long-term impacts for borrowing food or relying on help from relatives or friends (# of days)

	Cross-sectional			Diff-in-Diff		
Treatment	-2.610***			-1.272		
	(.923)			(1.122)		
Agri. Treatment		-4.572***			-4.710***	
		(1.392)			(1.597)	
Livestock Treatment			-1.131			1.852
			(1.720)			(2.148)
Duration of treatment	Yes	Yes	Yes	Yes	Yes	Yes
Duration X treatment type	No	Yes	Yes	No	Yes	Yes
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
Subdistrict FEs	Yes	Yes	Yes	Yes	Yes	Yes
# of Obs.	1,060	751	772	1,060	751	772
R-squared	0.258	0.309	0.261	0.187	0.249	0.178

*Notes. Covariates are gender, age and education level of household heads, household size, number of shocks, income shares from different economic activities, land restriction dummy, and water constraint dummy. Entropy balancing is done for the mean and variances of age, gender and education of household heads. Cross-sectional model based on wave 4; Diff-in-Diff=Differences-in-Differences model between wave 3 and 4. *p-value<0.10, **p-value<0.05, ***p-value<0.01. Standard errors in parentheses and clustered on the household level.*

In Table 9, we show that livestock interventions also significantly decreased the number of days that households had to reduce the number of meals eaten in a day by 8.2 days on average, and that they limit their portion sizes on average to 9.8 days less compared to control group households.

Table 9. Breakdown of long-term impacts of livestock Intervention on the use of food-related coping strategies (# of days)

Model	Cross-sectional		Diff-in-Diff	
	Reducing the number of meals	Limiting portion size	Reducing the number of meals	Limiting portion size

ATET	-8.234** (3.218)	-9.820*** (3.229)	-3.664 (3.973)	-9.208** (3.756)
Duration of treatment	Yes	Yes	Yes	Yes
Covariates	Yes	Yes	Yes	Yes
Subdistrict FEs	Yes	Yes	Yes	Yes
# of Obs.	772	772	772	772
R^2	0.473	0.477	0.524	0.438

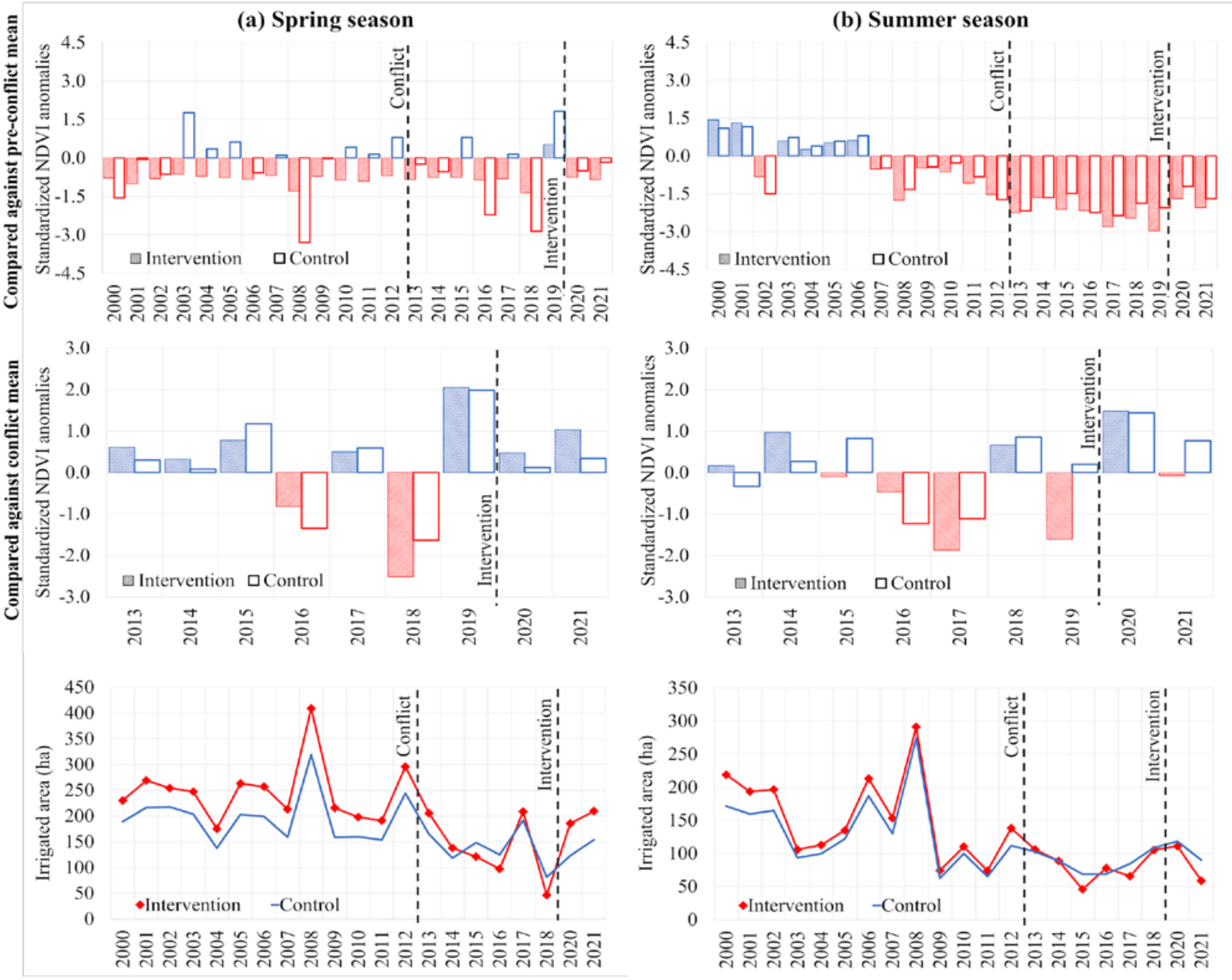
*Notes. Covariates are gender, age and education level of household heads, household size, number of shocks, income shares from different economic activities, land restriction dummy, and water constraint dummy. Entropy balancing is done for the mean and variances of age, gender and education of household heads. Cross-sectional model based on wave 4; Diff-in-Diff=Differences-in-Differences model between wave 3 and 4. *p-value<0.10, **p-value<0.05, ***p-value<0.01. Standard errors in parentheses and clustered on the household level.*

In summary, our short-, medium- and long-term findings suggest that asset transfer interventions targeted to small-holder farmers living in a crisis setting have significant and positive impacts on nutrition and food security and reduce the application of harmful livelihood coping strategies. Household resilience and food security are highly affected by conflict (Brück et al., 2019). Hence, the improved food and nutritional security as well as the decreased application of several harmful livelihood coping strategies emphasise that agricultural support offsets negative impacts of war. The findings are consistent with a study undertaken in conflict-affected Nigeria, investigating the impact of nutrition-sensitive agricultural support on food security and resilience (Baliki et al., 2018). Similarly, another study undertaken in South Sudan demonstrated, using mixed methods approaches, the positive impact of a livelihood support program that includes the provision of vegetable inputs, skill-building, and entrepreneurship intervention on dietary diversity and food security (Vallet et al., 2021). Additional to these studies, we show that livestock and vegetable interventions show differential impact spheres where the agricultural support component particularly improves food security and nutritional self-reliance while livestock support rather addresses household income related outcomes.

Impact of the irrigation rehabilitation on crop productivity

Next, we present the impact findings on agricultural and crop productivity following Sujud et al. (2022). These results are from the satellite imagery analysis as described in section 4 (Integration of remote-sensing). The time-series results of the standardised NDVI anomalies normalised by rainfall for intervention and control villages are shown in Figure 10. When comparing these anomalies against the pre-conflict mean, both intervention and control villages do not show an overall improvement in NDVI in either seasons – summer or spring.

Figure 10. NDVI compare against pre-conflict mean and irritated area for spring and summer season



Notes. Time-series of standardised NDVI anomalies normalised by rainfall as compared against pre-conflict mean and conflict mean and time-series of irrigated area as obtained from K-means clustering for intervention and control villages for a) spring seasons and b) summer seasons

However, when comparing results against the conflict-mean, different findings are observed. During the summer season, the intervention villages show an improvement in 2020 (i.e., the year directly after the intervention took place), but not in 2021 – where an overall decrease in NDVI is observed. Contrary to the intervention villages, there is an overall increase in NDVI in the years 2020 and 2021 within the control villages when compared to the conflict mean. During the spring season, both intervention and control villages show an overall increase in the post-intervention period (2020 and 2021), and the intervention villages show a stronger increase in

NDVI as compared to the control villages. The irrigated area of intervention villages increases in both years post-intervention more than the increase observed in the control villages.

These results show that rehabilitation of irrigation systems did have a small and significant impact in improving water usage and crop productivity, yet the impacts are not strong enough to increase the levels of productivity similar to the pre-conflict period. We unfortunately did not align the survey data with the satellite imagery; therefore, we are not able to test using survey data the mechanisms of why the effects were strong. Farmers could be facing other challenges in accessing water to their field, for example due to fuel shortage and electric cuts, which are needed regularly to pump water into the fields. Future research should assess both impacts from above and on the ground in order to provide a better picture of the mechanisms. Having said that, our attempt to measure impact only through remote-sensing in combination with machine learning proves to be feasible to generate an indicative impact analysis, where conventional data collection might be difficult.

Heterogeneity of impacts

Returning to our panel survey data analysis, Table 10 displays the main results from our heterogeneity analysis of treatment effects from the provision of vegetable kits on FCS using the honest causal forest algorithm (Weiffen et al., 2022). We split the sample by predicted treatment effect size into a group of low, medium and high Conditional Average Treatment Effects (*"Low CATE", "Medium CATE" and "High CATE"*), then we calculated the within-group means. We found that 38.4% of households in High CATE are female-headed, compared to 8.5% in Low CATE, which implies that more female-headed households benefited from the intervention. The mean age of the household head is 6 years younger in High CATE and Medium CATE compared to Low CATE. Furthermore, households with strong initial capital and agricultural endowments (such as owning livestock and home gardens) benefit more from the intervention, as well as households who did not experience drought episodes in the past 12 months. Finally, both indicators for direct exposure to violence show that the average number of fatalities from violent events per 100.000 inhabitants is significantly higher for low CATE. In summary, our heterogeneous findings emphasise that agricultural asset transfer benefits younger female-headed households with agricultural capital endowments who were not exposed to intense levels of violent conflict.

To better understand various levels of violent conflict intensity moderate treatment heterogeneity, we further divided the sample into quintiles based on the number of fatalities per 100,000 in the past year. We also divided the sample by the gender of the household-head to understand how the household's profile shapes the treatment response under different levels of exposure to violent conflict. Figure 11 displays the predicted CATE for each subgroup while holding all other covariates fixed at their medians. First, we observe that female-headed households have overall stronger food security impacts compared to male-headed households as a result of receiving support, regardless of the intensity of violent conflict.

Table 10. Comparison of household characteristics and contextual factors according to predicted treatment effect size on FCS

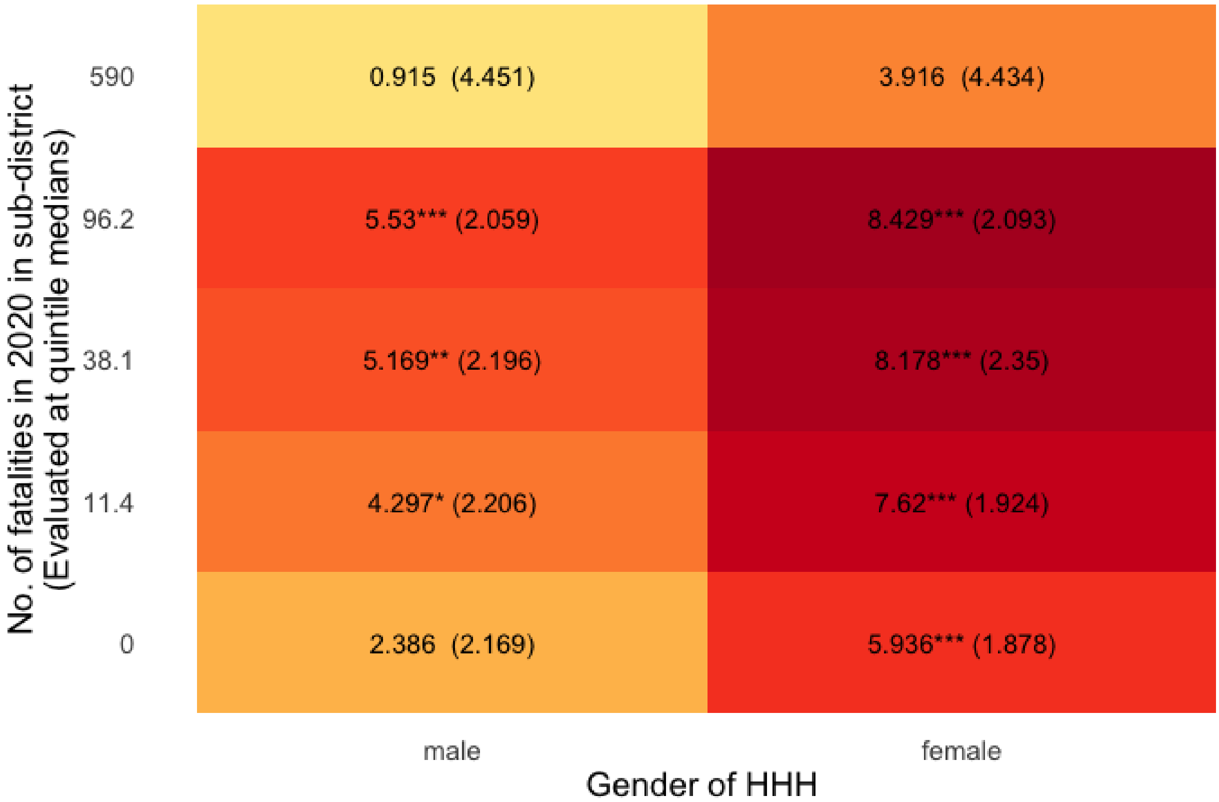
	Low CATE	Medium CATE	High CATE	p-value
CATE	-1.108 (0.144)	4.877 (0.144)	10.37 (0.144)	
Individual and household- level characteristics				
Prop. of female HHH	0.085 (0.024)	0.192 (0.024)	0.384 (0.024)	<0.01
Age of HHH (years)	56.06 (0.734)	49.99 (0.734)	49.07 (0.734)	<0.01
HHH is herder (baseline)	0.262 (0.029)	0.428 (0.029)	0.373 (0.029)	<0.01
Size of rainfed land (ha) (baseline)	0.411 (0.084)	1.038 (0.841)	0.761 (0.084)	<0.01
Size of irrigated land (ha) (baseline)	0.317 (0.036)	0.287 (0.036)	0.284 (0.036)	0.76
Prop. that owns chicken (baseline)	0.114 (0.024)	0.225 (0.024)	0.284 (0.024)	<0.01
Prop. that owns home garden (baseline)	0.347 (0.029)	0.568 (0.029)	0.738 (0.029)	<0.01
Exogenous shocks				
Prop. exposed to d rought in 2020	0.162 (0.018)	0.089 (0.018)	0.063 (0.018)	<0.01
Fatalities through violent events in 2020 (per 100.000 inhabitants)	20.16 (1.661)	12.27 (1.661)	6.94 (1.661)	<0.01

Fatalities through violent events in 2020 (per 100.000 inhabitants)	237.9 (15.71)	172.9 (15.71)	65 (15.71)	<0.01

Notes. Within-group means based on partitioning through predicted treatment effect size. Standard errors in parenthesis. P-values for binary variables from Pearson's chi-square tests, for continuous variables through ANOVA tests. Table only includes variables that are applied for at least 1% of the initial model splits.

Second, when the intensity of violent conflict is severe, we find no significant impacts of asset transfers on FCS. Similarly, at very low levels of conflict exposure, the predicted treatment effect size is small and insignificant for male-headed households. For female-headed households, the effect at low levels of exposure to violent conflict is at 5.9 points ($p<0.01$). This implies that on average, male-headed households who experienced few or no episodes of violent events in the past 12 months, did not benefit from the intervention. Finally, both male- and female-headed households who experienced moderate levels of violent events in the past 12 months, as shown in the three middle quintiles, benefited most from the intervention. Female-headed households who experience moderate to high levels of (quintile 4) improved their food security the most due to the intervention.

Figure 11. Conditional average treatment effect on food consumption score by household head gender and exposure to conflict



*Notes. CATE for No. of fatalities through violent events per 100.000 inhabitants split by quintiles and gender of the household head keeping other covariates fixed at their median. Standard errors in parenthesis. * =p<0.1, **=p<0.05, ***=p<0.01. CATE is based on adjusted honest causal forest model estimation with tuned parameters. HHH=Household head. Included covariates: Household head age and occupation, land size of rainfed and irrigated land, if the households own chicken or sheep, if they have a home garden, if they were affected by crop pests and droughts, proportion of disabled, widowed, female persons in the sub-district.*

In summary, these findings underscore the complex and intricate role of conflict in determining how agricultural aid translates to stronger household food security. Agricultural support might not be the right tool to improve the livelihood and food security of resource-poor households living under extreme levels of violence, where farm production is low and risks of harvest loss are high (George & Adelaja, 2021). Households living under moderate levels of conflict intensity on the other hand, are better equipped to benefit from such asset transfer support to improve their food security, particularly for younger female-headed households with a certain amount of initial endowment. This implies that without agricultural support, vulnerable households who are exposed to moderate levels of food security are going to be worse off. As for households who live in relatively peaceful areas, the agricultural input aid is not sufficient to provide a marginal benefit for small-holders to improve their overall food security levels, as control households have access to better opportunities to generate income other than farming. Hence , the results show that focusing only on studying average impacts in conflict and volatile settings conceals specific nonlinear variations in how households benefit from aid. At the policy level, moving away from one-size-fits-all programmes and designing conflict-sensitive and inclusive interventions ensure that no households are left behind.

Robustness

We conducted several robustness tests to validate our findings in the respective papers. For example, we applied different propensity score matching approaches including nearest neighbour propensity score matching 2:1 without replacement, 2:1 without replacement using Mahalanobis distance, and 3:1 with replacement yield similar results. Likewise, we proved the heterogeneity analysis with different specifications including subsample analyses (not displayed). The robustness tests support our interpretations.

6. Conclusions

Limitations

There are four main limitations of the study.

First, due to a change in the treatment assignment after baseline, we did not have complete panel data for about 40% of the observations, as we needed to increase the sample size in the treatment group at later stages. This change has invalidated the original sampling and design of the study and generated imbalances between the treatment and control groups. This inhibited us from applying more robust analysis for all the interventions apart from the provision of vegetable kits. Implementing an adaptive sample design, using entropy balancing and honest causal forests to estimate the average and individual treatment effects helped to reduce the impacts of this limitation. Future projects conducting impact evaluation in such settings should be always prepared for such last-minute changes in the treatment assignment and be able to deploy immediately to compensate for the loss in the sample size before or along the implementation of the intervention. This is feasible when evaluating agricultural interventions, as the impacts usually take time to materialise.

Second, our applied methods cannot account for unobserved endogeneity. Propensity score matching as well as entropy balancing as well as the honest causal forest algorithm only work with observable covariates. None of these methods accounts for unobservable differences which challenges the common trend assumption. Further, the nearest-neighbour matching approach as well as honest causal forest algorithm are subject to significant losses in statistical power since the first discards non-matched control households while the latter only uses half of the data to estimate the effect. We believe that the applied methods are the most adequate approaches to derive causal inference from observational data in highly complex settings.

Third, spillover effects could affect our overall impact magnitude. However, since this small-scale emergency intervention is spread across the vast geographical area of several governorates of Syria addressing a small share of the Syrian population, we exclude spillover effects on the macro level. At the meso-level, minor spillover effects are possible through a small share of control households living in treatment villages, which might benefit indirectly from the support. Still, the vast majority of control households reside in pure control villages, where they are unlikely to indirectly benefit from the support. Hence, the estimated overall treatment effects are unlikely to be biassed substantially by spillover effects.

Fourth, we were not able to consolidate the design and validate the findings from remote-sensing and survey analysis. We were not able to provide through the household survey data adequate ground-truthing of the changes in water use and agricultural productivity observed from satellite imagery. Hence, we are not able to estimate the impact of irrigation rehabilitation on households' food security and resilience. One of the main limitations is that the areas covered in the overall study are very large and require too large and expensive satellite images to cover the whole sample. Another challenge was ensuring that the households from our survey in these areas where the irrigation interventions took place, were exactly matched geo-spatially. The use of pen and paper questionnaires did not allow us to collect coordinates of households and their farms.

Lessons for interventions

We draw two overarching lessons for future interventions in similar settings:

First, building resilience requires comprehensive and integrated programmes with a long-time horizon to counter the multiple shocks in an emergency and conflict-affected setting. Clustering agricultural interventions, rather than spreading them widely and thinly leads to stronger benefits. Benefits from humanitarian support may persist in the long-term and yet not be enough to ensure self-reliance. At the same time, having an active humanitarian operation even in relatively better times (when needs are relatively lower) has a high value in case circumstances deteriorate once more. Our study demonstrated exactly this: starting up a new programme when the going got tough unexpectedly would not have been possible. Humanitarian interventions running consistently over long periods of time hence have strong benefits as a social safety net. The earthquake in early February 2023 in Southern Turkey and Northern Iraq emphasises this point.

Second, fine-tuning targeting by household characteristics and contexts, while challenging to do, is important as we found highly varying heterogeneous impacts across different household characteristics and contexts. Vulnerable households clearly benefit from the emergency support. However, initial capital endowments, such as access to land, are key to ensure that the long-term impacts are sustained. However, households living in areas at risk of severe violent conflict might require more tangible types of emergency support such as cash or food aid, instead of agricultural assets. This highlights the importance of accounting for the context, making sure the interventions are conflict sensitive.

Lessons for research

We draw three lessons for researchers conducting impact evaluations of complex interventions in humanitarian emergencies and conflict-affected settings.

First, in contexts where experimental study designs are not feasible, several approaches are available to construct credible counterfactuals. In SEEDS, we use alternative ways to develop quasi-experimental approaches and construct counterfactuals. Using adaptive research designs and applying flexible matching and balancing approaches to improve sample comparability allow conducting rigorous impact evaluation.

Second, using supervised machine learning and deep learning offer novel ways to overcome challenges in traditional data and impact evaluation designs, such as small sample sizes and assignment imbalances. Machine learning techniques such as the causal random forest allow exploring the data in depth and conducting impact heterogeneity analysis without losing statistical power.

Finally, using and combining various types of data such as remote-sensed data, conflict event data, and household survey data provide clear benefits. Moreover, it is important in hard-to-reach settings to use standardised measures to ensure that the findings can be externally validated and that the evidence is transferable to the other emergency settings where impact evaluations are difficult to conduct. Fine-tuning and standardising measures for 'unmeasurable' concepts and outcomes such as resilience and fragility is also crucial to ensure stronger learning.

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Annex A

Table A1. Intervention details

Intervention	Description	Governorates of implementation
Emergency Activities		
Livestock vaccination	Livestock vaccination to fight against severe disease on sheep and goats to reduce mortality and improve overall animal health, provision of salt licks	Deir-ez-Zor, Hama, Idleb
Vegetable kits	Provision of vegetables seeds, agriculture inputs and tools, including drip irrigation kits for homestead and micro levels gardens	Al-Hasakah, Aleppo, As-Sweida, Deiz-er-Zor, Quneitra
Vegetable seedlings	Provision of vegetables seedlings and agricultural inputs and tools	Al-Hasakah, As-Sweida, Dar'a, Deir-ez-Zor, Hama, Homs
Poultry kit	Provision of poultry kits and hatcheries	Aleppo, As-Sweida, Dar'a, Deiz-er-Zor, Quneitra
Early recovery and resilience activities		
Beekeeping	Beekeeping as an alternative income generating activity for households who do not own land or have a stable income from farming	As-Sweida, Dar'a, Hama, Homs, Quneitra
Irrigation rehabilitation	Rehabilitation of 15 pump stations in six villages to connect water from the Furat river to the plots	Deir-ez-Zor

Table A2. Panel attrition based on baseline characteristics

	Panel	Attrited households	p-value
n	840	130	
Female HHH	0.21 (0.41)	0.28 (0.45)	0.096
HHH Age	49.29 (12.83)	50.83 (12.49)	0.203
HHH is literate	0.24 (0.43)	0.25 (0.43)	0.866
HHH is a crop farmer	54.35 (34.27)	55.15 (38.22)	0.807
HHH is a herder	12.65 (21.87)	15.35 (26.11)	0.202
Owned irrigated landsize (donum)	7.59 (7.28)	8.38 (8.74)	0.519
Owned rainfed landsize (donum)	17.12 (16.58)	18.41 (19.63)	0.584
HH faces constraints to water	0.28 (0.45)	0.21 (0.41)	0.101
HH owns chicken	0.21 (0.41)	0.26 (0.44)	0.227
HH owns cattle	0.14 (0.35)	0.15 (0.35)	0.863
HH owns sheep	0.21 (0.41)	0.17 (0.38)	0.240
HH affected by drought in past 12 months	0.64 (0.48)	0.59 (0.49)	0.327
HH affected by crop pests in past 12 months	0.46 (0.50)	0.49 (0.50)	0.518
HH affected by livestock diseases in past 12 months	0.16 (0.37)	0.21 (0.41)	0.159
HH affected by high agr. input costs in past 12 months	0.60 (0.49)	0.61 (0.49)	0.868
HH affected by low agr. output prices in past 12 months	0.35 (0.48)	0.42 (0.50)	0.132
HH affected by severe illness of income earner in past 12 months (mean (SD))	0.10 (0.30)	0.13 (0.34)	0.329

Notes. We show the mean values and include the standard deviation in parentheses. The p-value shows the significance level of the mean (standard deviation) between the two groups. A value of less than 0.05 implies a significant difference. HHH: Household Head, HH: Household

Table A3 Baseline balance between treatment and control households before and after propensity score matching.

	Before PSM Adjustment			After PSM Adjustment			
	Control	Treatment	p-value	Overall	Control	Treatment	p-value
n	604	222		442	221	221	
Sociodemographic Characteristics of the Household							
HHH Gender (% Male)	504 (83.4)	149 (67.1)	0.001	302 (68.3)	154 (69.7)	148 (67)	0.609
HHH Age*	49.3 (12.8)	49.63 (12.6)	0.815	49.7 (12.9)	49.8(13.4)	49.6 (12.5)	0.832
HHH Completed Education (%)			0.021				0.841
No Schooling	131 (21.7)	67 (30.2)		139 (31.4)	72 (32.6)	67 (30.3)	
Primary	407 (67.4)	139 (62.6)		273 (61.8)	135 (61.1)	138 (62.4)	
Secondary +	66 (10.9)	16 (7.2)		30 (6.8)	14 (6.3)	16 (7.2)	
Number of Males*	3.63 (2.15)	3.52 (1.76)	0.501	3.50 (1.96)	3.48 (2.15)	3.52 (1.76)	0.809
Number of Females*	3.60 (2.21)	3.90 (2.04)	0.077	3.93 (2.22)	3.95 (2.39)	3.90 (2.05)	0.831
Resident (% Yes)	493 (81.6)	183 (82.4)	0.789	365 (82.6)	183 (82.8)	182 (82.4)	0.900
Agricultural Profile of Household (% Yes)							

HHH is Crop Farmer or Herder	558 (92.4)	207 (93.2)	0.676	407 (0.9)	201 (91)	206 (93.2)	0.380
Land Ownership	377 (62.4)	124 (55.9)	0.087	243 (55)	120 (54.3)	123 (55.7)	0.775
Livestock Ownership	224 (37.1)	80 (36)	0.782	159 (36)	80 (36.2)	79 (35.7)	0.921
Water Constraints	170 (28.1)	47 (21.2)	0.044	90 (20.4)	43 (19.5)	47 (21.3)	0.638
Exposure to Shocks in Past 12 Months (% Yes)							
Drought	380 (62.9)	141 (63.5)	0.874	264 (59.7)	124 (56.1)	140 (63.3)	0.121
Insecurity / Conflict	209 (34.6)	60 (27)	0.039	119 (26.9)	59 (26.7)	60 (27.1)	0.915
Crop Pests	278 (46)	107 (48.2)	0.580	207 (46.8)	100 (45.2)	107 (48.4)	0.506
Note: For categorical and binary variables, we show the frequency and include the percentage in parentheses; For continuous variables, we show the mean and include the standard deviation in parentheses (These variables are marked with *). The p-value shows the significance level of the mean (standard deviation) or frequency (percentage) difference between the two groups. A value of less than 0.05 implies a significant difference. HHH: Household Head.							

Annex B: Codebook

Variable name in questionnaire	Variable	Code	Type of variable	Wave 1	Wave 2	Wave 3	Wave 4
General Information							
Response ID	ID	NUMBER	NUMERIC				
Midline ID	Midline_ID	NUMBER	NUMERIC				
Endline ID	Endline_ID	NUMBER	NUMERIC				
Governorate	Governorate	SHORT TEXT (Dar'a, Hama, Quneitra, Deir-ez-Zor, As-Sweida, Al-Hasakah, Aleppo, Homs, Idleb)	FACTOR				
District	District	SHORT TEXT	FACTOR				
Subdistrict	Subdistrict	SHORT TEXT	FACTOR				
Village	Village	SHORT TEXT	FACTOR				
Household head name	HHHead_Name	SHORT TEXT	CHARACTER				
Respondent: Household Head	Respondent_HHHead	1 = Yes / 0=No	FACTOR				
Calculated: Imputed	Respondent_HHHead_imp	1 = Yes / 0=No	FACTOR				
Respondent: Other than Head of the household	Respondent_OthreThanHHH	SHORT TEXT (Spouse, Son/Daughter, Others, Parents)	FACTOR				

Respondent: Other than Head of the household age	Respondent_OtherHHead_Age	NUMBER (17-99)	NUMBER				
Respondent: Other than Head of the household marital status	Respondent_OtherHHead_MaritalStatus	SHORT TEXT (Married , Divorced, Single, Widowed)	FACTOR				
Respondent: Other than Head of the household education level	Respondent_OtherHHead_Educational_Level	SHORT TEXT (Illiterate, Primary/tertiary School , High School, higher education)					
Women respondent	Women_Respondent_Yes_No	0=No 1=Yes					
Sex of the Head of the household	HHHead_Sex	SHORT TEXT (Male, Female)	FACTOR				
Age of the Head of the household	HHHead_Age	NUMBER (19-99)	NUMERIC				
Marital status for the Head of the household	HHHead_MaritalStatus	SHORT TEXT (Married , Widowed, Divorced, Single)	FACTOR				
Age of the spouse of the head of the household	HHHead_SpouseAge	NUMBER	NUMERIC				
Number of persons with disabilities	Person_with_disability	NUMBER	NUMERIC				
Case/Control	Case_Control	Case, Control	FACTOR				
Sample Added	Sample	T1, T2, T3	FACTOR				
Intervention Type	Intervention	Poultry, Vegetable Kits, Vegetable Seedlings, Beekeeping, livestock vaccination, irrigation	FACTOR				

Women's empowerment							
If the respondent is women, how many hours have you spent in the past 24 hours in the following activities? (if the last day was holiday, indicate the last working day)							
Women respondent: hours spent on farming (agriculture/livestock)	Women_Respondent_Occ_Farmer	NUMBER	NUMBER				
Women respondent: hours spent non farming (as an employee, agriculture labor, private work)	Women_Respondent_Occ_NotFarmer	NUMBER	NUMBER				
Women respondent: hours spent at home (caring for family members, domestic work, cooking)	Women_Respondent_Occ_Home	NUMBER	NUMBER				
If the respondent is a woman, do you own any of the following livestock?	Women_Respondent_Own_Cows	No; yes, jointly; yes, privately	FACTOR				
If the respondent is a woman, do you own any of the following livestock?	Women_Respondent_Own_sheepGoats	No; yes, jointly; yes, privately	FACTOR				
If the respondent is a woman, do you own any of the following livestock?	Women_Respondent_Own_Chicken	No; yes, jointly; yes, privately	FACTOR				
If the respondent is a woman, do you own any of the following livestock?	Women_Respondent_Own_Beehives	No; yes, jointly; yes, privately	FACTOR				
If the respondent is a woman, do you own any of the following agricultural wealth?	Women_Respondent_Own_Land	No; yes, jointly; yes, privately	FACTOR				

if the respondent is a women, do you own any of the following agricultural wealth?	Women_Respondent_Own_Mechanical	No; yes, jointly; yes, privately	FACTOR				
if the respondent is a women, do you own any of the following agricultural wealth?	Women_Respondent_Own_NonMechanical	No; yes, jointly; yes, privately	FACTOR				
Occupation of Household head							
Main occupation of HH and proportion of livelihood contributed (income, employment or food obtained)	Occ_CropFarmer	Number %	NUMERIC				
Main occupation of HH and proportion of livelihood contributed (income, employment or food obtained)	Occ_Herder	Number %	NUMERIC				
Main occupation of HH and proportion of livelihood contributed (income, employment or food obtained)	Occ_Beekeeper	Number %	NUMERIC				
Main occupation of HH and proportion of livelihood contributed (income, employment or food obtained)	Occ_Labourer	Number %	NUMERIC				
Main occupation of HH and proportion of livelihood contributed (income,	Occ_Artisan	Number %	NUMERIC				

employment or food obtained)							
Main occupation of HH and proportion of livelihood contributed (income, employment or food obtained)	Occ_Other	Number %	NUMERIC				
Main occupation of HH and proportion of livelihood contributed (income, employment or food obtained)	Occ_OtherOption	SHORT TEXT (Aid, compensation, debt, employee, military, remittances, retirement, self-employment)	FACTOR				
Calculated	Calculated_Total_Income_Sources	Should be 100% or 0%	NUMERIC				
Type of agriculture activity practised by HH head	HHAgriActivity	SHORT TEXT	FACTOR				
Did you receive any type of intervention/training in the past year?	HHrecievedSupport_Yes_No	SHORT TEXT (Yes=1 / No= 0)	INTEGER				
If yes, what is the type of support received?	TypeOfSupport	SHORT TEXT (Nutrition and/or Cash and/or Agriculture Inputs and/or Training and/or Other)	FACTOR				
Did you receive any other type of intervention/training in the past year?	HhreceivedOtherSupport_Yes_No	0=No, 1=Yes	FACTOR				
If yes, what is the type of other support received?	TypeOfOtherSupport	SHORT TEXT (Nutrition and/or Cash and/or Agriculture Inputs	FACTOR				

		and/or Training and/or Other)					
In the past 30 days, what has been the total HH spending excluding debts?	TotalHHExpenditure_SP	NUMBER	NUMERIC				
In the past 30 days, how much has your family spent on food?	TotalHHExpenditureFood_SP	NUMBER	NUMERIC				
HH Composition							
Number of men above 65	Num_Men_+65	NUMBER	NUMERIC				
Number of women above 65	Num_Women_+65	NUMBER	NUMERIC				
Number of men aged >18 and <=65	Num_Men	NUMBER	NUMERIC				
Number of women aged >18 and <=65	Num_Women	NUMBER	NUMERIC				
Number of boys aged <=18	Num_Boys	NUMBER	NUMERIC				
Number of girls aged <=18	Num_Girls	NUMBER	NUMERIC				
Number of girls aged < 2 years	Girl_Less_2_Years	NUMBER	NUMERIC				
Number of boys aged < 2 years	Boy_Less_2_Years	NUMBER	NUMERIC				
Date of birth of first girl aged < 2 years	Girl_Less_2_Years_DOB1	Date	Date				
Date of birth of first boy aged < 2 years	Boy_Less_2_Years_DOB1	Date	Date				
Date of birth of second girl aged < 2 years	Girl_Less_2_Years_DOB2	Date	Date				

Date of birth of second boy aged < 2 years	Boy_Less_2_Years_DOB2	Date	Date				
Number of children < 5 years	Children_Less_5_Years	NUMBER	NUMERIC				
Residence status of the family	Resid_Status	SHORT TEXT (Displaced / Resident / Returnee)	FACTOR				
Length of stay for internally displaced persons from their homes	IDP_Duration	SHORT TEXT (less than or a year / 2 years / 3 years / more than 3 years)	FACTOR				
Displaced or returned from	Diasplaced_Re turened_From	SHORT TEXT (Hama, hasaka, helfaya, Khan Arnaba, qatana, Al-Hasakah, Damascus, Deir Ez-Zor, Rural Damascus, Quneitra, Ruwaished)	FACTOR				
Highest level of education attained by HH head							
Highest level of education attained by HH head	HHHead_Educ ational_Level	SHORT TEXT (1.High School, 2. Primary/tertiary School, 3.Illiterate)	ORDERED FACTOR				
Level of education of the Spouse	Spouse_Educa tional_Level	SHORT TEXT (1.Tertiary institution, 2. Primary School, 3. High School, 4. Illiterate)	ORDERED FACTOR				
Livestock assets							
Cattle number	Cattle_Num	NUMBER	NUMERIC				
Goats number	Goats_Num	NUMBER	NUMERIC				
Sheep number	Sheep_Num	NUMBER	NUMERIC				

Sheep and goat number	Sheep_Goat_Num	NUMBER	NUMBER				
Chicken number	Chicken_Num	NUMBER	NUMERIC				
Beehives number	Beehives_Num	NUMBER	NUMERIC				
Donkeys number	Donkeys_Num	NUMBER	NUMERIC				
Horses number	Horses_Num	NUMBER	NUMERIC				
Rabbits number	Rabbits_Num	NUMBER	NUMERIC				
Calculated	sheep_Goat_yes	Yes/No (1/0)	FACTOR				
Calculated	sheep_yes	Yes/No (1/0)	FACTOR				
Calculated	goat_yes	Yes/No (1/0)	FACTOR				
Calculated	cattle_yes	Yes/No (1/0)	FACTOR				
Calculated	chicken_yes	Yes/No (1/0)	FACTOR				
Calculated	donkeys_yes	Yes/No (1/0)	FACTOR				
Calculated	horses_yes	Yes/No (1/0)	FACTOR				
Calculated	rabbits_yes	Yes/No (1/0)	FACTOR				
Calculated	beehives_yes	Yes/No (1/0)	FACTOR				
Agricultural Land Holding and Access							
If you answered Owned / allocated, how much is Irrigated in donum?	Owned_Irrig_Land_Donum	NUMBER	NUMERIC				
if you answered cultivated, how much is Irrigated in donum?	Cultivated_Irrig_Land_Donum	NUMBER	NUMERIC				

if you answered sharecropped, how much is Irrigated in donum?	Sharecropped_Irrig_Land_Donum	NUMBER	NUMERIC				
if you answered Leased / hired, how much is Irrigated in donum?	LeasedIn_Irrig_Land_Donum	NUMBER	NUMERIC				
	LeasedOut_Irrig_Land_Donum	NUMBER	NUMERIC				
Calculated	Calculated_Total_Irrig_Land_Donum	NUMBER	NUMERIC				
if you answered Owned / allocated, how many is Rainfed in donum?	Owned_Rainfed_Land_Donum	NUMBER	NUMERIC				
If you answered cultivated, how much is rainfed in donum?	Cultivated_Rainfed_Land_Donum	NUMBER	NUMERIC				
if you answered Sharecropped, how much is rainfed in donum?	Sharecropped_Rainfed_Land_Donum	NUMBER	NUMERIC				
If you answered Leased / hired, how much is rainfed in donum?	LeasedIn_Rainfed_Land_Donum	NUMBER	NUMERIC				
	LeasedOut_Rainfed_Land_Donum	NUMBER	NUMERIC				

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