Farmer Misperceptions Might Matter: Revisiting the African Agricultural Intensification Hypothesis in the Presence of Measurement Error

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Abstract

As rural population densities grow and average farm and plot sizes shrink in sub-Saharan Africa, attention is returning to longstanding questions of whether farmers naturally increase the intensity of input application as the size of the plots they cultivate decreases. The prior literature has neglected, however, the challenge posed by measurement error in cultivated area, which is now known to be pervasive in farmer self-reported plot size data. Measurement error could represent simple misreporting that poses an econometric challenge correctable through improved measurement. But it might also or alternatively reflect farmer misperceptions that affect input use and related farmer behaviors. We show analytically that these alternative measurement error data generating processes carry different implications for the appropriate specification of the intensification equation, as well as for the sign and magnitude of bias in the intensification parameter estimate. We develop empirical tests to identify these alternative data generating processes for measurement error in land area. We empirically corroborate our predictions using nationally representative household data from four sub-Saharan African countries. In all four countries, we consistently find that input intensity diminishes with both farmer self-reported and true plot size, consistent with the intensification hypothesis. Input intensity also increases with measurement error in self-reported land size, consistent with the misperception hypothesis, suggesting a behavioral phenomenon that reinforces the more conventional intensification narrative. Further tests imply that measurement error in plot size reflects a mixture of farmer misreporting, with conventional econometric implications, as well as farmer misperceptions, a behavioral anomaly that affects input allocations.

Keywords: Agricultural inputs, agrochemicals, Boserup, fertilizer, improved seed, non-classical measurement error, optimal prediction error, Ruthenberg, smallholder agriculture

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1. Introduction

Rising population densities and low levels of agricultural productivity have brought renewed attention to the agricultural intensification process in sub-Saharan Africa (Binswanger-Mkhize and Savastano 2017, Holden, 2018). While rural populations decline in the rest of the world they continue to rise in sub-Saharan Africa (SSA), even in many land-constrained countries that have little or no surplus agricultural land to bring into cultivation (Jayne et al., 2014; Jayne and Headey, 2014). Farm and plot sizes are therefore declining and expected to continue to decline for many years. This observation has reignited interest in the agricultural intensification hypothesis first articulated by Boserup (1965), and later reinforced by Ruthenberg (1980), that African farmers will intensify modern input use – i.e., raise application rates per unit area cultivated – in order to compensate for shrinking farm and plot size, thus thwarting dire Malthusian predictions.

Relatively low aggregate rates of input intensity across SSA suggest to many observers that intensification is not occurring, although input use rates are relatively high in large parts of some of the most densely populated SSA countries, such as Ethiopia, Malawi, or Nigeria (Sheahan and Barrett 2017). Several recent studies fail to find evidence of intensification in SSA agriculture, with no statistically significant relationship between individual landholdings and input intensity (Holden and Yohannes, 2002; Binswanger-Mkhize and Savastano, 2017). The issue remains far from settled, however, as other recent studies find support for the intensification hypothesis (Pender and Gebremedhin, 2007; Headey et al., 2014; Josephson et al., 2014; Ricker-Gilbert et al., 2014). Still other papers contain more nuanced findings: a positive relationship between population density and intensification over lower population density ranges and a reversal thereafter (Muyanga and Jayne, 2012), or increased cropping intensity but no increase in fertilizer or irrigation use (Headey and Jayne, 2014).

Virtually all of these studies use survey data of farmer self-reported land size, which is now known to under-estimate large plots' size and over-estimate small plots in sub-Saharan Africa (Carletto et al., 2013; Carletto et al., 2015). Indeed, several recent studies of the farm size-productivity relationship in SSA find strong evidence that what appears as intensification – manifest as an inverse size-productivity relationship – is merely an artifact of non-classical measurement error (NCME) in plot size, crop output, or both (Desiere and Jolliffe 2017; Gourlay et al. 2017; Abay et al. 2018). It seems highly likely that NCME in plot size also affects the estimated relationship between size and input intensity. As best as we can tell, however, this possibility has not yet been addressed in the literature.

The recent literature on measurement error and farm productivity in SSA assumes, however, that farmers know and base farm management decisions upon true plot size, so that measurement error in self-reported survey data is merely an econometric obstacle to overcome through improved data collection. Yet a vast behavioral economics literature posits that people routinely misperceive actual conditions – about others' behaviors, relative prices, social norms, the probability of stochastic events, etc. – and act upon those systematic biases or misperceptions. If behavior truly depends on misperceptions, then analysts might easily 'over-correct' for measurement error, by substituting an objective measure for the subjective measure that a farmer reports and on which she acts. If farmer misperceptions matter, then one needs to take special care in studying and correcting econometrically for measurement error in self-reported data. In this paper we examine the association between both true plot size and measurement error in farmer self-reported plot size and agricultural input intensity, to explore jointly the intensification and misperceptions hypotheses.

We begin by analytically exploring three distinct data generating processes for measurement error in farmer-reported plot size and deriving the biases that arise in different estimates of the intensification parameter when the econometrician uses self-reported or objective plot size data. First, farmers might misreport plot size in a way that is related to true, underlying plot size, as would occur under a regression-to-mean process of under-estimating large plots and over-estimating small plots, or a focal point bunching process of rounding reported values to the nearest simple fraction. Second, farmers might misreport plot size endogenously based on known levels of input allocations, as would occur, for example, if they know they purchased a bag of fertilizer or seed of specific weight and applied it all to their plot, and they then estimate plot size based on accurate input volume data combined with their understanding of recommended seeding densities or fertilizer application rates.[1] Third, farmers might hold mistaken beliefs about plot size and both report and make input allocation decisions on the basis of those misperceptions.[2] They might also both misreport and misperceive plot size.

These three processes carry quite different implications for how best to estimate the intensification parameter of interest and the bias that might arise in such estimates. This matters

[1] Because plot size NCME enters both the input intensity regressand and the plot size regressor in all of these regressions, this particular form of optimal prediction error differs from the one-sided NCME in the explanatory or outcome variable studied by Hyslop and Imbens (2001).

[2] A fourth option is that the estimated intensification parameter may be biased by NCME in input levels that is correlated with NCME in plot size, following Abay et al. (2018). The data we use cannot address this possibility directly, but we do offer an econometric test that strongly suggests such NCME does not explain the patterns we observe in these data.

because one cannot directly identify the data generating process behind measurement error in self-reported plot size. We do, however, also derive and show how to estimate a novel parameter identifying the degree to which measurement error likely reflects a more conventional misreporting (an econometric challenge associated with the first two mechanisms) versus a farmer behavioral anomaly arising from the third, misperceptions mechanism.

We then employ nationally representative survey data from four African countries -- Ethiopia, Malawi, Tanzania and Uganda – where the data include both farmer self-reports and objective, geographic positioning system (GPS)-based measures of plot size. For each country, we study the intensity with which farmers apply the most commonly used inputs observed in the data: labor, improved seed, fertilizer and pesticides. We test the intensification and misperceptions hypotheses for each input in each country. Consistent with the Boserupian intensification hypothesis, we find that input intensity is indeed inversely associated with true plot size in all four countries, regardless of whether measurement error represents farmer misreporting, misperceptions, or a combination of the two.[3] The strength of the inverse relationship between input intensity and plot size also varies across countries as well as across land area measurement methods, consistent with our analytical predictions. But the evidence in favor of the intensification hypothesis is overwhelming.

Furthermore, conditional on true plot size, the measurement error in farmer self-reported plot size is also statistically significantly, positively associated with input intensity for virtually all input-country combinations.[4] This finding suggests that measurement error in plot size at least partly reflects farmers' true cognitive misperception of the land they manage, which also affects their input use decisions. Indeed, the new test we develop suggests that both types of phenomena are at play in these data. In particular, farmers seem to perceive plot area as close to the sizes they report, so that 'correction' for measurement error in self-reported plot size may more accurately represent the biophysical relationship between plot size and input use or productivity but risks biasing estimates of the behavioral parameters that guide farmer production decisions. Input allocation based on farmer misperceptions could help explain striking recent findings on input misallocation and agricultural total factor productivity in SSA and elsewhere (Adamopoulos and Restuccia, 2014; Bento and Restuccia, 2016; Adamopoulos et al., 2017; Gollin and Udry, 2017; Restuccia and Santaeulalia-Llopis, 2017).

[3] Farm size plays no independent role in the plot-level relationship between true plot area and input intensity.
[4] Bevis and Barrett (2017) briefly note a similar relationship in a different data set from Uganda.

The remainder of the paper proceeds as follows. In Section 2, we explore three plausible scenarios behind observed NCME in plot size, and examine the implications of each scenario for estimates of the input use-size gradient that defines Boserupian intensification. Section 3 then summarizes the four nationally representative panel datasets we use. Section 4 lays out an estimation strategy that is informed by our prior analytical findings. Section 5 reports our results. Section 6 concludes with some general observations.

2. Two-sided Non-Classical Measurement Error: Three Scenarios

Economists examining the existence of Boserupian intensification have estimated one or both of two equations below.[5] For many years, the most common method was to study agricultural input intensity as a function of self-reported (log) plot size, X. Less commonly, analysts use a more objective measure of (log) land size, X^* – typically collected by the survey enumeration team using a GPS or a compass and rope – so as to avoid the systematic measurement error that plagues many self-reported measures. To be more precise, the older literature often estimates equation 1, where input intensity, the log of input use volume, Y, per log unit self-reported area, X, expressed as log differences, on X:

$$Y - X = \beta X + \varepsilon \tag{1}$$

The Boserupian intensification parameter of interest is β. Given the voluminous evidence that self-reported plot size differs systematically from GPS-measured plot size, recent papers tend to assume that (log) self-reported land size, X, is measured with error, and instead estimate equation 2, using "true", GPS-measured (log) plot size, X^*, on both the left-hand size and the right-hand side:

$$Y - X^* = \beta X^* + \varepsilon \tag{2}$$

Measurement error in self-reported land size is generally assumed to enter additively. Following the standard representation of measurement error (Bound et al., 2001), log self-reported land size, X, is assumed a combination of true values (log plot size, X^*) and non-classical measurement error (NCME), v, also expressed in logarithmic form, as given in equation 3:

$$X = X^* + v \tag{3}$$

[5] In the interests of clarity, we abstract here from the covariates one appropriately includes in such regressions so as to isolate the relationships – and biases – of interest. The logic carries over directly from the oversimplified bivariate case we study here to the multivariate case, but the math becomes messier. In the empirical application below, we generalize to the multivariate regression case without re-deriving analytical results.

NCME ν is typically assumed uncorrelated with ε from either equations 1 or 2.

If self-reported land size is indeed measured with systematic error, then equation 1 includes this error on both sides. This two-sided measurement error differs in important ways from the univariate, classical measurement error model familiar from textbooks, as Abay et al. (2018) explain. In particular, even if measurement error is classical, then the textbook finding of attenuation bias due to (one-sided) classical measurement error does not hold; as we show below there is both attenuation and downward bias due to two-sided classical measurement error. Furthermore, if the measurement error is non-classical – e.g., correlated with the true plot size, and/or with input application, as is typically true – then the intensification parameter estimated under equation 1 may be biased in either direction if NCME exists in self-reported land size.

However, a naïve interpretation of equation 2 assumes that farmers have and act upon perfect information about plot size, despite the fact that they report it incorrectly. If farmers do not have perfect information about plot size, of if they harbor misperceptions (i.e., cognitive biases) in spite of having access to objective measures, then equation 2 estimates the true biophysical relationship between input intensity and plot size, but not the structural behavioral parameter that guides farmers' input application decisions and is the focus of the intensification hypothesis. In fact, if farmers perceive land size exactly as they report it, then their decision process is more correctly described by equation 1 even though equation 2 represents the biophysical relationship associated with the farmer's decision process under misperceptions. Therefore, it is important to test not only for prospective bias in the intensification parameter estimate that might arise from NCME in plot size, but also to test the farmer misperceptions hypothesis and to try to identify the degree to which measurement error reflects misperceptions rather than just misreporting.

We document below three scenarios of two-sided measurement error. The first two are generalizations of the most commonly hypothesized data generating processes behind farmer misreporting of plot size while the farmer acts on private knowledge of true plot size. In the third scenario, farmers misperceive the size of their plot and allocate inputs accordingly, reporting accurately the misperceived area. We show that the data generating process behind the measurement error matters to the appropriate regression specification to recover the intensification parameter of interest. We also develop a simple test to establish the degree to which measurement error arises from misreporting versus from misperceptions. For convenience, we focus on the intensive margin of input intensity and ignore the extensive margin of input use, because the Boserupian hypothesis concerns primarily the intensive margin of input intensity.[6]

Scenario 1: Measurement error driven by plot size

In the first scenario we assume that farmers have perfect information on plot size, and base the intensification decision on true (log) plot size, X^*, as in equation 2. In responding to the survey, however, they (mis)report (log) land size with error, v, as in equation 3. Several previous studies have found measurement error in self-reported plot size to be correlated with true plot area (Carletto et al. 2013; Carletto et al. 2015; Gourlay et al. 2017; Bevis and Barrett, 2017; Abay et al., 2018). This form of NCME in observed plot size is easily represented as

$$v = \alpha X^* + \psi \tag{4}$$

where ψ is uncorrelated with X^* and with ε from equation 2. Combining equations 3 and 4 provides the explicit NCME form.

$$X = (1 + \alpha)X^* + \psi \tag{5}$$

Equation 5 nests classical measurement error, which occurs when $\alpha = 0$. If $\alpha < 0$ then this specification encompasses both regression-to-the-mean and focal-point-bunching processes commonly observed in self-reported data. Let σ_x^2, $\sigma_{x^*}^2$, and σ_ψ^2 represent the variance of X, X^*, and ψ, respectively. Since the covariance of X^* and ψ is zero by assumption, equation 5 implies

$$\sigma_x^2 = (1 + \alpha)^2\sigma_{x^*}^2 + \sigma_\psi^2 \tag{6}$$

Under this scenario, estimation of equation 2 reflects the true, data-generating process and bypasses the NCME problem, yielding an unbiased estimation of the intensification parameter, β, which reflects both the decision-making process of the farmer and also the biophysical association between input intensity and plot size. Estimation of equation 1, however, will result in the intensification parameter estimate, $\hat{\beta}$, defined as:[7]

[6] By abstracting from the first stage decision to use or not use an input at all, we can employ linear least square estimators. The extension to censored dependent variable estimators that allow for change at the extensive margin, where input intensity equals zero, is conceptually straightforward but the math quickly becomes complex. Because the purpose of this analytical section is merely to illustrate the challenge posed by NCME in the context of testing the Boserupian intensification hypothesis, we leave generalization to the extensive margin to future work. In the empirical section, however, we will test the extensive margin of input use as a coarse robustness check against the possibility that NCME in input levels might confound inference using continuous input intensity measures.

[7] This first time, we lay out the algebra for the reader. Subsequent derivations skip the intervening algebraic steps in the interests of brevity.

$$\hat{\beta} = \frac{Cov([Y-X,X)}{Var(X)} = \frac{Cov(\{[(\beta+1)X^*+\varepsilon]-[(1+\alpha)X^*+\psi]\},\{(1+\alpha)X^*+\psi\})}{Var((1+\alpha)X^*+\psi)} = \frac{Cov(\{\beta X^*-\alpha X^*+\varepsilon-\psi]\},\{(1+\alpha)X^*+\psi\})}{Var((1+\alpha)X^*+\psi)}$$

$$\Longrightarrow \hat{\beta} = \frac{\beta(1+\alpha)\sigma_{x^*}^2}{(1+\alpha)^2\sigma_{x^*}^2+\sigma_{\psi}^2} - \frac{\alpha(1+\alpha)\sigma_{x^*}^2}{(1+\alpha)^2\sigma_{x^*}^2+\sigma_{\psi}^2} - \frac{\sigma_{\psi}^2}{(1+\alpha)^2\sigma_{x^*}^2+\sigma_{\psi}^2} \quad (7)$$

Equation 7 highlights the consequences of two-sided NCME, which remains largely unexplored in the literature but directly applies to the intensification hypothesis.[8] The NCME in plot size creates three biasing effects on the intensification parameter. The first term in equation 7 reflects the bias that enters through the right-hand side of the equation, and is well-known in the methodological literature on classical measurement error (e.g., Bound et al., 2001; Gibson and Kim, 2010). The second and third terms represent the bias arising through the dependent variable, and has only recently attracted attention (Abay et al., 2018). Under classical measurement error ($\alpha = 0$), the first term simplifies to the usual attenuation bias while the second term disappears. However, the third term remains, capturing omitted variables bias that arises from the shared presence of v in both the mismeasured explanatory variable and the denominator of the regressor, generating a spurious inverse relationship even when measurement error behaves classically (i.e., when $\alpha = 0$).

Thus, unlike the case of one-sided classical measurement error, we cannot a priori know whether $\hat{\beta}$ underestimates or overestimates the true relationship between plot size and input use intensity. The direction of bias depends on the comparative magnitude of systematic measurement error, $(1+\alpha)^2\sigma_{x^*}^2$ versus random measurement error, σ_{ψ}^2, from equation 6, and on the value of α, which defines the pattern of systematic measurement error. If α is close to zero, making v primarily dependent on ψ, then the first term in equation 7 attenuates the magnitude of the parameter estimate, as under classical measurement error, while the third term introduces downward bias, even if the measurement error is classical. If instead σ_{ψ}^2 approaches zero, then $\hat{\beta}$ approaches $\frac{(\beta-\alpha)(1+\alpha)\sigma_{x^*}^2}{(1+\alpha)^2\sigma_{x^*}^2} = \frac{(\beta-\alpha)}{(1+\alpha)}$. We cannot sign the bias associated with this coefficient; it over-estimates β for $-1 < \alpha < 0$, and under-estimates β for $\alpha > 0$. Additionally, unlike the case of one-sided classical measurement error (i.e., when $\alpha = 0$), NCME generates a spurious negative correlation between land area and input use intensity even if the true $\beta = 0$, because the second two terms are not multiplicative.

[8] See Abay et al. (2018) for a discussion in a more general context, with two different sources of NCME.

Scenario 2: Measurement error driven by input use

In the second scenario, we assume a new data generating process for v. Hyslop and Imbens (2001) hypothesize that individuals may report their best estimate of a key explanatory variable (e.g., plot size) based in part on information regarding a closely correlated proxy. In this context, farmers accurately perceive plot size – so that they act as in equation 2 – but when surveyed they report (log) land size with error, v, as in equation 3 because they estimate plot size for the survey enumerators using a known quantity of inputs they applied.[9] This might occur, for example, if farmers know and report that they purchased a bag of fertilizer or seed of specific weight and applied all of it to their plot, then they predict plot size based on that knowledge combined with their understanding of extension recommendations regarding seeding densities or fertilizer application rates. Such NCME will manifest a relationship between measurement error v and input levels Y as follows:

$$v = \delta Y + \omega \tag{8}$$

Combining equations 2 and 8 yields

$$v = \delta(\beta + 1)X^* + \delta\varepsilon + \omega \tag{9}$$

Defining a new parameter, $\kappa = \delta(\beta + 1)$, we can re-write equation 9 as

$$v = \kappa X^* + \delta\varepsilon + \omega \tag{10}$$

If $\kappa < 0$, measurement error again creates a regression to the mean effect, just as occurs if $\alpha < 0$ under scenario 1. The mechanisms behind the NCME differ, however, but a common reduced form relationship exists. Combining equations 3 and 10 results in

$$X = (1 + \kappa)X^* + \delta\varepsilon + \omega \tag{11}$$

which directly implies

$$\sigma_x^2 = (1 + \kappa)^2\sigma_{x^*}^2 + \delta^2\sigma_\varepsilon^2 + \sigma_\omega^2$$

where σ_ε^2 represents the variance of ε and σ_ω^2 the variance of ω. These equations are remarkably similar to those from scenario 1, despite the difference in underlying data generating process. Measurement error is still a reduced form function of true plot size, but with a second term that reflects the component of input levels not derived from plot size, ε. This leads to a second term in the variance of self-reported plot size.

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[9] It may seem difficult to imagine that farmers simultaneously know their true plot size (as assumed in equation 2) and yet report estimates of size on a proxy. But farmers commonly have a good intuition for plot size, but have trouble specifying that size in acres or hectares or some other survey unit of measure. And if seeding density or fertilizer application rate recommendations are common knowledge, they might feel it simpler, or more socially acceptable, to report the plot size that should correspond to the precisely known and reported amount of seed or fertilizer they used. The third scenario we develop below relaxes this assumption so as to acknowledge that farmers may have, act on, and report imperfect information on plot size.

Under this form of NCME, OLS estimation of equation 2 (i.e., using GPS-measured plot size), will again result in an unbiased estimate of β. However, estimation of equation 1, which relies on self-reported plot size, will yield a still-different estimated coefficient, $\tilde{\tilde{\beta}}$:

$$\tilde{\tilde{\beta}} = \frac{\beta(1+\kappa)\sigma_{X^*}^2}{(1+\kappa)^2\sigma_{X^*}^2+\sigma_\omega^2} - \frac{\kappa(1+\kappa)\sigma_{X^*}^2}{(1+\kappa)^2\sigma_{X^*}^2+\sigma_\omega^2} - \frac{\sigma_\omega^2}{(1+\kappa)^2\sigma_{X^*}^2+\sigma_\omega^2} + \frac{\delta(1-\delta)\sigma_\varepsilon^2}{(1+\kappa)^2\sigma_{X^*}^2+\sigma_\omega^2} \tag{12}$$

The first three terms of equation 12 resemble those of equation 7 under scenario 1, with κ taking the place of α and σ_ω^2 replacing σ_ψ^2. The new, fourth term stems from the fact that measurement error now enters through two sources: correlation between v and X^* (captured in the first three terms), and correlation between v and ε (captured in the last term). This framework again nests classical measurement error as a special case, when v is uncorrelated with input levels, so that $\delta = 0$, making $\kappa = 0$. Then the second and fourth terms disappear entirely, and the first term provides the attenuation bias of one-sided classical measurement error. However, the third term in equation 12 again remains, even under classical measurement error, creating a spurious negative relationship that could lead to mistaken inference that Boserupian intensification exists even if it does not.

Scenario 3: Measurement error reflects farmer misperception

In scenario three we relax the assumption that farmers have and act upon perfect information on plot size. Instead, let us assume that farmers misperceive plot size, make their intensification decision based on these (mis-)perceptions, and precisely report that misperceived plot size in surveys (Bevis and Barrett 2017). More specifically, farmers mistakenly perceive (log) plot size as, X, and equation 1 accurately reflects their intensification decision (although we relax this assumption momentarily). Equation 3 is assumed to capture the general form of their misperceptions, as well as the measurement error in self-reported plot size. Equation 2 reflects the statistical association – i.e., the true biophysical relationship – between true input intensity and true (GPS-measured) plot size. But it no longer captures the farmer's decision-making process, which is accurately reflected in equation 1.

In this scenario, we remain agnostic about the data generating process behind farmer misperceptions, except to allow that misperception v may be correlated with true plot size X^*, which describes the reduced form relationship between NCME and X^* in both scenarios 1 and 2 (equations 5 and 11), and could also encompass other forms of NCME. It also describes the well-documented empirical pattern of regression-to-the-mean and focal-point-bunching in self-reported plot size in sub-Saharan Africa (Carletto et al., 2013; Carletto et al., 2015; Bevis and Barrett 2017; Desiere and Jolliffe 2017; Gourlay et al. 2017; Abay et al. 2018).

Combining equation 1, which represents the farmer's true decision process in terms of in perceived plot size, X, with equation 3, which gives the general form of measurement error in X, results in the following relationship:

$$Y - X = \beta X^* + \beta v + \varepsilon \tag{13}$$

Thus, the intensification parameter chosen by the farmer may be recovered by estimating either equation 1, where self-reported plot size is used on both sides, or equation 13, where self-reported plot size on the right-hand side is split into GPS-measured plot size X^*, and measurement error v. Estimating equation 2, on the other hand, leads to yet another parameter estimate, $\bar{\beta}$:

$$\bar{\beta} = \frac{Cov([Y-X^*],X^*)}{Var(X^*)} = \frac{Cov([(\beta+1)(X^*+v)+\varepsilon-X^*],X^*)}{Var(X^*)} = \frac{Cov([\beta X^*+(\beta+1)v+\varepsilon],X^*)}{Var(X^*)}$$

$$\Rightarrow \bar{\beta} = \beta + (\beta+1)\frac{Cov(v,X^*)}{Var(X^*)} \tag{14}$$

If measurement error is negatively (positively) correlated with true plot size, as is most (less) commonly observed, then $\bar{\beta}$ will downwardly (upwardly) bias the intensification parameter estimate reflecting farmer behavior, defined in equations 1 and 13.

The econometrician might also be interested in the effect of plot size misperceptions on "true" input intensity (as calculated using GPS-measured plot size), holding true plot size itself constant. That is, econometricians might wish to estimate equation 15, where the parameters on X^* and v are not assumed, but derived from equation 13:[10]

$$Y - X^* = \beta X^* + (\beta+1)v + \varepsilon \tag{15}$$

Under the strong assumption that farmers report precisely the misperceived plot size on which they base their decisions, the difference between the parameter on log plot size X^* and the parameter on misperception of log plot size v is 1. However, this changes if we relax that assumption. Imagine instead that farmers *report* log plot size $X = X^* + v$ as in equation 3, but *perceive* log plot size to be the weighted average of true and reported size, as in equation 16, where $0 \leq \theta \leq 1$.

$$\tilde{X} = \theta X + (1-\theta)X^* = \theta v + X^* \tag{16}$$

Put differently, self-reported plot size reflects both measurement error and farmer misperceptions. However, farmers base their intensification decisions on perceived plot size, as in equation 17.

[10] To be more explicit, the econometrician might want to estimate $Y - X$ as a function of X^* and v, or to run the regression $Y - X = \delta_1 X^* + \delta_2 v + \varepsilon$. We can derive the analytical expression for δ_1 and δ_2 using Equation 13:
$Y - X = \beta X^* + \beta v + \varepsilon \Rightarrow Y - (X^* + v) = \beta(X^* + v) + \varepsilon \Rightarrow Y - X^* = \beta X^* + (\beta+1)v + \varepsilon$

$$Y - \tilde{X} = \beta\tilde{X} + \varepsilon \quad (17)$$

From equation 17 we can derive equation 18, which is similar to equation 13 except for the appearance of θ.[11]

$$Y - X^* = \beta X^* + (\beta + 1)\theta v + \varepsilon \quad (18)$$

Note that equation 18, regressing the true input intensity on true plot size and plot size measurement error, recovers the unbiased estimate of the intensification parameter chosen by the farmer, no matter the data generating process behind the measurement error. In this more flexible, hybrid case, since $0 \leq \theta \leq 1$, the coefficient estimate on v might be less than $(\beta + 1)$. In fact, one can identify the parameter θ given that β is identified by the coefficient estimate on true plot size, X^*. Empirically, θ can be recovered by dividing the coefficient on v by $\beta + 1$. If $\theta = 1$, then farmers perceive log plot size precisely as they report it, and act accordingly. If $\theta < 1$, then farmer perceptions of log plot size lie between true log plot size and reported log plot size. If $\theta = 0$, then farmers' plot size perceptions perfectly align with true plot size, implying that their input decisions follow the correct measure of plot size and that measurement error reflects misreporting only. So the θ parameter estimate directly establishes the degree to which measurement error reflects farmer misreporting, misperceptions, or a combination of the two.

3. Data

We use Living Standard Measurement Study-Integrated Surveys on Agriculture (LSMS-ISA) data from four countries: Ethiopia, Malawi, Tanzania, and Uganda. The LSMS-ISA data have been collected by national statistical offices, in partnership with the World Bank, under country-specific labels. These high-quality, nationally representative, agriculture-focused panel data are fairly comparable across countries. The Ethiopian Socioeconomic Survey data contain three rounds of household panel data, collected in 2011/12, 2013/14, and 2015/16. Malawi's Integrated Household Panel Survey also includes three rounds of household panel data, collected in 2010/11, 2013, and 2016/17. In both Tanzania and Uganda we have three rounds of household panel data and a fourth wave of non-panel data (i.e., they cover new respondent households). Uganda's National Panel Surveys took place in 2009/10, 2010/11, 2011/12, and 2012/14. Tanzania's National Panel Surveys took place in 2008/9, 2010/11, 2012/13, and 2014/15.

[11] To be more explicit, combining equations 16 and 17 implies $Y - (X^* + \theta v) = \beta(X^* + \theta v) + \varepsilon$ $\Rightarrow Y - X^* = \beta X^* + (\beta + 1)\theta v + \varepsilon$.

In all countries, we observe multiple agricultural plots or land parcels per household, and agricultural input and output data are reported at the plot/parcel level. Parcels are defined as contiguous land under the same ownership system. Plots are defined by cropping system, and are located within parcels. In all countries except Tanzania we view data at the plot level; the Tanzania data are at the parcel level.[12] Every survey measures plots/parcels via handheld GPS units, as well as by asking farmer respondents to report the size of the plot/parcel.[13] This allows us to examine error in farmer-reported size, relative to GPS measures of the same plot/parcels. In total, pooled across all survey rounds, we have 36,466 plots in Ethiopia, 53,475 plots in Malawi, 11,392 parcels in Tanzania, and 9,877 plots in Uganda, all with both farmer-reported and GPS-measured plot size. Uganda's panel includes two observations of many plots per year, covering both agricultural seasons, which are relatively equal in importance. In Tanzania we include only data from the main (*masika*) season, as the great majority of farmers do not grow crops during the secondary (*vuli*) season. In both Ethiopia and Malawi, only the main rainy season is included.

Following the prior literature, we employ GPS-based area measurement as the objective measure, and then characterize measurement error as deviation of self-reported plot sizes from the corresponding GPS measure (Carletto et al., 2013; Carletto et al., 2015). Denoting log self-reported plot size as X^{SR} and log GPS-measured plot size as X^{GPS}, measurement error is the difference between the two: $\hat{v} \equiv X^{SR} - X^{GPS}$. Because the comparison of GPS-based area and self-reported area is central to our analysis, we discard the relatively few plots that do not have both measurements.[14]

Table 1 provides summary statistics of households and plots for the four countries considered. Ethiopia, Malawi, and Uganda are densely populated and considered land constrained (Headey and Jayne 2014, Jayne et al. 2014). Tanzania is somewhat less densely populated, and less land-constrained. It is therefore unsurprising that farms and plots are larger in Tanzania than in the other three countries. While Tanzanian farms average 7.4 acres, Ugandan farms average just 5.1 acres, Ethiopian farms 3.8 acres, and Malawian farms only 3.5 acres. Malawi and Ethiopia also

[12] More specifically, in the Ethiopian case plots are small units of land within a parcel that is demarcated by hedges or paths and mostly assigned for a specific crop. In Malawi a plot is defined as ''a continuous piece of land on which a unique crop or a mixture of crops is grown under consistent crop management system.'' In Tanzania plots are defined as being a contiguous piece of land under a single form of tenure – cropping system is not mentioned. In Uganda, a parcel is defined as a contiguous piece of land with uniform tenure and land characteristics. A "plot" is defined as a contiguous piece of land within the parcel, on which a specific crop or crop mixture is grown.
[13] To avoid the influencing farmers' self-reported land size, farmers are first asked to report land size, and then the land is measured via GPS (Carletto et al., 2016).
[14] There are 7,846 plots in Ethiopia, 10,096 plots in Malawi, 6,371 plots in Tanzania, and 10,626 plots in Uganda.

have the smallest average plot sizes: 0.40 acres in Ethiopia, and 1.12 acres in Malawi. Uganda's plots average 2.43 acres, and Tanzania's plots average 3.07 acres. Per capita farm size average is largest in Tanzania (1.3 acres) and smallest in Ethiopia (0.8 acres).

Table 1: Pooled summary statistics of households and plots

Variable of interest	Ethiopia	Malawi	Tanzania	Uganda
Land area measurement				
Plot size: Self-reported (acre)	0.372 (1.362)	0.974 (0.78)	2.68 (6.47)	1.92 (5.22)
Plot size: GPS (acre)	0.398 (1.229)	1.116 (9.072)	3.07 (7.47)	2.43 (14.53)
Farm size: GPS or SR (acre)	3.840 (11.278)	3.487 (3.417)	7.43 (14.22)	5.11 (23.45)
Household characteristics:				
Gender household head (1=male)	0.84 (0.37)	0.739 (0.439)	0.77 (0.42)	0.72 (0.45)
Age of household head (years)	47.97 (14.27)	44.164 (16.32)	49.19 (15.61)	47.21 (14.99)
Household-head literate (1=yes)	0.58 (0.49)	0.13 (0.336)	0.69 (0.46)	0.65 (0.48)
Household size (persons)	5.67 (2.24)	4.81 (2.174)	5.98 (3.55)	7.02 (3.27)
Acres per person (acres/persons)	0.77(1.45)	0.94 (4.38)	1.33 (2.21)	0.93 (7.64)
Plot characteristics				
Pure stand (1= pure, 0 mixed crop)	0.61 (0.49)	0.597 (0.491)	0.40 (0.49)	0.39 (0.49)
Irrigation (1= irrigated land)	0.05 (0.21)	0.006 (0.076)	0.02 (0.14)	0.02 (0.13)
Soil quality is good (0/1)	0.33 (0.47)	0.477 (0.499)	0.43 (0.50)	0.60 (0.49)
Number of observations	36,466	53,444	11,392	9,877

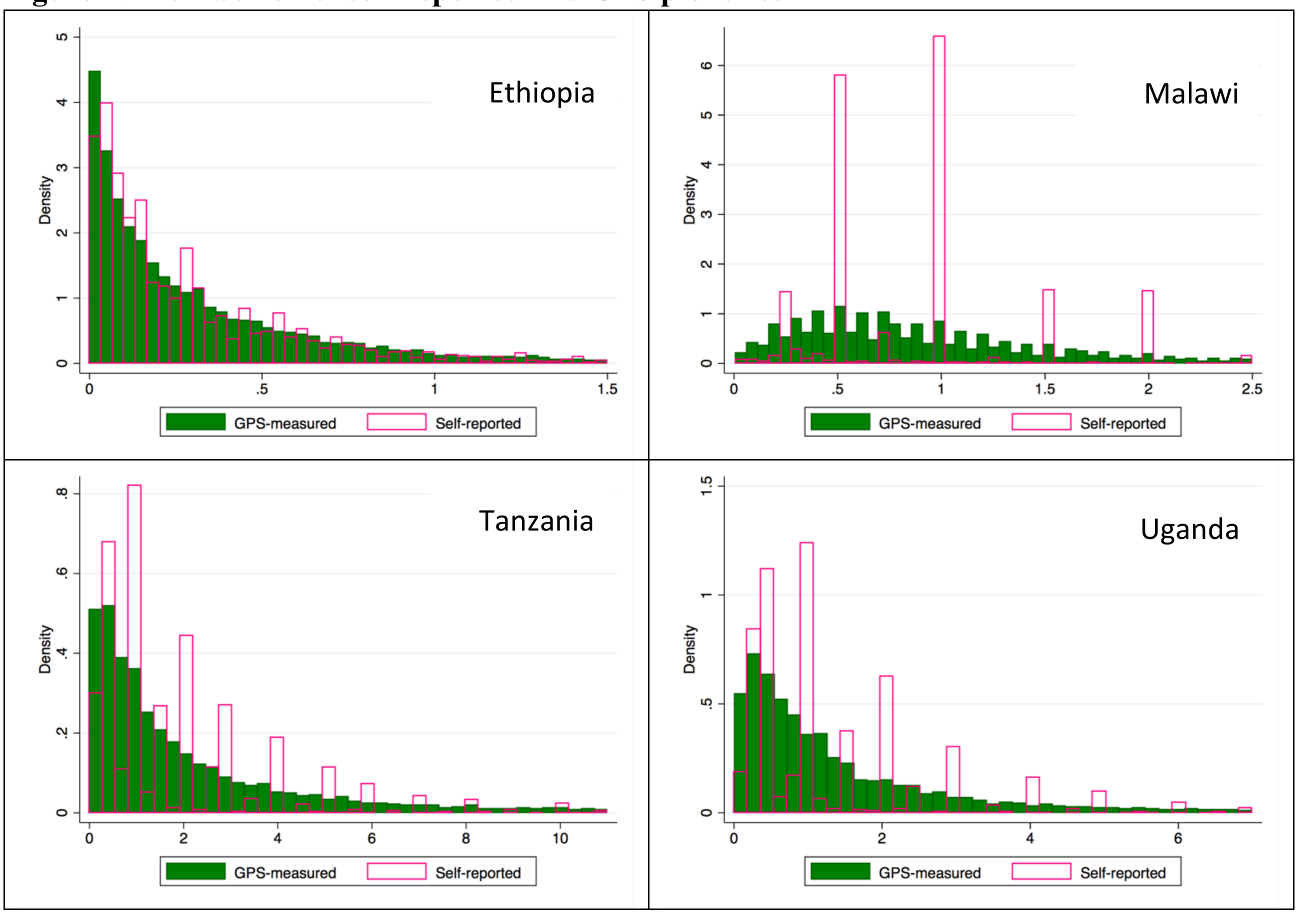
Notes: Except for plot size measures, the remaining information for the above variables are self-reported by farmers during the household survey. Farm size relies on GPS-measured plot sizes for those plots with GPS-measurement, and self-reported plot sizes for those plots without GPS-measurement. Values outside parenthesis provide mean values while those inside parenthesis stand for standard deviations.

Because the plot size distribution is skewed, these means exceed the median plot/parcel sizes of 0.22, 0.78, 0.94, and 1.26 acres, in Ethiopia, Malawi, Uganda and Tanzania, respectively. In Ethiopia, about 95% percent of plots are under 1 acre, and almost all plots are under 5 acres. In Malawi these figures are about 75 and 99 percent, respectively. In Uganda, they are 52 and 92, and in Tanzania, they are 42 and 85, respectively. So, these are smallholder-dominated agricultural sectors in all four countries.

Most other household and plot characteristics are similar across countries. Household heads are slightly more likely to be male in Ethiopia, and are notably less likely to be literate in Malawi. Household sizes are largest, on average, in Uganda, which also has the most diversified cropping system. Ethiopia and Malawi, which are heavily reliant on *teff* and maize, respectively, are most likely to have mono-cropped plots. Irrigation is almost non-existent in all countries. Ethiopia's farmers are least likely to list their plot as having good soil quality, while Uganda's farmers are most likely to do so. The differences between average self-reported and average GPS-measured plot size in Table 1 are fairly substantial: 7, 13, 13, and 21 percent of the mean GPS-measured plot size in Ethiopia, Malawi, Tanzania and Uganda, respectively. Part of this discrepancy is driven by a tendency of self-reports to bunch around "round" numbers (e.g., 0.5, 1, 1.5, 2 acres) that serve as natural focal points. Figure 1 depicts histograms that illustrate this bunching, which varies in magnitude across countries but is omnipresent.

More importantly, the bias in mean, self-reported plot size varies substantially over the distribution of true, GPS-measured plot size. In Table 2 bias is calculated as the difference between quartile-specific mean self-reported plot size and quartile-specific mean GPS-measured plot size. Relative bias is given as quartile-specific (mean) bias as a percent of (mean) GPS-measured plot size. The totals in the bottom row report the same calculation for the entire sample.

Figure 1: Distribution of self-reported and GPS plot sizes



Consistent with prior studies (Carletto et al., 2013; Carletto et al., 2015), measurement error in self-reported plot size declines with true (objectively measured) plot size, in both absolute and percentage terms. Relative bias is by far the largest for the smallest plots, which tend to be drastically over-estimated by farmers. Bias and relative bias are very low – close to zero – in the third quartile, for all countries. Notably, bias is positive for all quartiles except for the last; only the largest plots are generally under-estimated. However, the extent of under-estimation on these large plots is so great that it drives country-average self-reported plot size to be lower than country-average GPS-measured plot size, as seen in Table 1 and at the bottom of Table 2. This is notable since bias actually goes in the other direction for the vast majority of plots.

Table 2: Discrepancies between Self-reported and GPS-based measures

Plot Size Quintile (GPS)	Ethiopia		Malawi		Tanzania		Uganda	
	Bias (SR-GPS)	Relative bias (%)	Bias (SR-GPS)	Relative bias (%)	Bias (SR-GPS)	Relative bias (%)	Bias (SR-GPS)	Relative bias (%)
0-25%	0.05	138.93	0.26	97.81	0.35	129.37	0.24	103.15
25-50%	0.02	15.30	0.14	22.91	0.21	24.90	0.19	28.55
50-75%	0.00	0.45	0.04	4.03	0.02	0.96	0.12	8.73
75-100%	-0.16	-15.04	-1.03	-38.99	-2.16	-23.45	-2.60	-34.90
Total	-0.02	-5.93	-0.14	-12.71	-0.39	-12.77	-0.51	-21.09

Notes: GPS stands for area measurement using handheld Global Positioning Systems, while SR stand for self-reported plot size in acres. These are quartile-specific mean and relative biases as a percent of (mean) GPS-measured plot size.

In Table 3 we report agricultural intensification rates, considering four key inputs and using both self-reported and GPS-based plot sizes to calculate intensity. For all countries, we compute these conditional intensification rates only for those plots for which these inputs have been applied (i.e., are non-zero). The sample sizes in Table 3 are therefore smaller than those in Table 1. Additionally, a few small differences exist across countries due to the way the data were collected. In Uganda and Tanzania, data on improved seed use exists only for purchased seed, and is expressed in monetary value terms. Since most improved seed is hybrid, which loses vigor if one uses retained seed from a first crop, the understatement of improved seed use by using purchased improved seed is likely low. For Ethiopia we use improved seed application in kilograms. In Malawi, we are not able to identify improved and traditional seed variety for the initial survey rounds, so our analysis for improved seed is only based on the last round. Additionally, pesticide and herbicide use is given only as a binary indicator in Ethiopia, so although we describe it here, we omit it from the later intensification regressions because those would only describe change at the extensive margin, and thereby miss much of the Boserupian intensification of interest. For Malawi, pesticide and herbicide use is given in kilogram or liter. For Tanzania and Uganda, it is measured in monetary value of agrochemical applications per hectare.

Given the log-normal distribution of input intensity, we report both mean and median application rates in Table 3. The median and average application rates for most countries are comparable to those reported in other recent studies (e.g., Sheahan and Barrett, 2017). For Malawi, Tanzania, and Uganda, median input rates are similar across GPS and self-reported measurement, while mean input rates are substantially higher under GPS measurement. This reflects the under-estimation of input intensity on small plots, which are reported by farmers to be larger than they truly are. In Ethiopia, the same holds true for fertilizer, while mean input intensity actually appears higher under GPS-measurement for labor intensity and improved seed intensity. Again, however, median input use is comparable across the two measurement methods for Ethiopian inputs. These results, and those of Table 2, suggest that while mean input use rates are biased when generated with self-reported land size, this is generally driven by bias in land size for the smallest and largest plots. Median input use is therefore more reliable if generated with self-reported land measurement – it is less biased, and also better captures the central tendency of a skewed distribution.

Table 3: Input use rates (for those who applied these inputs)

	Input applied		Mean input intensity		Median input intensity	
Input use rates	# plots	% plots	(Self-reported)	(GPS)	(Self-reported)	(GPS)
Ethiopia						
Labor (days/acre)	33535	92	89.89	112.40	24.46	24.43
Fertilizer (kg/acre)	9,458	26	169.20	120.12	59.16	51.25
Improved seed (kg/acre)	11,491	32	71.31	66.09	19.65	17.80
Malawi						
Labor (days/acre)	48,815	91	226.32	252.70	149.33	160.98
Fertilizer (kg/acre)	32,832	61	78.72	91.76	50.00	50.01
Improved Seed (kg/acre)	4,976	9	16.22	17.74	10.00	9.21
Pest/herbicide (kg/acre)	1,121	2	22.71	26.39	0.8	0.71
Tanzania						
Labor (days/acre)	10,468	92	49.55	69.22	30.00	32.90
Fertilizer (kg/acre)	1,410	12	217.73	267.09	37.50	41.91
Improved Seed (value/acre)	1,552	14	15,846	19,663	8,000	9,128
Pest/herbicide (value/acre)	1,077	9	12,461	14,983	5,333	5,769
Uganda						
Labor (days/acre)	8,545	87	191.35	223.00	101.00	105.56
Fertilizer (kg/acre)	161	2	29.72	28.73	10.00	8.37
Improved Seed (value/acre)	762	8	17,340	21,345	8,333	8,333
Pest/herbicide (value/acre)	501	5	17,121	31,289	7,286	7,000

Notes: For Ethiopia and Malawi we use physical input use per acre. For Tanzania and Uganda fertilizer application are expressed in kilogram per acre while improved seed application is given in terms of value purchased per acre.

4. Estimation Strategy

Section 2 points to an estimation strategy for exploring empirically the implications of NCME in plot size for inference about the agricultural intensification and misperceptions hypotheses. First, we study the features and structure of measurement error in self-reported plot size. Then, we explore the consequences of such measurement error for inference about agricultural intensification. Finally, we test the misperceptions hypothesis and estimate the share of the measurement error in farmer self-reported plot size that appears to drive farmer behavior, rather than be merely a data challenge to overcome in estimation.

Understanding Measurement Error

We begin by testing whether measurement error in plot size behaves classically or non-classically, i.e., whether it is correlated with variables of interest. As section 2 showed, for data generating processes arising under either scenario, a reduced form non-zero correlation should exist between true plot size and measurement error, if measurement error is non-classical. So we estimate via ordinary least squares (OLS) the following regression, adding control variables *Z*:

$$\hat{v} = \pi X^{GPS} + \eta Z + \xi \tag{19}$$

Note that the parameter π may represent different combinations of the structural parameters associated with the various data generating processes of section 2.[15] The π parameter represents the reduced form relationship that nests within it the various structural mechanisms outlined in the preceding section.[16] From equation 19 we first test whether we can reject the classical measurement error null hypothesis that $\pi = 0$, in favor of the NCME alternate hypothesis. As explained in section 2, however, even if we fail to reject the NCME null, there still exists negative bias in the estimate of the β parameter with two-sided classical measurement error, not just the more familiar attenuation bias that arises in the one-sided classical measurement error case.

Identifying the Effect of Measurement Error and Testing the Intensification Hypothesis

The second step in our empirical strategy explores the impacts of measurement error – classical or non-classical – for estimates of the Boserupian intensification parameter of interest.

[15] It might also capture some other form of systematic NCME that mimics the behavior of the scenarios we explore. The key insight is that these can ultimately all be transformed into a reduced form relationship between the NCME and the true value of the explanatory variable of interest.

[16] Equation 19 assumes a linear relationship between $\hat{v}$ and X^{GPS}. Figure A1 shows that the assumption holds true for most of our sample; for 90% of observations in each country, the non-parametric relationship between $\hat{v}$ and X^{GPS} is almost indistinguishable from a parametric, linear relationship. However, we also loosen the assumption of linearity in subsequent robustness checks.

Our dependent variables are input intensity with respect to four different factors of production: labor, which is central to the original Boserupian hypothesis, and the three most common modern inputs found in the data: inorganic fertilizer, improved seed, and pesticides/herbicides. We begin by operationalizing equations 1 and 2, as unconditional regressions, as well as adding control variables, *Z*, for our preferred specifications:

$$Y - X^{SR} = \beta^{SR} X^{SR} + \tau^{SR} Z + \epsilon \tag{20}$$

$$Y - X^{GPS} = \beta^{GPS} X^{GPS} + \tau^{GPS} Z + \tilde{\epsilon} \tag{21}$$

The Z matrix includes farmer and plot characteristics, as well as household and year fixed effects, as listed in Table 1. The conditional regressions make more plausible the assumption that the error term is uncorrelated with true/GPS-measured plot size, although we emphasize that we can only establish associations in these observational data, not make clean causal inferences.

Under scenarios 1 and 2 farmers act on perfect information on true plot size, now captured by β^{GPS}. Therefore, the Boserupian intensification parameter of interest, β from equation 2, is now captured by β^{GPS} in equation 21. The intensification hypothesis holds that one can reject the null β=0 in favor of the one-sided alternate hypothesis that β<0, i.e., that input intensity declines with plot size. If farmers act on, but misreport, true plot size, then β^{SR} from equation 20 will be a biased estimate of the true intensification parameter, although the direction and magnitude of the bias are unknown, per section 2.

Under scenario 3, however, farmers act on their misperceptions and follow the process specified by equation 20, or perhaps a process that falls between those specified by equations 20 and 21, analogous to that specified by equation 17. In this case, β^{SR} captures the Boserupian intensification parameter of interest, and the β^{GPS} estimate from equation 21 captures only a statistical relationship, rather than the farmer's decision-making process. Next, we explore data generating process(es) behind the observed measurement error – misreporting and/or misperceptions – so as to identify an unbiased estimate of the intensification parameter.

Testing the Misperceptions Hypothesis

Under scenario 3 in section 2, farmers misperceive true plot size and both act on and accurately report their misperceptions. Then $\hat{v}$ reflects a measurement error that is less an econometric challenge due to a flawed survey process than it is a cognitive misperception that leads farmers to make systematic behavioral errors. We test the misperceptions hypothesis for this difference by estimating the conditional analogue of the unconditional relationship, equation 15, derived in section 2:

$$Y - X^{GPS} = \gamma X^{GPS} + \varphi\hat{v} + \tau^{GPS}Z + w \tag{22}$$

Note that equation 22 is just a more general version of equation 21, which imposes the exclusionary restriction that $\varphi = 0$. That restriction holds under scenarios 1 and 2 because measurement error has no behavioral effect and thus should be unrelated to input intensity once one conditions on true plot size, X^{GPS}. Thus, rejecting null hypothesis that $\varphi = 0$ in equation 22 supports the misperceptions hypothesis, that at least part of $\hat{v}$ reflects cognitive misperceptions on which farmers truly act.

More specifically, if scenario 3 holds and the farmer perceives plot size exactly as she reports it in survey – i.e., if $\hat{v}$ contains *only* cognitive misperception and no misreporting and the farmer's decision process therefore follows equation 20 – then $\varphi = 1 + \gamma$ and also $\gamma = \beta^{SR}$. (This can be seen in equations 1, 13 and 15 from the empirical section.) Conversely, if scenario 1 or 2 holds, and $\hat{v}$ exclusively represents farmer self-reporting errors on which they do not act, then we should find $\gamma = \beta^{GPS}$, holding constant the same control variables in *Z*. That is, under scenarios 1 or 2, the intensification parameter estimate is equivalent under equation 21 and its more general form, equation 22 because $\hat{v}$ is just a noise parameter under scenarios 1 and 2.

If the farmer's intuition on plot size lies somewhere between GPS-measured plot size and self-reported plot size, however, implying that $\hat{v}$ contains both farmers' cognitive misperception and misreporting, then φ may be less than $\gamma - 1$, because θ<1. We can calculate the parameter θ from equation 16 and 18 as

$$\theta = \varphi/(\gamma + 1) \tag{23}$$

The size of the parameter estimate θ represents the share of the observed measurement error due to farmer misperceptions. Tests of the two bounding null hypotheses, that $\hat{v}$ represents purely misperceptions (when $\hat{\theta}$ =1), or only misreporting (when $\hat{\theta} = 0$) therefore help identify which measurement error scenario most accurately describes the data. Since by definition $\theta \in [0,1]$, the predicted value $\hat{\theta}$ is necessarily censored at the lower and upper bounds of the unit interval.

So as to increase the efficiency of the non-nested hypothesis tests, we estimate equations 20-22 via seemingly unrelated regressions (SUR) with shared fixed effects (Blackwell, 2005). Due to the fact that fixed effects are shared across equations, however, SUR estimates vary slightly from OLS estimates. We therefore exploit SUR for conducting joint hypothesis tests of parameters, but base hypothesis tests around single parameters on the single-equation OLS that includes equation-specific fixed effects. We estimate θ according to equation 23, using the OLS-estimated parameters γ and φ from equation 22, bootstrapping our confidence intervals for θ so as to accommodate prospective non-normality in the distributions of either parameter estimate.[17]

5. Empirical Results and Discussion

We begin by estimating the reduced form relationship between the measurement error in farmer reported plot size, as reported in Table 2, and true plot size. This allows a simple test of whether measurement error in plot size behaves classically or non-classically. We then turn to the intensification parameter of interest, establishing the impact of plot size measurement error on the intensification parameter estimate, with implications for the findings of the prior literature, which overwhelmingly relies on farmer self-reports.

Table 4 reports OLS estimates of equation 19, the linear relationship between measurement error and true plot size. Odd-numbered columns report unconditional regression estimates, and even-numbered columns report conditional regression estimates. Under each specification, and for all countries, we easily reject the classical measurement error null hypothesis (that π=0) in favor of the NCME alternate, specifically that measurement error is negatively associated with true plot size, e.g., experiences regression to the mean. This is consistent with previous studies that find that farmers generally over-estimate the size of small plots and under-estimate the size of large plots (Carletto et al., 2013; 2015; Bevis and Barrett, 2017; Desiere and Joliffe, 2018; Abay et al., 2018).

Table 4: Measurement error correlated with true plot size

	(1) Ethiopia	(2) Ethiopia	(3) Malawi	(4) Malawi	(5) Tanzania	(6) Tanzania	(7) Uganda	(8) Uganda
Plot size (log acres)	-0.299***	-0.309***	-0.466***	-0.483***	-0.332***	-0.398***	-0.299***	-0.446***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.00777)	(0.0115)	(0.0121)	(0.0198)
Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Household chars.	No	Yes	No	Yes	No	Yes	No	Yes
Plot chars.	No	Yes	No	Yes	No	Yes	No	Yes
Crop FE	No	Yes	No	Yes	No	Yes	No	Yes
Household FE	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.236	0.241	0.377	0.385	0.351	0.335	0.260	0.298
No. obs.	36466	36466	53444	53444	11386	10765	9869	8736

Notes: Standard errors, clustered at household level, are given in parentheses. For each country, the second column controls for the household and plot characteristics listed in Table 1. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

[17] We use Stata's percentile confidence intervals, as they do not assume normality, and run 1,000 replications.

Having established a strong pattern of mean-reverting measurement error for all countries, we now explore how this type of measurement error affects the estimated intensification parameter. Our approach is agnostic with regards to the data generating process behind this mean-reverting measurement error; it could be driven by any scenario from section 2. In Table 5 we provide OLS estimates for equations 20 and 21, with the same controls as in Table 4's even numbered columns. Each input is a separate column. Each country is a separate vertically stacked panel within the table. For each country and input, the intensification parameter is first estimated using farmer self-reported plot size (estimating β^{SR} from equation 20), and then estimated in a separate regression using GPS-measured plot size (estimating β^{GPS} from equation 21). In the last row within each country panel, we estimate the bias in the intensification parameter due to NCME in self-reported plot size under the maintained hypothesis that farmers act on true plot size, that is, we report $(\beta^{SR} - \beta^{GPS})$. As these parameter estimates come from non-nested regressions, we additionally follow Blackwell (2005) and estimate equations 20-21 via seemingly unrelated regressions (SUR) with shared fixed effects and use that resulting covariance matrix to test the null hypothesis that the two parameters are equal.

Regardless of land area measurement methods, the estimates in Table 5 consistently show a strong inverse relationship between plot size and input use intensity for all countries and for all inputs, consistent with the Boserupian hypothesis and with many previous studies (Pender and Gebremedhin, 2006; Headey et al., 2014; Josephson et al., 2014; Ricker-Gilbert et al., 2014; Sheahan and Barrett, 2017).[18] Intensification parameters range from -0.4 to -0.8 across inputs, countries, and plot size measurement methods.

Tests of equality of the two non-nested intensification parameters (β^{SR} and β^{GPS}) show statistically significant differences for almost all countries and inputs. But the differences vary in sign and statistical significance, and most of the magnitudes are fairly small relative to either parameter estimate. In Malawi, Tanzania and Uganda, the intensification parameters under self-reported plot size are lower in magnitude (i.e., less negative) than the intensification parameters estimated under the GPS-measured plot size. In Ethiopia the difference is insignificant, or in one case reversed in sign.

Variation in the sign and magnitude of $(\beta^{SR} - \beta^{GPS})$ stems from variation in the behavior of country-specific measurement error. For instance, the difference between β^{SR} and β^{GPS} is

[18] This result holds if one allows for simple nonlinear relationships, as demonstrated by robustness checks in appendix Table A1.

smallest in Ethiopia, where measurement error is least correlated with GPS-measured plot size (Table 4 column 2), as we might expect. Uganda has the largest difference between β^{SR} and β^{GPS}, if we average across inputs, and Uganda also has a very strong regression-to-the-mean pattern in measurement error (Table 4 column 8), stronger than that in Tanzania or Ethiopia. Measurement error in Malawi also experiences strong regression to the mean – slightly stronger than that in Uganda (Table 4 column 4) – but the variation in Malawi's measurement error is also high, due to particularly pronounced focal point bunching (Figure 1). This causes variation in both measurement error and in the random component of measurement error – $\hat{v}$ and ξ from equation 19, respectively – to be particularly large relative to variation in GPS-measured plot size.[19] This ratio helps to determine the bias in the β^{SR} estimate, as described in equations 7 and 12, and may partially mitigate the effect of mean-reverting error in the case of Malawi. The key takeaway from table 5 is that the intensification hypothesis clearly holds and that any bias arising from plot size measurement error is of variable sign and magnitude, but does not affect the central qualitative finding in support of Boserupian intensification.

Table 6 reports OLS estimates of equation 22, now controlling for measurement error in plot size $\hat{v}$ alongside GPS-measured plot size X^{GPS}. This is our preferred specification because the coefficient estimate, γ, on GPS-measured plot size offers an unbiased estimate of the intensification parameter of interest no matter the data generating process behind observed measurement error in plot size. This is consistently negative, statistically significant, and of relatively large magnitude, falling in the range [-0.81, -0.36]. Again, the Boserupian intensification hypothesis finds strong support in these data.

What about the misperceptions hypothesis? The parameter φ provides one test of the hypothesis. If $\hat{v}$ is driven by reporting error only, and does not reflect farmer misperceptions of plot size, then we should not reject the exclusionary restriction on the measurement error term ($\varphi = 0$), and we should estimate an intensification parameter on X^{GPS} similar to that found under equation 21 and reported in Table 5 ($\gamma \cong \beta^{GPS}$). Conversely, if measurement error predicts input intensity ($\varphi \neq 0$), and if γ is approximately equal to β^{SR} from equation 20, this suggests that at least part of $\hat{v}$ reflects farmer misperceptions.

[19] Relative sample variation between measurement error and GPS-measured plot size ($\sigma_{\hat{v}}^2/\sigma_{x^*}^2$) is 0.352, 0.620, 0.313 and 0.344 in Ethiopia, Malawi, Tanzania and Uganda, respectively. Estimating $\hat{\xi}$, the sample analogue of ξ from equation 17, as the residual from a regression of $\hat{v}$ on X^{GPS}, we further find that sample variation between the random component of measurement error and GPS-measured plot size ($\sigma_{\hat{\xi}}^2/\sigma_{x^*}^2$) is 0.281, 0.386, 0.203, and 0.255 in Ethiopia, Malawi, Tanzania and Uganda, respectively.

Table 5: Intensification parameter estimates with and without plot size measurement error

	(1) Labor	(2) Seeds	(3) Fertilizer	(4) Pesticides
Ethiopia				
ln (SR plot size): β^{SR}	-0.800***	-0.475***	-0.486***	
	(0.005)	(0.013)	(0.018)	
Observations	*33535*	*11583*	*9453*	
R^2	*0.724*	*0.392*	*0.248*	
ln (GPS-measured plot size): β^{GPS}:	-0.798***	-0.486***	-0.459***	
	(0.004)	(0.013)	(0.018)	
R^2	*0.779*	*0.427*	*0.244*	
$\beta^{SR} - \beta^{GPS}$	-0.002	0.011	-0.027***	
Malawi				
ln (SR plot size): β^{SR}	-0.533***	-0.559***	-0.553***	-0.682***
	(0.012)	(0.062)	(0.021)	(0.064)
Observations	*48815*	*4976*	*32814*	*1118*
R^2	*0.329*	*0.333*	*0.278*	*0.417*
ln (GPS-measured plot size): β^{GPS}:	-0.614***	-0.630***	-0.607***	-0.642***
	(0.009)	(0.043)	(0.016)	(0.099)
R^2	*0.506*	*0.411*	*0.417*	*0.431*
$\beta^{SR} - \beta^{GPS}$	0.081***	0.070***	0.054***	-0.039
Tanzania				
ln (SR plot size): β^{SR}	-0.547***	-0.589***	-0.431***	-0.661***
	(0.0135)	(0.0457)	(0.0585)	(0.0592)
Observations	*9846*	*1487*	*1335*	*1016*
R^2	*0.333*	*0.366*	*0.189*	*0.379*
ln (GPS-measured plot size): β^{GPS}:	-0.618***	-0.627***	-0.488***	-0.783***
	(0.0107)	(0.0357)	(0.0456)	(0.0434)
R^2	*0.471*	*0.475*	*0.304*	*0.492*
$\beta^{SR} - \beta^{GPS}$	0.071***	0.038***	0.057***	0.121***
Uganda				
ln (SR plot size): β^{SR}	-0.722***	-0.798***	-0.589***	-0.665***
	(0.0190)	(0.117)	(0.205)	(0.142)
Observations	*8062*	*731*	*158*	*474*
R^2	*0.345*	*0.324*	*0.737*	*0.388*
ln (GPS-measured plot size): β^{GPS}	-0.724***	-0.900***	-0.893***	-0.733***
	(0.0164)	(0.125)	(0.238)	(0.0985)
R^2	*0.387*	*0.364*	*0.771*	*0.410*
$\beta^{SR} - \beta^{GPS}$	0.001***	0.101***	0.304***	0.068***

Notes: Standard errors are clustered at the household level. The bottom row for each country presents the difference between the OLS β^{SR} and β^{GPS} parameter estimates. Significance of this difference is obtained via seemingly unrelated regression (SUR) with shared fixed effects (Blackwell, 2005). All regressions include household and year fixed effects, plot and household controls, and plot dummies. For all rows, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Input intensity as a function of true plot size and measurement error

	(1) Labor	(2) Seeds	(3) Fertilizer	(4) Pesticides
		Ethiopia		
ln (GPS-measured plot size): γ	-0.779***	-0.430***	-0.404***	
	(0.005)	(0.013)	(0.018)	
Measurement error: φ	0.062***	0.211***	0.220***	
	(0.008)	(0.021)	(0.024)	
R^2	*0.781*	*0.441*	*0.264*	
$\gamma - \beta^{GPS}$	0.019***	0.056***	0.054***	
$\gamma - \beta^{SR}$	0.021***	0.045***	0.082***	
θ	0.279	0.371	0.369	
θ 95% CI	[0.349, 0.621]	[0.272, 0.523]	[0.299, 0.435]	
		Malawi		
ln (GPS-measured plot size): γ	-0.484***	-0.568***	-0.487***	-0.622***
	(0.010)	(0.061)	(0.019)	(0.094)
Measurement error: φ	0.268***	0.129	0.243***	0.080
	(0.015)	(0.100)	(0.023)	(0.088)
R^2	*0.538*	*0.412*	*0.443*	*0.433*
$\gamma - \beta^{GPS}$	0.130***	0.061***	0.120***	0.021***
$\gamma - \beta^{SR}$	0.049***	-0.009	0.066***	0.060***
θ	0.520	0.298	0.473	0.210
θ 95% CI	[0.539, 1]	[0, 0.779]	[0.148, 1]	[0, 0.751]
		Tanzania		
ln (GPS-measured plot size): γ	-0.520***	-0.574***	-0.361***	-0.658***
	(0.0126)	(0.0433)	(0.0504)	(0.0575)
Measurement error: φ	0.245***	0.158**	0.263***	0.316***
	(0.0196)	(0.0645)	(0.0740)	(0.0889)
R^2	*0.492*	*0.481*	*0.325*	*0.511*
$\gamma - \beta^{GPS}$	0.125***	0.053***	0.080***	0.057***
$\gamma - \beta^{SR}$	0.003	-0.005	0.009	-0.002
θ	0.510	0.371	0.411	0.925
θ 95% CI	[0.245, 0.639]	[0, 1]	[0.093, 1]	[0.397, 1]
		Uganda		
ln (GPS-measured plot size): γ	-0.662***	-0.808***	-0.658**	-0.644***
	(0.0193)	(0.127)	(0.258)	(0.138)
Measurement error: φ	0.138***	0.214	0.495**	0.226
	(0.0229)	(0.168)	(0.244)	(0.196)
R^2	*0.393*	*0.372*	*0.783*	*0.417*
$\gamma - \beta^{GPS}$	0.062***	0.092***	0.235***	0.090***
$\gamma - \beta^{SR}$	0.061***	-0.010***	-0.069***	0.022***
θ	0.409	1.000	1.000	0.635
θ 95% CI	[0, 1]	[0, 1]	[0,1]	[0,1]

Notes: γ and φ are estimated by OLS of equation 22. Standard errors are clustered at the household level. Significance of $\gamma - \beta^{GPS}$ and $\gamma - \beta^{SR}$ is obtained via SUR with shared fixed effects (Blackwell, 2005). θ is estimated via equation 22 and confidence intervals are bootstrapped, then values censored at the 0 and 1 lower and upper bounds, respectively. All regressions include household and year fixed effects, plot and household controls, and plot dummies. For all rows, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

The stronger form of testing for misperceptions-vs.-misreporting in measurement error focuses on the estimated parameter θ. If $\hat{v}$ contains only reporting error, and farmers have perfect information on plot size, then we expect $\varphi = 0$ and hence $\theta = 0$. If $\hat{v}$ contains only cognitive misperception, and farmers perceive plots precisely as they report them, then we expect $\theta = 1$. If $0 < \theta < 1$, then we may think of farmer perceptions of plot size as reflecting both reported plot size, with weight θ, and true, GPS-measured plot size, with weight $(1 - \theta)$. This, in turn, suggests that discrepancies between GPS-measured plot size and self-reported plot size reflect farmer misperceptions and misreporting. We bootstrap confidence intervals around the θ estimate, allowing for non-normality of θ, and censor values at the [0,1] bounds, when necessary.

The parameter estimates in Table 6 consistently indicate that plot size measurement error is positively and statistically significantly associated with input intensity (i.e., $\varphi > 0$), conditional on GPS-measured plot size. Consistent with this, the null hypothesis $(\gamma - \beta^{GPS}) = 0$ is rejected at the one percent level for almost all inputs and countries. Thus, the misperceptions hypothesis finds strong support in all four countries, and for most inputs. The fact that farmers who over-estimate plot size apply higher levels of inputs per acre suggests that the discrepancy between self-reported and GPS- measured plot size may arise, at least in part, from farmer misperceptions, i.e., a farmer behavioral error rather than just a survey reporting error.[20]

Estimated values of θ, and the confidence intervals around them,[21] further suggest that measurement error reflects both farmer misreporting and farmer misperceptions, with the precise mixture varying by input-country combination. All but two estimated values of θ lie between 0 and 1. Both exceptions are in Uganda, the result of very small sample sizes: 731 and 158 cases of improved seed use and fertilizer use, respectively. We generally reject the possibility that $\theta = 0$, since the 95 percent confidence interval lies above zero in 9 of 11 regressions, leaving out the small sample Uganda cases where the confidence bands are too diffuse to be informative about the true value of θ. This strongly suggests, again, that $\hat{v}$ reflects more than simple reporting error and at least partly reflects farmer misperceptions. In 6 of 11 non-Uganda cases, we reject the possibility that $\theta = 1$. This leaves open the possibility that in some cases, measurement error $\hat{v}$ reflects *only* misperception bias. However, on the whole, the θ parameter estimates and the confidence intervals

[20] This result holds when we break measurement error into over-estimates and under-estimates, allowing for prospective asymmetric behavior depending on the sign of measurement error (appendix Table A2). The misperception effect is reasonably symmetric. Overestimation (underestimation) of plot size leads to higher (lower) input intensity. For most country-input combinations, one cannot reject the null of equal coefficients on under- and over-estimation.
[21] We use bootstrapped, percentile-based confidence intervals because of the likely non-normal distribution of θ.

around them suggest that measurement error reflects both misreporting and misperceptions. The mixture varies by input-country combination, and the precision of the θ estimate is a function of the extent of use of the input.[22] Bootstrapped confidence intervals that fall outside of 0 and 1 may reflect sub-samples for which omitted variable bias is compounded by the non-linear nature of our estimation, or for which our structural assumptions do not fully hold.

It remains possible that the intensification parameter estimate remains biased by measurement error in input application levels that we cannot check in these data. The correlations between measurement error in plot size and input intensity in Table 6 can arise if input application levels suffer from measurement error that is correlated with the measurement error in plot size. Abay et al. (2018) show that the correlation between measurement errors in two variables can bias – even aggravate bias in – parameter estimates when one corrects for measurement error in only one variable. In that case, the correlations in Table 6 could just be picking up correlated NCME in input levels, and the intensification parameter estimates remain biased and there is no misperception effect.

One way to address that concern indirectly is to re-estimate equation 21 using only binary indicator variables for input use under the assumption that there will be little or no farmer misreporting of which inputs they use, even if farmers might significantly misreport the amount of any input they use. Note, however, that one is then testing for intensification at only the extensive margin, which is not the Boserupian hypothesis. Indeed, since plot size is endogenous to a host of other factors that are likely correlated with a farmer's decision of whether or not to use an input – e.g., crop choice, proximity to homestead – we no longer have a prediction about the coefficient estimate β^{GPS}. But estimation of equation 21 at the extensive margin of input use does provide a good test of the null that plot size measurement error is unrelated to input use. Rejecting that null seems a reasonable indirect way of establishing that our prior findings are unlikely due solely to unobserved NCME in input levels.

So we replicate Table 6 in appendix Table A3, now looking at the relationship at the extensive margin only, where measurement error in inputs is almost surely negligible. Note that we omit labor since very few cultivated plots employed no labor; we consider just improved seed, fertilizer and pesticide use. As shown in Table A3, we find qualitatively identical results: positive

[22] It is a bit perplexing that while we generally reject $\theta = 0$ and $\gamma = \beta^{GPS}$, we also generally reject $\gamma = \beta^{SR}$. Under scenario 3, where measurement error reflects misperceptions in any way, we expect $\gamma = \beta^{SR}$. While these γ and β^{SR} are uniformly found to be the same in Tanzania, we do not find this pattern in other countries. This may be due to biased estimation of β^{SR}, if patterns in self-reports tend to reflect farmer/plot characteristics, not included in our controls, that correlate with input intensity.

and statistically significant coefficient estimates on the plot size measurement error term in virtually all country-input combinations. That pattern is also reasonably symmetric across both over- and under-estimation, as shown in appendix Table A4. Thus, it does not appear that NCME in input application levels explains our results.

It is important to be note, of course, that even aside from this particular form of bias, our estimates of both the intensification parameter and the coefficient on plot size measurement error may be biased by omitted, relevant variables and by endogenous plot size selection, since neither GPS-measured plot size nor measurement error in self-reported plot size is exogenously determined. However, the fact that estimates of the parameter θ consistently fall in the [0,1] unit interval, as expected, suggests that such bias is likely small, if it exists at all. Also, the consistent story told by alternate specifications of our estimations in Tables A1-A4 suggests that omitted variables bias does not drive our estimates. We interpret these results as supporting the claim that our core findings in Table 6 hold, that farmers intensify input application on smaller plots and that farmer misperceptions account for part of the observed intensification pattern.

7. Concluding Remarks

This paper revisits the Boserupian input intensification hypothesis in sub-Saharan African agriculture, considering the implications of measurement error in farmer self-reports of plot size under alternative data generating scenarios for measurement error. In particular, we consider the possibility that measurement error might arise not just due to farmer misreporting, but perhaps due instead or as well to farmer misperceptions that lead to input allocation based on erroneous estimates of true plot size. Given the importance of the intensification hypothesis in the face of rising population densities in rural Africa, and widespread recent findings of apparent allocative inefficiency among African farmers, it seems important to sort out what measurement errors truly represent and how one should interpret, or correct econometrically, standard hypothesis tests.

We show that measurement error is pervasive in farmer self-reports of plot size in nationally representative longitudinal survey data from four African countries: Ethiopia, Malawi, Tanzania and Uganda. That measurement error is non-classical, reflecting strong focal-point-bunching and regression-to-mean patterns. We also find, using a new test we develop, that part of that measurement error represents farmer misperceptions, not misreporting. The evidence in support of the Boserupian intensification hypothesis – that input intensity is greater on smaller plots than on larger ones – is overwhelming and consistent across all inputs in each country. But part of the observed intensification seems to reflect a behavioral anomaly wherein farmers act on their misperceptions of plot size, amplifying observed input intensification beyond that which would exist if farmers allocated inputs based on fully accurate perceptions of plot sizes. Our results therefore speak to the evolving literature documenting pervasive factor misallocations in SSA agriculture (e.g., Gollin and Udry 2017; Restuccia and Rogerson, 2017; Restuccia and Santaeulalia-Llopis 2017). Farmer misperceptions of plot size may contribute to factor misallocation as well as to Boserupian intensification.

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Table A1: Measurement error (misperception) and input use intensity, including non-linear terms

	(1) Labor	(2) Seeds	(3) Fertilizer	(4) Pesticides
		Ethiopia		
ln (GPS-measured plot size)	-0.819***	-0.284***	-0.352***	
	(0.008)	(0.018)	(0.043)	
ln (GPS-measured plot size)^2	-0.009***	0.040***	0.017	
	(0.002)	(0.004)	(0.011)	
Measurement error	**0.073*****	**0.159*****	**0.210*****	
	(0.008)	(0.020)	(0.023)	
Observations	33535	11583	9453	
R^2	0.781	0.451	0.265	
		Malawi		
ln (GPS-measured plot size)	-0.503***	-0.625***	-0.529***	-0.522***
	(0.012)	(0.064)	(0.019)	(0.142)
ln (GPS-measured plot size)^2	-0.014***	-0.060**	-0.033***	0.071
	(0.005)	(0.026)	(0.009)	(0.092)
Measurement error	**0.274*****	**0.177***	**0.251*****	**0.092**
	(0.015)	(0.104)	(0.023)	(0.093)
Observations	48815	4976	32814	1118
R^2	0.538	0.416	0.447	0.441
		Tanzania		
ln (GPS-measured plot size)	-0.507***	-0.570***	-0.354***	-0.662***
	(0.0121)	(0.0439)	(0.0510)	(0.0581)
ln (GPS-measured plot size)^2	-0.0333***	-0.00517	-0.0675***	0.00813
	(0.00427)	(0.0139)	(0.0143)	(0.0144)
Measurement error	**0.276*****	**0.163****	**0.325*****	**0.318*****
	(0.0190)	(0.0661)	(0.0731)	(0.0881)
Observations	9846	1487	1335	1016
R^2	0.500	0.481	0.354	0.511
		Uganda		
ln (GPS-measured plot size)	-0.667***	-0.847***	-0.623*	-0.607***
	(0.0191)	(0.132)	(0.350)	(0.134)
ln (GPS-measured plot size)^2	-0.0189***	0.0928*	0.0682	-0.0542
	(0.00595)	(0.0476)	(0.267)	(0.0621)
Measurement error	**0.140*****	**0.213**	**0.508****	**0.257**
	(0.0227)	(0.158)	(0.247)	(0.191)
Observations	8064	730	158	474
R^2	0.394	0.386	0.784	0.421

Notes: this table provides relationships between alternative indicators of measurement error and input use intensity. We construct relative overestimations and underestimations in self-reported plot sizes, for those over and under-estimated plot sizes. All regressions include household and year fixed effects, plot and household controls, and plot dummies. For all rows, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Measurement error (misperception) and input use intensity

	(1) Labor	(2) Seeds	(3) Fertilizer	(4) Pesticides
Ethiopia				
ln (GPS-measured plot size)	-0.784***	-0.418***	-0.399***	
	(0.005)	(0.013)	(0.018)	
Overestimation (% area)	**0.034*****	**0.282*****	**0.259*****	
	(0.011)	(0.031)	(0.041)	
Underestimation (% area)	**-0.109*****	**-0.117*****	**-0.182*****	
	(0.012)	(0.031)	(0.033)	
Observations	33535	11583	9453	
R^2	0.781	0.442	0.264	
Malawi				
ln (GPS-measured plot size)	-0.480***	-0.600***	-0.490***	-0.608***
	(0.011)	(0.062)	(0.019)	(0.118)
Overestimation (% area)	**0.273*****	**-0.000**	**0.244*****	**0.184**
	(0.020)	(0.130)	(0.031)	(0.273)
Underestimation (% area)	**-0.255*****	**-0.258**	**-0.231*****	**-0.011**
	(0.024)	(0.161)	(0.040)	(0.158)
Observations	46586	4814	31327	1076
R^2	0.538	0.425	0.450	0.443
Tanzania				
ln (GPS-measured plot size)	-0.530***	-0.590***	-0.376***	-0.663***
	(0.0132)	(0.0452)	(0.0526)	(0.0613)
Overestimation (% area)	**0.209*****	**0.0141**	**0.120**	**0.329****
	(0.0282)	(0.0921)	(0.102)	(0.138)
Underestimation (% area)	**-0.279*****	**-0.280*****	**-0.403*****	**-0.256****
	(0.0294)	(0.102)	(0.105)	(0.104)
Observations	9595	1458	1293	995
R^2	0.496	0.490	0.332	0.517
Uganda				
ln (GPS-measured plot size)	-0.665***	-0.784***	-0.781***	-0.664***
	(0.0198)	(0.140)	(0.289)	(0.137)
Overestimation (% area)	**0.0954*****	**0.536***	**1.065**	**0.269**
	(0.0343)	(0.279)	(0.782)	(0.238)
Underestimation (% area)	**-0.189*****	**0.142**	**-0.565**	**-0.159**
	(0.0338)	(0.300)	(0.521)	(0.298)
Observations	7856	712	150	464
R^2	0.397	0.376	0.826	0.429

Notes: this table provides relationships between alternative indicators of measurement error and input use intensity. We construct relative overestimations and underestimations in self-reported plot sizes, for those over and under-estimated plot sizes. All regressions include household and year fixed effects, plot and household controls, and plot dummies. For all rows, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Measurement error (misperception) and extensive margin of input use

	(1)	(2)	(3)
	Improved seed (dummy)	Fertilizer (dummy)	Pesticide (dummy)
		Ethiopia	
ln (GPS-measured plot size)	0.038***	0.052***	0.021***
	(0.002)	(0.002)	(0.001)
Measurement error	**0.008****	**0.022*****	**0.006*****
	(0.004)	(0.003)	(0.002)
Observations	36374	36466	
R^2	0.560	0.193	0.182
		Malawi	
ln (GPS-measured plot size)	-0.035**	0.204***	0.004***
	(0.016)	(0.006)	(0.001)
Measurement error	**-0.040***	**0.098*****	**0.002***
	(0.023)	(0.008)	(0.001)
Observations	10381	53439	52524
R^2	0.399	0.256	0.004
		Tanzania	
ln (GPS-measured plot size)	0.014***	0.021***	0.031***
	(0.005)	(0.005)	(0.005)
Measurement error	**0.008**	**0.008**	**0.017*****
	(0.006)	(0.006)	(0.005)
Observations	9555	9912	9912
R^2	0.117	0.025	0.082
		Uganda	
ln (GPS-measured plot size)	0.0260***	0.006**	0.022***
	(0.005)	(0.003)	(0.00400)
Measurement error	**0.0195*****	**0.002**	**0.0135*****
	(0.006)	(0.003)	(0.005)
Observations	8738	8731	8731
R^2	0.039	0.006	0.0167

Notes: this table provides relationships between measurement error and extensive margin of input use decisions. We rely on binary (indicator) variables showing whether a farmer has applied a specific input in a specific plot. DAP and urea are the most common fertilizer types in Ethiopia. For Malawi Chitowe (NPK: 23:21:0+4S) and urea are the most common types of inorganic fertilizers. All regressions include household and year fixed effects, plot and household controls, and plot dummies. For all rows, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Measurement error (misperception) and extensive margin of input use

	(1)	(2)	(3)
	Improved seed (dummy)	Fertilizer (dummy)	Pesticide (dummy)
	Ethiopia		
ln (GPS-measured plot size)	0.037***	0.054***	0.021***
	(0.002)	(0.002)	(0.001)
Overestimation (% area)	**0.002**	**0.031*****	**0.007*****
	(0.005)	(0.004)	(0.003)
Underestimation (% area)	**-0.020*****	**-0.006**	**-0.005**
	(0.006)	(0.006)	(0.004)
Observations	36357	36449	
R^2	0.561	0.193	0.182
	Malawi		
ln (GPS-measured plot size)	-0.027	0.205***	0.004***
	(0.017)	(0.007)	(0.001)
Overestimation (% area)	**0.007**	**0.100*****	**0.002**
	(0.034)	(0.012)	(0.002)
Underestimation (% area)	**0.098*****	**-0.090*****	**-0.003**
	(0.035)	(0.014)	(0.002)
Observations	9980	51026	50143
R^2	0.397	0.256	0.004
	Tanzania		
ln (GPS-measured plot size)	0.012**	0.019***	0.0321***
	(0.005)	(0.005)	(0.00490)
Overestimation (% area)	**0.005**	**0.0118**	**0.0187****
	(0.008)	(0.009)	(0.00752)
Underestimation (% area)	**-0.008**	**0.001**	**-0.0180****
	(0.009)	(0.0103)	(0.008)
Observations	9318	9661	9661
R^2	0.117	0.0250	0. 0810
	Uganda		
ln (GPS-measured plot size)	0.0258***	0.006**	0.0205***
	(0.005)	(0.002)	(0.004)
Overestimation (% area)	**0.0181****	**-0.00117**	**-0.001**
	(0.008)	(0.00433)	(0.007)
Underestimation (% area)	**-0.0186****	**-0.00556**	**-0.026*****
	(0.009)	(0.00514)	(0.006)
Observations	8528	8521	8521
R^2	0.039	0.006	0.018

Notes: We rely on binary (indicator) variables showing whether a farmer has applied a specific input in a specific plot. All regressions include household and year fixed effects, plot and household controls, and plot dummies. For all rows, * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A1: Linearity of the Relationship Between Measurement Error and Log Plot size