Measuring dem-ilune adoption in Niger (past & present work)

emLab
UC SANTA BARBARA

Lauren Sharwood

3/21/23 TTT

Farming with limited & erratic water supply on degraded land

- Agricultural yield growth in sub-Saharan Africa has stagnated since the 1960s.
- To meet increasing consumption demands from a growing population, the agricultural sector has brought more land into production, pushing production into increasingly marginal soils.
- Interrupting this cycle of land degradation & poor yields requires intensive agriculture practices that increase water storage and replenish nutrients within the soil

Aker & Jack 2021

Rainwater Harvesting (RWH) Technologies

Demi-lunes (and zai) water catchment techniques to help rainwater infiltration into the soil.

They can help…

- reduce soil degradation
- lower risk of crop failure
- increase profits

Yet, demi-lune adoption remains low

Figure A1.1: The Demi-Lune

Notes: An example of a demi-lune in Niger after the rain, before water has infiltrated into the soil.

emLab UC SANTA BARBARA

Aker & Jack 2021

Aker & Jack 2021 RCT: Tested the importance of different barriers to demi-lune adoption

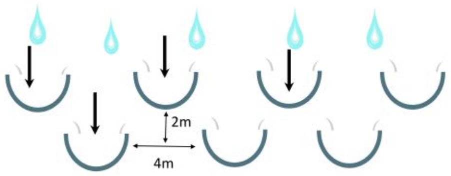
Study began in 2018, with Niger's Ministry of Environment

Assigned farmers in 180 villages to 1 of 4 treatment arms or a control arm:

- Treatment 1: Training only
- Treatment 2: Training + early-UCT (USD 20)
- Treatment 3: Training + CCT (USD 0.40/demi-lune)
- Treatment 4: Training + late-UCT (USD 20.50)
- Control: no training, no cash transfers

+ Spillover sample: indirect exposure to training

2. REPARTIR LA TERRE



2m (6 pas) entre les demi-lunes avant et derrière
4 m être les demi-lunes
Environs 300 demi-lunes par hectare

Figure A1.1: Training Manual

Notes: Example from training manual used to guide the classroom portion of the training and provided to farmers after the training. This diagram outlines the dimensions and spacing recommendations for demi-lunes.

Aker & Jack 2021

Results

Short-run adoption (~3 months after training):

- 4% of households on control villages adopted demi-lunes, whereas farmers in treated villages were 91% more likely to adopt
- No significant differences between the 4 treatment arms

Adoption over time (by the 3rd year, 2020):

- Adoption levels converged across treatments: training had a persistent effect on adoption that cash transfers did not

Adoption spillovers:

- Farmers in treated villages were 50% more likely to have a neighbor adopt than those in the control, but the effects of direct exposure to training on adoption were significantly larger than these indirect effects

Land quality and usage:

- interventions increased agricultural production and improved land quality

Explanation for high adoption rates:

1. Demi-lunes are privately profitable
2. Demi-lunes don't directly compete with other agricultural labor demands
3. There are few other substitutes for recuperating severely degraded soils in Niger
4. Study rules out the idea that liquidity constraints are persistent barriers to adoption

Why was training so successful?

1. Demi-lune construction requires few capital inputs (a shovel and pickaxe)
2. The training made the technical aspects of demi-lune construction accessible
3. The training combined "classroom" and "field-based" components

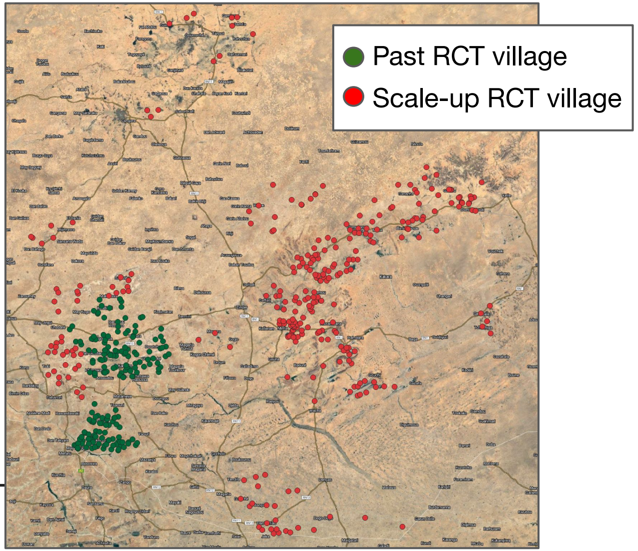
Scale-up RCT will focus on

1) Expanding adoption of the RWH technologies, demi-lunes and zai
2) Assessing the relative costs and benefits of using in-person vs. remote sensing to monitor initial and sustained adoption
3) Investigating whether larger trainings, which are cheaper to implement, deliver similar adoption impacts

Treatment 1: Training on demi-lunes
Treatment 2: Training on zai
Treatment 3: Training on demi-lunes+zai
Control: No Training

Two cross-cutting variations at the village level:
1) In-person vs remote sensing
2) Size of the group invited to training

230 villages in the Zinder and Diffa regions of eastern Niger



emLab
UC SANTA BARBARA

Goals for remote sensing component are to

(1) Measure RWH adoption across all villages

(2) Measure soil quality and vegetation cover, using spectral indices (NDVI) and soil moisture proxies

(3) Measure agricultural outcomes, resilience, and other welfare outcomes to estimate whether adoption increases resilience to weather shocks

Ultimately facilitate government monitoring of demi-lunes and to develop an identification protocol with accessible data

Remote sensing to measure adoption and production impacts

+ Automated: avoiding concerns about enumerator error

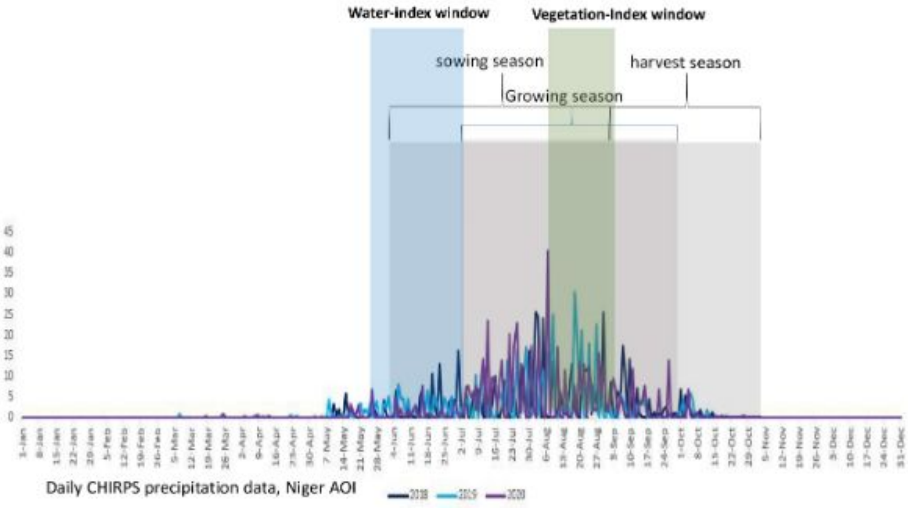
Challenges:

- Best suited for measuring coverage, as opposed to individual demi-lunes
- Significant fixed costs and very-high resolution imagery is expensive
- Object detection and image segmentation algorithms are data- and computationally-intensive
- Rain events bring clouds during the water window

Past remote sensing work (by Kendra)

Explored the feasibility of using Sentinel-2 & PlanetScope imagery to detect areas with a higher probability of demi-lune adoption (most degraded land, glacis) in order to narrow down the search area for measuring demi-lune adoption and benefits with very high-resolution imagery (< 3m).
This first-pass random forest classification was created using pixel-level labels from 450 demi-lune patches and 486 fields without demi-lunes from the first RCT

Features: Created water indices (NDWI, NDMI) and vegetation indices (NDVI, EVI2, SAVI, MSAVI)
- Change features were created for each index, based on the difference between a given index measured around the same day of year in 2017 (year prior to intervention) and 2018 (year of demi-lune construction)
- Monthly mean and max differences were used as final variables for each index during the temporal windows



Past remote sensing results (by Kendra)

Demi-lune adoption: This first-pass model would flag 80% of new demi-lunes while doing a fairly good job of filtering demi-lunes from non-demi-lune fields, with 77% user's accuracy. A second pass in areas showing high probability of demi-lune construction would be desirable to filter out the 23% of false positives.

Table 1. Top 20 variables and corresponding gini-importances for RF models

PlanetScope model		Sentinel-2 model	
Max_NDWId_06_W	0.055	Avg_SWIR1d_05_W	0.043
Avg_MSAVId_08_W	0.048	Max_NDWId_05_W	0.038
Avg_SAVId_08_W	0.046	Avg_NDWId_05_W	0.037
Avg_NDVId_12_W	0.035	Avg_MSAVId_08_W	0.029
Max_MSAVId_09_W	0.031	Max_SWIR1d_05_W	0.024
Max_MSAVId_08_W	0.030	Avg_NDWId_06_W	0.021
Max_NDVId_12_W	0.029	Max_NDWId_06_W	0.021
Max_MSAVId_10_W	0.026	Max_NDMId_12_W	0.020
Max_EVI2d_12_W	0.026	Avg_EVI2d_11_W	0.018
Max_NDWId_07_W	0.026	Max_SAVId_10_W	0.017
Max_MSAVId_11_W	0.026	Avg_NDWId_07_W	0.017
Max_EVI2d_11_W	0.026	Avg_NDMId_06_W	0.017
Avg_EVI2d_12_W	0.025	Max_NDWId_07_W	0.016
Max_SAVId_12_W	0.025	Avg_NDVId_11_W	0.016
Avg_NDVId_11_W	0.022	Max_MSAVId_10_W	0.016
Max_SAVId_11_W	0.022	Max_MSAVId_08_W	0.015
Avg_NDWId_07_W	0.021	Max_SWIR1d_11_W	0.015
Max_MSAVId_12_W	0.021	Max_NDVId_12_W	0.015
Avg_NDWId_06_W	0.020	Avg_SAVId_08_W	0.014

Demi-lune benefits: Comparison of treatment vs control fields before and after demi-lune construction shows a slightly greater spread between treatment and control index values post-intervention.

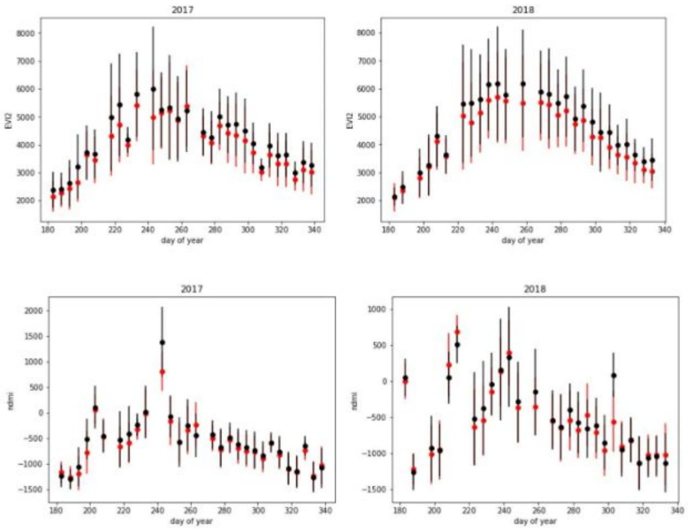


Fig 4. Demi-Lune plots (red) vs. non-demi-lune plots (black) in average vegetation estimates, measured by EVI2 (top) and moisture estimates, measured by NDMI (bottom) for 2017 and 2018. Points are average of all fields observed on a given day of the year and bars indicate spread.

Current remote sensing work

1. Creating a “degraded lands model” using satellite imagery that predicts whether or not an area is on highly-degraded land, or glacis/crusted soil, suitable for demi-lunes

2. This classification map will be used to narrow down search areas for the upcoming RCT's RWH adoption monitoring efforts, where very-high resolution imagery will be used to identify newly constructed demi-lune fields.

3. Satellite imagery from (1) degraded lands model will be used to measure agricultural output and measure soil quality in these areas.

Fig 1. 3m resolution PlanetScope image on left, used in first pass of demi-lune identification. Higher resolution imagery such as that on right would allow for more precise identification and measurement in second stage.

Remote sensing data

Field surveys for the upcoming RCT were completed in Jan 2023

- Surveyors collected perimeters of ~4300 fields labeled whether it's glacis or not. Pixel-level training features for the degraded lands model will be extracted from these polygons, along with polygons digitized around different/separable landcover types from USGS EROS Landcover (Gray Tappan) maps.

Data sources for the first-pass degraded lands prediction model:

- Satellite Imagery: PlanetScope (VIS, NIR), Sentinel-2 (VIS, NIR, SWIR), SAR Sentinel-1 (C band VH and VV polarizations)
- Ancillary data: CHIRPS for precipitation, SRTM DEM for elevation/slope, __ for soil moisture, USGS EROS maps for other landcover types

Next steps

- Incorporate the scale-up RCT’s survey data into the degraded lands model:
    - Download → correct/process → create features from Sentinel-1, Sentinel-2, and PlanetScope imagery over the scaled-up study area
    - Train the degraded lands model using field boundaries from the first RCT + scale-up RCT + ‘other’ landcover types → predict whether a pixel is glacis or not, over the scaled-up area
- Looking for a partner to obtain very-high spatial resolution imagery for the second-pass demi-lune ide
    - Starting to work with geoData from William & Mary
- If very-high resolution imagery is not available, other potentially helpful products:
    - Landcover map with areas of most degraded soil (Gray Tappan - USGS)
    - Smallholder field delineation product or textures from very-high resolution imagery (Google)

emLab
UC SANTA BARBARA

Thanks!

Questions, comments, concerns?

emLab
UC SANTA BARBARA