Developing a precision irrigation framework to facilitate smallholder dry-season farming in developing countries: A case study in northern Ghana

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Summary

Changing climate has resulted in increasingly unreliable weather patterns with prolonged dry-seasons in some parts of Sub-Saharan Africa. Food production in these areas is under threat because the people depend mostly on rain-fed farming. Enabling dry-season farming, in light of the prolonged dry-seasons, is central to sustainable food production and poverty alleviation in these areas. Efficient water management is key to successful dry-season farming. Ideally, efficient irrigation water management should involve real-time monitoring of soil moisture (SM) to guide irrigation scheduling. However, farmers in these areas are mostly poor smallholder farmers without the financial capacity to instrument their farms for real-time SM monitoring. We present a precision irrigation framework (PIF) as a low-cost alternative to site-specific SM monitoring to guide irrigation scheduling. PIF applies machine learning to integrate multi-scale ground-truth data and satellite imagery to create irrigation water management zones for an entire region. We demonstrate the strategy in the Pwalugu area in northern Ghana.

Introduction

Changing climate has resulted in increasingly unreliable weather patterns with prolonged dry-seasons (Yengoh et al., 2010) in some parts of Sub-Saharan Africa, specifically countries in the transition belt between the Sahara Desert and the tropical rainforest. The situation is adversely affecting food production. Northern Ghana (NG) is a classic example of an area in this transition zone. NG experiences a distinct dry season lasting seven to eight months and a wet season lasting only four to five months in a year. While over 70% of the inhabitants are farmers (Ghana Ministry of Food and Agriculture, 2007), the singular rainy season limits rain-fed farming to only four to five months of the year (Kyei-Baffour and Ofori, 2006), resulting in severe poverty in the northern half of the country. The poverty situation has fueled a coping mechanism of seasonal migration to major cities in the south in search of meager jobs (Quaye, 2008; Assan et al., 2009). Enabling dry-season farming is crucial to sustainable food production and poverty reduction in NG.

Recent irrigation farming along the White Volta River and its tributaries (Dinye and Ayitio, 2013) presents a unique opportunity for smallholder farmers to engage in dry-season farming and to create off-season employment during the long dry season. Efficient irrigation water management is central to successful dry-season farming. However, irrigation water management is completely ignored in the current irrigation practices in the area, resulting in water, energy, and fertilizer wastages with dire environmental consequences. In this project, we present a precision irrigation framework (PIF) as a low-cost strategy to guide efficient irrigation scheduling to facilitate smallholder dry-season farming. PIF applies machine learning to integrate multi-scale ground-truth data and satellite imagery to create irrigation water management zones for an entire region.

Project Region and Methods

Fontaine et al. (2018) presented results from the Project Year 1 fieldwork. We present preliminary results of the Project Year 2 (PY2) field work, which comprises an area of about 351 square kilometers in the Pwalugu area in the Upper East Region of Ghana (Figure 1). PY2 is about 30 miles north of the PY1 area. We repeated the experiments of Fontaine et al. (2018). The objective is to develop a precision irrigation framework (PIF) for the entire PY2 area (Figure 1) to facilitate smallholder irrigation farming during the dry-season. We consider creating the PIF for the entire project region in an effort to increase the number of long-term project beneficiaries beyond the five project participating farmers. To accomplish this, we adopted a multi-scale approach to unify high-resolution farm-scale data with a large-scale soil-texture map. This approach was employed because it was impractical to collect multiple high-resolution data types at the entire project scale.

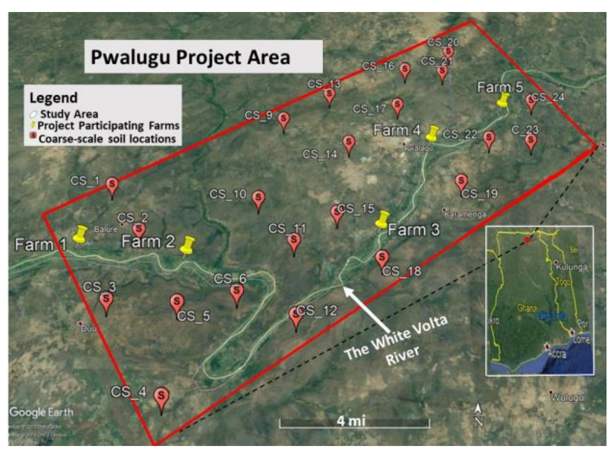

Figure 1: Project Year 2 (PY2) area showing locations of the five project participating farms and coarse-scale soil sampling locations. Inserted is a map of Ghana showing the location of the PY2 area.

Large-scale soil sampling

To create a soil texture map for the entire project region, we collected coarse-scale soil samples across the entire project region. A total of 22 coarse-scale soil samples were collected. Due to the sample-site inaccessibility issues encountered in PY1, we engaged the services of a motor bike, which helped to increase the number and spatial coverage of the coarse-scale soil samples (Figure 1). We collected the samples with a handheld auger over a composite depth of 0–0.4 meters. To promote representative sampling across the sampling depth, each soil sample was first mixed thoroughly in a bucket. Representative subsamples were then bagged and labelled.

Farm-scale surveys

We performed multiple farm-scale surveys to acquire high-resolution data to be unified with the large-scale soil texture map. The farm-scale surveys included electromagnetic induction (EMI) surveys, field infiltration tests, and high-resolution soil sampling, which were performed on the fields of five selected project participating farms (PPFs). To ensure good spatial coverage of the high-resolution data, we selected the PPFs almost evenly spaced across the length of the project area (yellow pins in Figure 1). All five PPFs are engaged in dry-season, small-scale irrigation farming. To gain a qualitative quick understanding of spatial variability in soil properties across a field, we conducted EMI surveys to generate apparent electrical conductivity (EC_a) maps for each of the five fields. We used the Geonics EM38-MK2 conductivity meter with a DAS70-AR2 Data Acquisition System. The meter was mounted in a custom-made portable protective sled and towed behind a tractor. Like Fontaine et al. (2018), we performed the EMI surveys for dry and wet field conditions to estimate high-resolution spatial variability in the water-holding characteristics of a field. To directly estimate the water-holding capacities (field-capacity (FC) and water depletion rate (WDR)) of soil units within a field, we performed infiltration tests at two selected locations within each field. The infiltration sites were chosen in accordance with dominant patterns observed in the EC_a maps in an attempt to capture representative hydraulic responses of the identified EC_a units. Additionally, soil samples were collected at each infiltration site to provide direct, co-located soil texture data for each infiltration profile. For the soil moisture monitoring, we used the Onset Time Domain Reflectometry (TDR) soil moisture probes with a HOBO USB Micro Station logger. We programmed the logger to log soil moisture every 30 s, providing high temporal resolution of soil moisture profiles to calibrate the water-holding characteristics of the soils.

Soil sampling and particle size analysis

Soil samples were collected from each field in both a grid-like design and in accordance with dominant patterns observed in the EC_a maps. A total of 85 soil samples were collected from the coarse-scale and farm-scale soil sampling efforts. All of the soil samples were analyzed at the Spanish Laboratory at the University for Development Studies (UDS) in Nyankpala, Ghana. Estimates of the sand, silt, and clay proportions of the soil samples were obtained using the hydrometer method (Bouyoucos, 1962). We used the soil texture calculator and plotting tool developed by the USDA’s Natural Resources Conservation Service (https://www.nrcs.usda.gov/wps/portal/nrcs/detail/soils/survey/?cid=nrcs142p2_054167) to classify soil texture based on the particle size analyses.

Creation of the Precision Irrigation Framework

Soil texture is the primary driver of water-holding characteristics of soils, which in turn informs irrigation scheduling. Hence, to create the PIF, we applied soil-texture as the basis to unify the high-resolution farm-scale data with the project-scale soil-texture map. Two important soil water-holding characteristics that inform irrigation scheduling are the FC and WDR. While WDR informs frequency of irrigation, FC helps to determine when to stop irrigation. We, therefore, applied estimated FC and WDR from the irrigation experiments to guide the creation of water management zones (WMZs). Irrigation experiments with similar FC and WDR were classified into the same WMZ. The WMZ classes were then assigned to their corresponding sand, clay, and silt proportions to create a “level 1” WMZ training set. While we collected a total of 85 ground-truth soil samples in PY2, it is impractical to perform irrigation experiments at all the 85 soil sample sites in order to calibrate their corresponding FC and WDR to determine their WMZ class. To include all the soil samples in the training set, we applied the “level 1” WMZ learning set to train a non-parametric machine leaning classifier, the k-nearest neighbors (KNN) algorithm (e.g., Harrington, 2012). We then applied the trained KNN classifier to assign WMZ labels to all the soil texture data. For a robust training set, we included 132 soil texture data from PY1, making a total of 217 ground-truth soil texture data. This constitutes the “level 2” WMZ training set.

To create the PIF, we employed the coarse-scale soil texture data to condition the prediction of the sand, clay, and silt proportions for the entire project area. Because the project-scale soil texture data have poor spatial resolution, we applied remote sensing data to compliment the coarse-scale soil texture data for the large-scale soil texture prediction. Specifically, Landsat 8 provides 30 m resolution of surface reflectance data coverage across the project area. Because Landsat 8 consists of nine spectral bands, we first performed exploratory analysis to identify the spectral band with the highest correlations with the soil texture data. Similar to Liao et al. (2013), we identified band-7 to have the highest correlations with the sand, clay, and silt proportions. Hence, to predict soil texture for the entire project area, we applied Landsat 8 band-7 as secondary data to co-krige with all the 85 soil texture data (Figure 1, including all the farm-scale soil samples) collected across the PY2 area. We performed the co-kriging in ArcMap®. We then applied the "level 2" WMZ learning set to train the KNN classifier, and then applied the trained KNN classifier to assign WMZ labels for the entire project region based on the co-kriged sand, silt, and clay proportions. The WMZ class map constitutes the PIF for the project area.

Results and Discussion

Figure 2 shows an example of the soil moisture time series data from the irrigation experiments. We deliberately over-irrigated to induce drainage. The rapid depletion (drainage zone) of soil water content (SWC) is followed by slow depletion rate (extraction zone) where the soil now holds water in its micro-pores that is available to the plant. The SWC corresponding to the intersection of a tangent to the drainage and extraction zones (Figure 2) provides an estimate of the FC of the soil (e.g., Zotarelli et al., 2010). We also estimated the WDR of the extraction zone. We identified three WMZs based on the FC and WDR. The corresponding sand, clay, and silt proportions for the WMZs were ("level 1" training set), respectively, in the ranges of 55-73%, 4-14%, and 19-30% (for WMZ 1), 40-49%, 20-30%, and 30-32% (for WMZ 2), and 15-25%, 42-61%, and 24-33 (for WMZ 3). We observed that the WMZ class was driven primarily by the relative proportions of sand and clay, with silt remaining fairly constant (19 - 33%). More precisely, WMZ1 is driven by high sand content with sand exceeding 55%. The sand content reduces in WMZ 2 with clay increasing. Clay dominants WMZ 3 with clay content exceeding 42%. Using the "level 1" training set and KNN classification, we assigned WMZ labels to all the ground-truth soil texture data. Figure 3 shows a scatter plot of the "level 2" WMZ training set

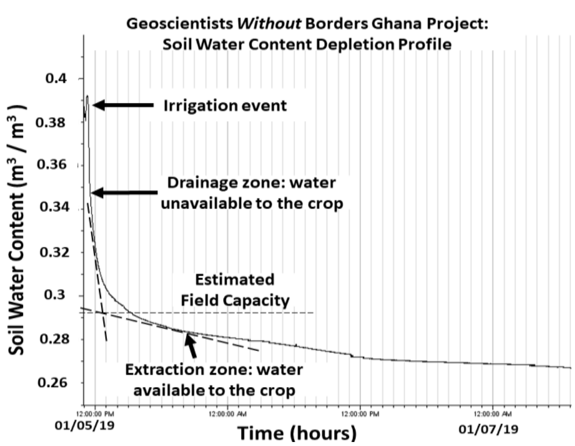

Figure 2: Soil water content depletion profile after an irrigation event showing the drainage and extraction zones, and estimated field capacity of the soil.

revealing distinct clustering of the WMZs in the 3D soil texture feature space.

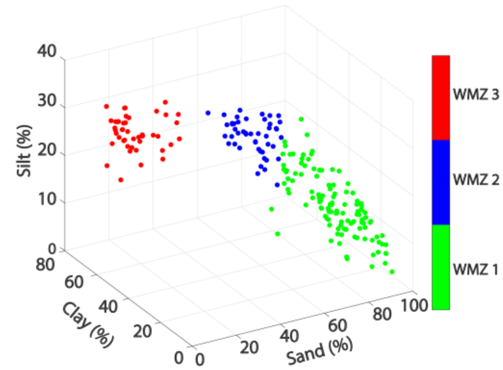

Figure 3: A scatter plot of the "level 2" water management zones (WMZ) training set showing distinct clustering of the WMZs.

To create the PIF, we applied the "level 2" WMZ training set (Figure 3) and KNN classification to assign WMZ classes to the entire project region based on the co-krigged sand, clay, and silt proportions. Figure 4 shows the created PIF for the Pwalugu area. The results show a general north-east south-west banding of the WMZs with a massive band of WMZ 1 in the mid-section of the project area. WMZ 3 is found only in the north-west corner of the project area, which was expected because soil samples with clay content exceeding 42% were found on only Farm 1. The average FC and WDR were WMZ 1: 0.28 m^3/m^3, 0.014 m^3/m^3/day; WMZ 2: 0.30 m^3/m^3, 0.006 m^3/m^3/day; and WMZ 3: 0.36 m^3/m^3, 0.005 m^3/m^3 /day. We are currently developing the irrigation scheduling recommendations for the WMZs.

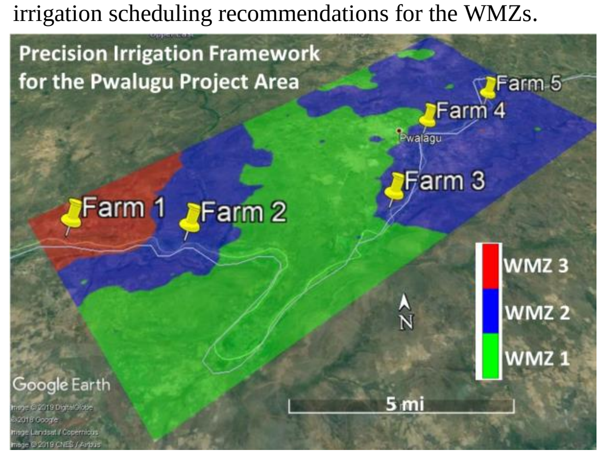

Figure 4: Precision irrigation framework for the Pwalugu project area in northern Ghana.

Project Sustainability Plan

Long-term sustainability of a project beyond the project years is a major pillar of the Geoscientists *Without* Borders (GWB) program. The concept of developing a PIF (Fig. 4) for the entire project area to benefit more farmers beyond the project participating farmers (PPFs) and to extend the project's impacts beyond the project years is an important aspect of the project's long-term sustainability plan. As part of the outreach program of the project, we organized two workshop series during the PY2 field work, one in each of the two project regions. A total of 150 farmers participated in the two workshops. Figure 5 shows a photo of the team with farmers after the workshop in the PY1 area.

The goal of the workshop was to educate smallholder irrigation farmers on the *importance* and the *need* for efficient irrigation water management practice to the success of their dry-season farming efforts. We also aimed to use the workshop to recruit non-PPFs to adopt the PIF.

Figure 5: A photo of the PY2 team and smallholder irrigation farmers after the training workshop in the PY1 area.

During the fieldwork, we identified some key limitations of their current irrigation practices and addressed them during the workshops. Specifically, their current irrigation practice is to make bunds around the crops and pond them (Figure 6A). This creates an issue of severe over-irrigation resulting in water, energy, and fertilizer wastage while increasing the environmental footprint of their farming. Ponding the crops in an 80-100 ^{0}F weather also translates into "cooking" the crops while growing. These issues were thoroughly discussed and addressed during the workshops. As we brought up the issues, some farmers identified potential consequences of ponding the crops in 80-100 ^{0}F weather that they have observed. They testified to observing that crops in the middle of the ponds that are submerged for a long period have poor yield and the produce rots quickly compared to the produce from crops at the edges of the bunds that are unsubmerged.

Furthermore, while there is growing interest in dry-season farming in the area, there is a general perception that it is a waste of time, energy, and resources, based on their experience. A successful demonstration of dry-season farming based on our irrigation recommendations is crucial to increasing awareness about the project and convincing more farmers to adopt the PIF. Toward this end, we used the fields of PPFs as dry-season farming trial fields. We supported the farmers by covering the costs of field plowing, seedlings and fertilizer. They were then asked to irrigate strictly according to our preliminary recommendations and keep the produce, which creates a win-win scenario to solicit the farmer's commitment to the trail. The trials on all the five fields were hugely successful. Figure 6B shows a farmer displaying the produce from the dry-season farming trial on his farm. We are confident that this will encourage other farmers to adopt the PIF and its recommendations, thereby extending the long-term impact of the project. We also hope to have multiple follow-up trials to extend and consolidate the success of the project. Finally, local chiefs have a lot of influence on their communities. Community entry should always involve introduction of the project to local chiefs and, if possible, solicit their participation. This is important to community engagement and participation.

Figure 6: (A) a photo of the current irrigation practice, and (B) a project participating farmer displaying the produce from the dry-season farming trial on his farm.

Summary

Food production in some parts of Sub-Saharan Africa is under threat due to changing climate that has resulted in prolonged dry-seasons. The situation is expected to only get worse. There is an urgent need for low-cost irrigation water management strategies to facilitate sustainable smallholder dry-season food production. Use of a precision irrigation framework (PIF) is a low-cost strategy to guide efficient irrigation scheduling. PIF applies machine learning to integrate multi-scale ground-truth data and satellite imagery to create irrigation water management zones for an entire region. Although we demonstrated the application of PIF in northern Ghana, it is applicable to any region with the need for low-cost irrigation water management practices.

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