Title: Identifying small-holder irrigation demand- Nigeria

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See dashboard: qsel.columbia.edu/cwp-epu-data-platform
Publications: Conlon, Terence, Christopher Small, and Vijay Modi. "A Multiscale Spatiotemporal Approach for Smallholder Irrigation Detection." Frontiers in Remote Sensing 3 (April 14, 2022): 871942. https://doi.org/10.3389/frsen.2022.871942.

Nigeria Stakeholders: Energizing agriculture, REA, WRI, World Bank
Ethiopia Stakeholders: DREAM/Veritas, MOWIE (Hon Min Seleshi Bekele), ATA/ATI (Dr. Yifru)

Theory of Change:

Irrigation is a primary driver for assured/added food production as populations grow. In areas with unimodal rainfall, irrigation in the dry season provides opportunities beyond the predominant practice of rainfed agriculture. But a single crop obtained through irrigation could need anywhere from 6000 to 12,000 m^3/ha. Energy to lift/move water is crucial for such irrigation and could become a binding constraint in the absence affordable grid power at the farm. Private and public providers of energy services are seeking knowledge of the location of such demand. So is the government seeking to know to find best locations for infrastructure investments that will improve livelihoods.

The theory of change here is that if farmers are adopting irrigation at even a very small scale, even on small plot sizes, that suggests that they have found ways to meet the other requirements, such as access to suitable soils, water source, seeds, fertilizer, and markets. Hence if one can detect such irrigation, not only does one detect the presence of existing energy demand but one also detects where cost effective energy may lead to even further growth since farmers have identified means to meet the other requirements. Note that much of dry season agriculture in Nigeria is either for rice, a water intensive staple or for high value horticulture crops. Yet because of energy constraints it is limited to 1 to 2% of the cropland in Nigeria.

Knowing the location/scale of existing demands is the first step towards determining the appropriate technological and infrastructural investments that have high return prospects- otherwise one could end investing where other non-energy constraints are present. But given small sub-hectare plot sizes, it is difficult to identify such individual plots at a national or regional scale through manual field surveys of all individual plots. We have addressed this issue for Northern Nigeria at scale and are able to identify plots as small as a tenth of a hectare with high accuracy.

The results are then shown in a zoomable, digital information product has been hosted on a public dashboard to make it viable to pinpoint the location of such energy demand. Using an innovative method that relies on labelling, remote sensing, and machine learning- we have carried out this effort in Nigeria. Note that methodologies reliant on certain spatiotemporal and multispectral satellite imagery products developed for one part of the world may not easily be applicable to other parts.

Abstract

This study explores an irrigation detection methodology developed for Ethiopia and the scope/extent of applicability across different regions of the Sahel. The methodology leverages spatiotemporal EVI (enhanced vegetation index) derived from multiscale satellite imagery, introducing a process of data collection through visual inspection of Sentinel 2 and sub-meter resolution imagery to supplement either limited or no ground-collected labels. This classification is driven by the distinct phenology of irrigated croplands in the dry season to differentiate dry season irrigated agriculture from surrounding vegetation, purely rain-fed agriculture and evergreen vegetation. This detection of dry season photosynthetic growth is dependent on a prolonged dry season that allows the non-irrigated vegetation to senesce and ensures the availability of cloud free imagery.

Phenology Map (Figure 1) guides the label collection over irrigated and non-irrigated agriculture. These labels are used to train classifiers to detect smallholder irrigation in areas that have a distinct and prolonged dry season. The methodology was applied to Northern Nigeria and Burkina Faso that are used as examples to prove where the methodology is applicable and Uganda serves to explain the limitations of the approach and the need for a different methodology. This report however focuses on the results in Nigeria where a transformer model an accuracy of above 97% for irrigated and non-irrigated classes over withheld regions.

A flowchart of the methodology (Figure 2) utilizes Sentinel 2 imagery collection for creating false color composites used in visualization and also creating temporal stacks of EVI at 10-day timesteps. Temporal interpolation and smoothing techniques are applied to remove the effects of cloud cover and missing imagery. Visually inspected labels are collected (Figure 3) for irrigated and non-irrigated plots through visual inspection of dry season images, EVI time series and cluster cleaning ensures removal of unwanted pixels. A classifier is trained to detect dry season irrigation. This model is used to make predictions over pixels that have passed admissibility criteria in regions of interest (Figure 4).

The Food and Agriculture Organization of the United Nations provides statistics for areas equipped for irrigation and maps with irrigated areas as a fraction of the areas equipped for irrigation. The FAO-Aquastat statistics are based on estimates, land cover maps, public irrigation schemes and river basin development authorities. These maps are used to cross check the predictions and examine where the predictions work well and other areas where the model struggles. An overall state by state comparison of the predictions and the FAO statistics is shown in Figure 5.

All of the tools used from collection of samples/labels to training models and irrigation prediction in Nigeria are open source and based on Google Earth Engine and Google Cloud Platform.

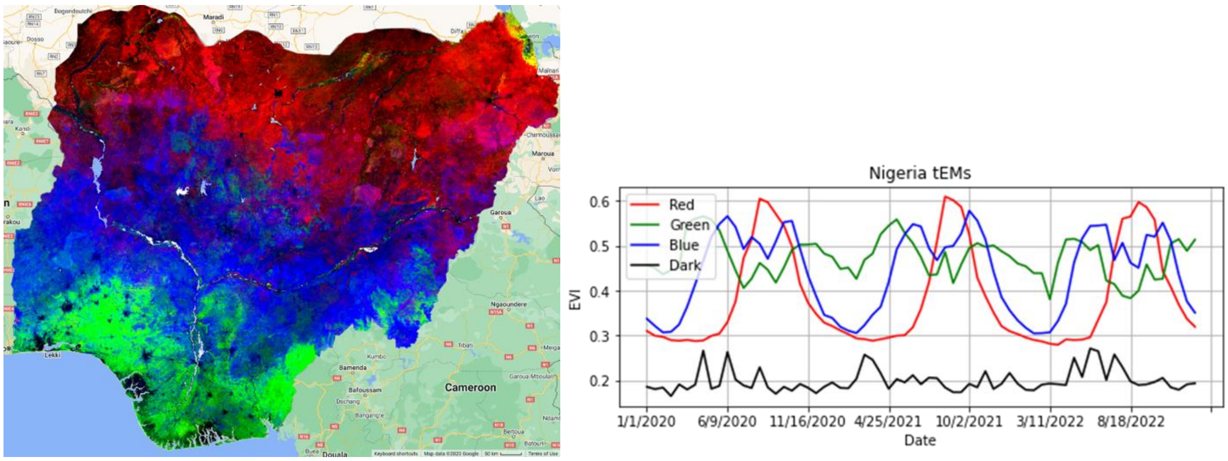

Figure 1: Phenology map for Nigeria using MODIS 250m imagery is shown on the left. Areas in red represent regions with single cropping cycles per year with prolonged dry season where the irrigation detection methodology works well. Areas in blue represent regions with dual cropping cycles per year and green represent evergreen regions. These temporal Endmembers are plotted on the right

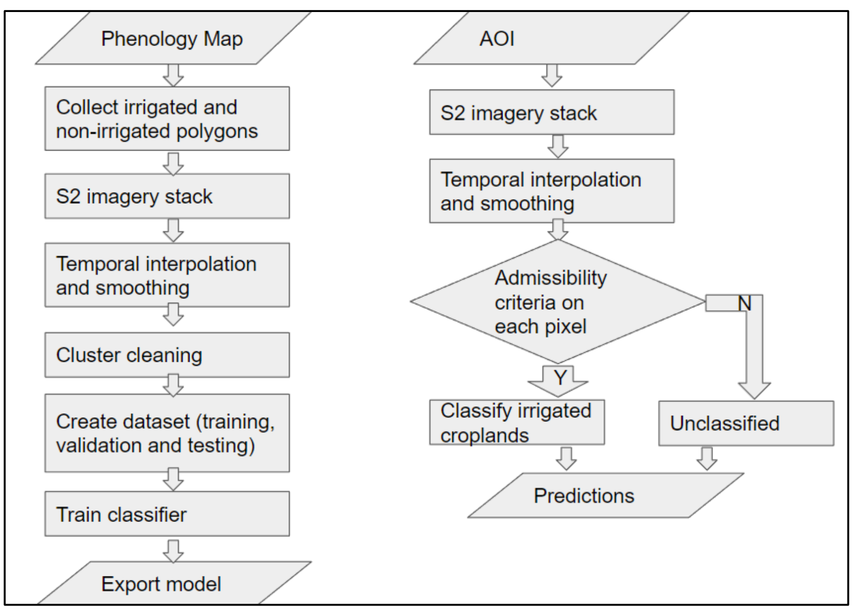

Figure 2: Flowchart of the irrigation detection methodology

a) *b)*

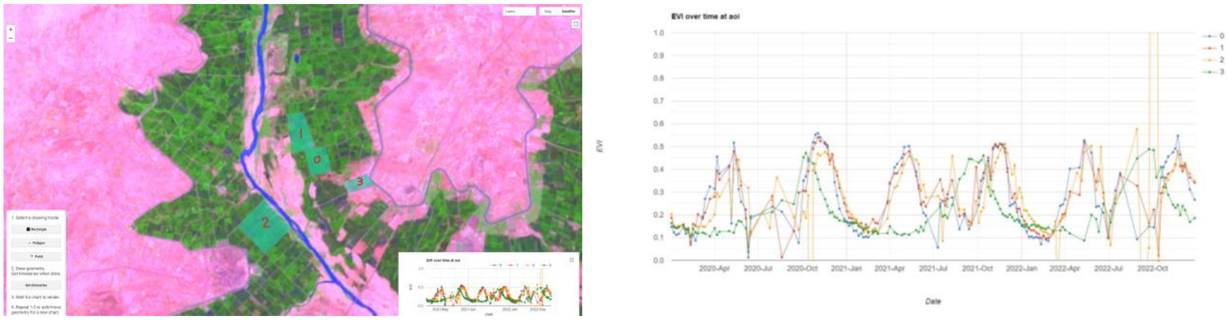

Figure 3: a) Visual label collection process, shown for irrigated samples (plots 0, 1 and 2), and non-irrigated sample (plot 3) b) Plots of EVI time series zoomed in. Irrigated plots 0, 1 and 2 have dry season peaks are observed in the period from March to July. Whereas non-irrigated plot 3 does not have a dry season EVI peak

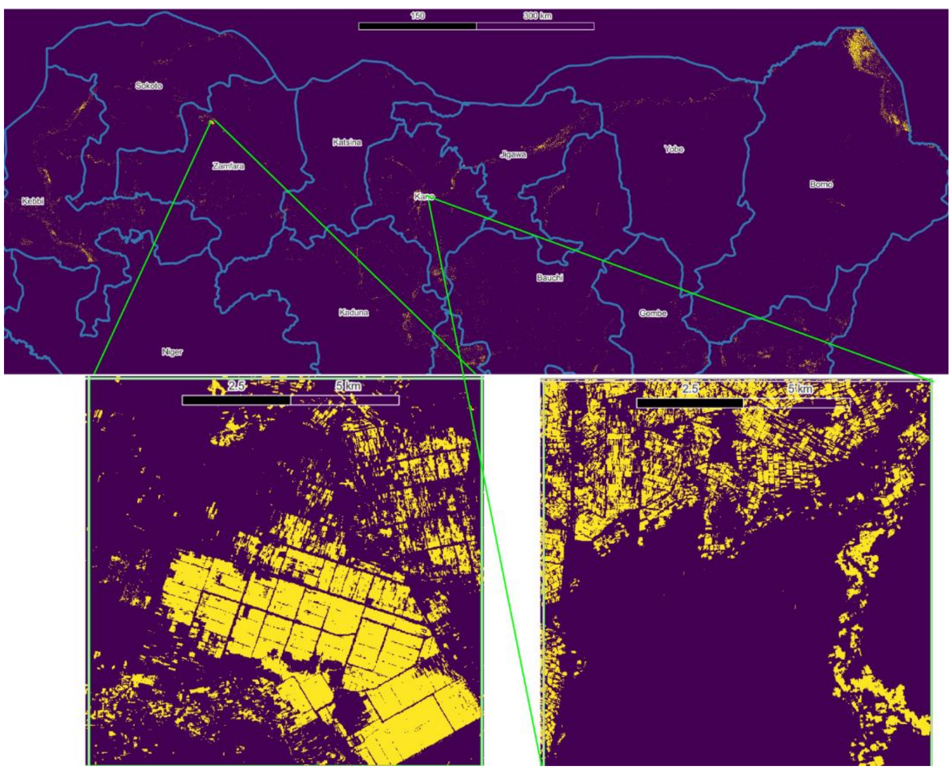

Figure 4: Irrigation Predictions in Northern Nigeria for 2021. Areas predicted to have dry season irrigation appear as yellow on the map. Total land area that the classifiers were used to predict over is roughly 400000km^2. Less than 1% of the total area is predicted to be irrigated

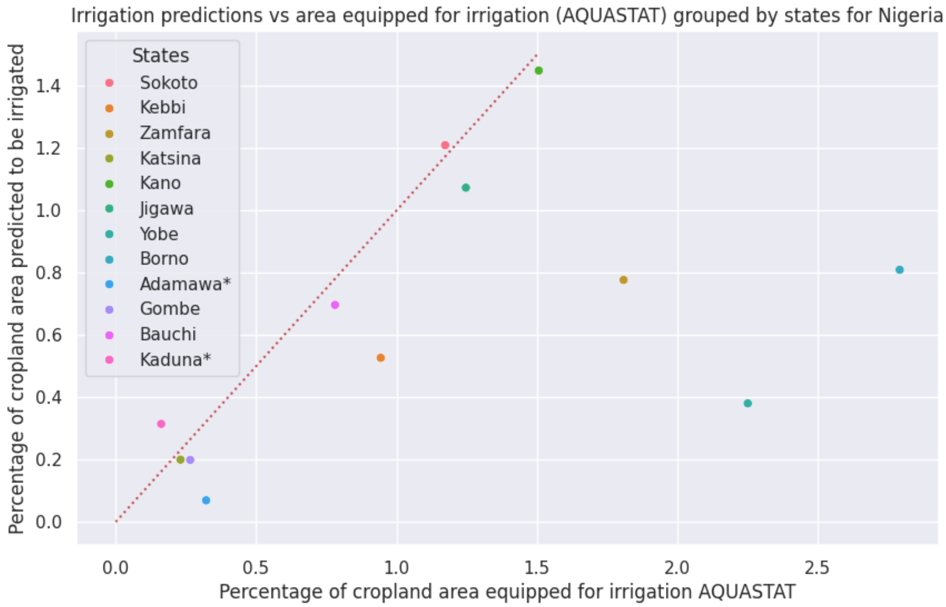

Figure 5: Comparison of percentage of cropland area predicted as irrigated to the percentage of cropland area equipped for irrigation from FAO AQUASTAT