Spatial Modeling of Agricultural Adaption

Agriculture and Climate Change

Over the past half century there has been a massive change in how farmers do the business of agriculture. Mechanization has increased, agro chemicals have been developed, and plant genetics have been altered for specific traits. These changes have greatly increased the productivity and adaptability of many farmers. Yet these gains have not been universal. Farmers in industrialized countries have made huge changes and reaped huge benefits. Small scale farmers in the developing world have, in many cases, made fewer changes and are being left behind.

Image credit:: Author, Sibinal San Marcos, Guatemala, 2013

This is particularly concerning given that manmade climate change is increasing the variability of weather patterns and in some cases is making traditional farming methods even less productive than they were before. Even now the Famine Early Warning System is reporting drought in the Horn of Africa causing a significant drop in production.

Image credit:: Author, San Sebastian, San Marcos, Guatemala, 2014

The encouraging fact is that there are a number of simple innovations or changes in agricultural practices that can be undertaken to improve resistance to climate fluctuations. These include the use of drought tolerant varieties, changing the timing of agriculture, and using improved land management practices.

Each year large multi national corporations and aid organizations spend millions of dollars promoting such changes in agriculture. In some cases, like the potato breeding and cultivating cooperative shown in the pictures above, the changes are taken up and agricultural yields are increased. In other cases the project falls flat and resources are wasted. There are a myriad of reasons why a farmer would choose to or not to change their agricultural practices but that exact reasoning process has often been shrouded in mystery. Smallholder agriculturalists are not backwards or inscrutable, they operate under their own reasoning and process. Therefore understanding how and why smallholder farmers are deciding to use climate sensitive practices is critical for better targeting of interventions that will help build resilience to the inevitable shocks that they will face.

CCAFS Data Set

To better understand how and why smallholder farmers are making the decisions that they are making the Consultative Group for International Agricultural Research (CGIAR) conducted a baseline survey of 2095 households spread across 15 sites in 12 different countries. This survey asked a series of questions relating to what kinds of agriculture was being practiced now as well as what kind of agriculture had been practiced in the past.

Figure 1: Global View of the CCAFS Baseline Data Set

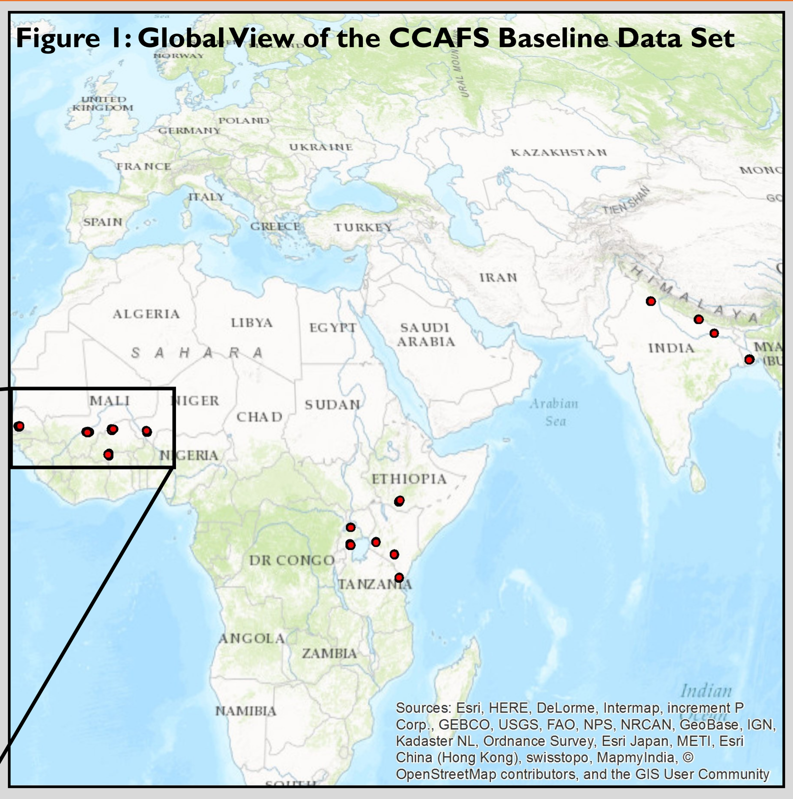


Figure 2: West African Portion of the CCAFS Data Set

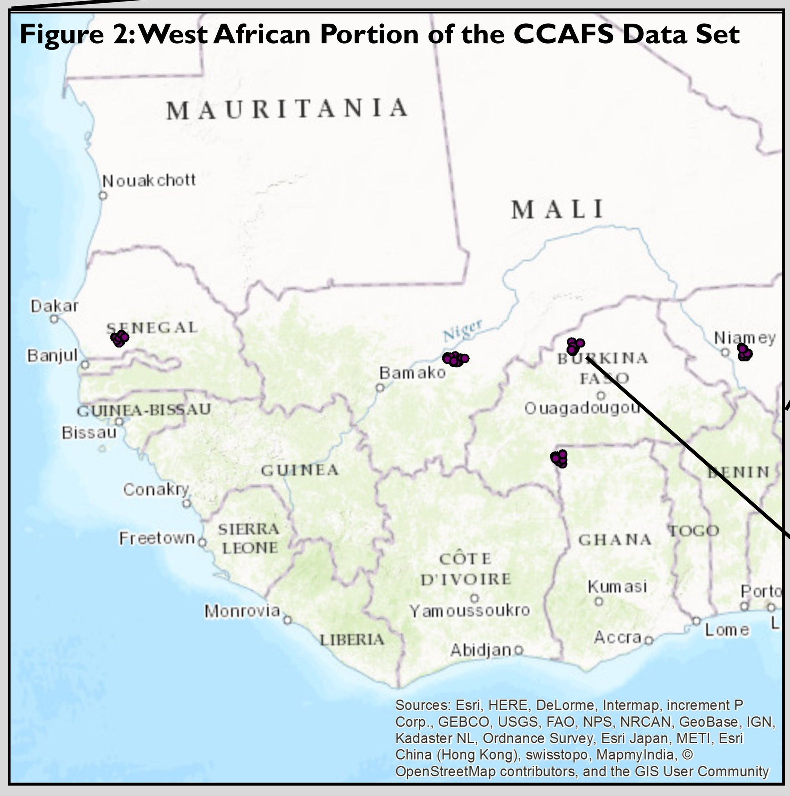
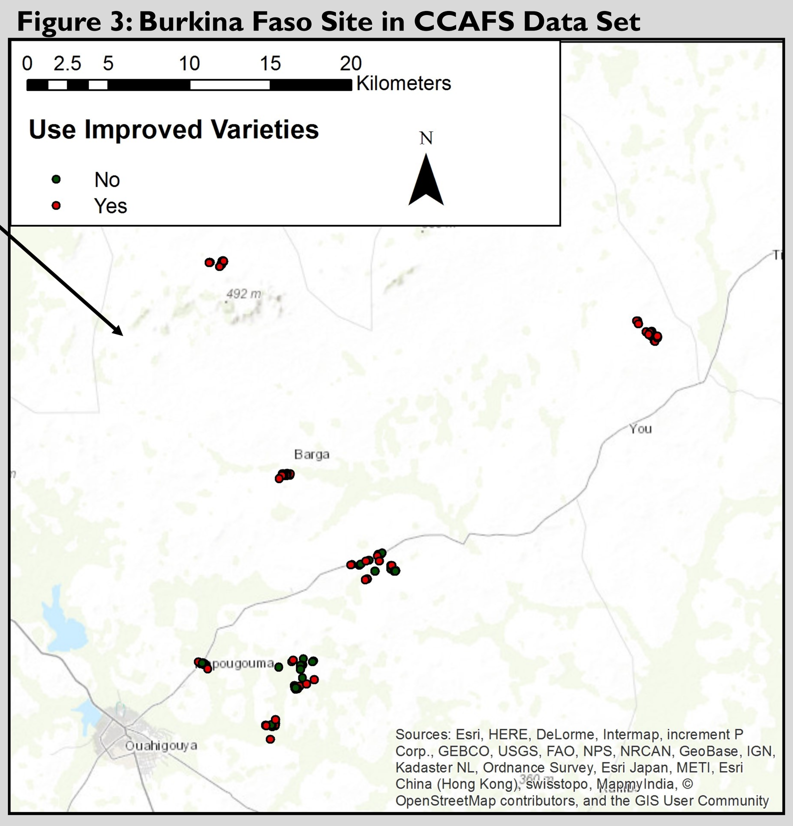


Figure 3: Burkina Faso Site in CCAFS Data Set



The survey was conducted in three broad regions, West Africa, East Africa, and South Asia (Figure 1). Each region had between 4 and 6 sites in it (Figure 2) and each site consisted of roughly 140 households (Figure 3: 20 each from 7 villages). The goal of this analysis it to evaluate how to best use this information to understand farmer decisions to adopt technologies or practice changes.

Logistic Regression of Adaption

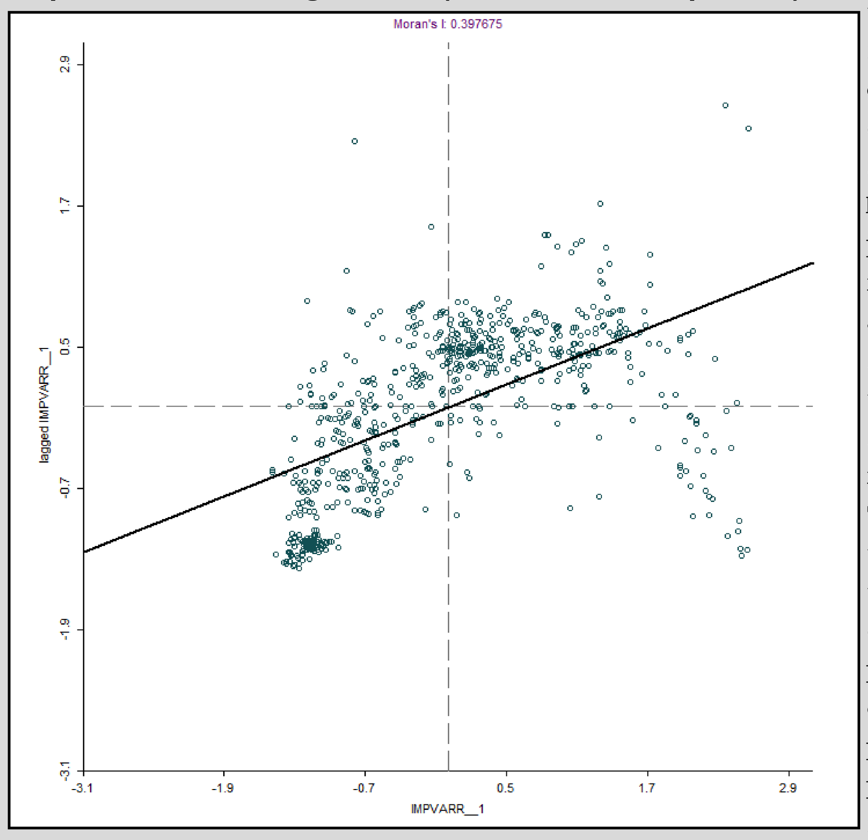
To better understand what impact different social and economic factors play a role in whether or not a farmer makes a change in their agricultural practices I used Logistic Regression Modeling. This type of modeling uses explanatory variables to predict whether or not a farmer would make one of the four changes listed as outcome variables in Table 1. To help control for regional differences the three regions were run independently from one another. This resulted in 12 regressions. The choice of variables was based on a 2014 article by Wood et al at Columbia University. The initial regressions were run in STATA using survey procedures to cluster the standard errors at the site level. For regression coefficients see accompanying paper.

Table 1: Variables Used in the Logit Modeling

Outcome Variables	Explanatory Variables	Control Variables
Use of Improved Seed Varieties	Receiving Weather Information	Education Level of the Head of Household
Changes in Agricultural Timing	Participation in Community Production Groups	Cash Income Sources
Changes in Land Management	Participation in Community Credit Groups	Household Size
Use of Inorganic Fertilizer	Asset Based Wealth Index	Gender of the Head of Household
	Hiring Farm Labor	Site Fixed Effects
	Producing Large Livestock	

The Problem of Spatial Autocorrelation

Figure 4: Moran's I for the Residuals of the West African Use of Improved Varieties Logit Model (Moran's I=0.3977, p<0.001)



One of the critical assumptions of logistic models is that the error inherent in them is random. Correlation between the error of a regression and another variable indicates that this other variable should be considered as well. When studying this in spatial data the statistical test used is Moran's I. A positive Moran's I indicates positive spatial auto-correlation while a negative number indicates a negative spatial autocorrelation. Strong spatial autocorrelation in either the outcome variables or the residuals of a model indicate that there is a spatial component to the data that is not appropriately considered in the model. This is the case with the logistic models that run to investigate agricultural adoption of practice changes. Figure 5 shows clustering of farmers who adopted the improved varieties. Figure 6 shows clustering of the Logit Model residuals when trying to predict which farmers would adopt the improved varieties. Figure 4 shows the Moran's I statistic for the clustering of the logit residuals is highly positive and significant, indicating that there are spatial characteristics in the data that need to be addressed.

Figure 5: Clustering of Adoption of Improved Varieties in Burkina Faso

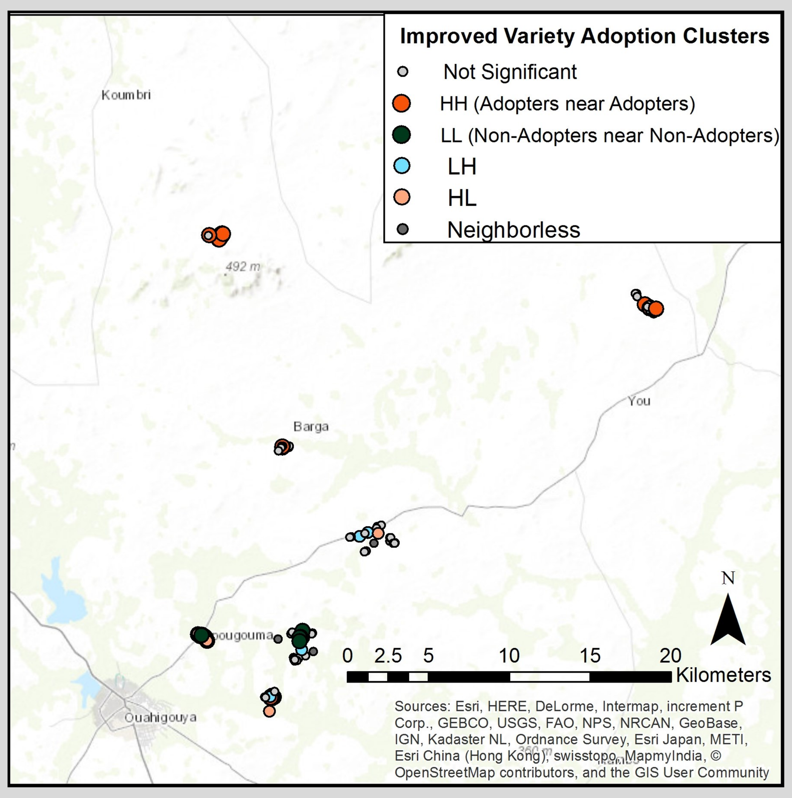
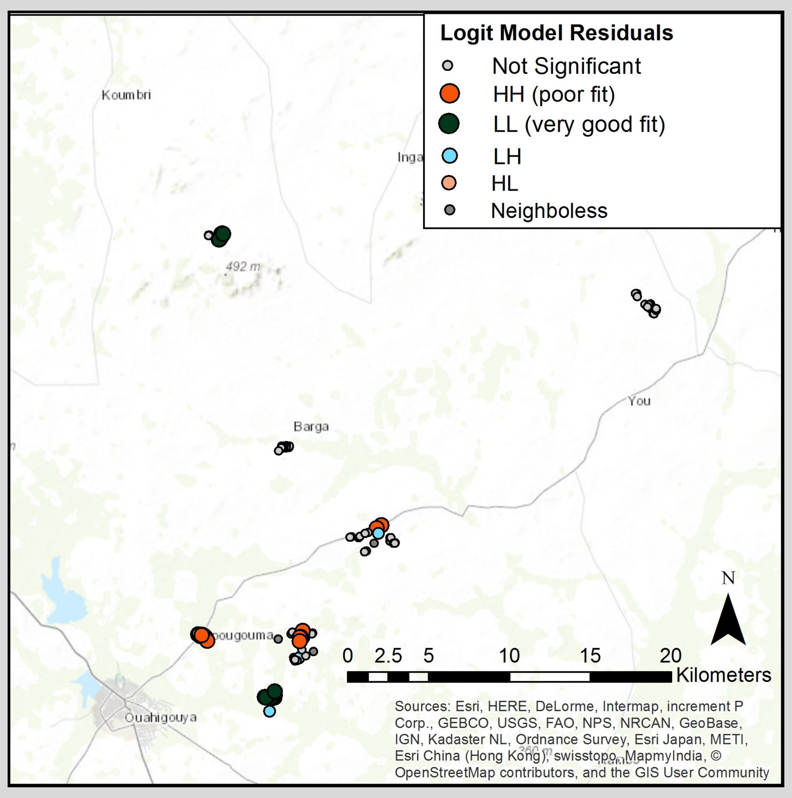


Figure 6: Clustering of Logit Residuals in Burkina Faso



Respecification

Table 2: Changes in Moran's I Through Model Respecification

	Use of Improved Seeds	Changes in Agricultural Timing	Changes in Land Management	Use of Inorganic Fertilizer
	Moran's I for Indicator Variable			
West Africa	0.233	0.413	0.195	0.226
East Africa	0.384	0.186	0.184	0.355
South Asia	0.388	0.363	0.324	0.161
	Moran's I for Simple Logit Residuals			
West Africa	0.398	0.282	0.230	0.213
East Africa	0.356	0.352	0.435	0.321
South Asia	0.411	0.188	0.369	0.362
	Moran's I for Spatial Auto-Correlation Residuals			
West Africa	0.255	0.300	0.194	0.188
East Africa	0.340	0.280	0.204	0.347
South Asia	0.210	0.249	0.266	0.158

To accommodate for the spatial autocorrelation in the data, specifically the residuals in the logit models I re-ran the logistic models using a auto-covariate specification. This Logistic Regression technique uses the covariation between the predicted values of the logistic regression to inform its predictive process. In essence if an observation is near other observations that the model predicts to be likely successes then it increases the likelihood that that observation will be a success. Table 2 shows the Moran's I values for the 4 outcome variables in each of the 3 regions. Note that all are highly positively spatially correlated. Below that are the Moran's I values for the classical logistic regressions used to predict weather a farmer adopts a new technology or practice. These are also highly positively spatially correlated. The last set of rows are the Moran's I for the auto-covariate logistic models. Cells coded in green saw a reduction in spatial autocorrelation while cells coded in red saw an increase. In general using an auto-covariation model reduces the spatial autocorrelation in the residuals, but not universally or sufficiently.

Table 3 shows how the significance of the explanatory variables changed dependent of which specification of Logit model was used. Cells coded in red indicate variables that were less powerful in predicting farmer behavior in the autocorrelation models while the green cells indicate variables which increased in their explanatory power.

Table 3: Changes in Variable Significance Through Model Respecification

	Weather Information	Production Groups	Credit Groups	Wealth Index	Hire Farm Labor	Produce Large Livestock
	Number of Classic Logit Model Which Found this Variable Significant					
West Africa	0/4	1/4	1/4	3/4	0/4	0/4
East Africa	4/4	1/4	1/4	1/4	0/4	1/4
South Asia	2/4	0/4	2/4	1/4	3/4	2/4
	Number of Auto-Correlated Logit Models That Found this Variable Significant					
West Africa	0/4	1/4	0/4	3/4	1/4	0/4
East Africa	3/4	1/4	1/4	2/4	0/4	1/4
South Asia	3/4	0/4	1/4	0/4	3/4	2/4

Conclusions

In the end the auto-covariate model did not make a significant dent in the spatial autocorrelation of the logit model residuals This indicates a need for more sophisticated spatial modeling of farmer technology adoption. One such option would be to use multi-level modeling which takes into consideration site level effects and how they interact with household level effects. A second alternative would be to use a spatial lag model which would look at what is the direct impact of having neighbors who have adopted the technology or practice change on the likely hood that a farmer would make that same change. This kind of modeling is critical for understanding patterns like we see in the Burkina Faso data in Figure 6. There is clear clustering of high and low residuals meaning that the model is very good at fitting in some areas and very poor at it in others. Those kinds if differences could be due to a specific education program or extension activity and are particularly interesting for planning agricultural interventions going forward.

Special thanks to Meredith Niles Ph.D., Assistant Professor at UVM for connecting me to this CCAFS data set

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Cartographer: John VanderHeide   Course: Advanced GIS/ UEP 294, Fall 2016

Data Sources:

Base Map: Esri Online

CCAFS: Climate Change, Agriculture, and Food Security, Baseline Survey

Image Sources: John VanderHeide

Reference Papers:

Wood, S. A., Jina, A. S., Jain, M., Kristjanson, P., & DeFries, R. S. (2014). Smallholder farmer cropping decisions related to climate variability across multiple regions. *Global Environmental Change*, *25*, 163–172. doi:10.1016/j.gloenvcha.2013.12.011

Förch, W., Kristjanson, P., Cramer, L., Barahona, C., & Thornton, P. K. (2014). Back to baselines: Measuring change and sharing data. *Agriculture & Food Security*, *3*(1), 13. doi:10.1186/2048-7010-3-13