AMERICAN UNIVERSITY OF BEIRUT

EVALUATING THE IMPACT OF HUMANITARIAN INTERVENTIONS ON AGRICULTURE PRODUCTIVITY IN SYRIA USING REMOTE SENSING AND MACHINE LEARNING

by
LARA HUSSEIN SUJUD

A thesis
submitted in partial fulfillment of the requirements
for the degree of Master of Science
to the Department of Agriculture
of the Faculty of Agricultural and Food Science
at the American University of Beirut

Beirut, Lebanon
January 2023

AMERICAN UNIVERSITY OF BEIRUT

EVALUATING THE IMPACT OF HUMANITARIAN INTERVENTIONS ON AGRICULTURE PRODUCTIVITY IN SYRIA USING REMOTE SENSING AND MACHINE LEARNING

by

LARA HUSSEIN SUJUD

Approved by:

	Signature
Dr. Hadi Jaafar, Associate Professor	
Department of Agriculture	Advisor
	Signature
Dr. Ali Chalak, Associate Professor	
Department of Agriculture	Member of Committee
	Signature
Dr. Rami Zurayk, Professor	
Department of Landscape Design and Ecosystem Management	Member of Committee

Date of thesis defense: January 10, 2023

AMERICAN UNIVERSITY OF BEIRUT

THESIS RELEASE FORM

Student Name: Sujud Lara Hussein
Last First Middle

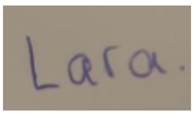
I authorize the American University of Beirut, to: (a) reproduce hard or electronic copies of my thesis; (b) include such copies in the archives and digital repositories of the University; and (c) make freely available such copies to third parties for research or educational purposes:

☐ As of the date of submission

☒ One year from the date of submission of my thesis.

☐ Two years from the date of submission of my thesis.

☐ Three years from the date of submission of my thesis.



06/02/2023

Signature Date

ACKNOWLEDGEMENTS

I would like to express my deepest appreciation to my advisor, Dr. Hadi Jaafar, for his invaluable guidance and support, and for generously sharing his knowledge and expertise with me. I am extremely grateful to my committee members Dr. Ali Chalak and Dr. Rami Zurayk, for their feedback and comments. Additionally, this work would not have been possible without the generous support of the Foreign, Commonwealth & Development Office (FCDO) of the United Kingdom.

I'd like to extend my sincere thanks and appreciation to Dr. Ghassan Baliki and Prof Tilman Bruck – from the International Security and Development Center (ISDC) Berlin, Germany – for their feedback and comments.

I am also grateful to my lab mates and classmates, Rim, Roya, Jad, George, and Abed, for their endless support during the past two years. Special thanks to Yara and Adam for helping with imagery and data preparation.

Lastly, thank you to my family, especially my parents, who always provided me with strength and support. And to the dearest people to my heart, Nagham, Marwa, Aida, and Yasmin, for their tremendous emotional support and belief in me.

ABSTRACT
OF THE THESIS OF

Lara Husein Sujud for Master of Science
Major: Irrigation

Title: Evaluating the Impact of Humanitarian Interventions on Agriculture Productivity in Syria Using Remote Sensing and Machine Learning

Recently, there has been an increased interest in developing new methods to measure the impact of complex humanitarian interventions in hard-to-reach areas to help guide policy decisions. Quantifying agricultural interventions post-conflict remains a challenge. The advancement in Earth observations and remote sensing techniques can provide a timely and precise evaluation of agricultural activities and production in such settings. Little research has been done on the potential use of remote sensing for impact evaluation of agricultural interventions in humanitarian settings. Here, we evaluate a complex humanitarian intervention that aims at strengthening agricultural activity in conflict affected Syria. The overall objective of this study is to develop a framework for evaluating the effectiveness of agricultural interventions in a conflict setting using remote sensing and machine learning techniques. We use a combination of vegetation indices which were normalized by rainfall for three identified periods: pre-conflict, conflict, and post-intervention, and an unsupervised machine learning classifier. Examination of the multi-temporal time series of anomalies and irrigated agriculture revealed distinct patterns in active agricultural areas during the three defined periods of study. The results showed an overall improvement in vegetation and irrigated areas in intervention villages post-intervention. Remote-sensing analysis showed that rehabilitation of irrigation systems significantly increased irrigated areas in some villages like pre-conflict levels.

TABLE OF CONTENTS

ILLUSTRATIONS

Figure

TABLES

Table

CHAPTER I

INTRODUCTION

With the rapid increase in humanitarian needs and hence the increase in humanitarian interventions (UNICEF, 2021), there is an urgency to ensure and verify the effectiveness of such interventions in enhancing livelihoods of rural households (Dhaliwal & Tulloch, 2012; Kubitza et al., 2020). Recently, there has been an increased interest in developing new methods to measure the impact of humanitarian interventions to guide policy decisions (Dhaliwal & Tulloch, 2012), particularly in hard-to-reach areas where conventional impact evaluation designs are difficult to implement (Puri, et al, 2017). Evaluating the success of agricultural interventions in humanitarian settings and conflict settings is a momentous task (Frerks & Hilhorst, 2002; Colombo & Checchi, 2018). Post-conflict agricultural interventions may lead to improvements, but quantifying these improvements remains a challenge. Generally, performing evidence-based impact evaluations requires access to sufficient data and information which may be inaccessible in a conflict-affected region. For instance, securing data resources (ground-truth data) can be very difficult in such a setting due to security reasons and accessibility restrictions (Aung et al., 2021).

Humanitarian interventions in conflict affected regions aim to promote not only peacebuilding, but also agricultural resilience and production (Giordano, 2011; Muscat, 2005; Rohwerder, 2017). Agriculture is known to be one of the most affected sectors in conflict (Jaafar, 2018). In response to crises, there have been many efforts to strengthen agricultural resilience post-crisis and support agricultural production in many countries

(Adu et al., 2018; Panel, 2020). For example, the Food and Agriculture Organization of the United Nations (FAO) has helped farmers apply new climate-smart agricultural practices, in Yemen, to improve productivity and water management (FAO, 2016).

Earth observations and remote sensing techniques have been known to provide a timely and precise evaluation of agricultural activities and production in such conflict settings (Jaafar, 2018). There is a growing body of literature that recognizes the fundamental role of remote sensing applications in complementing peace and security activities in conflict affected parts of the World (Avtar et al., 2021; Mukashov et al., 2022; Quinn et al., 2018). Several studies have applied remote sensing and GIS techniques in conflict-affected settings to test the impact of warfare and conflict on agricultural activity (Blankespoor, et al., 2020; Jaafar & Woertz, 2016; Jaafar et al., 2015; Olsen et al., 2021), food security (Brück & d'Errico, 2019; Olsen et al., 2021), land-use and land cover changes (Eklund et al., 2017; Hamoodi, 2021; Witmer, 2007) and the environment (Aung, 2021; Welp, 2020).

Moreover, remote sensing along with machine learning methods have been widely utilized for agricultural mapping and monitoring. With the advancement in remote sensing technologies and the increase in the number of satellites operating and roaming the earth, several techniques have been explored and evaluated in the literature for assessing agricultural activity. The most common application of remote sensing methods in agriculture includes precision farming (El Nahry & El Baroudy, 2011; Kumar, et al, 2022; Mani et al., 2021), yield estimation (Bolton & Friedl, 2013; Ferencz et al., 2004; Gumma et al., 2021; Jaafar & Ahmad, 2015), biomass estimation (Li & Liu, 2020; Roy & Ravan, 1996), irrigation mapping (Ozdogan & Gutman, 2008; Ozdogan, et al, 2010), and vegetation and productivity parameters (Basso et al. 2004;

Jaafar & Ahmad, 2015). For around two decades, the state-of-the-art application of machine learning for the analysis of remote sensing imagery have focused on using machine learning classifiers from random forests (Hao, et al., 2015; Lebourgeois et al., 2017), support vector machine (Devadas et al., 2012; Yekkehkhany, et al., 2014), k-nearest neighbors (McRoberts, et al., 2007), and neural networks (Ndikumana, et al., 2018) for land cover classification using multispectral imagery (Rivera et al., 2022; Sujud, et al., 2021). Currently, deep learning applications for image analysis and remotely sensed data include object detection (Tang et al., 2020), image segmentation (Hashemi-Beni & Gebrehiwot, 2020), scene classification and high-precision land cover mapping (de Camargo et al., 2021; Wang, et al., 2015).

One limitation of using machine learning and remote sensing applications for image analysis and processing is the availability of training datasets. It is often difficult to obtain ground-truth data from conflict-affected regions, and supervised machine learning models require ground truth data for best performance. The application of unsupervised classification algorithms can overcome this challenge. Unsupervised classification methods have been adopted for irrigation mapping (Ragettli, et al., 2018), crop mapping (Rivera et al., 2022), crop row detection, crop disease (Badnakhe & Deshmukh, 2011), and yield detection (Groenendyk, et al., 2014) among other applications (Cammalleri, et al., 2014; Kusak et al., 2021). Unsupervised clustering in combination with multi-temporal image analysis has proven to be successful in mapping irrigated areas (Adia, 2008; Ozdogan & Gutman, 2008; Ragettli et al., 2018).

Despite the plethora of studies that use remote sensing to evaluate agricultural productivity, studies that assess the effectiveness and impact of agricultural interventions using remote sensing remain limited (Salazar et al., 2021). Little research has been done on the potential use of remote sensing for impact evaluation of agricultural interventions in humanitarian settings. Assessing agricultural productivity post intervention and identifying fields with access to irrigation requires the combination of information from several data sources to control for climate, soil, vegetation type, socio-economic factors. To overcome these limitations, we present a framework to evaluate the impact of agricultural interventions (such as irrigation network rehabilitation, seeds provision, and water use association) in conflict-affected regions of Syria, mainly Deir Ez Zor. We investigate the advantage of using satellite imagery in combination with unsupervised clustering to analyze a time-series of satellite imagery for assessing agricultural productivity.

CHAPTER II

BACKGROUND

A. Outcomes of Syrian Conflict and Impact on Agriculture

Eleven years ago, anti-government protests in Syria abruptly evolved into a civil war. From then on, the Syrian conflict continues to be the most complex humanitarian crisis in the region (OCHA, 2022), which imposed immense suffering on the Syrian community. Around half a million people have lost their lives, about 7 million people have been internally displaced, and 13.5 million remain in diaspora (UNHCR, 2022). The conflict resulted in prevalent destruction of urban and agricultural infrastructure including health facilities, homes, schools, water supply and irrigation systems. Since the onset of the Syrian war, the political and economic situation of the country has deteriorated. The conflict had led to the displacement of many Syrians, from rural areas and dependent on agriculture for a living. Consequently, the agriculture sector - one of the most strategic pillars in the Syrian economy - has been severely impacted. During the main conflict period, agriculture remained a resilient sector to some extent in many Syrian Governorates. According to a report by the Food and Agriculture Organization of the United Nations (FAO, 2017), agriculture production in 2016 was estimated to account for 26 percent of the country’s GDP (Gross Domestic Production) despite dropping to 11 percent in 2011 (during the beginning of the war). However, major losses in agricultural production were observed and achieving national food security remains a challenge. This has caused migration and displacement of people living in rural areas, especially those dependent on agriculture, to look for better income sources.

The aftermath of the conflict has caused major challenges to farmers. The main challenges are 1) abandonment of agricultural land; 2) shortages in agricultural inputs (seeds, fertilizers, pesticides, fuel for irrigation); 3) increased input costs due to currency depreciation; 4) destruction of irrigation infrastructure; and 5) severe damage of storage facilities and farming equipment (FAO, 2017).

Agricultural infrastructure damage such as asset destruction accounts for half of the total damage to the agriculture sector (around USD 3.2 billion). In the most irrigated regions, irrigation infrastructure destruction has affected 70-90 percent of households, with 20 percent of households completely losing access to irrigation (FAO, 2017). In addition to the irrigation infrastructure damage, farmers are facing other challenges: low rainfall, heatwaves, and droughts, thereby aggravating water scarcity. To cover their irrigation needs, farmers are relying on surface wells. This will consequently reduce ground water levels leading to higher pumping costs. In Deir Ez Zor and Ar-Raqqah governorates, the water flow from the Euphrates River (from Turkey) has been lower than average leading to alarmingly lower water levels in the downstream reservoirs in Syria. Low water levels in the Euphrates does not only reduce drinking and domestic water access and use, but also causes harvest losses and water borne diseases (OCHA, 2022). Such vulnerabilities in the agriculture sector trigger widespread food insecurity which will continue to impact humanitarian assistance across Syria. Food insecurity is extremely high contributing to an increase in humanitarian needs among the population. As the economic situation deteriorates, the number of food insecure people increases reaching 12.4 million (FAO, 2019b). The FAO and World Food Programme (WFP) in Syria recommend working towards long-term agricultural production in order to achieve reconstruction and recovery of the agriculture sector (FAO, 2019b). FAO has been conducting an emergency response program that attempts to restore seed multiplication in Syria. The "Supporting emergency needs, early recovery and long-term resilience in Syria agriculture sector" program is a 3-year initiative funded by the United Kingdom's Foreign, Commonwealth & Development Office (FCDO). It is an agricultural intervention aiming to support food security through ensuring farmers access to quality seeds, strengthening agricultural production, rehabilitation of pumping systems for irrigation purpose, and building resilience (FAO, 2019a).

B. Description of the intervention

The FAO has implemented an irrigation system rehabilitation targeting villages in Deir Ez Zor (the Euphrates River Valley). It was reported that, in Deir Ez Zor, two irrigation pumping systems were restored; 13 motors and two pumps and irrigation pipelines were installed. Three Water Use Associations (WUA) were established (WUAs are a group of farmers along a water canal that select a set of rules to manage water distribution among farmers) to operate and maintain the irrigation systems and to distribute the water among beneficiaries by scheduling irrigation intervals. The project is expected to provide access to water for irrigation in target villages to irrigate 3,562 ha of agricultural land directly benefiting about 6,662 households, and to increase agricultural production while decreasing the cost of irrigation per unit area. A summary of the type of rehabilitation for each village of intervention is provided in Table 1, including area scheduled for irrigation, number of beneficiaries, and number of WUA established.

Table 1. Summary of the intervention implemented in every village in Deir Ez Zor.

Village	Population	WUA established	WUA members framed	Irrigated area (ha)	Households	Pumping stations
Mazloum	7500	2	750	500	900	3
Huwayij	10000	2	550	400	550	2
Hatla	25000	2	1062	1100	862	2
Marrat	25000	2	400	600	3300	3
Al-Qasabi	4000	4	450	600	750	4
Al-Jafrah	4000	2	350	400	300	3

CHAPTER III

MATERIALS AND METHODS

A. Overview of study objectives and methods

The overall objective of this study is to develop a framework for evaluating the effectiveness of agricultural interventions in a conflict setting using remote sensing and machine learning techniques. To achieve our objective, we test whether the post-intervention agricultural productivity as gauged from space improved significantly as compared to the conflict period (Section 3.7) for intervention and control villages. A schematic workflow diagram representing the suggested framework is presented in Figure 1. Using a combination of spectral information, vegetation indices, and machine learning, we develop time-series maps of irrigated areas, agricultural productivity (normalized difference vegetation index – NDVI (Pettorelli, 2013), and crop-water stress (normalized difference moisture index – NDMI (Wilson & Sader, 2002), and the modified normalized difference water index (Xu, 2006).

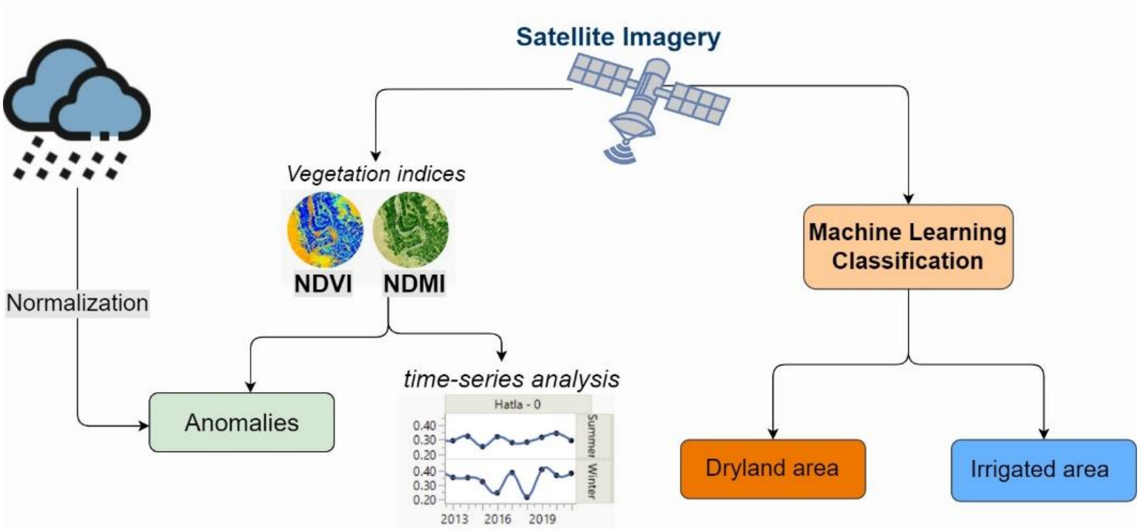


Figure 1. Overview of the study design.

B. Study Area

Syria is known for its dry desert climate and mild rainy winters between December and February. Annual rainfall could be as low as < 25 mm in some regions of Syria (arid and semi-arid desert southeast), around 200 mm in Damascus, and ranges between 300 – 500 mm in the coastal areas (such as Aleppo). The dominant vegetation types in Syria are sparse vegetation, open shrublands, and croplands, which are primarily distributed in the coastal and northern (Al-Hasakeh) parts of the country (Jaafar & Ahmad, 2015). The eastern governorates of the country (Ar-Raqqah, Deir Ez Zor, and Al-Hasakeh) provide around 80 percent of Syria's annual wheat and barley production, most of which rely heavily on irrigation (FAO, 2021).

The study area covers Deir Ez Zor Governorate in Syria. It consists of a total of six villages in Deir Ez Zor (Figure 2). Deir Ez Zor, found in eastern Syria, is located on the downstream of the Euphrates River – which is one of the main constituents of the Tigris-Euphrates basin and the longest river in Southwest Asia. Agricultural production in Deir Ezzor is significant. This governorate used to contribute 20% of total Syria's barley production, 9% of Syria's wheat, and 10% of the summer crops and vegetables. Due to irregular and low rainfalls, the agriculture sector in Deir-Ezzor River relies heavily (more than 98% of the lands) on irrigation (by pumping water from the Euphrates River or shallow groundwater wells nearby).

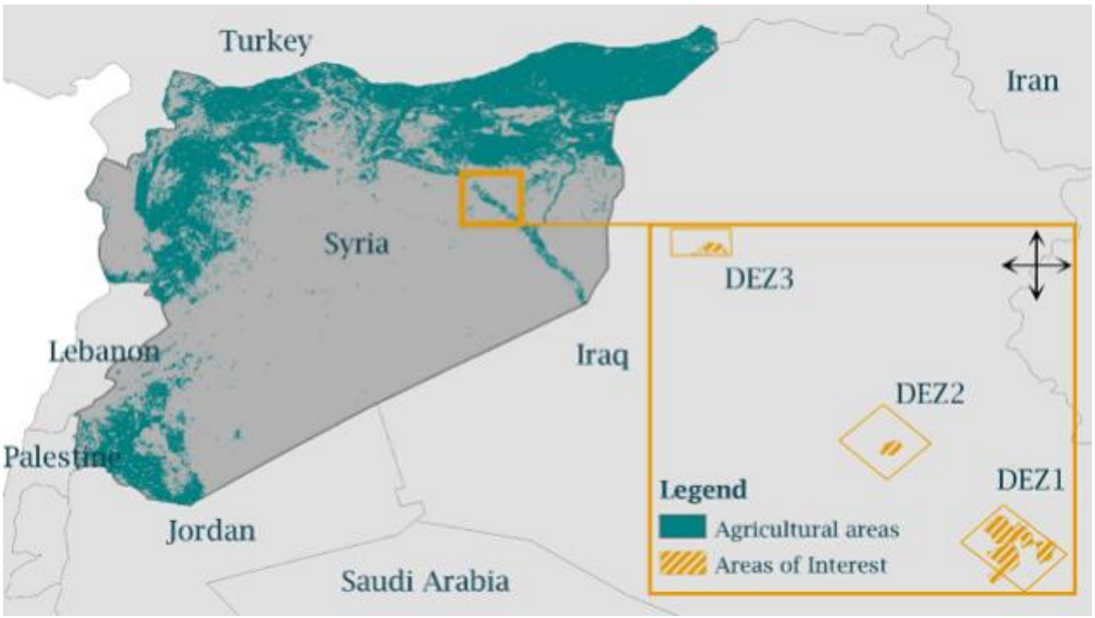


Figure 2. Study area map: intervention villages and Syrian agricultural areas.

C. Delineation of villages and selecting control villages

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 the 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 normalized 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). To disentangle the effect of the interventions from that of other agro-ecological factors, we selected control villages based on the following rationale adopted from Jaafar et al. (2015): 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 3 shows the control villages for each intervention village.

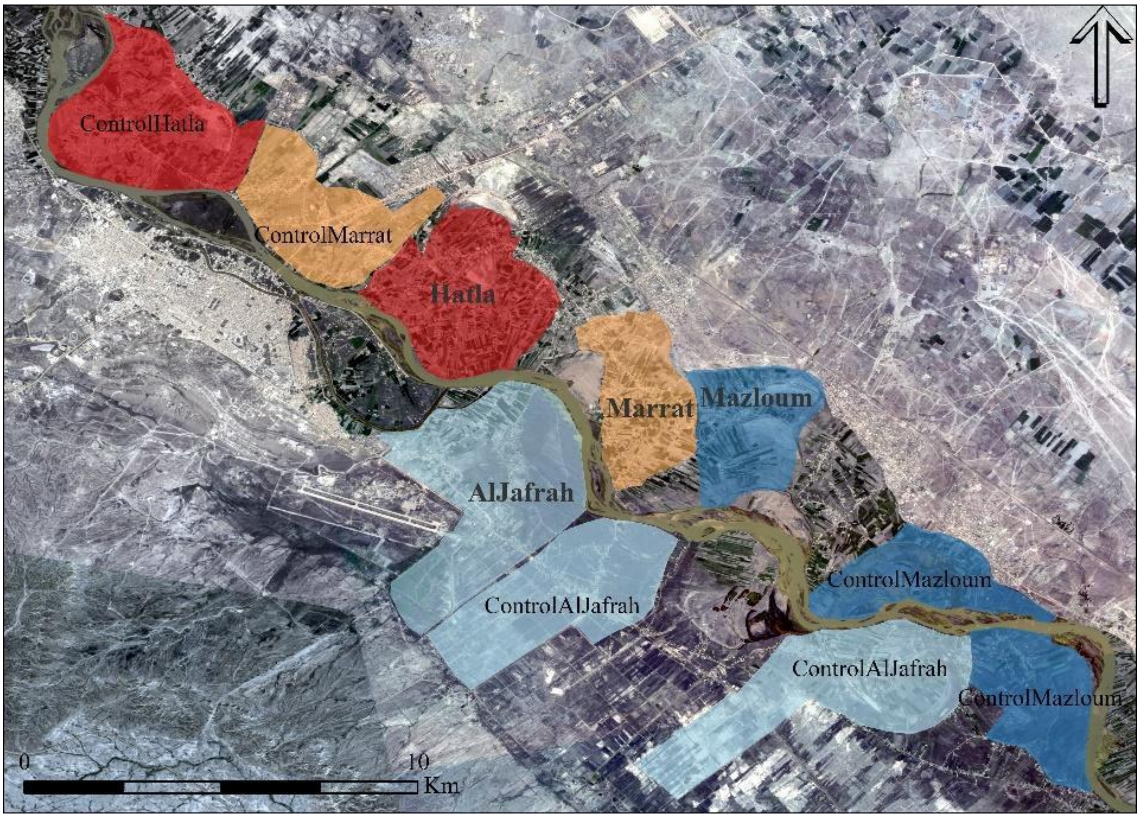


Figure 3. Control villages for Marrat, Hatla, Mazloum and Al-Jafrah

D. Satellite imagery and weather data

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 satellites have been operating since 1972, representing the longest continuously acquired collection of freely available moderate-resolution remote sensing data (Williams et al., 2006). Landsat provides optimal spatial resolution and spectral information that can efficiently monitor land use (Seto et al., 2002), biomass change (Powell et al., 2010), deforestation (Souza Jr et al., 2013), 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 normalized difference vegetation index (NDVI) using the near-infrared and red bands. 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 period of interest.

E. Time series of vegetation indices and their anomalies

Vegetation indices derived from satellite imagery such as the normalized difference vegetation index (NDVI) are effective in quantifying and evaluating vegetation cover and vegetation vigor. The most widely used index is the NDVI, it is expressed as:

NDVI = (NIR-R)/(NIR+R)

Where NIR and R are the near infrared reflectance (Band 4 from Landsat 5 and 7; and Band 5 from Landsat 8) and red reflectance (Bands 3 from Landsat 5 and 7; and Band 4 from Landsat 8) 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 vigor of the vegetation. We obtain seasonal mean NDVI values for every intervention village and its control. We also compute the seasonal standardized NDVI anomalies normalized by rainfall (Section 3.5) as compared to pre-conflict mean (2000

– 2012) as well as against the conflict period mean NDVI (2013 – 2018). We then observe during which season/year the normalized anomalies significantly deviated from the mean for each village.

F. Correcting for factors that impact agricultural productivity

Precipitation greatly affects agricultural productivity. For instance, insufficient and rainfall over Syria during 2013-2014 have caused a decrease in cereal production (see e.g. Jaafar & Ahmad, 2015). We analyze precipitation history and long-term trends per governorate to disentangle the impact of rainfall on agriculture production. Using CHIRPS data, we estimate annual rainfall per governorate for years 2000-2020 to use for normalization of standardized NDVI anomalies (Figure 4). We compute a rainfall ratio for each year by which we control for precipitation using the below formula:

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

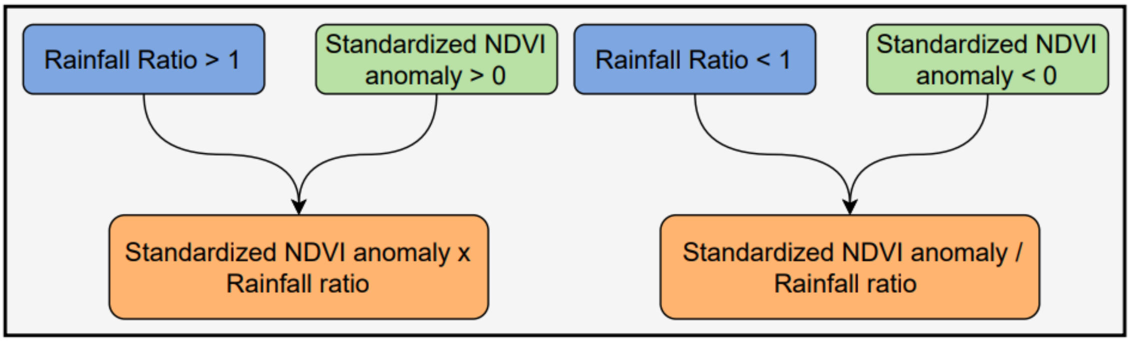


Figure 4. Criteria followed to normalize the standardized NDVI anomalies by rainfall.

G. Unsupervised machine learning classification

We perform k-means clustering over the intervention and control villages. Clustering relies on unsupervised machine learning because it works by grouping unlabeled objects. Here, we use k-means clustering algorithm (Likas, et al., 2003). It is an algorithm that groups objects based on features in k number of clusters or groups. The k-means algorithm determines the best k center 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 minimized.

First, we prepare the satellite imagery from Landsat 5,7, and 8 by filtering them to obtain cloud-free images. The Landsat 7 image collection was gap-filled using a focal mean function. The focal mean function applies a morphological filter to each band by inputting pixels in a custom kernel. We used a square kernel then applied a blend to fill the gaps of the original image. Then, we compute three indices – NDVI, the normalized difference moisture index (NDMI), and the modified normalized difference water index (MNDWI) to be used as input features for the clustering step. NDMI is considered a plant-water index and is defined using the NIR and shortwave infrared (SWIR) bands. NDMI is commonly used to determine vegetation moisture content, it is an indicator of crop water stress. The use of NDMI, in combination with other vegetation indices, have produced good results in irrigation mapping (Chance, et al., 2017). The MNDWI uses the green and SWIR bands, it is used to detect open water features as it removes urban features that are often correlated with water in other indices (Xu, 2006).

Later, we sample 10,000 pixels from each governorate and use them to train the k-means cluster algorithm. We apply the clustering algorithm on the NDVI, NDMI, and MNDWI bands and pre-define three "clusterers". We sort the clusteres 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.

H. Statistical analysis

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 Wilcoxon signed rank test is a nonparametric test commonly used for paired data. The use of this test herein avoids the assumption of normality which is a prerequisite to running other statistical tests such as the students-t 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.

CHAPTER IV

RESULTS

The results are evaluated using two sections – the first section presents NDVI and clustering results for intervention and control villages (averaged and one by one), and the second section presents the hypothesis testing results for the machine-learning derived irrigated areas, NDVI, and NDMI metrics.

A. Overall effectiveness of intervention

There is an overall increase in both NDVI and ML-derived irrigated areas in the spring season post-intervention period in the intervention villages (Figure 5a). There is also an increase in NDVI an irrigated area in summer season of 2020, followed by a decrease in 2021 for the intervention villages (Figure 5b).

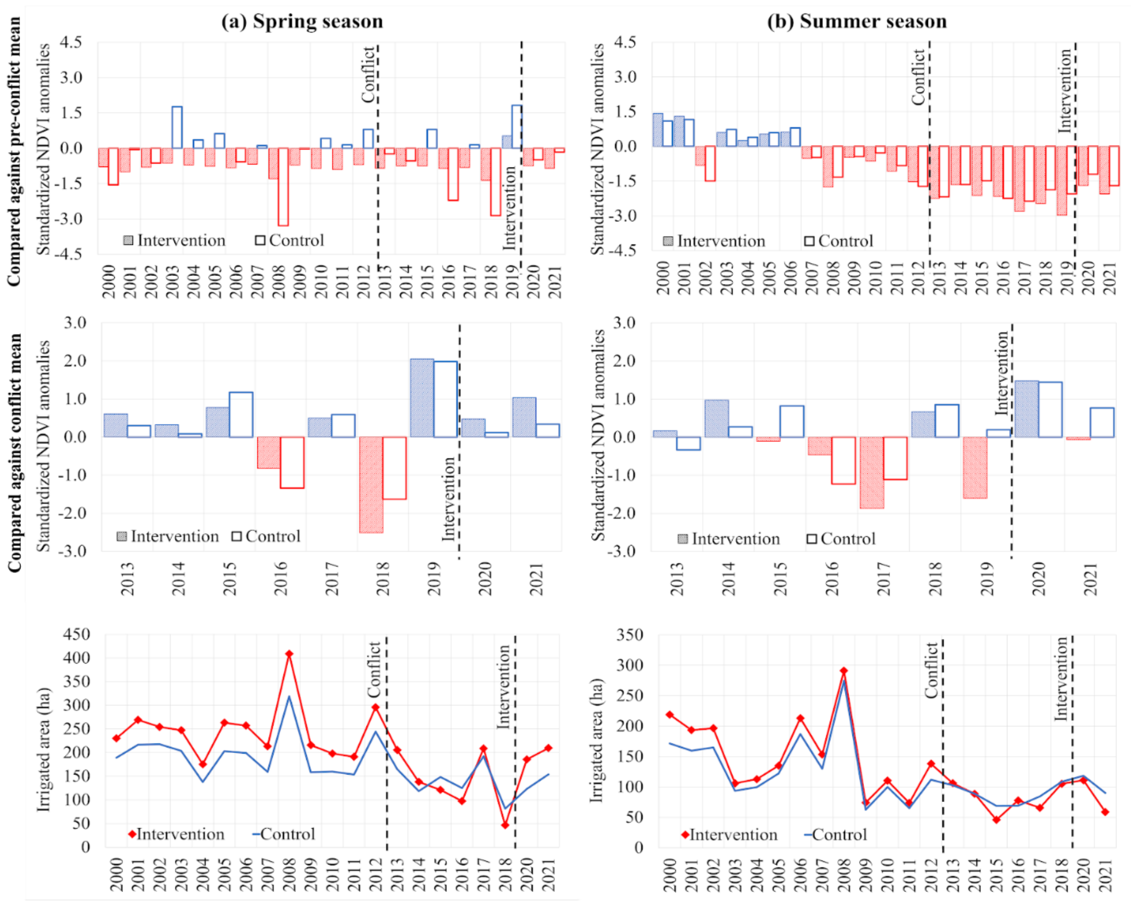


Figure 5. Time series of standardized NDVI anomalies normalized by rainfall as compared against pre-conflict mean and conflict mean, and time series of irrigated area as obtained from K-means clustering for intervention and control villages for (a) spring season and (b) summer season.

1. Time series analysis

The time-series results of the standardized NDVI anomalies normalized by rainfall for intervention and control villages are shown in Figure 5. 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. 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 was performed), 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 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 post-intervention period (2020 and 2021), and the intervention villages show a greater 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 (Figure 5a).

During the summer season, for both intervention and control villages, we find a slight increase in irrigated areas during year 2020 but not the same for year 2021 (Figure 5b).

2. Hypothesis testing results

Hypothesis testing shows that for intervention villages, there is significant improvement of the analyzed agriculture metrics during the summer season (Table 2). This contrasts with the control villages, where a significant increase in irrigated area (p value < 0.01) and NDVI (p value < 0.05) was observed during the summer season (Table 2a). We find that the irrigated area and NDVI of intervention villages significantly improved as compared to the conflict-period irrigated area (p-value < 0.0001) and NDVI (p-value < 0.01) during the spring season (Table 2b). However, there was no significant improvement of the irrigated area, NDVI, and NDMI for control villages. The hypothesis testing results confirm the results observed in Figure 5.

Table 2. Hypothesis testing results using Wilcoxon Signed-Rank test.

(a) Summer season

	Wilcoxon Signed-Rank		
	Irrigated area	NDVI	NDMI
Intervention	-87.0 Not sig.	-37.0 Not sig.	-11.0 Not sig.
Control	-369.0 **	-233.0 *	78.0 Not sig.

(b) Spring season

	Wilcoxon Signed-Rank		
	Irrigated area	NDVI	NDMI
Intervention	-227.0 ****	-1.660 **	-97.00 Not sig.
Control	-44.0 Not sig.	-93.0 Not sig.	308.0 Not sig.

B. Individual results for intervention villages

1. Intervention village 1: Hatla

Figure 6 shows the results of the time-series of standardized NDVI anomalies normalized by rainfall and irrigated area for Hatla and its control village during summer and spring season. Results are similar for both intervention and control villages in the spring and summer of 2020. As compared to the reference seasonal means of spring and summer (2000-2012), the NDVI improved only during the summer of 2020.

The second-row charts of Figure 6 present the standardized NDVI anomalies normalized by rainfall as compared to the conflict mean reference period (2013 – 2018), where Hatla shows an improvement in NDVI during summer and spring of 2020 and 2021. Similarly, the control village shows an improvement in both seasons except for spring 2021, where a decrease in NDVI is observed there, which is not witnessed in the intervention area.

During the summer season, irrigated area increased in 2020 in both Hatla and its control. However, a greater increase was observed in the control village. In summer 2021 the irrigated area decreased again. In the spring season, an increase in irrigated areas was observed during 2020 and 2021 in the intervention village but not in the control village.

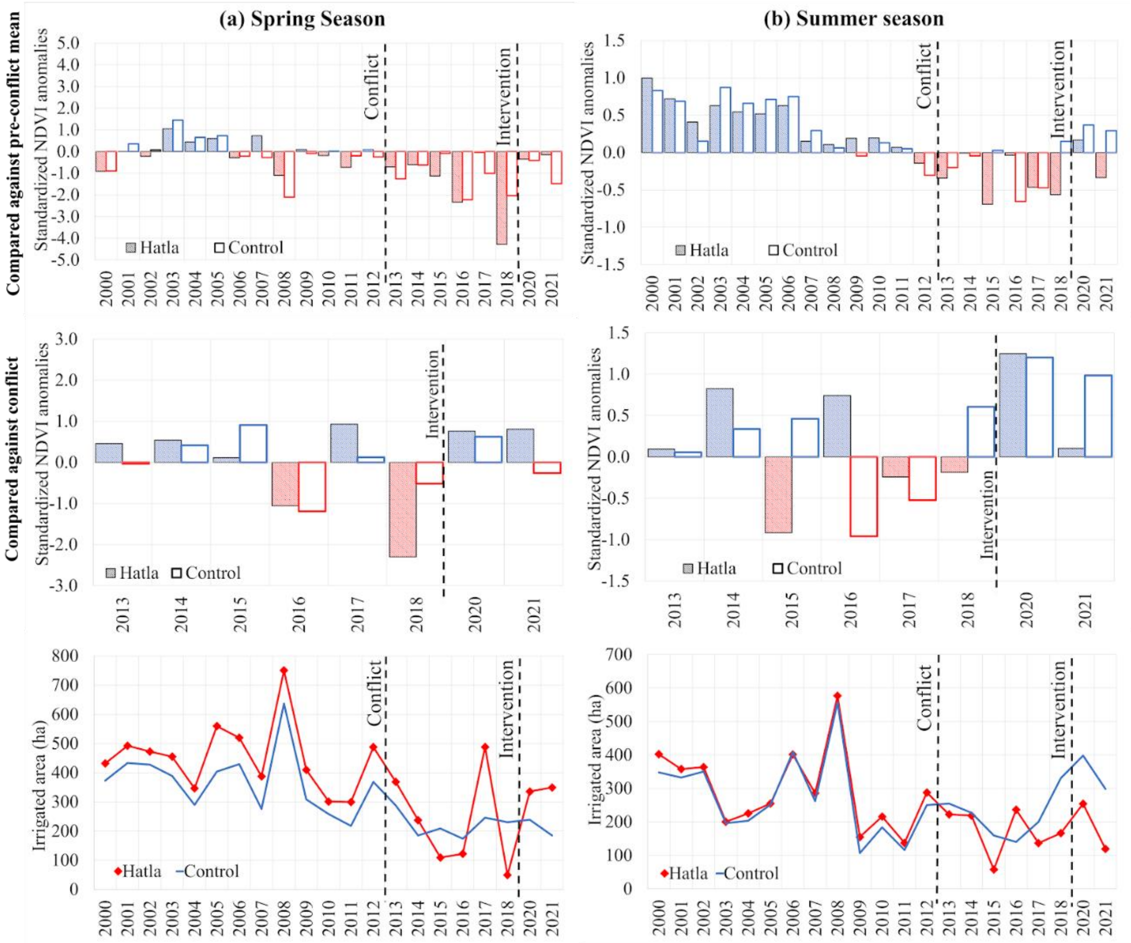


Figure 6. Results for Hatla village. Time-series of standardized NDVI anomalies (2000-2021) normalized by rainfall (the reference period against which the anomalies were calculated is the pre-conflict period: 2000 – 2012), and the time-series of standardized NDVNDVI anomalies (2013-2021) normalized by rainfall (The reference period against which the anomalies were calculated is the conflict period: 2013 – 2018 showing the NDVI deviation in post-intervention years as compared to conflict period), and the irrigated area as obtained from K-means clustering.

2. Intervention village 2: Marrat

The NDVI anomalies results for Marrat village show that there was an increase in NDVI during spring and summer 2020, followed by a decrease in NDVI during summer 2021. The control village of Marrat experienced a similar increase in NDVI values post-conflict (Figure 7). The clustering results show a similar trend in irrigated area (Figure

7). In the summer season of year 2020, the intervention village showed a greater increase in irrigated area as compared to the control village, followed by a drop in irrigated area in both during 2021. An increase in irrigated areas during spring season was observed during post-conflict years in both as well.

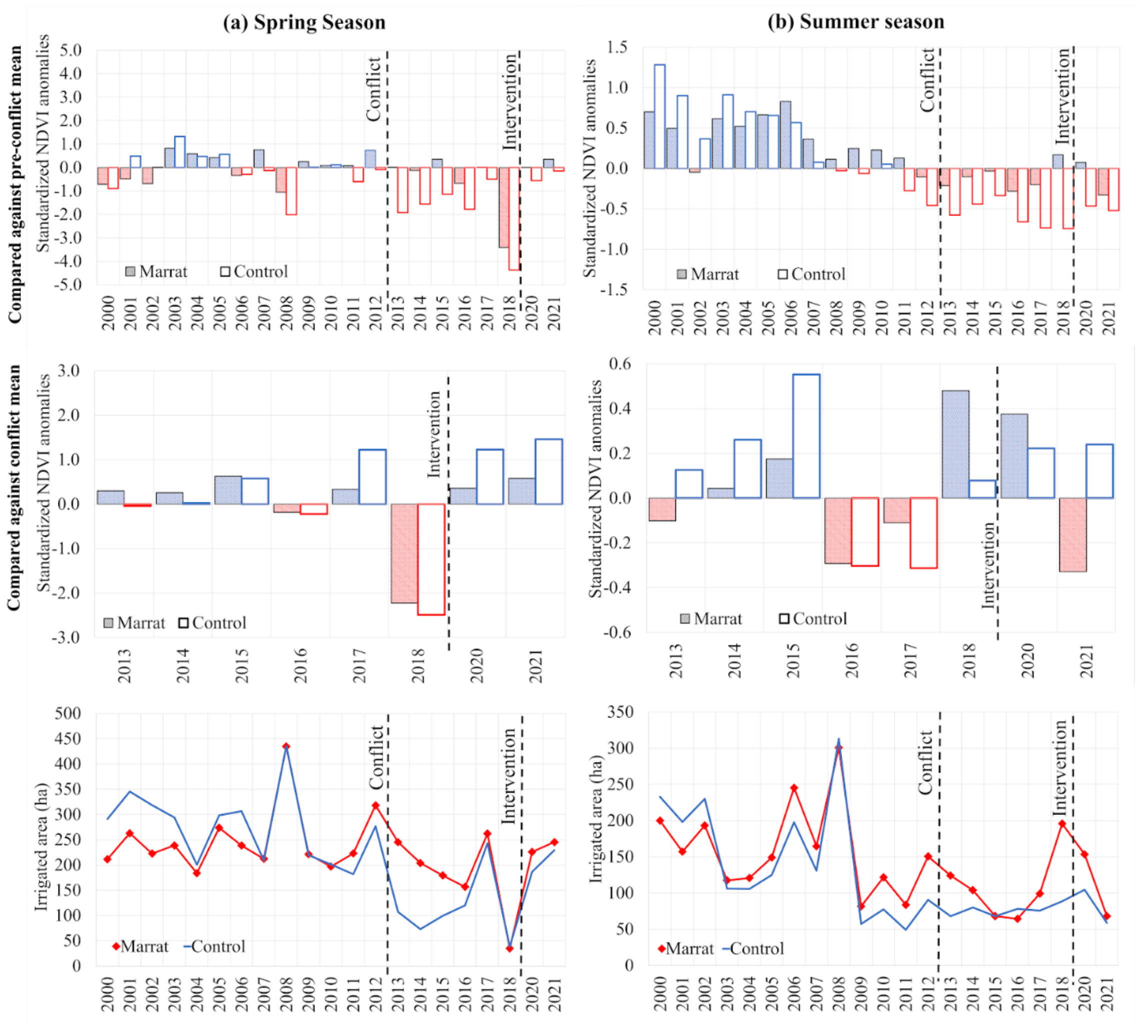


Figure 7. Results for Marrat village. Time-series of standardized NDVI anomalies (2000-2021) normalized by rainfall (the reference period against which the anomalies were calculated is the pre-conflict period: 2000 – 2012), and the time- series of standardized NDVI anomalies (2013-2021) normalized by rainfall (The reference period against which the anomalies were calculated is the conflict period: 2013 – 2018 showing the NDVI deviation in post-intervention years as compared to conflict period), and the irrigated area as obtained from K-means clustering.

3. Intervention village 3: Al-Jafrah

NDVI results during post-intervention years were lower than NDVI in pre-conflict period during summer and spring season for both Al Jafrah and its control villages. However, as compared to the conflict period, a slight improvement in NDVI of Al Jafrah can be observed during spring 2021 and 2021, and during summer 2020 (Figure 8). No improvement in NDVI was observed in control villages of Al-Jafrah during post-intervention period. As for the irrigated area, no change was observed during the summer season. A slight increase in irrigated area was observed in both intervention and control villages (Figure 8).

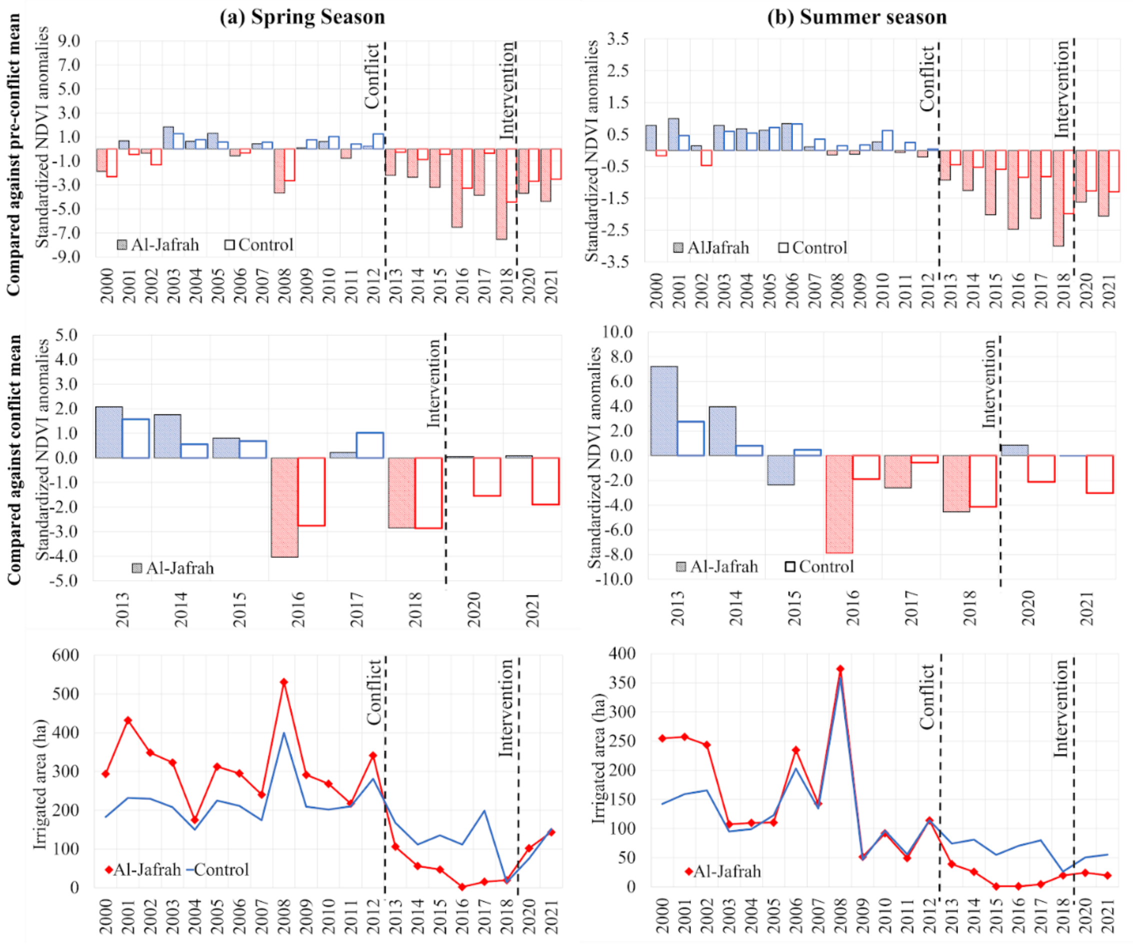


Figure 8. Results for Al-Jafrah village. Time-series of standardized NDVI anomalies (2000-2021) normalized by rainfall (the reference period against which the anomalies were calculated is the pre-conflict period: 2000 – 2012), and the time- series of standardized NDVI anomalies (2013-2021) normalized by rainfall (The reference period against which the anomalies were calculated is the conflict period: 2013 – 2018 showing the NDVI deviation in post-intervention years as compared to conflict period), and the irrigated area as obtained from K-means clustering.

4. Intervention village 4: Mazloum

For Mazloum village, an improvement in NDVI was observed only during spring season (2020 and 2021) as compared to pre-conflict and conflict period. As for the control village, no improvement was observed except for a slight increase in NDVI during summer 2020. As for the irrigated areas, and similar to the NDVI results, an increase was observed during spring season in the intervention village (Figure 9). A decrease in irrigated areas of Mazloum was detected during spring 2021, which is not the case for its control village.

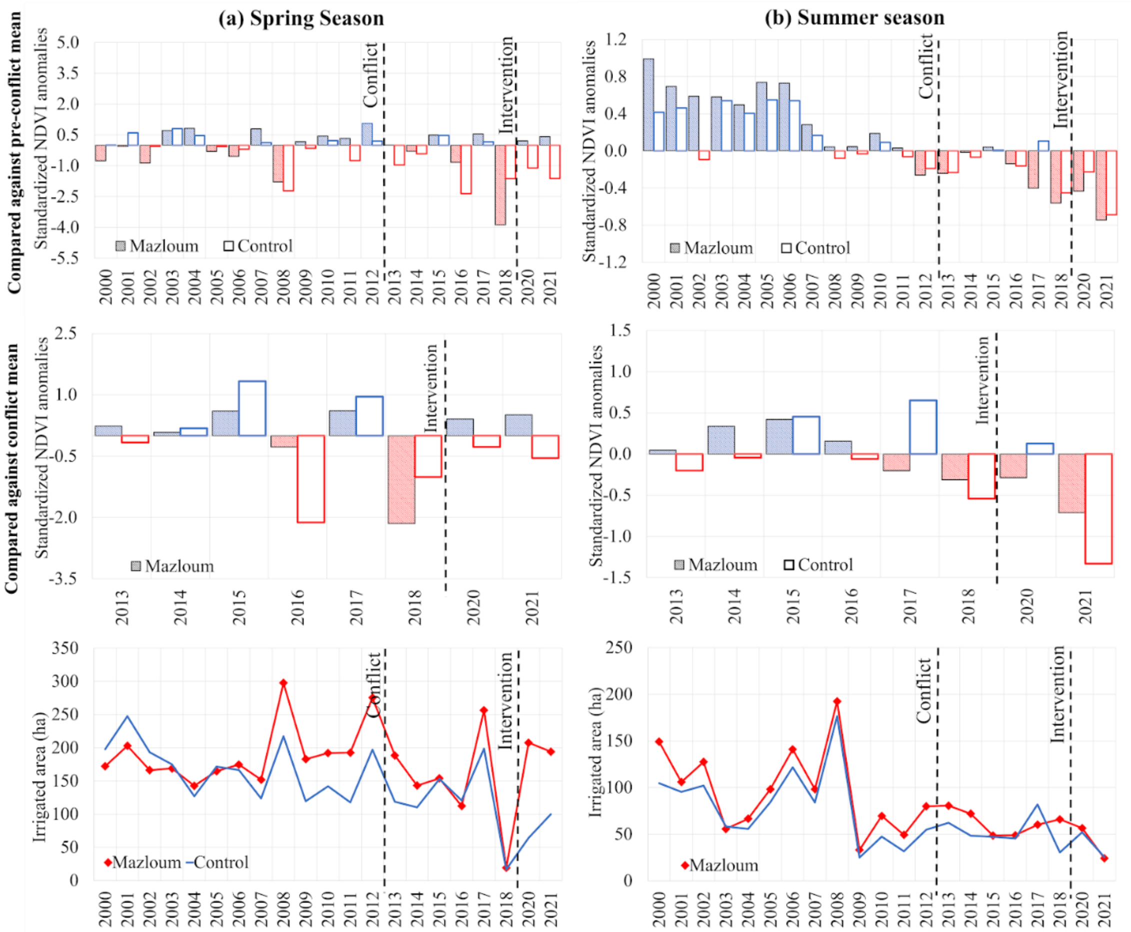


Figure 9. Results for Mazloum village. Time-series of standardized NDVI anomalies (2000-2021) normalized by rainfall (the reference period against which the anomalies were calculated is the pre-conflict period: 2000 – 2012), and the time-series of standardized NDVI anomalies (2013-2021) normalized by rainfall (The reference period against which the anomalies were calculated is the conflict period: 2013 – 2018 showing the NDVI deviation in post-intervention years as compared to conflict period), and the irrigated area as obtained from K-means clustering.

5. Intervention village 5: Al-Qasabi

Results from Al-Qasabi village show a greater improvement in NDVI as compared to the control village during post-intervention years (Figure 10). An increase in irrigated areas was also observed during the spring season (Figure 10). A similar trend was observed in both during the summer season: no change in 2020 followed by a decrease in 2021.

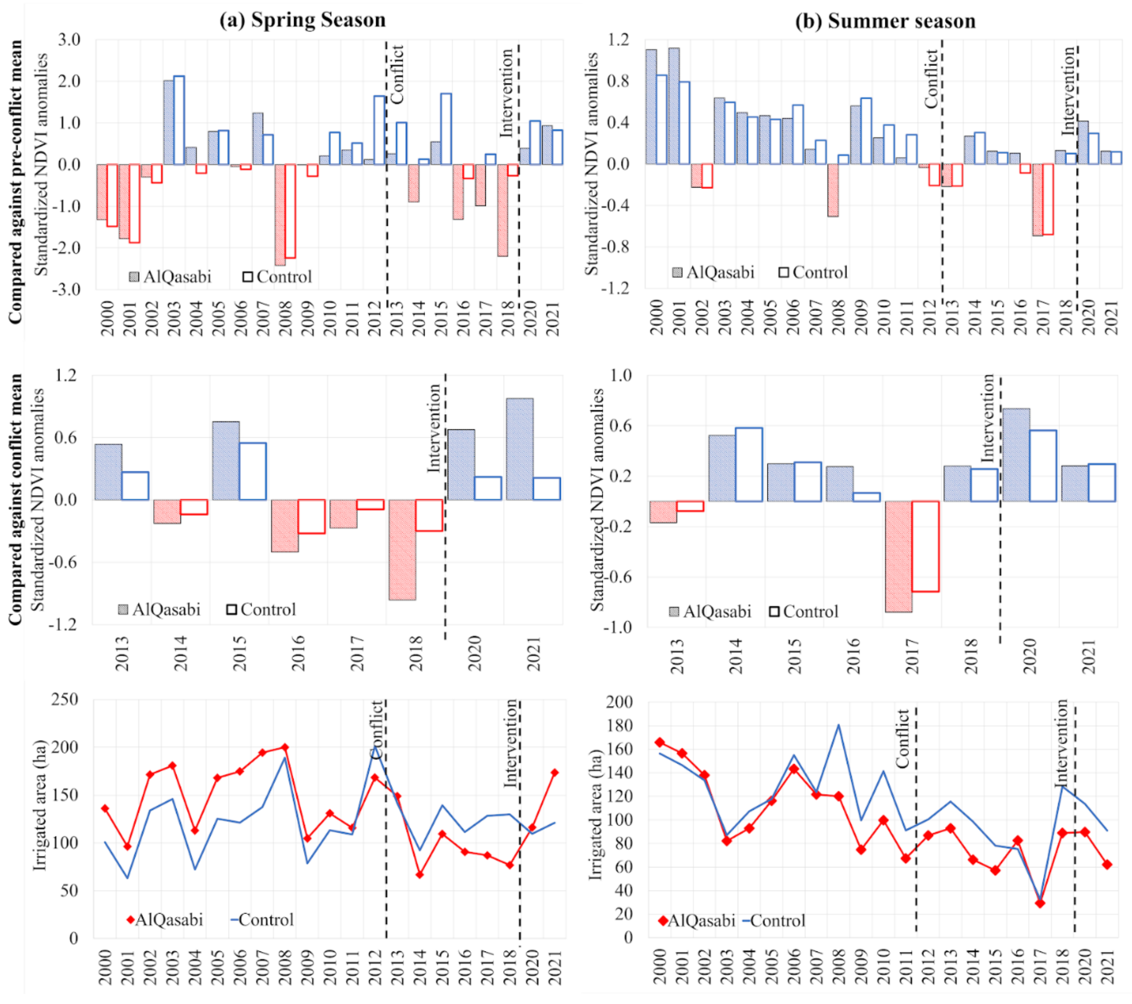


Figure 10. Results for Al-Qasabi village. Time-series of standardized NDVI anomalies (2000-2021) normalized by rainfall (the reference period against which the anomalies were calculated is the pre-conflict period: 2000 – 2012), and the time-series of standardized NDVI anomalies (2013-2021) normalized by rainfall (The reference period against which the anomalies were calculated is the conflict period: 2013 – 2018

showing the NDVI deviation in post-intervention years as compared to conflict period), and the irrigated area as obtained from K-means clustering.

6. *Intervention village 6: Huwayij*

An increase in NDVI anomalies was observed in Huwayij village during summer and spring seasons post-intervention, which was also observed in the control village (Figure 11). Irrigated areas increased during the spring season but decreased during the summer season for both intervention and control (Figure 11).

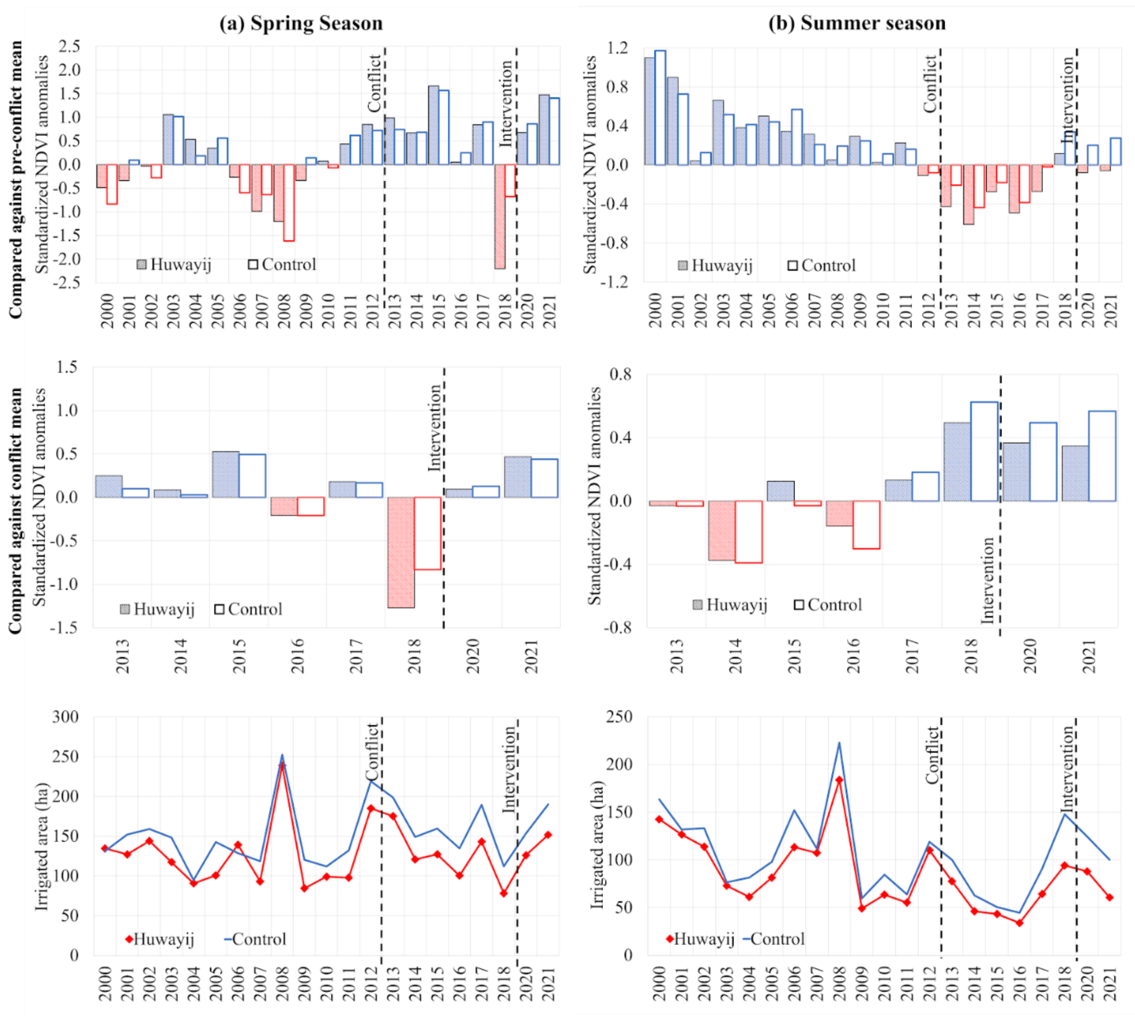


Figure 11. Results for Huwayij village. Time-series of standardized NDVI anomalies (2000-2021) normalized by rainfall (the reference period against which the anomalies were calculated is the pre-conflict period: 2000 – 2012), and the time-series of

standardized NDVI anomalies (2013-2021) normalized by rainfall (The reference period against which the anomalies were calculated is the conflict period: 2013 – 2018 showing the NDVI deviation in post-intervention years as compared to conflict period), and the irrigated area as obtained from K-means clustering.

C. Hypothesis testing results – village by village

1. Spring season

Irrigated area was significantly higher than conflict-mean irrigated area in three out of six intervention villages (Marrat, Al-Jafrah, and Al-Qasabi) (Table 3). None of the control villages show a significant increase in irrigated area except for the control of Marrat village, and a significant decrease in irrigated area was observed in the control of Mazloum village. Four out of six intervention villages show a significant increase in NDVI (Hatla, Marrat, Al-Qasabi and Huwayij); and only two control villages show similar results (control of Marrat and control of Huwayij). Finally, only Marrat village shows a significant increase in NDMI results and none of the control villages. Two control villages (control of Al-Jafrah and control of Mazloum) show a significant decrease in spring season NDMI.

2. Summer season

No significant increase in irrigated area was observed post-intervention for any of the intervention villages (Table 4). Two control villages (control of Hatla, and control of Huwayij) showed a significant increase in irrigated area post-intervention. One control village (control of Mazloum) showed a significant decrease in irrigated area. Al-Qasabi and Hatla villages showed a significant increase in NDVI and NDMI post-intervention as compared to the conflict period. Similarly, their control villages showed the same significant results. Although Huwayij village did not show any significant increase in any of the agriculture metrics being analyzed, its control village showed significant increase in all three of them (irrigated area, NDVI and NDMI).

Table 3. Hypothesis testing results (village by village) showing whether agricultural activity significantly changed as compared to pre-conflict mean (2013-2018) for the spring seasons.

Village	**Irrigated area**		**NDVI**		**NDMI**	
	Intervention	*Control*	*Intervention*	*Control*	*Intervention*	*Control*
Al Jafrah	++	0	0	0	0	--
Al Qasabi	++	0	++	0	0	0
Hatla	0	0	++	0	0	0
Huwayij	0	0	++	++	0	0
Marrat	++	++	++	++	0	++
Mazloum	0	--	0	0	0	--

Table 4. Hypothesis testing results (village by village) showing whether agricultural activity significantly changed as compared to pre-conflict mean (2013-2018) for the summer seasons.

Village	**Irrigated area**		**NDVI**		**NDMI**	
	Intervention	*Control*	*Intervention*	*Control*	*Intervention*	*Control*
Al Jafrah	0	0	0	0	0	0
Al Qasabi	0	0	++	++	++	++
Hatla	0	++	++	++	++	++
Huwayij	0	++	0	++	0	++
Marrat	0	0	0	0	0	0
Mazloum	0	--	0	0	0	--

Notes: ++ corresponds to significant improvement, -- corresponds to a significant decrease in agricultural activity, and 0 corresponds to no significant change.

CHAPTER V

DISCUSSION

Evaluating agricultural interventions using remote sensing methods poses some challenges. The use of multiple indices and methods rather than one simple index reveals that results can be different and may not lead to the same conclusion. Examination of the multi-temporal time series of anomalies (standardized NDVI, normalized by rainfall) and irrigated agriculture reveals distinct patterns in active agricultural areas during the three defined periods of study. Standardization and normalization of the standardized indices by rainfall promise to be a novel and robust method to assess changes in agricultural activity. Observations show a decrease in standardized NDVI anomalies normalized by rainfall during 2008 in all villages which was not reflected in the irrigated areas obtained from K-means clustering. Such a result explains why the unsupervised machine learning algorithm better distinguishes between irrigated areas and abandoned land since it uses a combination of NDMI, NDWI and NDVI - which when combined the accuracy of data on vegetation stress and cover is expected to become higher.

The methodology used in this study makes use of the SWIR band, which is sensitive to vegetation water content, and the NIR which is sensitive to the leaf dry matter. Canopy detection is done better using both the NDVI and NDMI, and vegetation stress is detected using the NDMI, and the NDWI helps in delineating open water surfaces and removing built up noise. As such, the unsupervised machine learning algorithm makes use of the information from three indices to produce 3 clusters of irrigated, non-irrigated, and abandoned land without being biased due to using one index.

When comparing the results of the irrigated areas classification to those of the NDVI and NDMI time series, there were some cases when they were not at par for the same village or zone. For example, a significant increase in irrigated areas was noted at Al-Jafrah for the spring season, but there was no significant increase in the NDVI or NDMI for the same. This phenomenon was repeated during the spring season at Hatla and Huwayij villages, where NDVI significantly increased but not the irrigated area or NDMI. Conversely, there was an increase in both irrigated area and NDVI for Marrat and Al-Qasabi for the spring season, but no significant increase in NDMI for the same period. In other cases, the conclusions from the three metrics were in agreement (for example, summer season for control of Hatla and control of Huwayij).

Selection of the control is also not a straight-forward task. It is not easy to identify villages next to the intervention village that share similar properties in terms of size, area, population, crop lands, irrigated areas, irrigation systems, and even governance. While we mainly relied on pre-conflict NDVI to identify and select homogenous areas, it seems that when running the irrigated areas analysis, it was evident that there were some differences between the villages and their respective controls in pre-conflict times. However, as the differences were not large, we believe they are due to the unavoidable natural variability characteristic of agriculture, climate, and farming life in general. The impact of control selection was not assessed here, and perhaps this would necessitate using a metric other than the mean standardized NDVI or NDMI, such as the maximum or the average between the mean and the maximum.

Further research could address utilizing higher resolution satellite imagery in combination with ground validation of planted crops.

CHAPTER VI

CONCLUSION

Adopting agriculture interventions and sustainable agriculture practices enhances agriculture productivity, especially in developing countries and war-torn countries. Within this context, rigorous impact evaluations offer valuable insights for monitoring and improving the impact of such interventions. Assessing the impact and success of agriculture interventions over time is challenging due to several constraints. We use remote sensing data to provide a standardized and objective assessment of vegetation cover of complex agriculture interventions in Syria, which can be applied to assess agriculture interventions in different hard to reach regions.

The use of satellite data and remote sensing techniques is still limited in studies focusing on impact evaluations of agricultural interventions. With the availability of global and open access products, rigorous impact evaluations can be implemented remotely and at low costs allowing researchers to study long term impacts.

It remains a challenge to arrive at conclusions with regards to whether the agricultural intervention was effective in improving agricultural productivity in target villages. The present findings confirm that there was an improvement in agricultural activity during the spring season, as both irrigated area and NDVI post-intervention were significantly greater than conflict period. However, the results were different for the summer season, where no significant increase was observed.

REFERENCES

Adia, O.-G. (2008). Change Detection of Vegetation Cover, using Multi-Temporal Remote Sensing Data and GIS Techniques. *37th COSPAR Scientific Assembly, 37*, 26.

Adu, M. O., Yawson, D. O., Armah, F. A., Abano, E. E., & Quansah, R. (2018). Systematic review of the effects of agricultural interventions on food security in northern Ghana. *PLoS One, 13*(9), e0203605.

Aung, T. S. (2021). Satellite analysis of the environmental impacts of armed conflict in Rakhine, Myanmar. *Science of The Total Environment, 781*, 146758.

Aung, T. S., Overland, I., Vakulchuk, R., & Xie, Y. (2021). Using satellite data and machine learning to study conflict-induced environmental and socioeconomic destruction in data-poor conflict areas: The case of the Rakhine conflict. *Environmental Research Communications, 3*(2), 025005.

Avtar, R., Kouser, A., Kumar, A., Singh, D., Misra, P., Gupta, A., . . . Dasgupta, R. (2021). Remote sensing for international peace and security: Its role and implications. *Remote Sensing, 13*(3), 439.

Badnakhe, M. R., & Deshmukh, P. R. (2011). *An application of K-means clustering and artificial intelligence in pattern recognition for crop diseases.* Paper presented at the international conference on advancements in information technology.

Basso, B., Cammarano, D., & De Vita, P. (2004). Remotely sensed vegetation indices: Theory and applications for crop management. *Rivista Italiana di Agrometeorologia, 1*(5), 36-53.

Blankespoor, B., Touray, S., & Katayama, R. (2020). *Estimating the effect of conflict on agricultural activity in the Central African Republic with remotely sensed data.* Paper presented at the AGU Fall Meeting Abstracts.

Bolton, D. K., & Friedl, M. A. (2013). Forecasting crop yield using remotely sensed vegetation indices and crop phenology metrics. *Agricultural and Forest Meteorology, 173*, 74-84.

Brück, T., & d'Errico, M. (2019). Reprint of: Food security and violent conflict: Introduction to the special issue (Vol. 119, pp. 145-149): Elsevier.

Cammalleri, C., Anderson, M., Gao, F., Hain, C., & Kustas, W. (2014). Mapping daily evapotranspiration at field scales over rainfed and irrigated agricultural areas using remote sensing data fusion. *Agricultural and Forest Meteorology, 186*, 1-11.

Chance, E. W., Cobourn, K. M., Thomas, V. A., Dawson, B. C., & Flores, A. N. (2017). Identifying irrigated areas in the snake river plain, Idaho: evaluating performance across composting algorithms, spectral indices, and sensors. *Remote Sensing, 9*(6), 546.

Colombo, S., & Checchi, F. (2018). Decision-making in humanitarian crises: politics, and not only evidence, is the problem. Epidemiologia e prevenzione, 42(3-4), 214-225.

de Camargo, T., Schirrmann, M., Landwehr, N., Dammer, K.-H., & Pflanz, M. (2021). Optimized deep learning model as a basis for fast UAV mapping of weed species in winter wheat crops. *Remote Sensing, 13*(9), 1704.

Devadas, R., Denham, R., & Pringle, M. (2012). Support vector machine classification of object-based data for crop mapping, using multi-temporal Landsat imagery. *International archives of the photogrammetry, remote sensing and spatial information sciences, 39*(1), 185-190.

Dhaliwal, I., & Tulloch, C. (2012). From research to policy: using evidence from impact evaluations to inform development policy. *Journal of Development Effectiveness, 4*(4), 515-536.

Eklund, L., Degerald, M., Brandt, M., Prishchepov, A. V., & Pilesjö, P. (2017). How conflict affects land use: agricultural activity in areas seized by the Islamic State. *Environmental Research Letters, 12*(5), 054004.

El Nahry, A., Ali, R., & El Baroudy, A. (2011). An approach for precision farming under pivot irrigation system using remote sensing and GIS techniques. *Agricultural Water Management, 98*(4), 517-531.

FAO. (2016). *Migration and Protracted Crises - Addressing the root causes and building resilient agricultural livelihoods*. Retrieved from https://www.fao.org/3/i6101e/i6101e.pdf

FAO. (2017). *Counting the Cost: Agriculture in Syria after six years of crisis*. Retrieved from https://www.fao.org/3/i7081e/i7081e.pdf

FAO. (2019a). FAO and DFID collaboration to recover the seed multiplication system in the Syrian Arab Republic. Retrieved from https://www.fao.org/resilience/news-events/detail/ar/c/1201280/

FAO. (2019b). *Special Report - FAO/WFP Crop and Food Security Assessment Mission to the Syrian Arab Republic.* Retrieved from Rome: https://www.fao.org/3/ca5934en/ca5934en.pdf

FAO. (2021). *Special Report: 2021 FAO Crop and Food Supply Assessment Mission to the Syrian Arab Republic*. Retrieved from Rome, Italy: https://www.fao.org/publications/card/en/c/CB8039EN

Ferencz, C., Bognar, P., Lichtenberger, J., Hamar, D., Tarcsai, G., Timár, G., . . . Székely, B. (2004). Crop yield estimation by satellite remote sensing. *International Journal of Remote Sensing, 25*(20), 4113-4149.

Forkuor, G., Conrad, C., Thiel, M., Ullmann, T., & Zoungrana, E. (2014). Integration of optical and Synthetic Aperture Radar imagery for improving crop mapping in Northwestern Benin, West Africa. *Remote Sensing, 6*(7), 6472-6499.

Frerks, G., & Hilhorst, D. (2002). Evaluation of humanitarian assistance in emergency situations.

Gao, F., Anderson, M. C., Zhang, X., Yang, Z., Alfieri, J. G., Kustas, W. P., . . . Prueger, J. H. (2017). Toward mapping crop progress at field scales through fusion of Landsat and MODIS imagery. *Remote Sensing of Environment, 188*, 9-25.

Gertler, P. J., Martinez, S., Premand, P., Rawlings, L. B., & Vermeersch, C. M. (2016). *Impact evaluation in practice*: World Bank Publications.

Giordano, T. (2011). Agriculture and economic recovery in post-conflict countries: Lessons we never learnt.

Groenendyk, D., Thorp, K., Ferré, T., Crow, W., & Hunsaker, D. (2014). A k-means clustering approach to assess wheat yield prediction uncertainty with a HYDRUS-1D coupled crop model.

Gumma, M. K., Kadiyala, M., Panjala, P., Ray, S. S., Akuraju, V. R., Dubey, S., . . . Whitbread, A. M. (2021). Assimilation of remote sensing data into crop growth model for yield estimation: a case study from India. *Journal of the Indian Society of Remote Sensing*, 1-14.

Hamoodi, M. N. (2021). Investigating the Effects of Armed and Political Conflicts on the Land Use/Cover Change and Surface Urban Heat Islands: A Case Study of Baghdad, Iraq. *Journal of the Indian Society of Remote Sensing, 49*(7), 1493-1506.

Hao, P., Zhan, Y., Wang, L., Niu, Z., & Shakir, M. (2015). Feature selection of time series MODIS data for early crop classification using random forest: A case study in Kansas, USA. *Remote Sensing, 7*(5), 5347-5369.

Hashemi-Beni, L., & Gebrehiwot, A. (2020). Deep learning for remote sensing image classification for agriculture applications. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, 51-54.

Jaafar, H. (2018). 6 Remote Sensing and GIS-based Technologies for Assessing the Impact of Conflict on Agricultural Production. *Crisis and Conflict in Agriculture,* 73.

Jaafar, H. H., & Ahmad, F. A. (2015). Crop yield prediction from remotely sensed vegetation indices and primary productivity in arid and semi-arid lands. *International Journal of Remote Sensing, 36*(18), 4570-4589.

Jaafar, H. H., & Ahmad, F. A. (2020). Time series trends of Landsat-based ET using automated calibration in METRIC and SEBAL: The Bekaa Valley, Lebanon. *Remote Sensing of Environment, 238*, 111034.

Jaafar, H. H., & Woertz, E. (2016). Agriculture as a funding source of ISIS: A GIS and remote sensing analysis. *Food Policy, 64*, 14-25.

Jaafar, H. H., Zurayk, R., King, C., Ahmad, F., & Al-Outa, R. (2015). Impact of the Syrian conflict on irrigated agriculture in the Orontes Basin. *International Journal of Water Resources Development, 31*(3), 436-449.

Kubitza, C., Krishna, V. V., Schulthess, U., & Jain, M. (2020). Estimating adoption and impacts of agricultural management practices in developing countries using satellite data. A scoping review. *Agronomy for Sustainable Development, 40*(3), 1-21.

Kumar, J. P., Singhania, D., Patel, S. N., & Dakwala, M. (2022). Crop Classification for Precision Farming Using Machine Learning Algorithms and Sentinel-2 Data *Science in Agriculture and Natural Resource Management* (pp. 143-159): Springer.

Kusak, L., Unel, F. B., Alptekin, A., Celik, M. O., & Yakar, M. (2021). Apriori association rule and K-means clustering algorithms for interpretation of pre-event landslide areas and landslide inventory mapping. *Open Geosciences, 13*(1), 1226-1244.

Lebourgeois, V., Dupuy, S., Vintrou, É., Ameline, M., Butler, S., & Bégué, A. (2017). A combined random forest and OBIA classification scheme for mapping smallholder agriculture at different nomenclature levels using multisource data (simulated Sentinel-2 time series, VHRS and DEM). *Remote Sensing, 9*(3), 259.

Li, Y., Li, M., Li, C., & Liu, Z. (2020). Forest aboveground biomass estimation using Landsat 8 and Sentinel-1A data with machine learning algorithms. *Scientific reports, 10*(1), 1-12.

Likas, A., Vlassis, N., & Verbeek, J. J. (2003). The global k-means clustering algorithm. *Pattern recognition, 36*(2), 451-461.

Mani, P. K., Mandal, A., Biswas, S., Sarkar, B., Mitran, T., & Meena, R. S. (2021). Remote sensing and geographic information system: a tool for precision farming *Geospatial Technologies for Crops and Soils* (pp. 49-111): Springer.

McRoberts, R. E., Tomppo, E. O., Finley, A. O., & Heikkinen, J. (2007). Estimating areal means and variances of forest attributes using the k-Nearest Neighbors technique and satellite imagery. *Remote Sensing of Environment, 111*(4), 466-480.

Mukashov, A., Breisinger, C., Engelke, W., & Wiebelt, M. (2022). Modeling conflict impact and postconflict reconstruction: The case of Yemen. *Economic Systems*, 100940.

Muscat, R. J. (2005). Reviving agriculture in the aftermath of violent conflict: a review of experience. *Journal of Peacebuilding & Development, 2*(2), 77-92.

Ndikumana, E., Ho Tong Minh, D., Baghdadi, N., Courault, D., & Hossard, L. (2018). Deep recurrent neural network for agricultural classification using multitemporal SAR Sentinel-1 for Camargue, France. *Remote Sensing, 10*(8), 1217.

OCHA. (2022). *2022 Humanitarian Needs Overview: Syrian Arab Republic*. Retrieved from https://reliefweb.int/report/syrian-arab-republic/2022-humanitarian-needs-overview-syrian-arab-republic-february-2022

Olsen, V. M., Fensholt, R., Olofsson, P., Bonifacio, R., Butsic, V., Druce, D., . . . Prishchepov, A. V. (2021). The impact of conflict-driven cropland abandonment on food insecurity in South Sudan revealed using satellite remote sensing. *Nature Food, 2*(12), 990-996.

Ozdogan, M., & Gutman, G. (2008). A new methodology to map irrigated areas using multi-temporal MODIS and ancillary data: An application example in the continental US. *Remote Sensing of Environment, 112*(9), 3520-3537.

Ozdogan, M., Yang, Y., Allez, G., & Cervantes, C. (2010). Remote sensing of irrigated agriculture: Opportunities and challenges. *Remote Sensing, 2*(9), 2274-2304.

Panel, G. (2020). Strengthening food systems in fragile contexts. *Policy Brief* (15).

Pena, J., Tan, Y., & Boonpook, W. (2019). Semantic segmentation based remote sensing data fusion on crops detection. *Journal of Computer and Communications, 7*(7), 53-64.

Powell, S. L., Cohen, W. B., Healey, S. P., Kennedy, R. E., Moisen, G. G., Pierce, K. B., & Ohmann, J. L. (2010). Quantification of live aboveground forest biomass dynamics with Landsat time-series and field inventory data: A comparison of empirical modeling approaches. *Remote Sensing of Environment, 114*(5), 1053-1068.

Quinn, J. A., Nyhan, M. M., Navarro, C., Coluccia, D., Bromley, L., & Luengo-Oroz, M. (2018). Humanitarian applications of machine learning with remote-sensing data: review and case study in refugee settlement mapping. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 376*(2128), 20170363.

Ragettli, S., Herberz, T., & Siegfried, T. (2018). An unsupervised classification algorithm for multi-temporal irrigated area mapping in central Asia. *Remote Sensing, 10*(11), 1823.

Rivera, A. J., Pérez-Godoy, M. D., Elizondo, D., Deka, L., & del Jesus, M. J. (2022). Analysis of clustering methods for crop type mapping using satellite imagery. *Neurocomputing, 492*, 91-106.

Rohwerder, B. (2017). Supporting agriculture in protracted crises and rebuilding agriculture after conflict and disasters.

Roy, P., & Ravan, S. A. (1996). Biomass estimation using satellite remote sensing data—an investigation on possible approaches for natural forest. *Journal of biosciences, 21*(4), 535-561.

Salazar, L., Palacios, A. C., Selvaraj, M., & Montenegro, F. (2021). Using Satellite Images to Measure Crop Productivity: Long-Term Impact Assessment of.

Seto, K. C., Woodcock, C., Song, C., Huang, X., Lu, J., & Kaufmann, R. (2002). Monitoring land-use change in the Pearl River Delta using Landsat TM. *International Journal of Remote Sensing, 23*(10), 1985-2004.

Souza Jr, C. M., Siqueira, J. V., Sales, M. H., Fonseca, A. V., Ribeiro, J. G., Numata, I., . . . Barlow, J. (2013). Ten-year Landsat classification of deforestation and forest degradation in the Brazilian Amazon. *Remote Sensing, 5*(11), 5493-5513.

Sujud, L., Jaafar, H., Hassan, M. A. H., & Zurayk, R. (2021). Cannabis detection from optical and RADAR data fusion: A comparative analysis of the SMILE machine learning algorithms in Google Earth Engine. *Remote Sensing Applications: Society and Environment, 24*, 100639.

Tang, Z., Wang, H., Li, X., Li, X., Cai, W., & Han, C. (2020). An object-based approach for mapping crop coverage using multiscale weighted and machine learning methods. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 13*, 1700-1713.

Thomas, N., Neigh, C. S., Carroll, M. L., McCarty, J. L., & Bunting, P. (2020). Fusion Approach for Remotely Sensed Mapping of Agriculture (FARMA): A Scalable Open-Source Method for Land Cover Monitoring Using Data Fusion. *Remote Sensing, 12*(20), 3459.

UNHCR. (2022). Refugee statistics. Retrieved from https://www.unrefugees.org/refugee-facts/statistics/

UNICEF. (2021). *Global Annual Results Reports 2020*. Retrieved from https://www.unicef.org/reports/global-annual-results-2020

Wang, C., Johnston, J., Vail, D., Dickinson, J., & Putnam, D. (2015). High-Precision Land-Cover-Land-Use GIS Mapping and Land Availability and Suitability Analysis for Grass Biomass Production in the Aroostook River Valley, Maine, USA. *Land, 4*(1), 231-254.

Welp, M. (2020). A global analysis on impact of conflicts on long-term greening trends. *Student thesis series INES*.

Williams, D. L., Goward, S., & Arvidson, T. (2006). Landsat. *Photogrammetric Engineering & Remote Sensing, 72*(10), 1171-1178.

Witmer, F. D. (2007). *The effects of war on land-use/land-cover change: An analysis of Landsat imagery for northeast Bosnia*. University of Colorado at Boulder.

Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing, 27*(14), 3025-3033.

Yekkehkhany, B., Safari, A., Homayouni, S., & Hasanlou, M. (2014). A comparison study of different kernel functions for SVM-based classification of multi-temporal polarimetry SAR data. *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, 40*(2), 281.

Pettorelli, N. (2013). *The normalized difference vegetation index*: Oxford University Press.

Wilson, E. H., & Sader, S. A. (2002). Detection of forest harvest type using multiple dates of Landsat TM imagery. *Remote Sensing of Environment*. doi:https://doi.org/10.1016/S0034-4257(01)00318-2

Xu, H. (2006). Modification of normalised difference water index (NDWI) to enhance open water features in remotely sensed imagery. *International Journal of Remote Sensing, 27*(14), 3025-3033.