Application of electromagnetic induction to develop a precision irrigation framework to facilitate smallholder dry season farming in the Nasia-Kparigu area of northern Ghana

*Jeremy M. Fontaine**, Alexander Percy, and Erasmus K. Oware, The State University of New York at Buffalo; Patience Bosompemaa, Ghana Geological Survey Authority; Vincent Gbedzi, University for Development Studies, Tamale-Ghana; John W. Lane, Jr., US Geological Survey*

Summary

Arid climatic conditions coupled with the prolonged dry season in northern Ghana (NG) place great restrictions on year-round smallholder farming. Because small-scale farming is the main source of livelihood for over 70% of rural inhabitants, limitations on dry season farming have contributed to severe poverty in NG. Although the adoption of individual smallholder irrigation in the area is enabling dry season farming, these practices do not account for spatial variability in physical soil properties (e.g., soil texture) that determine the amount of water available to plants. Hence, current irrigation practices in NG are inefficient. Here, we present preliminary results of the development of a precision irrigation framework (PIF) for the Nasia-Kparigu area in NG intended to enable smallholder farmers to make judicious use of limited irrigation water, and facilitate more sustainable dry season farming in the area. We also demonstrate the use of electromagnetic induction surveys to characterize field-scale spatial variability in soil water-retention capacity.

Introduction

Northern Ghana experiences a tropical savanna climate, with a distinct dry season lasting seven to eight months and a wet season lasting only four to five months. The singular rainy season limits rain-fed farming to these four to five months of the year (Kyei-Baffour and Ofori, 2006). Meanwhile, farming is the principal occupation of over 70% of northern Ghana's inhabitants (Ghana Ministry of Food and Agriculture, 2007). Consequently, the northern parts of Ghana are among the most impoverished regions in the country. While the rest of Ghana has seen a marked decrease in poverty over the last two decades, poverty incidence rates and extreme poverty remain high in the northern half of the country (Ghana Statistical Service, 2007, 2015). The poverty situation has fueled a coping mechanism of seasonal migration to major cities in southern Ghana in search of meager jobs (Quaye, 2008; Assan et al., 2009). Moreover, recent global climate trends have amplified the risk of prolonged dry spells during the short farming season (Yengoh et al., 2010), making dry season farming a crucial aspect of poverty reduction strategies in northern Ghana.

The recent adoption of individual irrigation schemes involving the use of water from the White Volta River and its tributaries (e.g., 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. However, their current irrigation practices do not account for the natural spatial variability in the physical properties of the soil, making their current practices inefficient. Specifically, soil texture (i.e., the relative abundance of clay, silt, and sand) and porosity control the water-holding and water-transfer capacities of soils, which ultimately determine the amount of irrigation water available to plants. Efficient irrigation management practices should, therefore, involve careful examination of the soil and accounting for the spatial variability in the underlying properties of the soil.

Geospatial measurement of soil apparent electrical conductivity (EC_a) using electromagnetic induction (EMI) is a quick and reliable ground-based sensing approach used for general characterizations of the spatial variability of soil properties, and is commonly applied to site-specific farm management practices (Corwin and Lesch, 2003, 2005). The soil texture and hydraulic characteristics of spatially distinct soil units may be estimated with data from particle size analyses of samples and from field infiltration tests, respectively. Continuous monitoring of soil water content (SWC) during field infiltration tests produces time series data that may be analyzed to estimate relevant agricultural parameters, such as field capacity (FC) and permanent wilting point (PWP) (e.g., Zotarelli et al., 2010). These provide practical estimates of SWC ranges for soils, and allow for more efficient irrigation management practices. Data will be used to construct a large-scale soil texture map of the project area which details the optimal SWC ranges of major soil texture units. This map will guide site-specific water management practices (e.g., frequency and duration of irrigation) in the project area.

Project region

The project region comprises an area of about 205 square kilometers extending between the villages of Nasia and Kparigu in Ghana's Northern Region (Fig. 1).

Methods

To develop a precision irrigation framework (PIF) for the entire study area in an attempt to increase the number of long-term project beneficiaries, we adopted a multi-scale approach to unify a large-scale soil texture map with high-

Figure 1: Map of the project region. (*lower right*) the location of Ghana within the African continent; (*left*) a line map of Ghana showing the location of the project region (small square) within the Northern Region (red outline); (*upper right*) enlargement of the project region, detailing the study area shaded in red.

resolution farm-scale data. This approach was employed because it is impractical to collect multiple high-resolution data at the regional scale.

Large-scale soil sampling

A coarse-scale soil sampling of the entire project region was conducted. Sampling sites were chosen in a rough grid layout across the project region. Although a total of 30 coarse-scale soil samples were earmarked for collection, only 18 samples were actually gathered due to inaccessibility of some of the earmarked sample locations. Samples were collected 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; subsamples were then bagged and properly labelled.

Farm-scale surveys

We performed multiple farm-scale surveys in an effort to acquire high-resolution data to be unified with the large-scale soil texture map. The farm-scale surveys included EMI surveys, field infiltration tests, and high-resolution soil sampling. To accomplish this, we selected three project-participating farms (PPFs) across the project area engaged in small-scale irrigation farming. The three selected farms comprise a total of five fields and include:

- Sammy Farm, comprising two fields (designated SF1 and SF2), located at 10.14307° N, 0.80719° W;
- Nasia-Kukobila Farm (KNF), located at 10.11339° N, 0.81966° W;
- Kparigu Farm, comprising two fields (KF1 and KF2), located at 10.29633° N, 0.65272° W.

EMI surveys to generate EC_a maps for PPFs

For a 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 DAS70-AR2 Data Acquisition System. The meter was mounted in a custom-made portable protective sled and towed behind a tractor. For two of the fields (SF1 and KNF), the EMI survey was conducted for both dry and wet conditions. That is, after the survey for the dry field, the field was flooded and allowed to drain for three days; the survey was then repeated for the wet condition. Allowing the field to drain for three days provides ample time for varying rates of infiltration to occur, resulting in variable moisture distributions that will reflect in the EC_a measurements. To calibrate the dry and wet surveys to the same scale, a region of the dry field was excluded from the flooding to serve as a control region.

Field infiltration tests

To directly estimate the water-holding capacities (FC and PWP) of soil units within a field, we performed infiltration tests at eight selected locations within each field. The infiltration sites were chosen in accordance with dominant patterns observed in the EC_a maps 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. IRROMETER's IRROmesh wireless soil moisture monitoring system was used for the infiltration tests. The IRROmesh system consists of several solar-powered, intercommunicating units (nodes) capable of sharing data collected from a network of soil moisture sensors. At each test site, a pair of WATERMARK granular matrix soil moisture sensors were installed at 0.1 m and 0.3 m depths, to provide multi-level soil moisture monitoring during the infiltration tests.

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 124 soil samples were collected in both 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).

Results and Discussion

To classify the soil texture from the proportions of the separates obtained from the particle size analysis tests, we used a 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). The classification of the soil texture types for all 124 soil samples are shown in Fig. 2. The soil textures from each participating farm seem well

10.1190/segam2018-2997867.1

grouped. For instance, soils from Sammy farm are mostly silty-clay, whereas those from Kparigu and Nasia-Kukobila farms have, respectively, loamy sand and sandy loam textures. The silty-clay texture of soils from Sammy farm coincide with a flood plain of the Nasia River. The coarse-scale samples, conversely, reveal more variability in the soil texture across the project area, as expected.

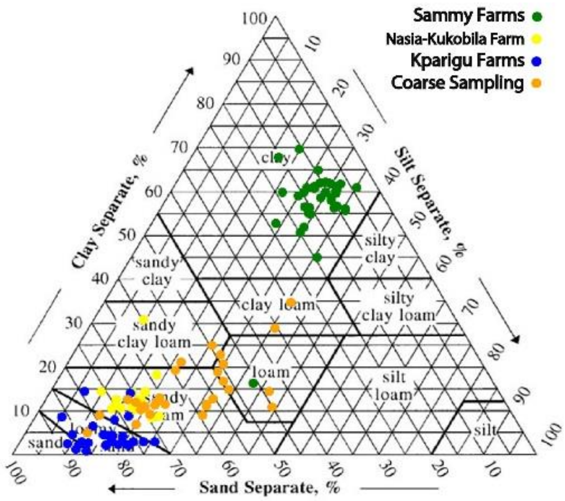

Figure 2: A soil texture classification triangle showing the proportions of sand, silt, and clay for all 124 soil samples.

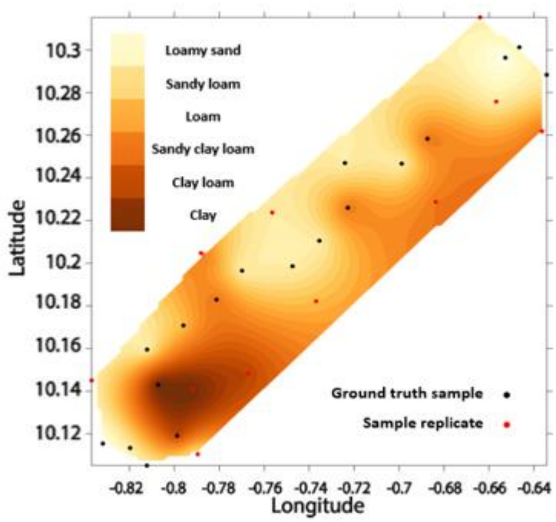

Figure 3: Preliminary soil texture map of the project region. Inserted points mark actual (black) and replicated (red) sample sites.

Creation of a coarse-scale soil texture map of the region

Because soil texture is the primary driver of water-holding capacities of soils, which in turn inform irrigation scheduling, we use a soil texture map of the project area as the basis for the creation of the PIF. To create the initial coarse-scale soil texture map of the project area, the coarse-scale soil texture data (Fig. 2) were assigned integer values ranging from 1 (loamy sand) to 6 (clay) (with values increasing with clay content [see scale in Fig.3]). Because not all of the areas within the overall project region were accessible for soil sampling, a series of sample replicate sites were established to extend the perimeter of the soil map. These replicate sites were chosen based on the co-occurrence of ground truth samples with large-scale soil patterns and features in the project area identified through comparative analyses of both satellite imagery and published mineralogical maps. The ground truth sample locations are shown with black filled circles while replicated sample sites are marked with red filled circles in Fig. 3.

The integer parameterized soil texture data were then kriged with a linear variogram using Surfer® 14 software to produce a preliminary soil texture distribution map of the entire project area (Fig. 3). Examination of Fig. 3 indicates a general split of the area into loamy sand and sandy loam with a clay-rich zone in the southwestern corner of the project area. The clay-rich area coincides with a flood plain of the Nasia River.

EMI characterization of spatial variability in water-holding characteristics of soils

Knowledge of spatial variability in water-holding capacities of soils is critical to variable-rate irrigation scheduling. We processed the EC_a data for the dry and wet conditions to estimate high-resolution spatial variabilities in the water-holding characteristics of the PPFs. Particularly, while an attempt was made to obtain co-located wet and dry data points between the dry and wet surveys, it is impractical to achieve this goal precisely. Hence, we employed a Euclidean distance criterion to find the nearest wet measurement for every dry data point. We noted several instances where multiple dry data points had the same nearest wet measurement, which may be due to discrepancies in the speed of the towing vehicle between the two surveys. To adjust for this, we paired the wet data point with the average of the dry data points instead of having several dry data points co-located with the same wet data point. This increased the correlation coefficient between the dry and wet co-located data points within the control region (from ~0.40 to ~0.85 in the case of SF1).

Furthermore, we assumed that differences in the EC_a measurements between the two surveys in the control region were due mainly to differences in instrument calibration and external environmental factors, such as temperature. To adjust for this, we fit a least-squares curvilinear regression model to the co-located EC_a values within the control region from the two surveys. A scatter plot of the co-located control region EC_a values for SF1 (Fig. 4a) shows a strong correlation between the two datasets with a curvilinear trend. An inspection of the distributions of the prediction errors (Fig. 4b) indicates a fairly uniform error distribution with a near zero mean and slightly increased prediction errors for EC_a values less than 8 mS/m. Nevertheless, the model appears reasonable for the range of EC_a values observed in the two surveys (Fig. 5). The regression model was

 10.1190/segam2018-2997867.1

subsequently applied to recalibrate the entire wet dataset to the same scale as those of the dry survey. We then subtracted the dry EC_a values from the corrected wet data to produce a difference dataset. Because we anticipate general increases in EC_a values in the wet versus dry surveys, data points with negative difference values were considered outliers and excluded from the final data for the kriging of the final EC_a maps (Fig. 5). The initial 38,810 co-located data points were reduced to 16,184 after the complete data cleaning effort with 3,207 located in the control region.

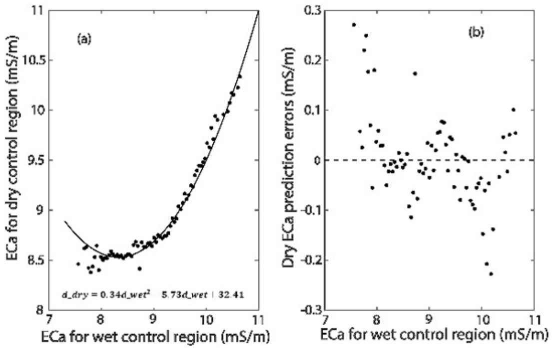

Figure 4: (a) scatter plot of EC_a values in the control region for the wet and dry surveys of SF1 fitted with a curvilinear regression model; (b) distribution of prediction errors around a zero mean line. The number of data points appears smaller than the plotted 3,207 due to multiple overlaps in their plots.

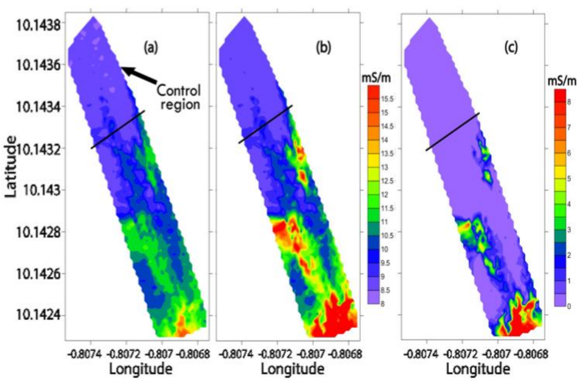

Figure 5: EC_a maps of SF1: (a) dry survey, (b) wet survey, and (c) difference map. The inserted line demarcates the control region.

Examination of the dry EC_a map (Fig. 5a) reveals two general EC_a units (EC_a between 8 and 10.5 mS/m and $EC_a >$ 10.5 mS/m), representing two possible soil units within the field. The wet EC_a map (Fig. 5b) shows a clear increase in the EC_a values of the $EC_a >$ 10.5 mS/m unit compared to those of the 8–10.5 mS/m EC_a region, suggesting a high water-holding capacity of the $EC_a >$ 10.5 mS/m unit. This trend is highlighted in the difference map (Fig. 5c), which presents an innovative approach to indirectly characterize high-resolution spatial variabilities in water-holding capacities of soils within a farm field.

Summary and Future Work

Coarse soil sampling across the study area was conducted to establish a preliminary large-scale soil texture map of the project region. High-resolution, farm-scale data were obtained from EMI surveys, infiltration tests, and soil sampling conducted at each PPF. This information was used to further characterize distinct soil types identified in the region, and will be integrated with large-scale data in order to refine the coarse-scale soil texture map. We demonstrate an innovative application of EMI surveys to characterize the spatial variability of soil-water retention at the farm scale.

Ongoing work involves the analysis and integration of data obtained during field infiltration tests. Data from the tests will be used to calibrate direct water-holding characteristics of soil samples across the study area. Time series soil water content (SWC) data will be analyzed to determine the field capacity (FC) and permanent wilting point (PWP) of the soil present at each station. Each unit on the coarse-scale soil map will therefore be defined by both a characteristic soil texture and, by extension, characteristic water-holding and water-transfer capacities. Accordingly, each unit will comprise a unique water management zone (WMZ) — a region with specific water management recommendations. To prevent crop water stress, SWC thresholds above the PWP will be recommended as the maximum allowable depletion (MAD) for common crops grown in the area. The SWC range between the FC and the MAD will constitute the optimal operating range of SWC for each WMZ.

Acknowledgements

We thank the Society of Exploration Geophysicists Geoscientists *Without* Borders Program for their financial support for this project. We also thank the technicians at the Spanish Laboratory of UDS and two UDS students, Simon Amuzu and Sahaban Abdulmumin, who assisted with the fieldwork. We thank Eric Doe of the International Institute of Tropical Agriculture for his volunteer time on the project. We thank the University at Buffalo Global Health Equity for their travel support for Alexander Percy.

Any use of trade, firm, or product names is for descriptive purposes only and does not imply endorsement by the U.S. Government.

 10.1190/segam2018-2997867.1

REFERENCES

Assan, K. J., C. Caminade, and F. Obeng, 2009, Environmental variability and vulnerable livelihoods: Minimising risks and optimising opportunities for poverty alleviation: Journal of International Development, **21**, 403–418, https://doi.org/10.1002/jid.v21:3.

Bouyoucos, G. J., 1962, Hydrometer method improved for making particle size analyses of soils: Agronomy Journal, **54**, 464–465, https://doi.org/10.2134/agronj1962.00021962005400050028x.

Corwin, D. L., and S. M. Lesch, 2003, Application of soil electrical conductivity to precision agriculture: Theory, principles and guidelines: Agronomy Journal, **95**, 455–471, https://doi.org/10.2134/agronj2003.0455.

Corwin, D. L., and S. M. Lesch, 2005, Apparent soil electrical conductivity measurements in agriculture: Computers and Electronics in Agriculture, **46**, 11–43, https://doi.org/10.1016/j.compag.2004.10.005.

Dinye, R. D., and J. Ayitio, 2013, Irrigated agricultural production and poverty reduction in Northern Ghana: A case study of the Tono Irrigation Scheme in the Kassena Nankana District: International Journal of Water Resources and Environmental Engineering, **5**, 119–133.

Ghana Ministry of Food and Agriculture, 2007, Rural livelihoods in Ghana: Policy, planning, monitoring and evaluation directorate: Ghana Ministry of Food and Agriculture.

Ghana Statistical Service, 2007, Pattern and trends of poverty in Ghana 1991–2006: Ghana Statistical Service.

Ghana Statistical Service, 2015, Ghana poverty mapping report: Ghana Statistical Service.

Kyei-Baffour, N., and E. Ofori, 2006, Irrigation development and management in Ghana: Prospects and challenges: Journal of Science and Technology (Ghana), **26**, 148–159, https://doi.org/10.4314/just.v26i2.32996.

Quaye, W., 2008, Food security situation in Northern Ghana, coping strategies and related constraints: African Journal of Agricultural Research, **3**, 334–342.

Yengoh, G. T., F. A. Armah, E. E. Onumah, and J. O. Odoi, 2010, Trends in agriculturally relevant rainfall characteristics for small-scale agriculture in Northern Ghana: Journal of Agricultural Science, **2**, 3–16, https://doi.org/10.5539/jas.v2n3p3.

Zotarelli, L., M. D. Dukes, and K. T. Morgan, 2010, Interpretation of soil moisture content to determine soil field capacity and avoid over-irrigating sandy soils using soil moisture sensors: University of Florida Cooperative Extension Services, Publication No. AE460.

10.1190/segam2018-2997867.1