Understanding compliance in programs promoting conservation agriculture: Modeling a case study in Malawi

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Understanding compliance in programs promoting conservation agriculture: Modeling a case study in Malawi*

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Abstract

Land degradation and soil erosion have emerged as serious challenges to smallholder farmers throughout Southern Africa. To combat these challenges, conservation agriculture (CA) is widely promoted as a "sustainable" package of agricultural practices. Despite the many potential benefits of CA, however, adoption remains low. Yet relatively little is known about the decisionmaking process in choosing to adopt CA. This article attempts to fill this important knowledge gap by studying CA adoption in southern Malawi. Unlike what is implicitly assumed when these packages of practices are introduced, farmers view adoption as a series of independent decisions, rather than a single decision. Yet the adoption decisions are not wholly independent. We find strong evidence of interrelated decisions, particularly among mulching crop residues and practicing zero tillage, suggesting that mulching residues and intercropping or rotating with legumes introduces a multiplier effect on the adoption of zero tillage.

Keywords: conservation agriculture; Malawi; technology adoption; multivariate probit

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1 Introduction

To preserve ecosystem services in agricultural landscapes, a range of "sustainable" agricultural packages are promoted across the world. These often find strong support within the agricultural development and donor communities, despite much evidence of context-specificity, evidence of limited adoption and subsequent dis-adoption, and contestations within the broader scientific community. Many of these contestations arise from the complexity of these approaches and the behavioral change that is required for transformative change, since such programs often involve bundled interventions comprised of several distinct technologies or practices exhibiting biophysical complementarities. As a result, such interventions have met with limited success, despite short term incentive schemes to promote adoption and long term benefits for the farmer in terms of more resilient and sustainable yields.

Across Southern Africa, one of the most important areas where behavior change could prove most beneficial is in regards to soil management. Degradation and loss of soils is becoming more acute, not just through poor farming practice, but due to changing weather patterns with climate change (in particular more intense rainfall leading to more runoff and soil loss). To combat this, conservation agriculture (CA)–a package involving, typically, the mulching of crop residues, reduced or minimum tillage of soils, and intercropping or rotation with legumes–is widely promoted by the development community as a major part of sustainable agriculture. For example, José Graziano da Silva, Director General of the FAO, commented, "Conservation Agriculture offers the prospect of a better future to both large-scale and smallholder farmers, and a means to raise productivity and secure economic and environmental benefits" (Jat et al., 2013, p. xiv). CA offers many potential benefits to smallholder farmers in Africa, both in terms of increased crop productivity as well as reduced costs and, consequently, higher profits. Reducing the need for tillage means that farmers can shift planting dates in line with weather as well as reducing labor costs (Giller et al., 2011). At the same time, reduced tillage and mulching residues minimizes soil erosion and increases retention of soil moisture, while incorporating legumes as an intercrop or in a rotation helps with managing organic soil matter and nitrogen (Friedrich et al., 2009; FAO, 2011).

Yet in the midst of this compelling narrative there arises a paradox: If CA is really unambiguously beneficial for farmers, why is adoption so low overall? A range of different programs have encouraged and continue to encourage CA (Andersson and Giller, 2012), and alongside this work has grown a significant literature on the agronomic and economic impacts of CA for smallholders, as well as patterns of adoption (e.g., Giller et al., 2009; Kassam et al., 2009; Ngwira et al., 2012; Pannell et al., 2014; Corbeels et al., 2014). Despite the many potential benefits, CA is not without its critics. It is often observed farmers may pick and choose which practices to follow, so that the result is not adoption of CA, but rather a hybrid agricultural practice that foregoes some of the benefits that would arise due to complementarities between reduced tillage, mulching of crop residues, and nitrogen fixation through cultivation of legumes. Giller et al. (2009) convincingly argue that CA may not be suitable for the majority of farming systems in Africa south of the Sahara. While they do not downplay the potential benefits of CA observed on experimental stations, they argue that the context-specificity with which benefits accrue should limit the emphasis of many development programs in promoting CA. Other researchers have acknowledged these problems, but have invested significant efforts in designing systems capable overcoming these challenges (Wall, 2007). To date, however, there appears to be relatively little robust analysis regarding farmers' actual perceptions about the benefits of CA practices, either in isolation or in tandem, which would provide valuable insight into farmers' decisionmaking regarding CA.

This article attempts to fill this important knowledge gap by studying CA adoption as part of a pilot study currently being conducted under the Government of Malawi's Agriculture Sector-Wide Approach (ASWAp), which encourages CA as a comprehensive package of three practices: the mulching of crop residues, zero tillage of the soil, and intercropping or rotation with legumes (Malawi, 2011). Where this pilot program differs from all existing CA programs is its incorporation of agglomeration payments within the program design. Agglomeration payments are an innovation that has emerged in the economics literature to address issues of spatial contiguity of land conservation for the purposes of enhancing biodiversity (e.g., Parkhurst et al., 2002; Parkhurst and Shogren, 2008; Hartig and Drechsler, 2010; Drechsler et al., 2010; Watzold and Drechsler, 2014). Structurally, they are typically a two-part incentive: a direct payment for the adoption of some practice or technology on the registrant's own land, plus a bonus payments for adoption of the same practice or technology by any neighboring farms. These bonus payments create a social network externality through which adoption by any one farm shifts the potential value of adoption for any neighboring farms, such that farms whose reservation price for adoption is higher than offered through the program's direct payment might be sufficiently incentivized once other neighbors have adopted–allowing, in effect, a form of heterogeneous payment for adoption.

Our objectives in this study are two-fold. First, we evaluate whether the structure of agglomeration payments has any influence on adoption of CA. Second, we examine compliance with the three component practices (zero tillage, mulching of crop residues, and intercropping of legumes) to better understand the structure of the decision(s) that underlie compliance with the requirements of CA as specified by the incentive scheme. We make use of a dataset from an early stage of the aforementioned pilot study in the Shire River Basin in Southern Malawi. We find initial evidence that agglomeration payments may help to promote adoption of conservation agriculture, via the encouragement of crop residue mulching. In addition, we show that compliance with the scheme's requirements is governed by the costs (simply perceived or otherwise) of each practice and requires separate decisions to undertake intercropping and mulching, with zero-tillage being crowded-in by the adoption of mulching. Adoption of the comprehensive package is therefore more complex than is often assumed, but innovative approaches can raise compliance with the requirements of sustainable agriculture.

2 Theory

We begin by assuming a relatively simple farm production technology decision. Farmers are faced with the choice of two production technologies for a particular plot of arable land, a traditional technology and a new technology, in producing a homogeneous product; the new technology claims to make more sustainable use of land resources, but in ways that may not be apparent or readily valued by adopters at the time of adoption. These production technologies are characterized by continuous, twice differentiable production functions, denoted as $f_0(\cdot)$ and $f_1(\cdot)$, respectively. Each technology uses the same vector of traditional inputs ($\mathbf{z}$), though with potentially different levels. Furthermore, production under each of the technologies is stochastic, with production uncertainty characterized by ξ. Implicitly, we assume that farmers face the same production risks, regardless of the technology chosen, but the choice of the technology affects how these risks translate to production outcomes. With these additional specifications, we can write our production functions in reduced form as $f_0(z_0, \alpha_0, \xi_0)$ and $f_1(z_1, \alpha_1, \xi_1)$, respectively, where α_0 and α_1 are, respectively, vectors of production function parameters mapping inputs into output via the alternative technologies. We assume that ξ_j is the only source of risk that farmers face, as output prices p and input prices $\mathbf{r}$ are both non-stochastic, and furthermore the same regardless of which technology is used.[1] We can therefore write the current profit functions for farmer i under the two alternative technologies as

$$\pi_{i0} = pf_0(\mathbf{z}_{i0}, \alpha_0, \xi_{i0}) - \mathbf{r}'\mathbf{z}_{i0} \tag{1a}$$

$$\pi_{i1} = pf_1(\mathbf{z}_{i1}, \alpha_1, \xi_{i1}) - \mathbf{r}'\mathbf{z}_{i1} \tag{1b}$$

It is assumed that farm households maximize the current expected utility of farm profits. Under each technology, therefore, the farmer determines the optimal input vector that maximizes the expected profit:

$$\max_{\mathbf{z}_{ij}} \left\{ EU\left[pf_j(\mathbf{z}_{ij}, \alpha_j, \xi_{ij}) - \mathbf{r}'\mathbf{z}_{ij} \right] \right\}, \quad j \in 0, 1 \tag{2}$$

where E is the expectations operator and $U(\cdot)$ is a von Neumann-Morgenstern utility function. After solving for the first-order necessary conditions, the optimal input vector can be written as

$$\mathbf{z}^*_{ij}(\alpha_j) = \underset{\mathbf{z}_{ij}}{\operatorname{argmax}} \left\{ EU\left[pf_j(\mathbf{z}_{ij}, \alpha_j, \xi_{ij}) - \mathbf{r}'\mathbf{z}_{ij} \right] \right\} \tag{3}$$

[1] Given the relatively close proximity of the sample farms, it is perhaps not too controversial to assume that spatial factor price variability is low (Huffman and Mercier, 1991). Additionally, this assumption requires that the technology doesn't affect the quality of the output, such that, other things equal, the output price should be the same across space and technology choice. In the particular application here, since the technology primarily affects the mix of inputs (and hence the costs of production), it seems a reasonable assumption. If other things are not equal, for example if the new technology reduces the time necessary for cultivation and allows for an earlier harvest, then the assumption of homogeneous output prices across technologies becomes slightly more controversial, especially given the extremely high temporal output price variability that Malawi has experienced in recent years. So as to not abstract from the main purpose of the article, we maintain the simplifying assumption that output prices are homogeneous.

Given that the two technologies will augment factors of production differently, we will generally observe $\mathbf{z}_{i1} \neq \mathbf{z}_{i0}$, though the results do not hinge upon this. Then let $V_{ij}^* = EU\left[pf_j(\mathbf{z}_{ij}^*, \alpha_j, \xi_{ij}) - \mathbf{r}'\mathbf{z}_{ij}^*\right]$ be the maximum expected utility over farm profits that could be obtained from utilizing technology $f_j(\cdot)$. Once farmers compute these maximum expected utilities of farm profits under each of the technologies, they compare these maximum utilities and choose to adopt the technology that provides the maximum. In other words, they choose technology f_j such that $V_{ij}^* > V_{ik}^*$, or, equivalently, $V_{ij}^* - V_{ik}^* > 0$. Formally, we observe the dichotomous technology decision

$$f_j(\cdot) = \begin{cases} f_1(\cdot) & \text{if } V_{i1}^* - V_{i0}^* > 0 \\ f_0(\cdot) & \text{otherwise} \end{cases} \tag{4}$$

This expression indicates that the farmer will choose to produce using the new technology if the expected utility of farm profits derived from using the new technology is greater than the expected utility of farm profits derived from using the traditional technology. If the von Neumann-Morgenstern utility function was linear, exhibiting risk neutrality, this specification would be no different than selecting the profit maximizing technology. By not imposing any such restrictions on the curvature of the utility function, we allow for greater generality and flexibility.

3 Empirical model and estimation strategy

To motivate this theoretical model empirically, let us assume that this difference in the maximum expected profits between the two technologies can be characterized in a simple linear fashion as a function of household and farm-level characteristics. To begin, let us write $y_i^* \equiv V_{i1}^* - V_{i0}^*$, and further write $y_i^* = \mathbf{x}_i'\beta + \varepsilon_i$, where $\mathbf{x}_i$ is a vector of household and farm-level characteristics, β is a vector of parameters that translate these characteristics into the perceived differences in the expected utility of the two technologies, and $\varepsilon_i \sim N(0, \sigma^2)$ is an independently and identically distributed disturbance term that captures the effects of all unobservable factors on the evaluation of the profit differential, including, among other things, idiosyncratic errors in evaluating this differential. This difference in the expected utilities, y_i^* is not directly observable, but we can treat the technology choice indicator y_i for whether this latent variable is positive:

$$y_i = \begin{cases} 1 & \text{if } y_i^* = \mathbf{x}_i'\beta + \varepsilon_i > 0 \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

The probability that a farmer will choose to adopt the new technology can be written as a function of the household and farm-level characteristics: $\Pr(y_i = 1|\mathbf{x}_i) = \Pr(\mathbf{x}_i'\beta + \varepsilon_i > 0)$, which, by the symmetry of the normal distribution, can be re-written as

$$\Pr(y_i = 1|\mathbf{x}_i) = \Pr\left(\varepsilon_i < \mathbf{x}_i'\beta\right) = \Phi\left(\mathbf{x}_i'\beta\right) \tag{6}$$

where Φ is the normal cumulative distribution function. This yields the familiar probit model, which can be estimated by maximum likelihood. In this expression $\mathbf{x}$ are therefore household and farm-level characteristics that condition the probability that an individual will follow through and comply with practicing the new technology.

We may also be interested in understanding some of the factors resulting in partial compliance with the CA program. If the decisions to practice zero tillage, residue mulching, and intercropping are independent decisions, then we can simply model these decisions through a series of univariate probit regressions (as in equation 6). If this independence assumption does not hold, however, simply modeling the decisions using a univariate probit model fails to capture the richness and complexity of the decisionmaking process. We can, however, consider a system of related probit models in which there is free correlation in the disturbance terms.[2] This is accomplished by generalizing equation 6 to the multivariate case. Consider the system of three latent variable equations

$$y_{i1}^* = \mathbf{x}_i'\beta_1 + \varepsilon_{i1}, \qquad y_{i1} = 1 \text{ if } y_{i1}^* > 0,\ 0 \text{ otherwise} \tag{7a}$$

$$y_{i2}^* = \mathbf{x}_i'\beta_2 + \varepsilon_{i2}, \qquad y_{i2} = 1 \text{ if } y_{i2}^* > 0,\ 0 \text{ otherwise} \tag{7b}$$

$$y_{i3}^* = \mathbf{x}_i'\beta_3 + \varepsilon_{i3}, \qquad y_{i3} = 1 \text{ if } y_{i3}^* > 0,\ 0 \text{ otherwise} \tag{7c}$$

[2]The development of the multivariate probit regression model that follows draws largely from Greene (2003).

where y_{i1}, y_{i2}, and y_{i3} are the discrete indicators regarding whether the farmer practiced zero tillage, residue mulching, and intercropping (or crop rotation), respectively, and $\varepsilon_{i1}, \varepsilon_{i2}$, and ε_{i3} are distributed multivariate normal with mean zero and variance-covariance matrix V, where V has values of 1 on the leading diagonal and off-diagonal elements given by the correlation coefficients $\rho_{jk} = \rho_{kj}$ for $j, k \in 1, 2, 3$ and $j \neq k$.

To specify the likelihood function, let $w_{ij} = (2y_{ij} - 1)\mathbf{x}_i'\beta_j$ and let Ω be the symmetric 3×3 matrix with values of 1 on the leading diagonal and $\Omega_{jk} = (2y_{ij} - 1)(2y_{ik} - 1)\rho_{jk}$ for $j, k \in 1, 2, 3$ and $j \neq k$. The log-likelihood function can then be written

$$\ln L = \sum_{i=1}^{N} \ln \Phi_3 \left(w_{i1}, w_{i2}, w_{i3}; \Omega \right)$$

where Φ_3 is the trivariate standard normal cumulative distribution function. Estimation by maximum likelihood would require simultaneously solving for six derivatives of the log-likelihood function (three derivatives with respect to the three parameter vectors β_1, β_2, and β_3, and three more with respect to the three correlation coefficients ρ_{12}, ρ_{13}, and ρ_{23}). Directly approximating the three-dimensional integral necessary for computing the trivariate probability is computationally intensive, so simulation methods have been developed and employed for this purpose. Of particular note is the Geweke-Hajivassiliou-Keane (GHK) smooth recursive conditioning simulator, which approximates the trivariate probability as the product of recursively-computed univariate probabilities (see Greene, 2003, pp. 931–933 for a brief introduction to the GHK simulator).

4 Data

The data used in the ensuing analysis consist of both observational and experimental data accumulated during a monitoring survey conducted after the first year of a randomized controlled trial intended to evaluate the impacts of different incentives and monitoring efforts in promoting conservation agriculture in the Shire River Basin in southern Malawi (see Figure 1). The sampling design used to select the treatment villages entailed initially drawing a large number (10^6) of simple random samples of 60 villages, with the resulting village selection being the one that maximized the minimum distance between participating villages. This sample of 60 villages was then randomly allocated to one of six different treatments.

Figure 1 approximately here

The different treatment arms were a two level factor for incentive type crossed with a three level factor for monitoring of compliance. The incentive was either a conventional voucher given to CA adopters or an agglomeration payment consisting of a comparatively smaller conventional voucher administered to CA adopters plus an additional payment given to the participant for each of his or her neighbors that also adopt CA. The monitoring factor levels were of increasing likelihood of monitoring: no monitoring (farmer's self-reported compliance only); partial monitoring (a random selection of 50 percent of treatment farmers have follow-up visit to the registered plots); and full monitoring (all farmers have follow-up visit to registered plots). Based on work from an earlier discrete choice experiment (administered at the time of the project baseline in early 2014; see Ward et al., 2015 for more details), the conventional voucher payment was set at approximately USD 30 per acre of adopted land, awarded for increments of 0.1 acres, up to a total of 1 acre. The agglomeration payment treatment was then structured so that participants would receive USD 15 per acre (again in increments of 0.1 acres) for practicing CA on their own plots, plus an additional bonus of USD 5 per acre (pro-rated against their own level of adoption) for each neighbor that also practiced CA, for up to at most 4 neighbors. With 4 neighbors adopting, the agglomeration payment has a slightly higher maximum value (at USD 35 per acre, compared to USD 30 per acre in the conventional voucher treatments), but embeds uncertainty in the dependence on the willingness of neighbors to register.

Prior to the promotional activities, villages were sensitized on the impending efforts at promoting three different CA practices. During these sensitization activities, officers from National Smallholder Farmers Association of Malawi (NASFAM) visited each village and gave a short (30-45 minute) presentation to village members about the requirements of the program (namely to practice zero tillage, crop residue retention and mulching, and legume intercropping or rotation on some plot or plots), the limits of registration (that is, the cap on which the area of land for which they could register to receive program incentives, namely up to one acre of land), and treatment-specific information on the incentive they were eligible for. Villagers were not made aware that other treatments in the program existed, or that other villages would receive any different form of incentive. Villagers were given some time to decide whether to participate (as close to two weeks as logistics allowed, with villages receiving 1-2 days notice of the return visit), at which time trained enumerators from Lilongwe University of Agriculture and Natural Resources (LUANAR) returned to the villages to register all interested farmers in the program. Following these sensitization meetings, interested participants would then register to participate in the program. Our sample for the ensuing analysis consists of 712 observations from this pool of registrants. Summary statistics for the households included in our sample are reported in Table 1. From the onset, the nature our sample (i.e., that it consists of self-selecting program registrants) precludes us from being too ambitious in saying anything substantive about the factors that might lead someone to transition from not practicing CA to practicing CA, since the farmers in our sample had at least indicated a willingness–if not a desire–to practice CA, even if only incentivized by the vouchers. Nevertheless, if the focus of the analysis is limited to the farmers' decision to take up CA after registering to do so, there is still value in exploring the factors that contribute to program compliance, furthering our understanding of the decisionmaking process among farmers that have been introduced to CA.

Table 1 approximately here

In addition to collecting information on household characteristics and other traditional elements of household questionnaires, the monitoring survey also conducted a series of experiments to elicit respondents' attitudes towards risk and potential losses within the framework of Cumulative Prospect Theory (CPT; Kahneman and Tversky, 1979; Tversky and Kahneman, 1992). As an alternative to traditional Expected Utility Theory (EUT), CPT allows for a greater degree of flexibility in characterizing behavioral responses to risky situations. CPT does not reject EUT outright, but rather is a general model of decisionmaking under uncertainty within which EUT is a specific case. Under CPT, there are three important parameters that characterize individual behavior. The first parameter dictates the curvature of the prospect value function, and can be thought of as a measure of risk aversion. The second parameter characterizes loss aversion, scaling utility to reflect the often-observed phenomenon that individuals experience more pain from losses than gains of an equivalent magnitude. The third parameter captures the degree to which low probability outcomes are disproportionately weighted when individuals consider uncertain prospects. Together, these three parameters jointly characterize the valuation of risky prospects. The experiments used to elicit these preferences were modified from experiments previously conducted in other developing countries (Tanaka et al., 2010; Liu, 2013; Ward and Singh, 2015), using the axiomatically derived weighting function introduced in Prelec (1998).

Data were collected using computer-assisted personal interviewing (CAPI) technologies, specifically CSPro 6.0.1 (U.S. Census Bureau, 2014). Data processing and analysis was conducted using `R` 3.2.2, an open-source language and environment for statistical computing (R Core Team, 2013). Multivariate probit regressions were estimated using the `mvProbit` package (Henningsen, 2015).

5 Empirical results

5.1 Factors influencing full adoption of CA

Close to 24 percent of the respondents who registered with the program were fully compliant. In and of itself, it is interesting that farmers would register to participate in the program, and then fail to follow through with these commitments. This may reflect time inconsistency of preferences, or may simply reflect the reality that signing up is costless, while actually taking up the practices imposes some costs on the farmers, if only perceived as opposed to actual. Treating the full program compliance as a binary indicator variable, we can estimate a probit model like the one introduced in equation 6 above, presented Table 2. All in all, the model does a fairly good job of fitting the data, correctly predicting 87 percent of overall responses. This model predicts that roughly 9 percent of program participants would fully comply with the program's CA requirements, which is less than half the actual observed compliance rate. There is a pretty big difference in its ability to predict compliance vs. non-compliance. The model is very capable of predicting non-compliance, correctly predicting 96 percent of noncompliance. It does a relatively poorer job of predicting compliance, correctly predicting only 57 percent of compliance. This divergence in the model's overall ability to predict non-compliance with greater accuracy than compliance suggests that there are other, unobserved factors not captured in the model that exert strong influences on the compliance decision. Such factors may include actual (or merely perceived) biophysical or economic complementarities which may crowd-in the adoption of the component practices. In predicting compliance, the model errs more on the side of false negatives rather than false positives (i.e., the model is more prone to predict a false non-compliance rather than a false compliance), which provides us with a moderately conservative model with which to draw conclusions about the factors that contribute to CA compliance.

Table 2 approximately here

The results suggest that, on average, farmers with larger holdings are more likely to comply with the full CA scheme and follow through with practicing zero tillage, residue mulching, and intercropping (or crop rotation), as are more educated farmers. Farmers who produce maize as their main crop, on the other hand, are less likely to fully comply with the CA program. Farmers who have more neighbors complying with the CA program are more likely to themselves fully comply with the program's requirements, though we cannot strictly identify whether this effect is itself causal (and in which direction the causality would go), whether this effect is due to farmers and their neighbors having similar characteristics leading to full compliance, or whether there are unobserved, contextual effects that lead to both parties complying with the program. This is yet another example of Manski's "reflection problem" (Manski, 1993). While there are challenges for interpreting these peer effects, the evidence suggests that there is either some form of learning from others or social reinforcement that contributes to increased program compliance.

Interestingly, we do not find that the promised program payment (whether the simple base payment or the agglomeration payment) has an effect on program compliance. Rather, what appear to be more relevant is whether the farmer's behavior was directly observed through program monitoring. The negative coefficient, however, suggests that those farmers who were visited by a monitor were less likely to fully comply with the CA program than those who were not visited by a monitor. Given the roughly uniform sensitization exercises at the beginning of the program and the random assignment of the monitoring treatments, we would, other things being equal, expect farmers to comply with roughly the same frequency, regardless of whether or not their actions were monitored. What this is likely capturing is dishonesty on the part of farmers who were not visited by monitors. These farmers simply had to self-report their farming practices. Since their payments were based upon this self-reporting, they have a financial incentive to indicate program compliance, without no recourse for dishonesty. At this stage, we are not able to actually assess whether the farmers were dishonest or if they actually complied with the program, but that remains an area of considerable interest going forward.

5.2 Factors influencing partial compliance

While relatively few farm households fully complied with the CA program, almost every registrant undertook at least one of the CA practices. For example, 39 percent of registrants practiced zero tillage, 86 percent mulched crop residues, and 63 percent practiced either intercropping or crop rotation. In its own right, it is interesting that so many farmers practiced residue mulching, since one of the reasons often cited for the failure of CA to take hold in many contexts is that there are competing uses for crop residues, specifically for providing fodder for livestock or for biofuels production. Malawi has a relatively low livestock density in the first place (Thierfelder et al., 2013), and, at least in the case of the Shire River Basin, these other alternative uses must not be particularly rampant. Additionally, the paucity of zero tillage highlights how engrained ridging is within farmers' mindsets. Particularly problematic is the use of ridging in the direction of slopes, rather than along contours, which exacerbates problems of soil erosion.

While there may be agronomic synergies that are only (or at least primarily) realized when the three pillars of CA are taken in tandem, this piecemeal compliance may reflect a learning or experimentation process, whereby farmers, in a way, isolate the causal effects of technology choice on resulting yields. Table 3 reports a series of binary triplets that highlight the different combinations of practices that be conceived as forms of partial compliance. Relatively few farmers practiced only one of the three practices. From our sample, only 8 percent of farmers practiced only intercropping or crop rotation, while only 0.4 percent of farmers practiced only zero tillage. Even fewer practiced both intercropping and zero tillage without also mulching residues. The largest form of partial compliance involved mulching residues and intercropping, with 31 percent of registrants practicing these two while not taking up zero tillage. An additional 14 percent of registrants practiced zero tillage and residue mulching, while forgoing intercropping.

Table 3 approximately here

These patterns of partial adoption suggest that perhaps the decisions to undertake different CA practices are not independent, in which case analysis of simple univariate probit models would not sufficiently capture the decisionmaking process and the effects of various household and farm-level characteristics on the technology decision. Tests of two-way independence (top panel of Table 4) suggest that the decision to practice zero tillage is not independent from the decision to mulch residues, though the decisions to practice both of these are independent from the decision to intercrop. The dependence between the decisions to practice zero tillage and mulch residues, in many ways, is sensible, since it would be very difficult to combine conventional tillage (i.e., forming ridges) in fields laden with maize stover. In addition, there are other agronomic synergies between mulching residues and conservation tillage. In the absence of crop residues, practicing zero tillage can result in increased runoff, soil erosion, and weed pressure (Andersson and Giller, 2012).

Table 4 approximately here

We also conducted tests of three-way independence based on analysis of log-linear regression models (bottom panel of Table 4). We used three variants of the base log-linear model, which allowed us to test (a) whether the three practices were pairwise independent, (b) whether there was partial independence (i.e., of one practice with respect to a composite of the other two practices), and (c) whether there was conditional independence (i.e., of one practice relative to another, conditional upon the third practice being undertaken). These results are largely consistent with the two-way tests of independence, but with subtle nuances that enhance the complexity of our understanding of these decisions. From the test of mutual independence, we can soundly reject the hypothesis that the decisions to undertake these three practices are completely independent from one another: in some way or another, these decisions are related. The tests of partial independence reveal that the decision to practice zero tillage is not independent from the composite decision of practicing residue mulching and intercropping, nor is the decision to practice residue mulching independent from the composite decision of practicing zero tillage and intercropping. We fail to reject, however, the hypothesis that the decision to intercrop is independent from the decision to practice zero tillage and mulching residues. From the tests of conditional independence, we find further evidence that the decisions to practice zero tillage and residue mulching are interrelated, while neither decision is significantly related to the decision to practice intercropping.

With at least some interrelatedness in the adoption decisions, we can control for this interrelatedness through estimating a multivariate probit model as given in equations (7) by simulated maximum likelihood. These results are reported in Table 5. Many of the results are consistent with those observed from the simple univariate analysis above for full program compliance. Across all three of these related regression equations, we find that farmers with more neighbors complying with the program are more likely to take up the individual practices, though the same caveats regarding the interpretation of these coefficients apply. In the case of zero tillage, loss aversion acts as a constraint to adoption, as does a farmer's propensity for subjectively overweighting objectively unlikely scenarios when evaluating risky situations, though neither effect is statistically significant at conventional levels. Of the three practices promoted, zero tillage is the least conventional (that is, the most out of the norm), and thus farmers may perceive a higher probability of tail events resulting in poor yield realizations, which results in increased aversion to conservation tillage. Larger farmers, on the other hand, are more likely to practice zero tillage, as the labor requirements associated with conventional tillage make conservation tillage relatively more attractive. We also find that larger farmers are more likely to intercrop. While we cannot say for certain, this result may arise because larger farmers have more land and are more able to bear the risk of yield reduction for their main crop arising from resource competition between the main crop and the intercrop.

Table 5 approximately here

Farmers that were visited by program monitors were deemed to have practiced zero tillage and residue mulching less than those that self-reported (without any monitoring), which again suggests a proclivity for dishonesty about taking up these practices. There is no significant effect of monitoring on intercropping. Since intercropping is more of a traditional practice, there is perhaps less pressure to falsely report practicing intercropping. It is also noteworthy that farmers who cultivate maize as their main crop are less likely to practice zero tillage. Given that the vast majority of farmers in our sample (85 percent) cultivate maize as their main crop, this has important implications. The traditional practice for maize cultivation is to use ridging (a practice introduced by the British). In theory, ridging done along (parallel to) topographical contours can reduce soil erosion and reduce water logging. Many farmers in Malawi, however, construct ridges down with up- and down-slope orientation, which simply exacerbates problems associated with runoff, waterlogging, gully formation, and overall poor management. We suspect that farmers are most reluctant to adopt zero tillage because they doubt that a flat bed can be better for maize than ridges. If they do not break the soil hardpan on conversion to conservation tillage, this perception may get re-enforced, since the rooting zone is even shallower than with the ridges. It takes time to improve water infiltration capacity, so they may require the use of a deep cultivator and animal draft power or grow deep rooting legumes for a few seasons to break the hardpan and increase infiltration.

We can also make important observations regarding the correlation coefficients ρ_{12}, ρ_{13}, and ρ_{23}. These correspond to the correlations in the error terms between the zero tillage and mulching equations, the zero tillage and the intercropping equations, and the mulching and intercropping equations, respectively. Since these error terms represent, among other things, unobservable factors that condition the observed technology choices, these correlations reveal something about how these technology choices are related. If, for example, the correlation between the errors in the zero tillage probit equation and the errors in the residue mulching probit equation is positive (as indeed it is) this suggests that unobservable factors that increase (decrease) utilization of zero tillage also increase (decrease) residue mulching. Alternatively, if the correlation coefficient was negative, then unobservable factors that condition increased (decreased) utilization of zero tillage would reduce (increase) residue mulching.

The results suggest a strong and positive relationship between the choice to practice zero tillage and the choice to mulch crop residues, as evidenced by the positive and statistically significant correlation coefficient ρ_{12}. This is largely consistent with the results from the earlier tests of statistical independence, in which there was ample evidence that these binary technology choice variables were dependent upon one another. Somewhat surprisingly, the results also suggest a negative relationship between the decisions to practice zero tillage and intercropping, evidenced by the negative and statistically significant estimate for ρ_{13}. In the previous statistical tests, we were unable to reject independence between the decision to practice zero tillage and the decision to intercrop based on the χ^2 two-way tests of independence, though we soundly rejected the null hypothesis of independence between the decision to practice zero tillage and the composite decision to practice residue mulching and intercropping. In tandem, these results suggest some push and pull with respect to zero tillage. Mulching residues seems to crowd-in zero tillage, while intercropping crowds-out zero tillage. In the case of mulching and zero tillage, there are actual biophysical and economic complementarities between the two practices, and these complementarities are very clearly perceptible to the farmers. These complementarities reduce the perceived transaction costs between the two practices, such that practicing one increases the (perceived) returns to practicing the other. The relationship between intercropping and practicing zero tillage is more nuanced. Because intercropping is a more-or-less traditional practice, while zero tillage is contrary to much of the conventional wisdom regarding best management practices, unobservable factors such as a preference towards tradition or a desire to adhere to societal norms, which would increase intercropping, would be negatively correlated with unobservable factors that lead to the decision to practice zero tillage.

5.3 Multiplier effect of CA component practices

While it is possible to derive marginal effects from a multivariate probit regression, the utility of such an endeavor is weakened by the fact that there is a large number of effects that can be estimated, including both direct and indirect effects for each covariate. In other words, there is a direct effect of, say, land area on the probability of a farmer practicing zero tillage, but there is also an indirect effect through the effect of land area on the probabilities of the farmer practicing both residue mulching and intercropping, mediated on the probability of practicing zero tillage through the correlation coefficient.

It is useful, however, to compare the conditional probabilities of practicing each these three CA practices, given assumptions about whether or not the farmer is practicing the other two. Table 6 reports the mean conditional probabilities of farmer's practicing each the three CA practices, first conditional upon the other two being practiced, then conditional upon the other two not being practiced. In both cases, the probabilities are further conditioned by the household and farm-level characteristics as well as the correlation coefficients from the multivariate probit regressions. These conditional probabilities, therefore, take into consideration–where applicable–the interrelatedness of the farm technology-choice decisions.

Table 6 approximately here

Since we have estimates for conditional probabilities under these different assumptions regarding other practices, we can estimate the joint effect of, for example, residue mulching and intercropping on the probability that an average farmer will practice zero tillage. This is computed as simply

$$M_{ZT} = \frac{\Pr(\text{Zero tillage} = 1|\text{Mulching} = 1, \text{Intercropping} = 1, X, \rho_{12}, \rho_{13}, \rho_{23})}{\Pr(\text{Zero tillage} = 1|\text{Mulching} = 0, \text{Intercropping} = 0, X, \rho_{12}, \rho_{13}, \rho_{23})}$$

For values greater than one, the composite of practicing mulching and intercropping crowds in adoption of zero tillage. This suggests a multiplier effect that captures the joint contribution the other two practices. Table 7 reports these multiplier effects for each of the three practices. The composite of practicing both residue mulching and intercropping increases the probability that a farmer will also undertake zero tillage by a factor of 3, which suggests that practicing these other two technologies greatly increases farmers' likelihood of also practicing zero tillage. Given the strong positive correlation coefficient between the disturbance terms in the zero tillage and mulching equations, this is likely driven by perceived complementarities between mulching residues and practicing zero tillage. This is particularly true in light of the negative correlation coefficient between the zero tillage and intercropping equations, which actually partially mutes the zero tillage - mulching multiplier effect.

Table 7 approximately here

6 Conclusion

The empirical evidence we present indicates that adoption of new pro-environmental farming technologies is a complex decision influenced by many factors. These include a range of variables that describe household and farm characteristics. Larger farms are more likely to adopt the new technology, as are ones with more females in the household (perhaps due to access to labor). More highly educated households are also more likely to be willing to adopt. Peer compliance is also correlated with adoption rates. In themselves, these findings are confirmatory rather than novel such relationships have been found around the world (e.g., Sutherland et al., 2012 talks about the neighbor effect in adopting organic farming; many studies have shown income/size to correlate to technological uptake). With respect to the design of the incentive scheme, we show that monitoring effort, rather than the incentive size itself, was more important.

We show that adoption is a complex process. Only a small proportion of adopters (about a quarter) comply with the three component practices of CA. Instead, most only partially comply, adopting one or two of the three component practices. Detailed analysis shows the complexity of the adoption process, as the decisions to take up each of the three practices are not independent.

Mulching residues seems to promote zero tillage, as tillage becomes harder if the soil surface is covered in maize stems; conversely, intercropping reduces the probability of adopting zero tillage. In the case of mulching and zero tillage, the advantages of adopting both practices are very clearly perceptible to the farmers. The relationship between intercropping and zero tillage is more uncertain, but our hypothesis is that preference towards tradition or a desire to adhere to societal norms may promote intercropping (a traditional practice) and reduce the uptake of no-till (a non-traditional practice).

While decisionmaking is characteristically complex, it also illuminates the fact that "leverage" points can be found that promote adoption. Encouraging the adoption of the whole package, leads to very low compliance. In fact, we show that farmers are effectively making two decisions whether to mulch crop residues (and not till the soil), and whether to do intercropping or rotation. We show that practicing both residue mulching and intercropping increases the likelihood of a farmer adopting zero tillage by a factor of 3. This implies either that encouraging mulching and intercropping will be more beneficial in promoting uptake of all three practices, or, conversely, if a farmer adopted zero-tillage they may perceive greater benefits for adopting the other two approaches. There appear to be three different kinds of encouragement to be made. For those (possibly more traditional) farmers who engage in intercropping or rotation but do not do CA, encouragement specifically of the value of crop residue mulching (which in turn crowds in zero tillage) may be important. For other farmers, a focus first on encouraging intercropping or crop rotation might be a better priority. For "innovators and early adopters" (to use the terminology of Rogers, 1995), perhaps the focus could be on encouraging zero-till on the basis that the other two practices may follow.

The structure of the voucher program varies across different treatments in this study, with farmers (i) being offered either a bonus of USD 30 per acre, or a bonus of USD per acre plus USD 5 per neighbor adopting, and (ii) being monitored either by field monitoring visit(s), or by self-reported compliance. A formal evaluation of treatment effects against is an analysis that waits for our endline survey, and the data in the current study captures only farmers who chose to register for our program in its first year; we do not capture farmers who did not participate, nor do we yet have multiple time periods of data with which to evaluate any possible sequential adoption of different CA practices or disadoption. However, as a first signal of how agglomeration payments might act to encourage adoption of conservation agriculture, we find in our probit analyses that farmers offered an agglomeration payment were significantly more likely to undertake crop residue mulching, even after controlling for the peer effect of other neighbors' adoption. This is an encouraging finding that hints at a place for agglomeration payments as a policy tool in agricultural development beyond their envisaged role in encouraging spatial coordination in biodiversity conservation.

Finally, while our empirical evidence is based on data from rural Malawi, the theoretical model and the major conclusions may well be more generalizable. Similar patterns have been found before with respect to the role of farm-size (or profit-orientation, e.g., Aoki, 2014) on adoption of new technology, or education (e.g., Genius et al., 2014; Kersting and Wollni, 2012; Reimer et al., 2012). While we did not study the sequence of adoption in the present study, we found strong peer compliance which suggests a range of hypotheses, including social learning and support (e.g.,Genius et al., 2014). Additionally to these generic factors influencing adoption, we show that adoption is rarely about a single decision, rather a sequence of decisions. Kersting and Wollni (2012) indicate there is a similar hierarchy of decision making in adoption of GlobalGAP standards, and Reimer et al. (2012) shows that there are a range of attributes that are correlated with adoption, including the observability of benefits and the way it fits with current practice and the advantages. In addition, Reimer et al. (2012) show that some practices are adopted because of co-benefits (similar to the biophysical complementarities we suggest and resulting in crowding-in effects like we report). Therefore, while this study is based in Malawi, our results are similar to others being reported in detailed studies of technology adoption: decisions are often the integration of a complex mix of factors, which vary with farm and environmental characteristics, social setting, farmer attitudes, as well as costs and benefits–both real and perceived.

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Table 1: Summary statistics of sample households

Variable	Mean	Standard deviation
Complied with CA program	0.237	0.426
Practiced zero tillage	0.389	0.488
Practiced residue mulching	0.864	0.343
Practiced intercropping or crop rotation	0.628	0.484
Area	0.281	0.388
Loss aversion coefficient	6.859	4.560
Probability weighting parameter	0.632	0.269
Value function curvature	1.112	0.469
Peer compliance	0.794	1.879
Maximum education of household members	2.334	0.515
Age of household head	43.944	14.820
Gender of household head	0.312	0.464
Number of males in household	2.493	1.331
Number of females in household	2.569	1.340
Share of income from agriculture	3.605	1.347
Number of plots	1.726	1.003
Any crop residues	0.240	0.427
Any zero tillage	0.190	0.392
Any inorganic fert.	0.687	0.464
Main crop: maize	0.846	0.362
Main crop: cotton	0.027	0.161
Soil type: loam	0.770	0.421
Soil type: sandy loam	0.424	0.495
Soil type: clay loam	0.136	0.343
Soil type: sandy clay	0.096	0.294
Visited by monitor	0.449	0.498
Program payment	0.563	0.496

Note: Loss aversion coefficient, probability weighting parameter, and value function curvature are behavioral parameters derived from Cumulative Prospect Theory (Tversky and Kahneman, 1992). These parameters are estimated using a series of lottery-based experiments similar to those presented in Tanaka et al. (2010); Liu (2013); Ward and Singh (2015) and others.

Table 2: Univariate probit analysis of conservation agriculture adoption

	Full compliance		
	Coefficient	Standard error	
Intercept	-2.356	0.654	***
Area	1.504	0.172	***
Loss aversion	-0.009	0.014	
Prob. weighting	-0.335	0.251	
Value func. curv.	0.130	0.140	
Peer compliance	0.168	0.054	***
Max educ. of HH	0.354	0.121	***
Age of HH head	0.005	0.004	
Gender of HH head	-0.025	0.147	
Num. of males in HH	0.020	0.049	
Num. of fem. in HH	0.150	0.048	***
Income from agric.	-0.083	0.054	
Number of plots	0.073	0.076	
Any crop residues	0.294	0.196	
Any zero tillage	0.124	0.214	
Any inorg. fert.	0.089	0.162	
Main crop: maize	-0.490	0.229	**
Main crop: cotton	-0.888	0.618	
Soil type: loam	-0.197	0.205	
Soil type: sandy loam	0.218	0.174	
Soil type: clay loam	-0.025	0.252	
Soil type: sandy clay	0.399	0.334	
Visited by monitor	-1.036	0.152	***
Program payment	-0.039	0.158	
Village controls	Yes		
Observations	712		
Log-likelihood	-259.45		
Pseudo R^2	0.34		
Pct. correctly classified	0.87		
Sensitivity, Pr(Pred + | Actual +)	0.57		
Specificity, Pr(Pred - | Actual -)	0.96		
False + for actual -	0.04		
False - for actual +	0.43		

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

Table 3: Binary triplets characterizing patterns of conservation agriculture practices

	Frequency	Proportion
Zero tillage = 1, Mulching = 1, Intercropping = 1	169	0.24
Zero tillage = 1, Mulching = 1, Intercropping = 0	103	0.14
Zero tillage = 1, Mulching = 0, Intercropping = 1	2	0.00
Zero tillage = 1, Mulching = 0, Intercropping = 0	3	0.00
Zero tillage = 0, Mulching = 1, Intercropping = 0	125	0.18
Zero tillage = 0, Mulching = 1, Intercropping = 1	218	0.31
Zero tillage = 0, Mulching = 0, Intercropping = 1	58	0.08
Zero tillage = 0, Mulching = 0, Intercropping = 0	34	0.05

Note: A '1' indicates that the practice is undertaken, while a '0' indicates that the practice is not undertaken.

Table 4: Tests of independence of conservation agriculture practices

χ^2 tests of two-way independence			
	Null hypothesis	χ^2 test statistic	p-value
H_0:	Zero tillage is independent of residue mulching	52.185	5.05e-13
H_0:	Zero tillage is independent of intercropping	0.146	0.702
H_0:	Residue mulching is independent of intercropping	0.008	0.928

Log-linear tests of three-way independence			
	Null hypothesis	Likelihood ratio test statistic	p-value
Mutual independence			
H_0:	Zero tillage, residue mulching, and intercropping are pairwise independent	69.142	3.44e-14
Partial independence			
H_0:	Zero tillage is partially independent of the composite of mulching and intercropping	69.101	6.66e-15
H_0:	Mulching is partially independent of the composite of zero tillage and intercropping	68.929	7.22e-15
H_0:	Intercropping is partially independent of the composite of zero tillage and mulching	1.202	0.752
Mutual independence			
H_0:	Zero tillage is independent of mulching, given intercropping	68.888	1.11e-15
H_0:	Zero tillage is independent of intercropping, given mulching	1.161	0.56
H_0:	Mulching is independent of intercropping, given zero tillage	0.989	0.61

Table 5: Multivariate probit regression results

	(1) Practiced zero tillage			(2) Practiced residue mulching			(3) Practiced intercropping		
	Coefficient	Standard error		Coefficient	Standard error		Coefficient	Standard error	
Intercept	-0.507	0.602		1.162	1.057		-0.698	0.572	
Area	0.795	0.165	***	0.211	0.311		1.189	0.192	***
Loss aversion	-0.019	0.013		-0.021	0.020		0.014	0.012	
Prob. weighting	-0.387	0.239		-0.490	0.292	*	0.106	0.223	
Value func. curv.	0.085	0.133		0.062	0.177		0.022	0.121	
Peer compliance	0.123	0.053	**	0.376	0.133	***	0.101	0.050	**
Max educ. of HH	0.176	0.118		0.060	0.190		-0.114	0.119	
Age of HH head	0.005	0.004		-0.005	0.006		0.002	0.004	
Gender of HH head	0.109	0.133		0.011	0.188		-0.022	0.139	
Num. of males in HH	-0.023	0.045		-0.013	0.071		-0.010	0.047	
Num. of fem. in HH	0.107	0.044	**	0.025	0.068		0.063	0.044	
Income from agric.	-0.055	0.052		-0.042	0.064		-0.100	0.048	**
Number of plots	0.069	0.074		0.133	0.112		0.013	0.076	
Any crop residues	0.447	0.183	**	0.170	0.385		-0.046	0.195	
Any zero tillage	0.044	0.218		-0.404	0.370		-0.153	0.218	
Any inorg. fert.	0.031	0.155		0.309	0.184	*	-0.006	0.138	
Main crop: maize	-0.661	0.246	***	-0.309	0.302		0.313	0.215	
Main crop: cotton	-0.823	0.527		-0.536	0.464		-0.166	0.405	
Soil type: loam	0.065	0.195		0.172	0.287		-0.014	0.186	
Soil type: sandy loam	-0.027	0.157		-0.081	0.242		0.112	0.157	
Soil type: clay loam	-0.481	0.219	**	0.556	0.462		0.399	0.233	*
Soil type: sandy clay	0.866	0.275	***	-0.340	0.578		-0.991	0.327	***
Visited by monitor	-0.945	0.143	***	-0.484	0.236	**	-0.118	0.139	
Program payment	-0.048	0.150		0.726	0.226	***	-0.005	0.142	
ρ_{12} (zero tillage, mulching)	0.570	0.113	***						
ρ_{13} (zero tillage, intercropping)	-0.200	0.074	***						
ρ_{23} (mulching, intercropping)	-0.091	0.103							
Observations	712								
Log-likelihood	-974.329								
Pseudo R^2	0.185								

Note: * Significant at 10% level; ** Significant at 5% level; *** Significant at 1% level.

Table 6: Conditional probabilities from multivariate probit regressions

Conditional probability	Mean
Pr(Zero tillage = 1 — Mulching = 1, Intercropping = 1, X, ρ_{12}, ρ_{13}, ρ_{23})	0.385
Pr(Mulching = 1 — Zero tillage = 1, Intercropping = 1, X, ρ_{12}, ρ_{13}, ρ_{23})	0.968
Pr(Intercropping = 1 — Zero tillage = 1, Mulching = 1, X, ρ_{12}, ρ_{13}, ρ_{23})	0.552
Pr(Zero tillage = 1 — Mulching = 0, Intercropping = 0, X, ρ_{12}, ρ_{13}, ρ_{23})	0.123
Pr(Mulching = 1 — Zero tillage = 0, Intercropping = 0, X, ρ_{12}, ρ_{13}, ρ_{23})	0.828
Pr(Intercropping = 1 — Zero tillage = 0, Mulching = 0, X, ρ_{12}, ρ_{13}, ρ_{23})	0.687

Table 7: Multiplier effects of composite of other conservation agriculture practices

Multiplier effect on:	
Zero tillage	3.128
Residue mulching	1.168
Intercropping	0.804

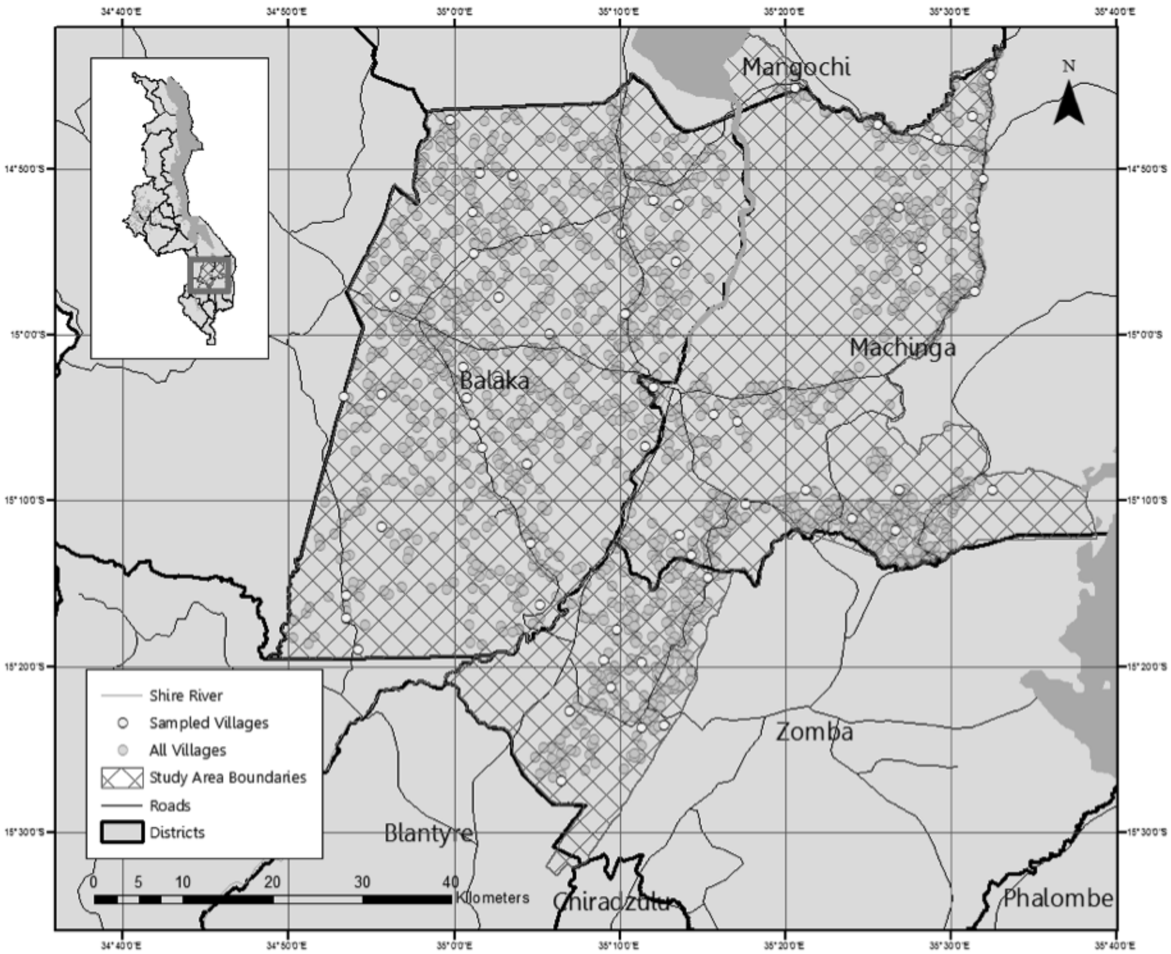

Figure 1: Sample area, Shire River Basin, Malawi