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Zambia Buy In

BEYOND THE "INVERSE RELATIONSHIP": AREA MISMEASUREMENT AFFECTS ACTUAL PRODUCTIVITY, NOT JUST HOW WE UNDERSTAND IT

By

William J. Burke, Stephen Morgan, Thelma Namonje, Milu Muyanga, and Nicole M. Mason

Food Security Policy *Research Papers*

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ABSTRACT

Although measurement error in agricultural field area and productivity data for developing countries is widely acknowledged, there is still a shortage of evidence on what the errors imply for researchers, and even less evidence on what the implications may be for farmers. In this study we investigate field size measurement errors on Zambian maize fields to examine the nature of these errors and the implications they have for: 1) our ability to understand productivity, 2) actual productivity, and 3) our broader understanding of total land use. Using a nationally representative dataset on Zambian smallholder maize plots, we compare self-reported (SR) and global positioning system (GPS) measures of land area on a farm's largest maize plot to assess how measurement error might affect productivity estimates and farmer input use. Consistent with other studies, we find strong evidence that the land area of relatively smaller fields is overstated, and relatively larger fields is understated. However, correcting for this measurement error using GPS measurements appears to strengthen the evidence of an inverse relationship between field size and productivity. Additionally, we find strong evidence to suggest farmers themselves believe the area figures they report to enumerators and that their input use is more closely aligned with the reported field sizes than actual field sizes. Based on these results and insights from semi-structured interviews with farmers and extension agents, we argue that measurement error may affect real productivity in addition to productivity estimates. Strengthening extension efforts to improve farmer understanding of land area measurements may be an important and affordable way to improve productivity. Moreover, improving the accuracy of data collection for area seems feasible and will improve researchers' understanding of productivity.

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ACRONYMS

CF	Conservation Farming
CFU	Conservation Farming Unit
CME	Classical Measurement Errors
CSO	Central Statistics Office
FAO	Food and Agriculture Organization of the United Nations
GPS	Global Positioning System
ha	hectare
IAPRI	Indaba Agricultural Policy Research Institute
IR	Inverse Relationship
kg	kilogram
LMFs	Largest Maize Fields
MAL	Zambian Ministry of Agriculture and Livestock
NCMEs	Non-classical Measurement Errors
RALS	Rural Agricultural Livelihoods Survey
SEAs	Standard Enumeration Area
SR	Self Reported
ZARI	Zambia Agricultural Research Institute

1. INTRODUCTION

Although measurement error in agricultural field area and productivity data for developing countries is widely acknowledged, there is still a shortage of evidence on what the errors imply for researchers, and even less evidence on what the implications may be for farmers. In this study, we aim to investigate field size measurement errors on Zambian maize fields to examine the nature of these errors and the implications they have for: 1) our ability to understand productivity, 2) actual productivity, and 3) our broader understanding of total land use.

Increasing availability of objective field size measurements linked to self-reported (SR) field sizes has provided strong evidence that measurement error is a widespread problem throughout Sub-Saharan Africa (SSA). Comparing SR data with either global positioning system (GPS) or compass-and-rope (CR) measurements under a mixed methods approach has consistently revealed the existence of land size measurement error in SR methods (De Groote and Traoré 2005; Carletto, Savastano, and Zezza 2013; Holden and Fisher 2013; Carletto, Gourlay, and Winters 2015; Dillon et al. 2019; Abay et al. 2019). SR measurements are imprecise by definition; even if, at some point, every survey respondent had been told with absolute certainty the hectarage of their fields, there is a non-zero probability that some people will err (or deceive) when reporting these figures to an enumerator.[1]

While the existence of area measurement error is not surprising, it may also be true that even very large measurement errors within a dataset are not particularly concerning (at least not to the analysts studying the data). Classical measurement errors (CME) are random and decrease the precision of, say, regression parameter estimates but they are still unbiased and consistent. With a large enough sample, we can derive sufficiently narrow confidence intervals around these estimates to make them useful even in the presence of CME.

Although measurement error is not terribly surprising and CME need not overly worry analysts, a proliferation of evidence suggests land area (and thus agricultural productivity) data suffer from measurement errors that are not random (De Groote and Traoré 2005; Carletto, Gourlay, and Winters 2013; Gourlay, Kilic, and Lobell 2019). These non-classical measurement errors (NCMEs) may be correlated with either the actual level of the value they endeavor to measure or other key variables. In the case of field size measurement, an example of NCME would be mismeasurement that is correlated with the actual size of the field—that is, if large field sizes are more likely to be underreported by survey respondents or vice versa. NCMEs are more troubling than CMEs because estimates of, say, yield or the correlation between yield and field size will be biased and inconsistent in the presence of NCME. Moreover, the direction of bias in the latter case is unclear because the mismeasurement affects both sides of the correlation equation (Abay et al. 2019).

There is strong evidence to suggest that NCME is present in farmer-reported plot- and farm-level area measurements across SSA: small plot or farm areas tend to be overstated and large plot or farm areas tend to be understated relative to their true values (De Groote and Traoré 2005; Holden and Fisher 2013; Carletto, Gourlay, and Winters 2015; Dillon et al. 2019; Abay et al. 2019). Drawing on data from Malawi, Tanzania, Uganda, and Niger, Carletto, Gourlay, and Winters (2015) demonstrate that the magnitude of measurement error varies across country contexts when comparing SR and GPS instruments. For example, on small plots (< 0.5 ha), measurement errors range from 90% in Malawi to 580% in Niger (Carletto, Gourlay, and Winters 2015). Looking at large plots (>5 ha), bias ranges from -28% in Uganda to -59% in Malawi; however, medium-size plots (1-5 ha) report smaller errors. Similar relationships exist when comparing SR with CR instruments (Dillon et al. 2019; Abay

[1] Enumerators themselves may err, for that matter, but this is true of recording objective measures as well.

et al. 2019). It is important to note that while GPS measurements are superior to SR, they may be subject to some small measurement error in their own right. Dillon et al. (2019) find that GPS measurements understate land area in Nigeria on medium plots by 2.8% and small plots by -2.0% compared to CR methods.

The majority of this literature has focused on the implications NCMEs have with respect to researchers' understanding of agricultural productivity. Of particular interest has been what is often referred to as the *inverse relationship* (IR) between field size and yield, or the historical tendency for SR data to suggest that smaller fields achieve higher yields than larger fields. This relationship was first observed in Russia (Chayanov 1926) and India (Sen 1962), and has been found in a wide variety of production agriculture settings (Collier and Dercon 2014), including Zambia (Kimhi 2003). Barrett, Bellemare, and Hou (2010) consider three alternative drivers of the IR: imperfect factor markets, omitted variables, and measurement error. Most factor market imperfections rely on the idea that smaller farms engage surplus labor (Sen 1966) or monitor more effectively (Feder 1985), leading to higher productivity. Barrett (1996) argues that imperfect land and insurance markets may lead small (large) farms to undersupply (oversupply) labor to protect against price fluctuations. Omitted variables for important variables in the production process (e.g., soil organic carbon) can lead to spurious correlation, due to unobserved plot heterogeneity (Benjamin 1995; Bhalla and Roy 1988). Finally, Lamb (2003) highlights how measurement error in land size that is correlated negatively with landholdings can lead to findings of an IR.

Recent evidence suggests the IR may well be a function of NCME in plot areas or output. Holden and Fisher (2013) find significant evidence in Malawi that measurement error leads to overestimation of the IR on the smallest farms (<1 ha) and underestimation in the entire sample. Carletto, Savastano, and Zezza (2013) control for measurement error using GPS estimates in Uganda, finding stronger evidence of an inverse relationship while Gourlay, Kilic, and Lobell (2019) find constant returns. The context of estimating the IR is important, as Carletto, Gourlay, and Winters (2015) overall find that the IR is stronger when estimated with SR data (e.g., Tanzania), but this result may differ based on the country of analysis. Similar NCME issues exist when using yield data. Desiere and Jolliffe (2018) compare SR and crop-cut yield measures in Ethiopia, finding strong evidence that the IR disappears when correcting for bias in output measurements. Abay et al. (2019) demonstrate that correcting for NCME in both plot size and output accounts for the IR using data from Ethiopia; however, correcting only a single variable's NCME can bias results in any direction.

This study makes several key contributions to the literature. First, we assess the prevalence of NCME and the implications for yield estimates and the IR using nationally representative data for the case of Zambia. To the best of our knowledge, this is the first study to compare SR and GPS measures of farm size in Zambia.

Our second contribution is to address an important question that we feel has been overlooked in the measurement error conversation. Specifically, if the farmers providing SR data have a poor understanding of how many hectares they are tending, does this affect their input use rates and, therefore, the efficiency with which inputs are used?

Before trying to answer this question, it is important to be clear that the potential problem lies not with a farmer's misunderstanding of a field's size, but with the disconnect that may exist between a farmer's description of size and the descriptions used to convey agronomic recommendations. A farmer looking out at the piece of land they are farming knows how big it is in a real sense. However, they may not have very accurate knowledge of how big a piece of land is in terms of the units of measurement that are used to communicate recommendations for application of inputs like seed and fertilizer. The problems such a disconnect would present could be immensely important. If a farmer believes they are following recommendations (or even if they are going against recommendations but using recommendations as a benchmark), one major potential downside is that the yields they realize will be inconsistent with what they were told to expect. This makes it more difficult to plan for input purchases, jeopardizes fragile incomes and food security, and has the added disadvantage of lowering the perceived credibility of the advice they are given. Instead they will ultimately be left to rely solely on their own practical knowledge and experimentation—which is of enormous value, to be sure, but which would be better if it were complemented with the knowledge of collective experience and scientific research. A major contribution of this article will be to examine this issue.

Third, this article also explores why SR data have (potentially non-classical) measurement errors. Specifically, are these honest, but incorrect measurements (as described above), or is it also possible that farmers are compelled to deceive data collectors? There is ample incentive for the latter case—often times, especially in Zambia, enumerators are employees of the same government statistics office that may be responsible for assessing tax liabilities (incenting farmers to underreport field sizes to possibly avoid taxation), or employees of an agricultural ministry responsible for allocating input subsidies (giving farmers incentive to overreport field sizes and thus, fertilizer needs). On the other hand, if farmers appear to be generally honest with enumerators, but often factually inaccurate, it is worth investigating the correlations with measurement error so that policy makers can aim to improve farmer knowledge of their farm sizes in the units used for extension recommendations, for example. Reducing field size measurement errors would benefit farmers and researchers alike.

Finally, we explore the broader implications non-classical errors may have for our ability to quantify total land use, and specifically how much land is actually being used in aggregate. Africa is often described as land abundant, while African farmers are described as land constrained (see Chamberlin, Jayne, and Heady (2014) for discussion). This apparent contradiction may also be partially due to non-classical measurement error. Those describing Africa as land abundant point to evidence of total land present (measured with maps or other broad representations) less total land used (defined by farm data). If the quantity of land used has been systemically understated, the conflicting descriptions of land abundance from a continental perspective and land scarcity from a farmer's perspective could be revealed as artifacts of poorly measured area data.

In summary, to meet our objective of understanding the implications of field size measurement for researchers using the data, farmers providing the data and overall knowledge of land use, we answer five primary research questions, focusing on the case of Zambia:

1. Does SR field size measurement suffer from NCME, or are these data generally accurate?
2. How does area measurement error affect estimates of the aggregate land use?
3. What does measurement error imply for the IR discussion?
4. Do measurement errors affect smallholder input use?
    a. If errors are non-classical, how do reported and actual input use rates vary across different field sizes and between those who over and underreport field size?
    b. What are the yield implications of these findings for input use (would better knowledge lead to higher yields)?
    c. What do these findings suggest regarding whether respondents are deceptive, or honest but incorrect?
5. Do education level and access to agricultural extension explain measurement errors?

We proceed as follows. Section 2 describes the data and overall methods. Section 3 presents the results for each of the research questions highlighted above. Section 4 summarizes our findings and discusses specific implications for researchers and policy makers and proposes feasible ways forward.

2. DATA AND METHODS

This study employs data from the 2012 Rural Agricultural Livelihoods Survey (RALS) carried out in May and June 2012 as a collaborative effort between the Zambian Ministry of Agriculture and Livestock (MAL), the Central Statistics Office (CSO) and the Indaba Agricultural Policy Research Institute (IAPRI). Standard enumeration areas (SEAs) used by the CSO for census purposes were selected using probability proportional to size, and a constant sample size of 20 households was surveyed in each SEA. Pursuant to standard MAL protocols, within each SEA preference was given to certain underrepresented groups (e.g., those growing more than 5 ha, or those tending to certain types of livestock). To compensate for this non-randomness, CSO assigned each observation with a probability weight reflecting the likelihood of being included in the sample so that weighted results are considered representative at the national level and within provinces of smallholder farm households (defined in Zambia as those cultivating less than 20 ha).

The RALS questionnaire covered a broad range of household economic data covering the 2011 harvest and 2012 marketing season.[2] Four of the 20 selected observations in each SEA were chosen at random[3] to be included in the subsample used for this analysis, for which another small survey collected information related to the 2012 harvest for the household's largest maize field.[4] The area of each subsampled field in our sample was recorded from the farmer's self-reporting in whatever units they specified (e.g., hectares, acres, limas (quarter hectares), or a farmer-specified fraction thereof), then converted to hectares using standard conversion values. Then, each field was also measured by walking the perimeter with a Garmin eTrex GPS unit with a 3-meter margin of error. For a full description of sampling methods see IAPRI (2012). A map of sample village locations can be found in Burke et al. (2019).

The largest maize fields were chosen primarily because it was not feasible to measure all fields, and this was identified as the simplest way to standardize protocol. We acknowledge the caveat, however, that using only the largest field might introduce some sampling bias (e.g., if the largest maize fields tend to be more or less likely to be mismeasured than other maize fields). It is thus worth noting that the majority of households in the RALS (over 60%) have only one maize field to choose from. However, if our mean effects are drastically different than those found in earlier studies, this possible sampling drawback should be considered.

In total, RALS respondents provided information for 1,680 largest maize field (LMF) surveys. Of this group, 16 (<1%) were missing GPS measurement data and 8 (<0.5%) were missing SR field sizes. Of the remaining 1,657 fields, four whose GPS-measured area is greater than 10 ha are omitted as outliers, but it is worth noting that all of our main results are also robust to their inclusion. The bulk of our analysis, therefore, is conducted using a full sample of 1,653 field-level observations. In Table 2 and Table 3, we also omit four observations whose fertilizer application rates are outliers (application rates over 5 tonnes/ha), which were most likely data entry errors, but these observations are included in all of the analysis that does not include a discussion of fertilizer rates.

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[2] The full questionnaire is available on-line at http://www.iapri.org.zm/images/Surveys/2012_Rural_Agricultural_Livelihoods_Survey.pdf

[3] Since the subsample was chosen at random, sample weights developed for the full sample can be used without adjustment for regression analysis or reporting means. For estimating aggregate statistics like total land at the national level, the weights need to be multiplied by 5.

[4] The smaller questionnaire has not been posted on-line but can be made available.

The methods employed to answer each research question will differ to fit each purpose. Rather than go through a detailed description of specific methods here, each will be described as results are presented in order to maintain a comprehensible organization. However, there are two broad categories that are used throughout, which we will define here. First, we identify each field as smaller or larger than 1.25 ha when measured by GPS.[5] Second, each field is categorized depending on whether SR measurements are underreported, accurate, or overreported.

The motivation for choosing 1.25 ha as the cutoff point is based on the analysis in Figure 1 because this seems to be a consistently identified point at which the nature of mismeasurement changes. To define SR measurements as either accurate or not we rely on the measurement error for the GPS units themselves, which can identify a location on the ground within 3 meters. Fortunately, this is much more precise than the ±15 meters described as standard position accuracy by Dillon et al. (2019).[6] The Garmin eTrex units actually report a unique measurement error any time a measurement is taken, however enumerators were instructed to wait for enough satellite reception to reach a high degree of position accuracy. Typically, a 3-meter error was acquired in less than two minutes: 94% of enumerators recorded a 3-meter margin error and 99% were within 9 meters.

Therefore, we define a farmer as having accurately reported the area of the field if the SR measurement is within the bounds defined by $\left(\sqrt{Area_{GPS}} \pm 3\right)^2$. Admittedly, this range implicitly suggests all fields are square, which is decidedly untrue. However, we believe no other definition could be much more sensible without also being more arbitrary.

[5] There are no cases where the GPS measurement is exactly 1.25 ha.

[6] The eTrex specification sheet (https://www8.garmin.com/specs/eTrex_spec_sheet_0105.pdf) does say an error of less than 15 meters 95% of the time is typical. In practice, for us, this turned out to be a very conservative claim.

3. RESULTS

In this section, we will investigate each of the research questions outlined in the introduction in the order they were described.

3.1 Accurate Field Measurement, CME or NCME?

The first question we must address is whether SR field size measurement indeed suffers from measurement error and, if so, whether those errors are random or non-classical. Specifically, we want to know whether differences between the reported field area measurements and GPS measured area are systemically correlated with actual (GPS) field size.[7] The first part of this question can be answered simply by comparing the sample means of the SR and GPS area measurements, as in the far right column of Table 1. On average, the objectively measured field size is 0.96 ha, or 0.07 ha greater than the average SR field size; this difference is statistically significant at a 1% level. Importantly, even if this difference were not significant, we might still find evidence of NCME, but this result alone is sufficient for us to conclude that there is *at least* CME.

Table 1 also suggests that measurement errors are non-classical and, indeed, correlated with actual field size. For example, of the 1,167 fields smaller than 1.25 ha, the majority (598, or 51%) are reported by farmers as more hectares than they actually are. Conversely, on relatively larger fields two-thirds of respondents understate their field sizes. The tendency for the area of small fields to be overstated and large fields to be understated is consistent with nearly every example in the literature that examines this relationship (De Groote and Traoré 2005; Carletto Savastano, and Zezza 2013; Holden and Fisher 2013; Desiere and Jolliffe 2018; Abay et al. 2019; Dillon et al. 2019).

To examine this relationship more explicitly, four estimated relationships are illustrated over a scatterplot of the full dataset in the left panel of Figure 1; the right panel shows a closeup of the highlighted region. All four estimates treat SR measurement as the dependent variable and GPS area as the explanatory variable. There is also a dashed line indicating perfect accuracy, or an intercept at 0 and a slope of 1.

Table 1. Evidence of Self-Reported Field Size Measurement Error on Zambian Maize Fields

	Smaller fields (<1.25 GPS ha)			Larger fields (>1.25 GPS ha)			
	Under-estimate	Accurate	Over-estimate	Under-estimate	Accurate	Over-estimate	Full Sample
Area Measure	Mean hectares by category						
Actual (GPS)	0.65	0.48	0.43	2.48	2.33	2.12	0.96
Self-reported	0.40	0.48	0.82	1.45	2.32	2.96	0.89
Difference	0.25***	0.00	-0.39***	1.03***	0.01	-0.84***	0.07***
N	384	185	598	328	54	104	1,653

Source: CSO/MAL/IAPRI (2012), LMF subsample.

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Hypothesis testing is only conducted on difference values (highlighted).

[7] Henceforth we will refer to actual, GPS-measured, and objectively measured results interchangeably.

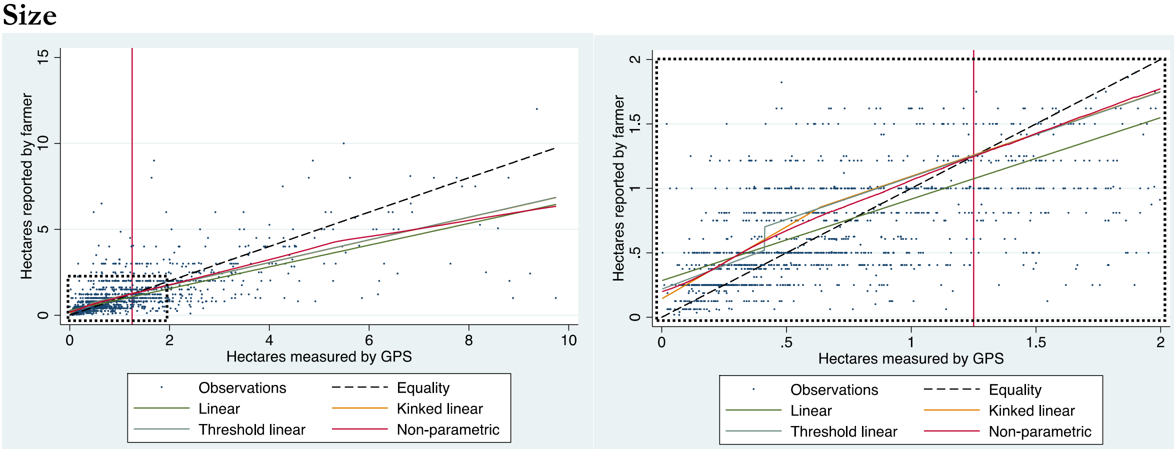
The least flexible (simple linear) regression estimates the intercept at 0.28 ($p<0.01$) and a slope of just 0.63 ($p<0.01$). Moreover, the slope is statistically significantly different from 1 ($p<0.01$). In words, these results tell the same story as above: small field sizes are overestimated while larger fields are underestimated.

The most flexible model presented in Figure 1 is the non-parametric LOWESS regression. These results do not lend themselves to straightforward hypothesis testing, but it is again clear that smaller field sizes tend to be slightly overstated while larger fields are underreported. Moreover, the magnitude of the (negative) measurement error seems to be increasing with field size amongst the overreported fields (similar to the linear regression results).

Between this least and most flexible models are, of course, many alternative specifications. For example, two linear in parameters models would be the constant elasticity and quadratic models. The two we highlight here are threshold-based models. In short, these allow for the structural relationship in a linear regression to fundamentally shift at some threshold value. The threshold itself is estimated using a grid search procedure first introduced by Balke and Fomby (1997) using time series data, and later adapted for various cross-sectional and panel contexts (e.g., Marenya and Barrett 2009; Burke et al. 2019). Essentially, the procedure is to estimate the model with cutoff values at all feasible points and the optimal threshold is identified as that which best fits the data. Figure 1 illustrates 2 threshold models: one is non-linear in parameters and imposes the restriction that the regression line be continuous (the kinked linear model), and the other allows for the regression line to be discontinuous (the threshold linear model). Full results are in Appendix A to conserve space, but notably F-tests for both models reject the null hypothesis of no structural change at the 1% level. Interestingly, all four models tell essentially the same story to the extent that fitted lines are virtually indistinguishable for large segments of Figure 1.

In summary of Table 1 and Figure 1, we find strong evidence to suggest: 1) there is measurement error in SR field size data among Zambian maize producers, and 2) it is NCME that seems to be strongly correlated with actual field size.

Figure 1. Scatter Plot and Four Models Comparing Self-Reported Field Size to Actual Field Size



Source: CSO/MAL/IAPRI (2012), LMF subsample and the authors' calculations. Right panel is an enlargement of the highlighted area in the left panel. Vertical reference line is at 1.25 ha as measured using a Garmin eTrex unit.

Also, of note is the vertical reference line in Figure 1, which sits at 1.25 ha along the GPS-measured axis. Somewhat surprisingly, this is approximately the point at which 3 of the 4 presented fitted lines intersect the line of equality. In other words, below 1.25 objectively measured hectares, most models predict field sizes will be overreported on average, and vice versa on fields larger than 1.25 objectively measured hectares. This is the reason 1.25 is used as the cutoff point at which we disaggregate the analysis in Table 1 and later tables.

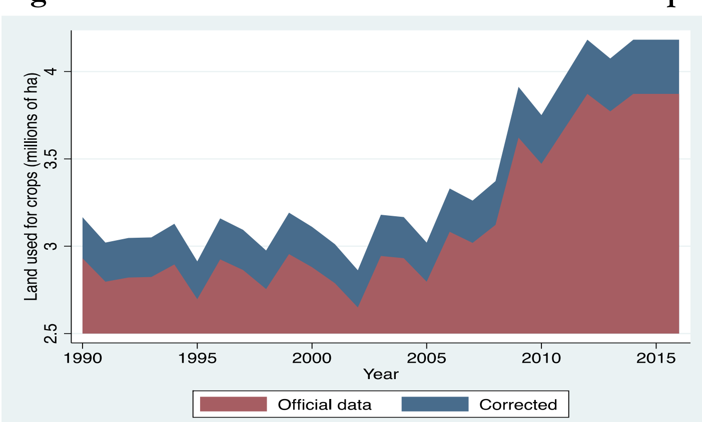
3.2 What Does Area Measurement Error Imply for our Understanding of Aggregate Land Use?

One question of analytical importance is whether and how much reporting errors could be affecting the understanding of total land use. A common source that researchers turn to for these data is the Food and Agriculture Organization of the United Nations (FAO), which, in turn, often accumulates data from official sources. In the case of land use in Zambia, for example, FAO reports official data that are collected by the government. Since 2000, Zambia's official data on annual land use has been based on Crop Forecast and Post-Harvest Surveys. In other words, much of the FAO data comes from SR farmer data that we have shown is subject to NCME and exhibits an overall tendency to understate field sizes.

This sample is of the largest maize fields only, so it cannot be used to compute total area under cultivation for the entire country. However, it is a nationally representative sample of households, meaning that the difference between total area reported by farmers and total area measured by GPS as a proportion can be used to extrapolate how measurement error affects aggregate estimates of area under cultivation. In total, the GPS-based field measurements suggest the largest maize fields of smallholder farmers in Zambia represent 1,269,697 total hectares under cultivation.

The same sample, using farmer-reported field sizes, suggests largest maize fields of smallholder farmers in Zambia represent 1,175,397 hectares in total. In other words, the area measured by GPS is 8% greater than the area reported by farmers, so the aggregate statistics that are based on farmer-reported data systemically understate the amount of land that is being used (or overstate the amount of arable land that is still available). In terms of national total land use, an 8% error in aggregate statistics could mean official data represent 300,000 fewer hectares under cultivation of annual crops than are actually being used (FAOStat 2019; Figure 2).

Figure 2. Land under Annual and Permanent Crops: Official Data and 8% Correction



Sources: FAOStat and authors' calculations.

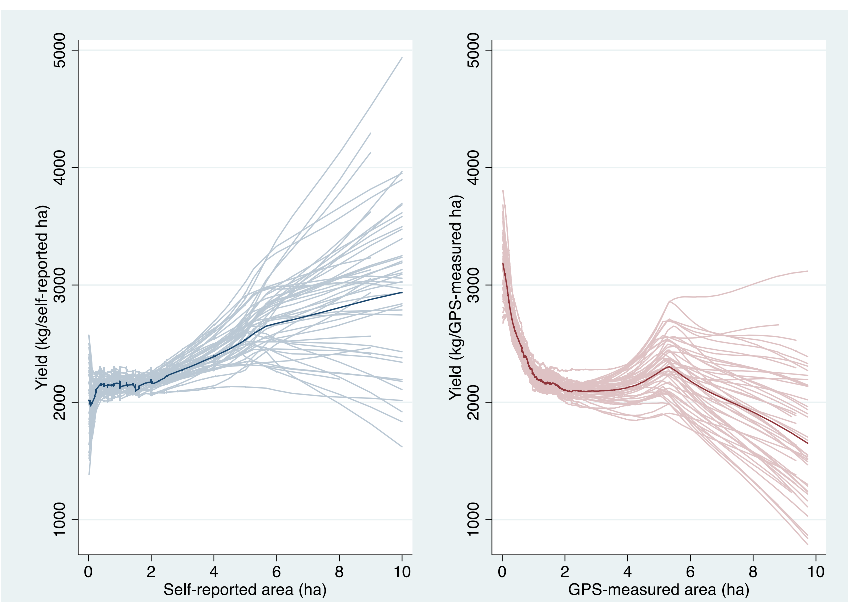
3.3 What Does Field Size Measurement Error Imply for the Inverse Relationship Discussion?

Evidence examining whether an IR between yield and field size appears in Zambian maize plots, and how that relationship is influenced by field measurement, is presented in Figure 3. The dark line in the foreground of the left panel is the non-parametric LOWESS regression of yield computed using the SR measurement on the SR values of field area. In other words, the left panel of Figure 3 shows what we would understand the relationship to be in a dataset lacking objective area measurements. In the background, the lighter lines are the results from 50 bootstrapped repetitions of the same regression using the same sample size that was selected randomly with replacement (these serve as an alternative to a confidence band that might be presented with results of a parametric regression). The right panel of Figure 3 is analogous, but values along both axes reflect the area measurements obtained using GPS units.

Unlike with many prior SR-based data, the left panel does not reflect the presence of an inverse relationship. To the contrary, as farmer-reported area increases, the yield estimates based on SR data seem to increase. Evidenced in the bootstrapped results, the relationship on larger (as reported by farmers) fields is based on fewer observations, however, so the estimates on the right side of the left panel are notably less precise.

If we shift focus to the right panel, instead, we find fairly strong evidence of an IR between yield and farm size when both are considered using the actual field size. Here too, the results on the right side of the graph panel are less precise, but the evidence that yields seem to decrease as field size increases is very apparent on areas smaller than 2 ha (which constitutes 85% of our sample).

Figure 3. Non-parametric Relationship between Yield and Field Size: Self-Reported vs. GPS-Measurements



RALS 2012, LMF subsample and the authors' calculations. Notes: Results are LOWESS (non-parametric, bandwidth=0.8) regressions of yield on field size. Darker lines are the full-sample results (N=1,653), lighter lines are 50 bootstrapped repetitions where re-sampling N is equal to full sample N, chosen randomly, with replacement.

In short, Figure 3 suggests that more objective measures of field size add to the strength of the IR evidence, rather than dismissing it as a data artifact. This is in contrast to Holden and Fisher (2013), Desiere and Jolliffe (2018), and Dillon et al. (2019), all of whom found the IR was weaker with objective measures compared to SR measures.[8] We caution the reader, however, from over-emphasizing the importance of this discrepancy. There is no reason to suspect our data were collected in a way that was any more or less valid than those of other studies that reach the opposite conclusion with respect to the IR. Rather, as Abay et al. (2019) highlight, the direction of bias in the presence of non-classical measurement errors on both sides of the correlation equation is unclear. Indeed, Carletto, Savastano, and Zezza (2013) also found a stronger IR with objectively measured field sizes than SR measurements, and Bevis and Barrett (2019) do not find IR to be explained by area measurement errors. Together with other results in published literature, ours illustrate that the effect of NCME on IR estimates within a given dataset can differ substantively from its effect in another dataset. To us, the salient implication of this finding is that researchers would do well to pursue more reliable area measurements moving forward. We contend there is no singular answer to whether past evidence of an IR from studies using SR area data is more fact or artifact.

3.4 Input Use on Misstated Size Fields

The question of how mismeasured fields may be affecting actual input use has been largely overlooked in existing literature. In the context of mixed methods for measuring field sizes, only Dillon et al. (2019) give much attention to the implications of measurement error for input demand, but their focus is on the bias introduced by mismeasurement on estimates of the determinants of input demand. This is an important contribution, but our question—whether misunderstandings of field size on the farmer's behalf actually lead to differences in use of inputs—is quite different.

To investigate our question, we consider the distributions of actual and reported seed and fertilizer application rates presented in Table 2.[9] Once again, we've disaggregated the sample into six categories according to whether the GPS-measured field size is smaller than 1.25 ha and, within field size categories, whether the farmer underreported field size, was accurate, or overreported field size.

In addition to describing the data, the significance levels are indicated for hypothesis tests of whether application rates on under- and overreported fields differ from those accurately reported within each farm size group (as opposed to whether they differ from zero, as might be more commonly reported[10]). For example, the 64.6 kg/ha for the overreported fields in the first row of results is significantly different from the 27.7 kg/ha on accurately reported fields at the 1% level, whereas the 22.8 kg/ha on underreported fields is significantly different from the 27.7 kg/ha on accurately reported fields at the 5% level. Standard errors for these tests are not reported to conserve space but can be provided.

[8] Dillon et al. (2019) employed crop cuts, so they did not rely on farmer-reported data for either the numerator or the denominator of yield calculations, which is an additional difference compared to ours and the other studies mentioned.

[9] Effectively all of the fertilizer used in Zambia is either urea (top dressing, NPK=46-0-0) or Compound D (basal, NPK=10-20-10)

[10] The mean application rates for the fields accurately described in the SR data are the baselines for hypothesis testing in other columns, which is why they (and the full sample means) are shaded and no significance levels are reported. Obviously, all observations used seed, and the results in the rows pertaining to basal and urea rates only include observations using those fertilizers, so naturally all of the means are significantly different from zero.

Table 2. The Effects of Field-Size Misestimation on Input Use and Yield

		Smaller fields (<1.25 GPS ha)			Larger fields (>1.25 GPS ha)			
Application rates (kg/ha)		Under reported [a]	Accurate [b]	Over reported [a]	Under reported [a]	Accurate [b]	Over reported [a]	Full Sample
Seeding	Actual (at GPS)	22.8**	27.7	64.6***	15.3**	19.3	30.8***	37.8
	Reported	38.4***	28.1	31.6	29.8***	19.4	22.2	32.0
Basal fertilizer[c]	Actual (at GPS)	124.7***	175.8	310.5***	88.3**	122.6	170.8***	193.2
	Reported	204.3**	176.5	149.5***	152.0	122.7	122.3	163.8
Urea fertilizer[d]	Actual (at GPS)	120.7***	169.1	299.2***	88.0*	116.7	166.2***	186.6
	Reported	198.2**	170.1	144.0***	152.3*	116.9	118.4	159.8
N=	Full sample	383	185	595	328	54	104	1649
	Basal users	203	117	367	237	40	85	1049
	Urea users	214	122	372	239	42	86	1075

Source: CSO/MAL/IAPRI (2012), LMF subsample.

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. a. Hypothesis tests are for whether application rates on under- and overreported fields differ from those accurately reported within the farm size group. b. Results in these columns are the baseline for hypothesis testing in other columns, which is why no significance levels are reported. Naturally, all are significantly different from zero. c. Means in these rows only include basal fertilizer users. d. Means in these rows only include urea users.

On smaller fields, where the actual size is less than 1.25 ha, reported seed rates are similar between fields where area is accurately reported and those where area is overreported (28 and 32 kg/ha, respectively) and not significantly different from each other. These are both similar to the mean reported seed application rate for the full sample (32 kg/ha), which is over 50% greater than the 20 kg/ha seed application rate recommended by the Zambia Agricultural Research Institute (ZARI). The recommended seed application rate is expected to produce 44,000 plants/ha (ZARI 2002). The reported seed rate on fields that farmers say are smaller than they actually are (the underreported fields) is significantly higher at 38 kg/ha. If farmers believe what they are reporting, this could seem sensible—the less land they believe they have, the more incentive they may have to increase plant population density to maximize output (even if that means exceeding the agronomically efficient seeding rate). As Holden and Fisher (2013) illustrated, food self-sufficiency goals can motivate intensification on smaller farms.

Unlike reported seeding rates, though, actual seed rates follow an opposite trend. On accurately reported fields, by definition, the actual seed rate is essentially identical to the reported seed rate (28 kg/ha). On fields where area is overreported, however, the actual seed rate is more than twice as high (65 kg/ha), and significantly different at the 1% level from actual rates on accurately reported fields. In other words, where farmers report their land is more hectares than it actually is, they tend to have dramatically exceeded recommended and even average seed rates. Conversely, on the smaller fields where the reported area is lower than the actual area, seed rates are lower on average (23 kg/ha) compared to accurately reported fields, and that difference is significant at the 5% level.

This pattern is very similar on larger fields (those greater than 1.25 ha). The reported seed rates on accurately and overreported fields are 19 and 22 kg/ha respectively, compared to 30 kg/ha on underreported field sizes. The actual seed rates, however, are significantly lower (at 15 kg/ha) on underreported fields and significantly higher (at 30.8 hg/ha) on overreported fields.

The pattern is also similar when we examine fertilizer use. (Note the rows describing fertilizer application rates in Table 2 only include the users of that type of fertilizer in the reported means.) We can say, for example, that on smaller fields those who use basal fertilizer and accurately describe their hectarage report applying 177 basal kg/ha. Those who understate the size of their fields report applying basal at a significantly higher rate (204 kg/ha), but actually apply at a lower rate (125 kg/ha). Conversely, those who overstate their field size report basal application rates that are significantly lower (150 kg/ha) than the accurately reported fields, while their actual application rates are quite substantially (and statistically significantly) higher (311 kg/ha). The results for urea closely follow the same pattern.

In summary, the trends evident in Table 2 are very clear. On the fields that farmers believe to be (or report to be) fewer hectares than they actually are, they report relatively intensive input use rates, but their actual input use rates are lower than average. On the fields that farmers report being more hectares than they actually are, reported input use rates are more similar to those on accurately reported fields, but in reality, they are applying fertilizer and seed significantly more intensively.

3.5 Misstated Field Size Compared to Actual Yield

The next question we ask is whether the differences we see between reported application rates and the actual application rates would be expected to make any meaningful difference with respect to the yields farmers might expect. To this end, we turn to a series of simulations in Table 3 below. These show: i) expected yields at the actual (as measured by GPS) seed and fertilizer application rates; ii) the difference in expected yields if fertilizer and seed rates had actually been what farmers reported they were; and iii) what the expected yields would have been if all seed and fertilizer inputs had actually been applied at the rates in which they were reported to have been applied. All of these simulations are again broken down according to whether the field in question is smaller or larger than 1.25 ha, and whether the farmer accurately reported hectarage or if they under- or overreported field size. In order to carry out these simulations, we rely on the estimates of yield and yield response to fertilizer from Burke et al. (2019), which are based on the same data and using GPS measures we use for this analysis.

Specifically, we use the Model 1 results from that study, which include the level and square of the application rate for each input as well as controls for many other potential yield determinants such as soil organic matter, soil pH, the timing of basal applications.

If we only observe the means of the full sample, it does not appear that self-reported or GPS-measured application rates make much difference: the difference is only 56 kg/ha between the expected yields at actual application rates compared to farmer-reported rates. This, however, masks considerable variation between the overreporting and underreporting groups of farmers. Upon closer inspection, the results in Table 3 are very consistent with the results in Table 2. In general, if the farmers who underestimated field size had applied seed and fertilizer at the rates they reported, their yields would have been 39% (2,300/1,651) and 44% (2,192/1,522) higher on smaller and larger fields respectively. If the farmers believed they were applying inputs at the rates they reported, these results have important implications. In particular, based on the amount of inputs per hectare the farmers said they were using, they would likely have expected yields much higher than those ultimately realized.

Table 3. The Impact of Field-size Misestimation on Input Use and Yield

	Smaller fields (<1.25 ha)			Larger fields (>1.25ha)			Full Sample
	Under reported	Accurate	Over reported	Under reported	Accurate	Over reported	
i) Expected yields at actual seed and fertilizer application rates (as measured by GPS)[c]:							
	1,651	2,228	2,906	1,522	2,064	2,725	2,209
ii) Counter-factual difference in expected yield if[c]:							
Actual seed rate=reported seed rate	309.9	7.7	-469.8	308.5	2.5	-192.4	-38.4
Actual basal rate=reported basal rate[a]	267.8	0.9	-336.9	237.4	2.0	-174.8	-14.4
Actual urea rate=reported urea rate[b]	346.5	4.7	-443.3	325.1	0.8	-217.1	-14.7
iii) Expected yields if all actual seed and fertilizer rates were at reported fertilizer rates[c,d]:							
	2,300	2,239	1,991	2,192	2,068	2,232	2,153

Source: CSO/MAL/IAPRI (2012), LMF subsample.

Notes: a – Only includes basal fertilizer users. b – Only includes urea users. c – All simulations and expected values are computed using parameters reported in Burke et al. (2019), which estimate yield and response to fertilizer and seed using the same dataset as the present study. d – The total difference between expectations at actual and counter-factual application rates do not equate to the sum of the differences from the three partially counter-factual simulations because the individual differences examining fertilizer effects excludes those who do not apply fertilizer (the total difference includes all observations).

The converse appears to be the case for the farmers that overstated the hectarage of their fields: expected yields at reported input application rates on smaller fields are just 67% of the expected yield at the actual (higher) rates. On larger fields, the difference is 80%.

There are two more important observations about Table 3. First, for all of the groups that have mis-stated their field sizes, it appears as though differences between expected and actual seed use are more important than differences in either basal or urea use (see section *ii* of Table 3). Moreover, the figures in the rows describing effects of basal and urea differences exclude the fact that many farmers use no fertilizer at all (as was the case, for example, on 36% of fields in Table 2).

So, the relative importance of seed rates is greater than it appears to be in these results. The final point from Table 3 is regarding the evidence of truthfulness amongst respondents.

3.6 Telling Lies or Making Honest Mistakes?

The expected yields based on the input use rates that farmers report in Table 3 are all fairly similar, ranging from 1,991 kg/ha on the overreported smaller fields to 2,300 on the underreported smaller fields. By contrast, yields that should have been expected based on actual application rates vary considerably. Moreover, the correct expected yields are lowest on the underreported fields (1,651 and 1,522 kg/ha on smaller and larger fields respectively), and highest on the overreported fields (2,906 and 2,725 kg/ha). These differences are more drastic than the expectations at reported input rates and, we also believe, evidence that farmers are not intentionally deceiving data collectors. We rather believe the evidence is more consistent with respondents being honest and incorrect when reporting the number of hectares they are farming.

It is important to ask whether the discrepancies we see between reported and measured field sizes reflect dishonesty from respondents or just a misunderstanding of hectarage, because the answer largely determines the scope of the implications of the present and similar studies. If respondents are being dishonest, the implications essentially rest in the importance of collecting more reliable data going forward. If, on the other hand, respondents are honest but incorrect, the implications extend further to identifying a need to better educate farmers.

Either case is plausible. There may be incentives for a farmer knowledgeable about hectarage to lie in either direction depending on to whom they believe they are giving information (a subsidy provider versus a tax assessor, for example). It is also quite feasible that a farmer with a very sound understanding of their field size in a real sense does not have a concrete understanding of the area in terms of hectares (or acres or other units that are also collected and converted to hectares *ex post*). The question of honesty is, by its nature, a difficult one to address empirically. Admittedly, it is impossible to say definitively whether farmers are typically lying to enumerators or are making honest mistakes when they misreport their farm sizes, but we believe the data do offer some clues.

First, counterfactual expected yields based on reported applications—that is, the expected yields if farmers really used inputs at the rates they report using them—are similar across groups. Predicted yields at the actual application rates, on the other hand, vary more substantially depending on field size and reporting error. These results are more consistent with farmers making honest reporting errors than intentionally deceiving enumerators. In short, this argument is reduced to the question of whether farmers are likely all aiming for a similar yield (i.e., they believed the reported rates themselves), or if some farmers are aiming for drastically different yields (i.e., they knew the actual application rates and lied), and that those differences are correlated with whether or not they eventually speak to an enumerator. On its face, the former possibility seems, to us, more likely, but the real linchpin is in the last part of the latter case. Given that farmers did not know whether they would eventually be speaking to an enumerator, the case where farmers' tendency to lie is highly correlated with intended yields seems highly unlikely.

A parallel argument could be made about the relative similarity in reported input use compared to the actual input rates. We look at this more explicitly in Table 4, showing results from linear regressions of total seed and fertilizer use (amongst those who use it) on the actual size of the field. We include as additional regressors the difference in the number of hectares reported and the actual size of the field, with separate variables for the absolute values of the overestimates and underestimates. To be clear, these are not input demand equations that would need to include a battery of other explanatory variables, such as prices of inputs, expected prices of outputs, transaction costs, and so on. The important roles of these variables are investigated at length elsewhere in the literature and are well beyond our scope. Rather, Table 4 allows us to simply address a straightforward question: given the actual size of the field, do farmers who incorrectly describe their fields as larger (or smaller) use more (or fewer) inputs? If they do—if the coefficients on the overreported and underreported hectares are significantly different from zero—it suggests they actually believe the incorrect area measurements they have told to enumerators.

The evidence leans heavily towards the conclusion that farmers are making honest mistakes. Take, for example, the use of seed. In addition to the intercept term, on fields that are accurately reported (i.e., where the number of hectares over- or underreported is nil), the mean seed use rate would be 19.5 kg/ha. This is essentially identical to the 20 kg/ha seed rate recommended to farmers (ZARI

2002). Moreover, when fields are misreported by farmers, the actual application rates are highly consistent with the combination of recommendations and the area the farmer seems to think they are tending. For every hectare below the actual size of the field that the farmer says they are planting, they use 17.9 kg less seed; for every hectare over the actual size they report, farmers use an additional 19.3 kg of seed. Both of these results are again close to the 20 kg/ha recommendation. The results for basal and urea fertilizer use tell a similar story: although actual and perceived application rates are lower than recommended, they are more closely proportional to the reported field size than the actual field size. In short, when farmers misreport their field sizes, the quantities of inputs they use suggest they believe what they report to enumerators to be accurate.

Table 4. Do Farmers Who Over (Under) Report Field Size Use More (Fewer) Inputs?

	Seed	Basal	Urea
Actual field size (ha, measured by GPS)	19.48***	102.62***	103.13***
	(1.78)	(9.99)	(9.89)
No. of hectares below actual size reported by farmer	-17.91***	-97.02***	-95.23***
	(2.54)	(14.77)	(14.72)
No. of hectares above actual size reported by farmer	19.28***	63.08***	62.32***
	(1.66)	(12.38)	(12.21)
Constant	5.47***	39.13***	34.88***
	(1.19)	(6.30)	(6.14)
Observations	1,653	1,052	1,078
R-squared	0.436	0.439	0.447

Source: CSO/MAL/IAPRI (2012), LMF subsample.

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels, respectively. Robust standard errors in parentheses.

3.7 Extension, Education and Non-classical Measurement Errors

If farmers are truthful in their responses to enumerators, the implications of our finding that they are very often incorrect about their field size is problematic, not just for data analysts, but for farmers too. We have seen that misperceptions of field size can lead to fertilizer and seed application rates that are quite different from those the farmers seem to believe they are using. Again, the major issue is that farmers are often given advice on how many seeds or kg of fertilizer they should be using in per hectare terms. Earlier, for example, we highlighted some of these recommendations that come from the extension arm of ZARI, which is in turn part of MAL: 20 kg/ha of seed and 200 kg/ha each of basal and urea fertilizers.

Having established that field size errors are prevalent and important, we now turn to the question of which farmers are more likely to misunderstand the hectarage of their fields. In particular we will examine the relevance of access to extension and of formal education levels. For extension, we are particularly interested in whether farmers have had exposure to the concepts of conservation farming (CF), which has gained much attention in recent years (e.g., Haggblade and Tembo 2003; Thierfelder and Wall 2009; Haggblade, Kabwe and Plerhoples 2011; Umar et al. 2011). The tenets of CF emphasize minimum tillage, crop residue retention, and crop rotation—these are typically the focus of CF studies. Another aspect of CF, however, is careful monitoring of input use, which essentially as a prerequisite, includes knowing the area of one's field (Haggblade and Tembo 2003).

So, we might expect those with exposure to CF information to know the area of their fields more accurately.[11] Similarly, we might expect those with a higher degree of formal education to better understand area measurements in the units used to disseminate advice (and collect data).
There are several ways a farmer might have become exposed to CF, including through contact with ZARI/MAL extension officers. The Conservation Farming Unit (CFU)[12] is a non-governmental organization sponsored by UKAID, which teaches precise spacing of rows or planting basins, making farmers more likely to know their actual field sizes. Farmers also respond that other NGOs sometimes teach CF. Private companies may teach CF techniques to the farmers from whom they purchase goods, as is common in cotton contract farming. Finally, some farmers may be told about CF practices from their peers.

Table 5 presents results from a regression-based examination of the differences in NCME, disaggregating the full sample according to their primary source of information on CF. Since the several specifications represented in Figure 1 show qualitatively similar results, we focus here on just one simple linear regression of reported hectares on GPS measured hectares for each group. There are only two parameters in each regression; if farmers are accurate on average, the intercept would be zero and the coefficient on the GPS-measured plot size (the slope parameter) would be one. We also present post-estimation tests at the bottom of Table 5 for each group of the null hypothesis that the slope parameter is one (versus the alternative that it is not). So a good result, i.e., one indicating farmers are accurate on average, would be a failure to reject the null hypothesis for the intercept in the main results coupled with a failure to reject the null in the post-estimation analysis. As a visual aid for interpreting these results, Figure 4 shows all linear relationships, vis-à-vis each other, and a dashed line indicating perfect one-to-one accuracy.[13]

The first group, column (*i*), are farmers who responded they have not received any information on CF. Perhaps unsurprisingly, these farmers are the least accurate on average, with an intercept that is 0.33 ($p<0.01$) and a slope estimate that is 0.49 less than, and statistically significantly different from unity ($p<0.01$). Results are only marginally improved for farmers that were exposed to the tenets of CF practices by another farmer (column (*v*) in Table 5). As can be seen in Figure 4, these two groups perform essentially the same in most contexts that are meaningful to smallholders (e.g., where actual field sizes are below 2 ha, which covers 85% of our sample; also see Figure 1). It is worth noting that, together, those who have not heard of CF and those who learned from another farmer comprise the majority (52%) of our sample.

Conversely, the 137 farmers responding that they learned CF from a private firm are the most accurate. Amongst this group the estimated intercept term is not significantly different from zero and the slope parameter is just 0.11 less than and not significantly different from unity (column (*iii*) of Table 5).

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[11] Other than CF, no specific variety of extension advice we know of emphasizes area measurement, though certainly it is often taught as part of some general extension services. Treating "access the extension" more generally as a categorical variable is not as revealing as the results in Table 5.

[12] https://conservationagriculture.org/

[13] All of the separate regressions in Table 5 can be estimated simultaneously in one regression that nests models in columns (i) – (vi), which is reported in Appendix B. Those results, using *no training* as the base category, show that none of the intercepts are significantly different from the base estimate of 0.325; the slope estimates for GPS-recorded ha in the ZARI/MAL, private firm, and CFU training groups are significantly different from the base estimate of 0.515 ($p<0.06$, $p<0.02$ and $p<0.01$ respectively); the slope estimates for GPS-recorded ha in the training groups for another farmer and "other/NGO" are not significantly different from the base estimate.

Moreover, these farmers' estimates appear to be relatively precise as well as accurate; 70% of the variation in reported field size is explained by the actual farm size. This compares to just 38% of the variation in reported farm size explained for the group that has not learned of CF and 52% for the sample overall. The small group of 82 farmers in our sample that were trained by the CFU performed similarly well. Although the intercept estimate for this group is statistically significantly different from zero, the magnitude is relatively small (0.23; $p<0.10$) and the slope estimate is not significantly different from unity. In the depiction in Figure 4, the regression lines for these two groups are virtually indistinguishable.

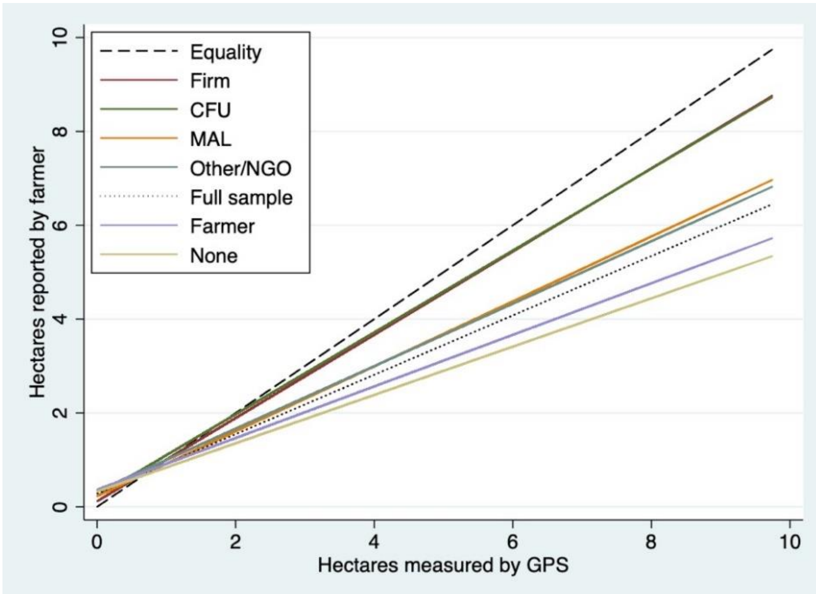
Table 5. Non-classical Field Measurement Error in the Context of Access to CF Extension

	No CF	ZARI/ MAL	Private firm	CFU	Another farmer	Other/ NGO	Full sample
Reported ha=	(i)	(ii)	(iii)	(iv)	(v)	(vi)	(vii)
GPS ha	0.515***	0.692***	0.887***	0.872***	0.550***	0.665***	0.633***
	(0.075)	(0.054)	(0.134)	(0.093)	(0.171)	(0.138)	(0.053)
Constant	0.325***	0.227***	0.118	0.228*	0.367**	0.352**	0.284***
	(0.049)	(0.050)	(0.130)	(0.134)	(0.156)	(0.137)	(0.043)
Observations	693	472	137	82	171	96	1,653
R-squared	0.384	0.579	0.702	0.638	0.514	0.542	0.515
Post-estimation test (GPS ha coef.=1)	-0.485***	-0.308***	-0.113	-0.128	-0.450**	-0.335***	-0.367***
	(0.075)	(0.054)	(0.134)	(0.093)	(0.171)	(0.138)	(0.053)

Source: CSO/MAL/IAPRI (2012), LMF subsample.

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Robust standard errors in parentheses.

Figure 4. Reporting Error by Conservation Farming Knowledge Source (Results from Table 5)



Source: CSO/MAL/IAPRI (2012), LMF subsample.

Note: Lines are listed in the legend in the order that they appear (top to bottom) on the far-right side of the figure

Table 6. Non-classical Field Measurement Error in the Context of Access to Formal Education

	No school	1-7 yrs	8-12 yrs	College/ certificate	Full sample
Reported ha=	(i)	(ii)	(iii)	(iv)	(v)
GPS ha	0.285***	0.682***	0.617***	0.786***	0.633***
	(0.067)	(0.076)	(0.098)	(0.063)	(0.053)
Constant	0.442***	0.248***	0.353***	0.121***	0.284***
	(0.064)	(0.060)	(0.083)	(0.044)	(0.043)
Observations	171	903	490	89	1,653
R-squared	0.215	0.562	0.494	0.704	0.515
Post-estimation test					
(Coefficient–1) =	-0.715***	-0.318***	-0.383***	-0.214***	-0.367***
	(0.067)	(0.076)	(0.098)	(0.063)	(0.053)

Source: CSO/MAL/IAPRI (2012), LMF subsample.

Notes: *, ** and *** indicate statistical significance at the 10%, 5% and 1% levels respectively. Robust standard errors in parentheses. The "post-estimation test" is the null hypothesis that farmer-reported field size estimates are correct vs. the alternative that they are incorrect.

Table 6 is organized similarly to Table 5, therefore, interpretation can be carried out in much the same way.[14] Here, though, the sample is disaggregated according to the highest level of formal

[14] Estimates of a nesting model for columns (i) – (iv) are reported in Appendix C using *no education* as the base category; the slope estimates for GPS-recorded ha in each education group is significantly different from the base estimate of

education obtained by the head of the household responsible for managing each field. This is meant to examine whether more educated farmers (who may be more literate in the units of measurement used to record data) are more accurate. Although all of the intercept terms in Table 6 are significantly different from zero, and all of the slope terms are significantly different from unity, there is, indeed, evidence that education makes a difference.

The farmers with 1-7 years of formal education perform similarly to those with 8-12 years of education, and both of these groups are on par with the overall sample. If there is any difference between these two groups, the farmers with 1-7 years of education appear to be slightly more accurate, on average. However, amongst the 10% of respondents, whose household heads have no formal education; we see the slope parameter is actually closer to nil than it is to unity. Roughly, the opposite is true for the 5% of the respondents whose household heads achieved post-secondary (college or certificate) education. In short, these results point to a fairly dramatic, albeit unsurprising, relationship between literacy and the ability to accurately relate the size of one's field in standard units. As the uneducated are disproportionately also poor, this relationship provides a telling example of the importance of education with respect to welfare.

0.285 ($p<0.01$ in each case). We also test and fail to reject the null hypothesis that slope coefficients are the same for those with college/certificate, 1-7 years, and 8-12 years of education.

4. DISCUSSION AND CONCLUSION

While data has long relied on farmers to provide descriptions of themselves or their land, there is mounting evidence that their ability to do so is systemically inaccurate with regards to field areas. This has many problematic implications. Several studies have focused on how area measurement errors affect the ability to describe farmers. This study contributed to the growing evidence, showing that smaller field sizes tend to be overstated, while larger fields tend to be described as smaller than they actually are in this sample of Zambian maize fields.

Interestingly, we found that using more objective measurements actually strengthened the evidence of the often-called inverse relationship between field sizes and yields. This finding is in contrast to most other analyses of data employing mixed methods for measuring fields. Our findings do not rule out the possibility of self-reported data as a potential source for IR artifacts in other data and country contexts; rather, our results underscore that the magnitude and direction of bias and its implications for the IR can differ from one dataset to another. The important conclusion, we believe, is that quality agricultural area data collection should be prioritized by researchers and those funding research. This is likely to become increasingly feasible as the cost and measurement errors of tools like handheld GPS equipment inevitably decline. Also, holding confidence in our results constant, less measurement error would mean we could rely on smaller samples, which would reduce costs. On the other hand, the cost of measuring all fields will not be the same – on farms where some fields are very far from home, for example, there is a time-cost for the enumerator that cannot be ignored. There is a need for research on weighing the costs and benefits of minimizing field area measurements that is not possible with these data.

Nevertheless, improved data collection will be useful for better understanding, for example, the relationship between field sizes and yield at the farm level, but also for generating aggregate statistics. Our results suggest that past figures on national land use may have underestimated crop land by 8%, or 300,000 hectares in recent years, because of the reliance on farmer-reported data.

The major contribution of this study, however, has to do with our findings pertaining to how misunderstandings of measurement affect input use. It bears repeating what our and several other datasets have evidenced: farmers in developing countries are often not literate in the units of measurement used to advise them. The evidence we presented here suggests that farmers themselves believe the area figures they report to enumerators—their input use is more closely aligned with the reported field sizes than with actual field sizes. This is problematic, because the advice they receive is often based on area units (e.g., plant 20 kg of seed per hectare; use 200 kg of urea per hectare).

The finding also begs the question, how do farmers come up with the figures they seem to believe are accurate when reporting to enumerators? As a follow up to this analysis we visited several farmers and extension agents (both with the MAL and CFU) to get a sense.[15] The most common

[15] Interviews were conducted with research and extension officers from the Zambian Agricultural Research Institute (ZARI), which is part of the Ministry of Agriculture, and the Conservation Farming Unit (CFU) to gain a better understanding on the information farmers receive regarding field size measurements. Interviewees were invited to share their knowledge on topics including the methods extension officers train farmers to determine field sizes, the most common methods farmers actually use, and the agents' perceptions of how accurate farmers are. A small group of seven farmers (four female) were also interviewed. It is important to acknowledge these farmers were chosen based on their availability and are, thus, not a random sample. While their sampling cannot be considered statistically representative, we value their insights into the general knowledge of how fields are measured.

way farmers are taught, and the most common method employed when fields are 4-sided, is either the step or pacing method. The step method teaches that 10 lengths of a person's anatomical foot is equal to one meter, whereas the pacing method teaches a meter is one pace. Both of these methods have the obvious and acknowledged flaw that not everyone's feet and paces are the same length. Another flaw is that many fields are not 4-sided, and many do not even have straight sides. In the case of irregularly shaped fields, farmers are trained to estimate their field size according to how much seed they use—that is, for a maize field, wherever they plant 20 kg of seed, they should assume one hectare. For maize fields, it is thought the seed method is the most commonly used way field size is estimated. The flaw, of course, is that if seed application rates are used to measure field size, field size is not a reliable way to recommend seed application rates—any field size estimation error becomes self-reinforcing. The seed method might be acceptable if the only objective of recommendations is to ensure, say, fertilizer-to-seed ratios, but seed-to-area and fertilizer-to-area ratios may be subject to agronomically important mistakes, as our data suggest they are.

Therefore, a major implication of this study is that farmers would be well served by better training on how to measure field areas. For example, if seed and row spacing is taught to be done with a higher degree of precision, the seed method might prove more reliable. Training in this area would need to take into account the fact that many farmers do not read and write; distributing ropes with knots tied at 90-centimeter intervals may be more useful (and less expensive), for example, than distributing measuring tapes. One interviewee recalled a failed effort to distribute GPS units, which most farmers struggled to put to meaningful use. It may also be helpful just to emphasize the value of accurately knowing one's field size. Extension agencies tell us that knowing field size is a low priority with most focus instead placed on saving money to purchase fertilizer.

Finally, there is the issue of extension efforts overall receiving a low priority in the agricultural budget—just 1% of the agricultural budget on average from 2010-2019, for example (ZMF, various years). Our interviews with officials reveal that every government camp officer is meant to be responsible for educating up to 4,000 farmers—significantly more than their CFU counterparts—and the actual number in their areas can be much higher. Moreover, they are usually ill-equipped to travel to farmers in remote areas, or to bring farmers to them. Demonstration plots could be a useful mechanism or venue to incorporate explicit training on accurate field size measurement, but again funding is seldom allocated for them. One earlier study found, based on estimates developed in consultations with MAL, that maintaining a demonstration plot in every extension camp in Zambia would cost less than 6% of the annual budget allocation to the fertilizer subsidy program (Burke, Jayne, and Black 2017).

In short, we believe this study emphasizes how inaccurate knowledge of field size, at least in terms of the units of measurement that are used to communicate recommendations, is an important disconnect between farmers and the advice they receive. The obvious potential downside is that the yields farmers realize will be inconsistent with what they were told to expect. This makes it more difficult to plan ahead and jeopardizes fragile incomes and food security but has the added disadvantage of lowering the perceived credibility of extension agents and information. Instead, farmers are often left to rely on their own practical knowledge and experimentation, which is of enormous value, but which would be better if it were complemented with the knowledge of collective experience and scientific research. Strengthening extension efforts to improve farmer understanding of hectarage seems important and may be a cost-effective way to improve productivity.

REFERENCES

Abay, K.A., G.T. Abate, C.B. Barrett, and T. Bernard. 2019. Correlated Non-Classical Measurement Errors, 'Second Best' Policy Inference, and the Inverse Size-Productivity Relationship in Agriculture. *Journal of Development Economics* 139: 171–184.

Balke, N.S. and T.B. Fomby. 1997. Threshold Cointegration. *International Economic Review* 38: 627–645.

Barrett, C.B. 1996. On Price Risk and the Inverse Farm Size-Productivity Relationship. *Journal of Development Economics* 51.2: 193–215.

Barrett, C.B., M.F. Bellemare, and J.Y. Hou. 2010. Reconsidering Conventional Explanations of the Inverse Productivity–Size Relationship. *World Development* 38.1: 88–97.

Benjamin, D. 1995. Can Unobserved Land Quality Explain the Inverse Productivity Relationship? *Journal of Development Economics* 46.1: 51–84.

Bhalla, S.S. and P. Roy. 1988. Mis-specification in Farm Productivity Analysis: The Role of Land Quality. *Oxford Economic Papers* 40.1: 55–73.

Bevis, L.E.M. and C.B. Barrett. 2019. Close to the Edge: High Productivity at Plot Peripheries and the Inverse Size-Productivity Relationship. *Journal of Development Economics* in press.

Burke, W.J., T.S. Jayne, and J.R. Black. 2017. Factors Explaining the Low and Variable Profitability of Fertilizer Application to Maize in Zambia. *Agricultural Economics* 48.1: 115–126.

Burke, W.J., E. Frossard, S. Kabwe, and T.S. Jayne. 2019. Understanding Fertilizer Adoption and Effectiveness on Maize in Zambia. *Food Policy* 86 (2019): 1–12.

Carletto, C., S. Gourlay, and P. Winters. 2015. From Guesstimates to GPStimates: Land Area Measurement and Implications for Agricultural Analysis. *Journal of African Economies* 24.5: 593–628.

Carletto, C., S. Savastano, and A. Zezza. 2013. Fact or Artifact: The Impact of Measurement Errors on the Farm Size–Productivity Relationship. *Journal of Development Economics* 103.C: 254–261.

Central Statistical Office, Ministry of Agriculture and Livestock and Indaba Agricultural Policy Research Institute. 2012. Rural Agricultural Livelihoods Survey Data. Lusaka, Zambia: CSO/MAL/IAPRI.

Chamberlin, J., T.S. Jayne and D. Heady. 2014. Scarcity Amidst Abundance? Reassessing the Potential for Cropland Expansion in Africa. *Food Policy* 48 (2014): 51–65.

Chayanov, A.V. 1926. *The Theory of the Peasant Economy*. Ed. D. Torner, B. Kerblay, and R.E.F. Smith. Homewood, Illinous: Irwin.

Collier, P. and S. Dercon. 2014. African Agriculture in 50 Years: Smallholders in a Rapidly Changing World? *World Development* 63 (November): 92–101.

De Groote, H. and O. Traoré. 2005. The Cost of Accuracy in Crop Area Estimation. *Agricultural Systems* 84(1):21–38.

Desiere, S. and D. Jolliffe. 2018. Land Productivity and Plot Size: Is Measurement Error Driving the Inverse Relationship?" *Journal of Development Economics* 130: 84–98.

Dillon, A., S. Gourlay, K. McGee, and G. Oseni. 2019. Land Measurement Bias and Its Empirical Implications: Evidence from a Validation Exercise. *Economic Development and Cultural Change* 67.3: 595-624.

FAO. 2019. FAOSTAT Annual Time Series Data for Cropland, Land under Permanent Crops, and Land under Permanent Pastures in Zambia. Available at: http://www.fao.org/faostat/en/#data/RL

Feder, G. 1985. The Relation between Farm Size and Farm Productivity. *Journal of Development Economics* 18.2–3: 297–313.

Gourlay, S., T. Kilic, and D.B. Lobell. 2019. A New Spin on an Old Debate: Errors in Farmer-Reported Production and Thier Implications for Inverse Scale-Productivity Relationship in Uganda. *Journal of Development Economics* 141 (2019): 102376. DOI: 10.1016/j.jdeveco.2019.102376

Haggblade, S., S. Kabwe, and C. Plerhoples. 2011. *Productivity Impact of Conservation Farming on Smallholder Cotton Farmers in Zambia*. Food Security Research Project Working Paper No. 47. East Lansing, MI: Michigan State University.

Haggblade, S. and G. Tembo. 2003. *Conservation Farming in Zambia*. EPTD Discussion Paper No. 108. Washington, DC: International Food Policy Research Institute.

Holden, S.T. and M. Fisher. 2013. *Can Area Measurement Error Explain the Inverse Farm Size Productivity Relationship?* CLTS Working Paper No. 12/13. Ås in Akershus: Norwegian University of Life Sciences.

Indaba Agricultural Policy Research Institute (IAPRI). 2012. The 2012 Rural Agricultural Livelihoods Survey: Instruction Manual for Listing, Sample Selection, and Largest Maize Field Data Collection. RALS Documentation. Lusaka, Zambia: IAPRI.

Kimhi, A. 2003. *Plot Size and Maize Productivity in Zambia: The Inverse Relationship Revisited.* Agricultural Economics Department Discussion Paper No. 10.03. Rehovot, Israel: The Hebrew University of Jerusalem.

Lamb, R.L. 2003. Inverse Productivity: Land Quality, Labor Markets, and Measurement Error. *Journal of Development Economics* 71.1: 71–95.

Marenya, P.P. and C.B Barrett. 2009. State-conditional Fertilizer Yield Response on Western Kenyan Farms. *American Journal of Agricultural Economics* 91.4: 991–1006.

Sen, A.K. 1962. An Aspect of Indian Agriculture. *The Economic Weekly* February: 244–246.

Sen, A.K. 1966. Peasants and Dualism with or without Surplus Labor. *Journal of Political Economy* 74.5: 425–450.

Thierfelder, C. and P.C. Wall. 2009. Effects of Conservation Agriculture Techniques on Infiltration and Soil Water Content in Zambia and Zimbabwe. *Soil and Tillage Research* 2 (2009): 217–227.

Umar, B.B., J.B. Aune, F.H. Johnsen, and O.I. Lungu. 2011. Options for Improving Smallholder Conservation Agriculture in Zambia. *Journal of Agricultural Science* 3.3: 50–2.

Zambia Agricultural Research Institute (ZARI). 2002. Maize Production Guide. In *Permian Exploration, Boundaries, and Stratigraphy*, ed. G.C. Kaitisha, P. Gondwe, M.V. Mukwavi, and G.M. Kaula. Soils and Crops Research, Ministry of Agriculture and Cooperatives, Mt. Makulu, Zambia

Zambia Ministry of Finance (ZMF). Various years. Estimates of Revenue and Expenditure: Activity Based Budget. Lusaka, Zambia: Government Printer.

APPENDICES

APPENDIX A: FULL RESULTS FOR FIGURE 1 NOT PRESENTED IN THE MAIN BODY

Threshold linear model:

```
. t1search ha_p ha_G, thold(ha_G) shift(ha_G) gen
Optimal Threshold
   Threshold: .41100001

F test for significant sample split:
F-stat =6.9688453[1651, 1649]; P[F-stat>0]=.0009687

Regression results

      Source |       SS           df       MS      Number of obs   =     1,653
-------------+----------------------------------   F(3, 1649)      =    603.42
       Model |   1336.4873         3  445.495765   Prob > F        =    0.0000
    Residual |  1217.42945     1,649  .738283473   R-squared       =    0.5233
-------------+----------------------------------   Adj R-squared   =    0.5224
       Total |  2553.91674     1,652  1.54595444   Root MSE        =    .85923

------------------------------------------------------------------------------
    ha_plant |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      ha_GPS |   .7257247   .3869153     1.88   0.061    -.0331724    1.484622
      _00dum |    .210399   .1081659     1.95   0.052     -.001758     .422556
  _00dha_GPS |  -.0663101   .3873436    -0.17   0.864    -.8260473    .6934271
       _cons |   .2200335   .1015124     2.17   0.030     .0209268    .4191402
------------------------------------------------------------------------------
```

Kinked linear model:

```
. skink ha_p ha_G, plot predict(kinked)

Estimates the non-linear model:
`lhs' = {b0} + {b2}*-`i'*_00dum + {b1}*`rhs' + {b2}*`rhs'*_00dum)
Optimal Threshold
   Threshold: .6376

F test for significant sample split:
F-stat =12.011893[1651, 1650]; P[F-stat>0]=.00054216

Regression results
(obs = 1,653)

Iteration 0:  residual SS =  1218.846
Iteration 1:  residual SS =  1218.846


      Source |      SS            df       MS
-------------+----------------------------------    Number of obs =      1,653
       Model |  1335.0705          2  667.535226    R-squared     =     0.5228
    Residual |  1218.8463       1650  .738694722    Adj R-squared =     0.5222
-------------+----------------------------------    Root MSE      =   .8594735
       Total |  2553.9167       1652  1.54595444    Res. dev.     =   4187.363

------------------------------------------------------------------------------
    ha_plant |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         /b0 |   .1431724   .0631947     2.27   0.024     .0192221    .2671226
         /b2 |  -.4620562   .1333181    -3.47   0.001    -.7235466   -.2005657
         /b1 |   1.119326   .1249809     8.96   0.000     .8741878    1.364464
------------------------------------------------------------------------------
  Parameter b0 taken as constant term in model & ANOVA table
```

APPENDIX B: RESULTS FROM MODEL NESTING COLUMNS (I)-(VI) OF TABLE 5

```
Linear regression                               Number of obs     =      1,653
                                                F(11, 1641)       =      39.37
                                                Prob > F          =     0.0000
                                                R-squared         =     0.5405
                                                Root MSE          =     .67504
```

Hectares planted =	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
CF training						
MAL	-.097944	.0704934	-1.39	0.165	-.2362104	.0403225
Private firm	-.2068071	.138289	-1.50	0.135	-.4780485	.0644344
ZNFU/CFU	-.0966368	.141497	-0.68	0.495	-.3741705	.1808968
Other farmer	.0418685	.1635216	0.26	0.798	-.2788646	.3626016
Other/NGO	.009673	.1447418	0.07	0.947	-.2742251	.2935711
ha_GPS	.5147806	.0751944	6.85	0.000	.3672936	.6622676
ha_GPS*MAL	.177012	.0926104	1.91	0.056	-.0046351	.3586591
ha_GPS*Private firm	.3723018	.1532741	2.43	0.015	.0716683	.6729354
ha_GPS*ZNFU/CFU	.3574708	.1193166	3.00	0.003	.1234419	.5914998
ha_GPS*Other farmer	.0349714	.1863472	0.19	0.851	-.3305319	.4004747
ha_GPS*Other/NGO	.1508963	.1566471	0.96	0.336	-.156353	.4581457
_cons	.324881	.0491881	6.60	0.000	.2284028	.4213591

APPENDIX C: RESULTS FROM MODEL NESTING COLUMNS (I)-(IV) OF TABLE 6

```
Linear regression                               Number of obs     =      1,653
                                                F(7, 1645)        =      57.79
                                                Prob > F          =     0.0000
                                                R-squared         =     0.5352
                                                Root MSE          =     .67813
```

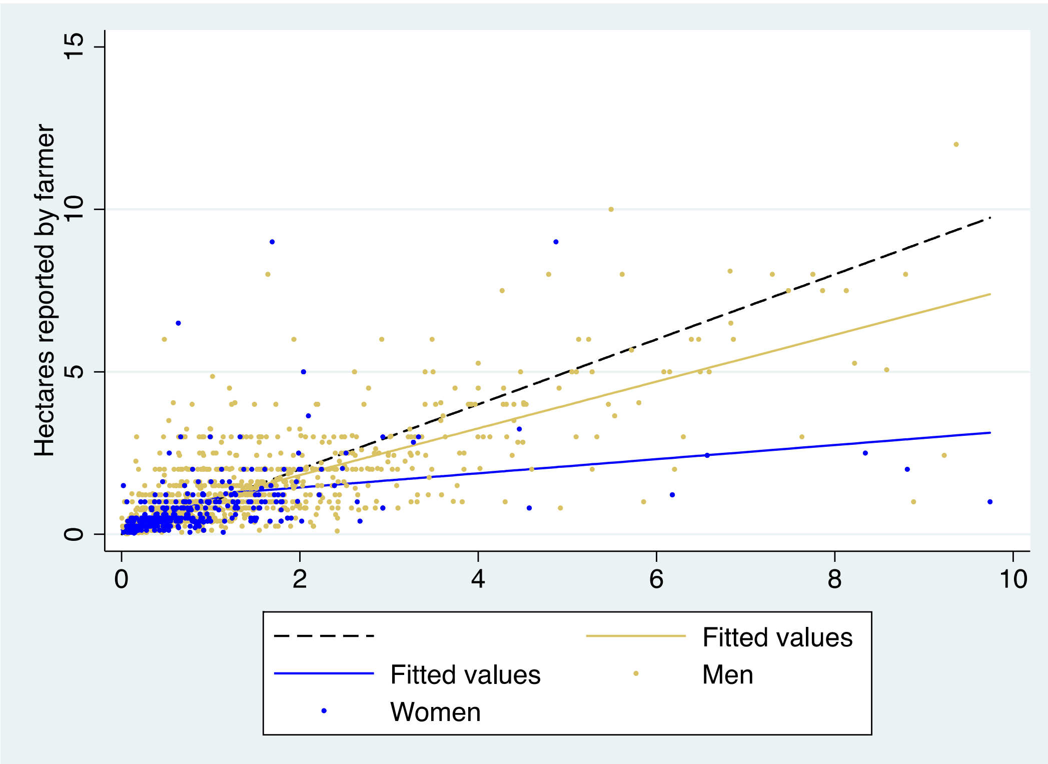
Hectares planted =	Coef.	Robust Std. Err.	t	P>|t|	[95% Conf.	Interval]
educ						
Standard (1-7 yrs)	-.1939405	.0879339	-2.21	0.028	-.3664147	-.0214662
Form (8-12 yrs)	-.0891461	.1048529	-0.85	0.395	-.2948054	.1165132
College/Certificate (>12 yrs)	-.3214143	.0772603	-4.16	0.000	-.4729532	-.1698754
ha_GPS	.285434	.066568	4.29	0.000	.154867	.416001
ha_GPS*Standard (1-7 yrs)	.3969493	.1011758	3.92	0.000	.1985024	.5953962
ha_GPS*Form (8-12 yrs)	.3313848	.1182604	2.80	0.005	.0994281	.5633415
ha_GPS*College/certificate	.5006625	.0914271	5.48	0.000	.3213369	.6799882
_cons	.4422658	.0640054	6.91	0.000	.3167251	.5678065

**Note: a test of the null hypothesis that the slope parameter on ha_GPS for those with 1-7 years education is the same for those with 8-12 years education yields the test statistic 0.066, se=0.124, p>0.60). We fail to reject the hypothesis that there is no difference.

APPENDIX D: OTHER FACTORS CONSIDERED

Gender of main decision maker

Figure A 1. Gender and Accuracy of Field Size Reporting



Source: RALS (2012), LMF subsample and the authors' calculations.

Remoteness

Initial look at data does not suggest any clear correlations between errors (positive or negative) with things like distance to market, distance to town, etc. Some results below:

Overestimated field size (hectares over=ha_over) regression on kilometers to market (mrktkm):

```
. reg ha_o mrktkm if ha_o

      Source |       SS           df       MS      Number of obs   =       754
-------------+----------------------------------   F(1, 752)       =      0.33
       Model |  .191417874         1  .191417874   Prob > F        =    0.5629
    Residual |  429.728702       752  .571447742   R-squared       =    0.0004
-------------+----------------------------------   Adj R-squared   =   -0.0009
       Total |   429.92012       753  .570943054   Root MSE        =    .75594

------------------------------------------------------------------------------
     ha_over |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      mrktkm |   .0005499   .0009502     0.58   0.563    -.0013154    .0024152
       _cons |   .4984501   .0363162    13.73   0.000      .427157    .5697432
------------------------------------------------------------------------------
```

Underestimated field size (hectares under=ha_under) regression on kilometers to market (mrktkm):

```
. reg ha_u mrktkm if ha_u

      Source |       SS           df       MS      Number of obs   =       810
-------------+----------------------------------   F(1, 808)       =      0.29
       Model |  .197870993         1  .197870993   Prob > F        =    0.5934
    Residual |  560.348871       808  .693501078   R-squared       =    0.0004
-------------+----------------------------------   Adj R-squared   =   -0.0009
       Total |  560.546742       809  .692888433   Root MSE        =    .83277

------------------------------------------------------------------------------
    ha_under |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      mrktkm |  -.0005237   .0009805    -0.53   0.593    -.0024483    .0014008
       _cons |   .5315086   .0388597    13.68   0.000     .4552308    .6077865
------------------------------------------------------------------------------
```

Underestimated field size (hectares under=ha_under) regression on kilometers to town (townkm):

```
. reg ha_u townkm if ha_u

      Source |       SS           df       MS      Number of obs   =       817
-------------+----------------------------------   F(1, 815)       =      0.04
       Model |   .02811381         1   .02811381   Prob > F        =    0.8407
    Residual |  566.989957       815  .695693199   R-squared       =    0.0000
-------------+----------------------------------   Adj R-squared   =   -0.0012
       Total |  567.018071       816  .694875087   Root MSE        =    .83408

------------------------------------------------------------------------------
    ha_under |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      townkm |  -.0001783   .0008871    -0.20   0.841    -.0019196     .001563
       _cons |   .5273743   .0457785    11.52   0.000     .4375167     .617232
------------------------------------------------------------------------------
```

Overestimated field size (hectares over=ha_over) regression on kilometers to town (townkm):

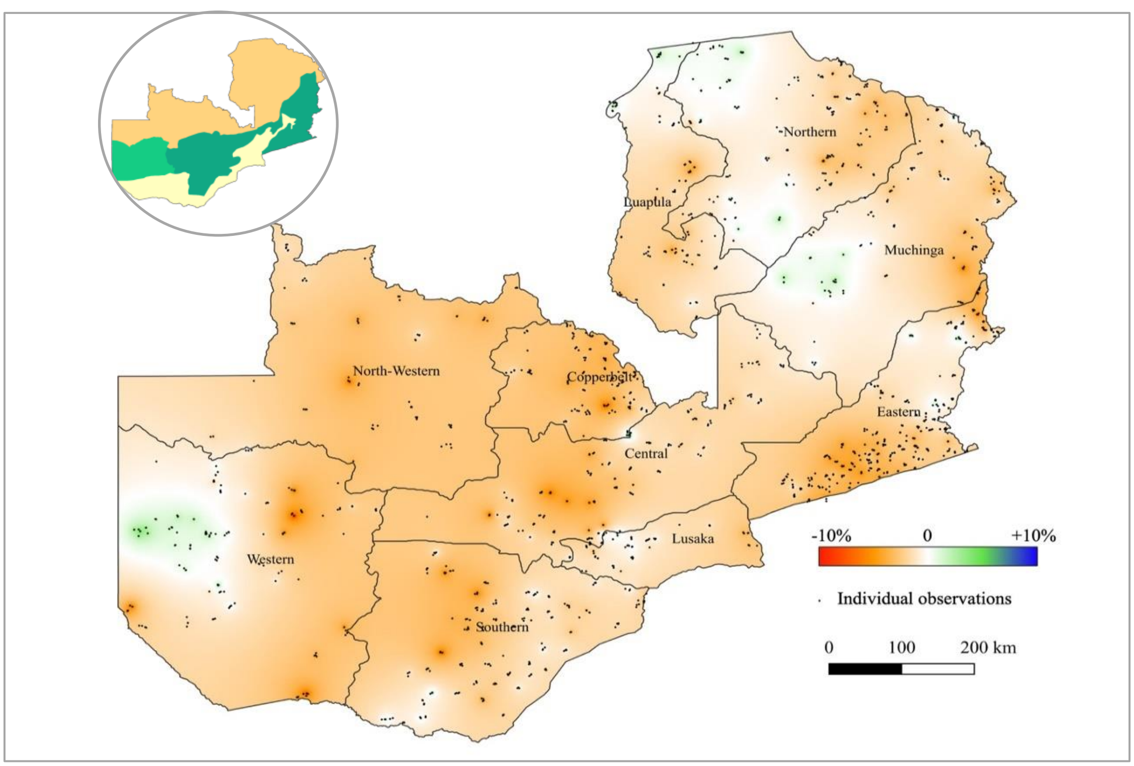
```
. reg ha_o townkm if ha_o

      Source |       SS           df       MS      Number of obs   =       761
-------------+----------------------------------   F(1, 759)       =      2.19
       Model |  1.13825016         1  1.13825016   Prob > F        =    0.1394
    Residual |  394.690694       759   .52001409   R-squared       =    0.0029
-------------+----------------------------------   Adj R-squared   =    0.0016
       Total |  395.828945       760  .520827559   Root MSE        =    .72112

------------------------------------------------------------------------------
     ha_over |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
      townkm |   .0012092   .0008173     1.48   0.139    -.0003953    .0028137
       _cons |   .4552799   .0413496    11.01   0.000     .3741067    .5364531
------------------------------------------------------------------------------
```

Geographic Correlation

One of the issues that may be worth looking at is spatial correlation in area measurement error. To examine this, we compute the log of the ratio of the self-reported area (areaSR) to GPS-measured area (areaGPS), which, for small errors, is analogous to a percent measurement error in areaSR. This is preferred to difference in absolute measurement because the mean of absolute measures could give disproportionate weight to larger fields. A straight percentage difference would give equal weight to large and small areas but is susceptible to influential outliers. The log of the ratio (or, equivalently, the difference in logs) circumvents both these pitfalls.

A regression-based comparison (next page) shows provincial fixed effects explain less than 1% of the variation in ln(areaSR/areaGPS), and none of the differences between provinces are statistically significant. District level fixed effects, on the other hand, explain about 10% of the data variation, and several districts stand out as being more or less likely to show farmers underestimating or overestimating field size. So, while there does appear to be some spatial correlation, it is at the sub-agro zone level. This is also reflected in the figure below, which is a nationwide map interpolating field measurement errors (with a map of agro-ecological zones inset). Interpolation pixels are 0.019 decimal degree squares, or roughly 4.5 square kilometers. Interpolated values are computed with a distance coefficient of 0.5 (that is, each pixel is the weighted mean of all observed values, where the weight is the inverse of the square root of the distance between the pixel and the observation).

Figure A 2. Geographic Interpolation of Percent Measurement Errors in Self-Reported Field Size Measurement (Agro-ecological Zones Inset)



Source: CSO/MAL/IAPRI (2012): Interpolation method described in body of text.