Cheaper, Faster, and More Than Good Enough: Is GPS the New Gold Standard in Land Area Measurement?

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In rural societies of low- and middle-income countries, land is a major measure of wealth, a critical input in agricultural production, and a key variable for assessing agricultural performance and productivity. In the absence of cadastral information to refer to, measures of land plots have historically been taken with one of two approaches: compass and rope (accurate, but cumbersome), and farmers' self-report (cheap, but marred by measurement error). Recently, the advent of cheap handheld GPS devices has held promise for balancing cost and precision. Guided by purposely collected primary data from Ethiopia, Nigeria, and Tanzania (Zanzibar), and with consideration for practical household survey implementation, the paper assesses the nature and magnitude of measurement error under different measurement methods and proposes a set of recommendations for plot area measurement. The results largely point to the support of GPS measurement, with simultaneous collection of farmer self-reported areas.

Keywords: Land, Agriculture, Measurement, Surveys

1 Introduction

Land area measurement has been of concern to humanity since the dawn of time. Some of the buildings constructed in ancient Egypt as early as 2700 BC testify to the knowledge of land surveying techniques. Evidence of boundary surveying in Mesopotamia and the Nile Valley from around 1400 BC have also been found (Lyman & Wright, 2015). The word "geometry" originated in ancient Greece from the Greek words for "measure" and "Earth'. Similarly, ancient traces of the command of surveying techniques have been found in China (Swetz, 1992) and India (Joseph, 1997). The need to measure land originated from concerns as diverse as the construction of buildings, tax collection, and the need to demarcate properties and boundaries. Those concerns are still valid today, and many of the basic principles and techniques have remained remarkably similar over the millennia, even though technology has certainly advanced and allows for measurements that are both easier and more precise than they might have once been.

With over 70 percent of the developing world's poor residing in rural areas where agriculture is the primary means of livelihood, high quality agricultural data and analysis are paramount to informing policy aimed at poverty reduction (IFAD, 2010). Land is a key measure of absolute and relative farmer wealth, a critical input in production, and a key variable for normalizing agricultural input use and output measures. Although easily overlooked by analysts, the quality of land area measurement can have non-trivial implications for agricultural statistics, economics, and policy analysis (Carletto, Gourlay, & Winters, 2015, 2013; Dillon, Gourlay, McGee, & Oseni, 2016).

While the focus of this study is on the importance of area measurement in smallholder agriculture in developing country contexts, the implications of land area measurement extend well beyond agricultural productivity. For instance, disaggregated land ownership data are an input into analyses of agrarian structures and how these evolve with economic and demographic change, the related analyses of land inequality, and how this might be related to income inequality and its trends. Unequal distribution of land has been linked to less pro-poor growth, participation in and occurrence of civil strife, and delayed long-run human capital development (André & Platteau, 1998; Baten & Juif, 2013; Deininger & Squire, 1998; Macours, 2011). Carletto et al. (2015) find that the area measurement methodology used in calculating the land Gini coefficient has consequences on the level of inequality observed, with self-reported area estimates resulting in underestimated land inequality. Failure to adequately measure land limits the ability to analyze the agricultural economy and its relationship with land inequality. Addition-

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ally, land registration and titling programs require high quality land area measurement for fair program implementation. Such programs are frequently met with opposition and accusations of corruption or favoritism. Ongoing land certification reform efforts in Ethiopia have recently moved from the first stage of certification, which consisted of identification of plots by land markings and neighbor recall, to the second stage certification in which GPS measurements would replace the first stage data. International organizations have also emphasized the importance of objective area measurement in land registration and redistribution.

Area measurement holds significant value in the developed country context as well. In Europe, national authorities conduct a regular Farm Structure Survey employing a common methodology devised by Eurostat (Istat, 2008). The EU FIELDFACT Project is one of many schemes that aim to raise farmer awareness on the use of GPS in land measurement for the purposes of precision agriculture and more accurate and transparent subsidy claims through the EU's Common Agricultural Policy[1]. Frequent land measurement is encouraged by several developed country governments (e.g. USA, UK, Germany, Australia) at the individual farmer level in promotion of precision agriculture, whereby the production process is tailored to farmland size estimates obtained via GPS/GNSS and remote sensing. By knowing exact area measurements, farmers are able to adjust input use accordingly and, thus, optimize yields while cutting down on costs. Effective land area measurement, therefore, also contributes to a more focused application of fertilizers and pesticides that could, in turn, alleviate environmental degradation and pollution.

The methodological menu for collecting land area measurements is diverse and selection of the appropriate method depends on several factors. This paper focuses on the methods that hold relevance for agricultural and household surveys [2]. Readers interested in a broader approach to the measurement of agricultural land are referred to FAO (1982), Sud et al. (2015). This is an important distinction because several measures of agricultural land that are important for agricultural statistics can be collected separately from information about the holding or the household (e.g. when the goal is to estimate crop land or area under specific crops at the national or other administrative level). For the analysis of household level processes and outcomes, on the other hand, it is vital that the land area being measured can then be linked to other variables concerning the agricultural production, or welfare outcomes, or other variables of interest for the same household or holding[3]. The main types of surveys for which these measurements are relevant are agricultural sample surveys, agricultural censuses, multi-topic surveys that cover agriculture (such as most Living Standard Measurement Study (LSMS) surveys), and smaller scale household surveys carried out for research purposes.

This paper aims to provide some elements to inform the selection of measurement methods, based on empirical evidence gathered by the Living Standard Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) team of the World Bank in Ethiopia, Tanzania, and Nigeria during methodological fieldwork aimed at understanding the relationship between farmer estimates, GPS measurement and the traditional compass and rope method. This paper focuses on the analysis of area measurement data from the abovementioned studies. For more detailed guidance on costing, training, implementation, and other practical considerations for area measurement in household surveys, refer to the complementary guidebook (Carletto, Gourlay, Murray, & Zezza, 2016).

2　Methods for land area measurement in surveys

Three main methods are used in the context of agricultural statistics data collection for the measurement of land area: respondent self-reported land area; compass and rope, traditionally held as the "gold standard'; and, the most recent addition, GPS-based measurement. Each area measurement option has unique costs and benefits that need to be carefully assessed in view of the scale of the data collection of which they are a part, the intended use of the data, and the characteristics of both the plots to be measured and the respondents to the survey. Different methods also present different challenges in terms of their implementation: a potentially accurate method can become highly inaccurate if poorly implemented in the field, or it may simply not be feasible on a larger scale. The specific limitations, challenges, and benefits of each of the abovementioned measurement methods are addressed in detail below.

2.1　Self-Reported Area Estimation

Household surveys, particularly in developing countries, have historically relied on subjective measurements of land area, and for good reason. The marginal cost of adding one or two questions to a survey that is already being administered to a household is trivial and the exercise can be completed in a matter of minutes, with no need to visit the plot. As a result, item non-response for this item is usually negligible in existing surveys. The minimal financial investment required by this method, however, does not come without challenges, particularly in terms of data quality.

Several factors influence the accuracy of subjective farmer self-reported estimates of area, including respondent charac-

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[1]http://www.gsa.europa.eu/introduction-and-promotion-gnss-agriculture

[2] The focus will also be on low income countries with little or no cadastral or administrative information to integrate this type of data collection.

[3]Similarly, for plot level productivity analysis it is essential that input and output data can be combined at the plot level.

teristics, plot characteristics, and the land registration or titling system. Land in developing countries is often passed down from generation to generation or distributed by the community, and rarely are there property rights or documentation to inform farmers of their true land area. In many cases measurement units are not standardized and determining accurate conversion factors is a time-consuming and often ill-fated exercise. The most worrying aspect of some of the measurement error associated with self-reporting is that it may be systematic, and associated with key variables of interest.

The literature has shown the accuracy of subjective estimates to be sensitive to respondent characteristics. More educated farmers might be more numerate and more at ease at quantifying their own land area, while absentee landlords, or respondents for whom farming is only a secondary activity, may be less aware of the characteristics of their plots. Using data from Uganda, Carletto et al. (2013) analyze the determinants of the difference between farmer self-reported plot area and GPS measurements, finding that the age of the household head has a significant and positive relationship with measurement bias.

The quality of data collected through farmer self-reporting is also significantly degraded by the natural inclination of respondents to round off numbers, as has been documented by several national level studies. Distributional analysis of GPS and self-reported areas of the 2010/2011 Malawi Integrated Household Survey shows clear evidence of heaping at whole numbers and common fractions, such as 0.5 acres. Carletto et al. (2015, 2013) and Desiere and D'Haese (2015) find rounding to be a significant factor in the discrepancy between GPS area and farmer self-reported estimates. Plot characteristics, such as boundary delineation and the existence of property rights, are known to significantly influence the measurement bias (Carletto et al., 2015, 2013). Plot slope or crop-type may also play a role in the ability of a farmer to estimate plot size. De Groote and Traoré (2005) assessed the accuracy of a method in which farmer self-report is elicited during a visit to the plot, and a discussion with a trained enumerator. Comparing this method to rope and compass in southern Mali they find that on average plots areas were underestimated by 11 percent, with smaller plots being overestimated and larger plots underestimated, and measurement error being smaller for cotton fields than for cereals, which supports the idea that farmers may be better able to estimate the area of plots on which cash crops are cultivated.

Farmer self-reported area estimates are influenced not only by plot and respondent characteristics, but also by a variety of cultural considerations and logistics of survey implementation. One major such factor is the prevalence of traditional or non-standard units. In many countries, respondents are often not familiar with standard measurement units such as acres, square meters, or hectares as they are used to expressing area measures in traditional units. Those units are not standardized and may vary in size by region, or even across villages or farms. Goldstein and Udry (1999), for example, report a correlation between self-reported and GPS measured plot size of just 0.15 using data from Eastern Ghana, which they attribute to the agricultural history of the region where local field measurements are traditionally based on length rather than area, and respondents are not accustomed to converting them to two dimensional area measures.

Recent studies emphasize not only the presence of large measurement error in self-reported measures, but also the systematic association of the magnitude and sign of the error with important plot characteristics. Carletto et al. (2015), using LSMS-ISA data from Malawi (2010/11), Tanzania (2010/11), Niger (2011) and Uganda (2009/10), identify a common trend in the magnitude of measurement bias, defined as self-reported minus GPS area for plots for which both measures were available and taken independently. The smallest of plots (less than 0.5 acres) are systematically over-reported. The degree to which these are over-reported varies, but in all countries the mean self-reported area is overestimated by at least 90 percent of the mean GPS area of plots in that particular class. With increasing plot size the degree of over-estimation decreases and, eventually, converts to under-estimation for the largest plots. Carletto et al. (2013) find the same trend in 2005/6 data from Uganda while Dillon et al. (2016) provide evidence of similar systematic trends in data from Nigeria. In a methodological study conducted in Southern Mali comparing area estimates with compass and rope measurement on larger plots (average 0.816 ha, maximum 8.78 ha) De Groote and Traoré (2005) find that the same is true: farmers (while aided by expert observers) are inclined to over-estimate the area of plots less than one hectare, while the degree of area under-estimation increases with plot size.

2.2 The "Gold-Standard": Compass and Rope Measurement

The compass and rope (CR) method is widely used in farm surveys and is often considered to be the gold standard (FAO, 1982). When properly implemented, the compass and rope method returns highly accurate measures that can also provide a benchmark against which to judge the precision of other methods. However, its implementation is time-consuming and burdensome, and is often unfeasible in the context of national household surveys and censuses.

This method requires that the enumerator and respondent travel to the plot and clear its boundaries from obstacles to the extent possible. Before the measurement can begin, the farmer must pace the perimeter of the plot with the enumerator in tow to ensure the measurement captures the proper area. The enumerator will mark the corners of the plot with ranging poles. When plots are irregularly shaped, enumerators use their best judgment in declaring the corner points. The boundary of bushy plots will need to be cleared (with the

permission of the farmer) prior to commencing measurement in order for the ranging poles to be visible. Only then can the enumerator start the task of measuring the plot, which entails measuring the distance and compass bearing between every two consecutive corner points and then using these measures to construct a polygon and compute the area (aided by a programmable calculator or other computational tool). An example of instructions for completing the compass and rope measurement can be found in FAO (1982), while an example questionnaire format can be found in Carletto et al. (2016).

To some degree, the measurement error associated with compass and rope is observable. The closure (or closing) error is an important element of quality control in the compass and rope method. It is a measure of the gap between the reported start and end points of the constructed polygon, and gives an indication of the accuracy of the measurement. If the closing error is calculated while in the field, the measurement can be conducted again when found to be above a pre-determined threshold. The closing error will not confirm that the plot corners have been accurately assessed, however, only that the bearings and distances recorded form a full closed figure. The precision of the measurement is still subject to human error as identifying the plot corners can be a burdensome task on its own, particularly for irregularly shaped plots.

When corners are not clearly defined (as is the case in many irregularly shaped plots) enumerators must plot the "best" corner they can, and take the compass bearings. With each additional corner, therefore, there is additional room for error in the misreading of the compass or the measurement of the distance between two corners. Misreading of the compass by one or two degrees on one corner is not likely to result in material changes to the area measurement. However, aggregated over several plot corners, these small deviations add up, implying that the area calculation is not for the true plot boundaries. While field protocols usually include closing error thresholds beyond which the measurement needs to be retaken, this adds to the time necessary to take the measurement.

The limitations to the compass and rope method lie primarily in the burdensome nature and time required to complete the measurement. The time requirements will vary by plot size, but the compass and rope method is expected to be consistently and significantly more time-intensive than GPS. However, when properly implemented this method is considered the gold standard and, as such, it offers the benchmark against which to evaluate the trade-offs with competing, less time-intensive methods.

2.3   Measurement with Handheld GPS Devices

Measurement with Global Navigation Satellite Systems, such as the Global Positioning System, collectively referred to hereafter as GPS, requires that the enumerator first tra-

verse and clear the plot boundary with the farmer, as is the case with compass and rope measurement. The enumerator then begins at a designated corner of the plot, starts the GPS area measurement function, paces the perimeter at the recommended speed (pausing at all corners to allow for coordinate capture) and completes the area measurement upon returning to the initial corner (instructions may vary by GPS unit).

GPS technology and GPS-enabled devices offer a practical approach to objective area measurement (Kelly & Donovan, 2008). Measuring land area with portable GPS devices is becoming increasingly popular among survey practitioners around the world. The method is relatively cheap, accurate and precise if careful measuring protocols are devised and implemented. Currently, decent handheld GPS devices can be procured for under $300 each[4]. The main concerns with the method relate to the measurement of plots that cannot be visited by survey staff (resulting in missing data), and the accuracy of the measurement on very small plots. Advancements in GPS technology show promise for increased accuracy in the coming years as more satellites are launched and the availability of satellite augmentation systems spreads to reach all world regions (at the time of writing, augmentation systems do not currently extend across Africa to any useful degree)[5].

Time can often be the most restrictive resource in survey implementation, and existing studies comparing the time use for GPS and compass and rope find that compass and rope can take approximately 3.5 times as long as required for GPS (Keita & Carfagna, 2009; Schøning, 2005). Keita and Carfagna (2009) provide a discussion of the area measurement performance of different GPS devices compared to compass and rope. Their discussion is informed by a field experiment, the results of which indicate that the GPS-based area measurement is a reliable alternative to compass and rope and that 80 percent of the sample plots were measured with negligible error.

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[4]The GPS devices used for the Ethiopia and Tanzania studies discussed below, the Garmin eTrex 30, are priced at $299.99 at the time of writing in March 2017 (http://www.garmin.com). The device used in the Nigeria study discussed below, the Garmin GPS Maps 62 has been discontinued but was of a similar price point.

[5]In 2011 the Russian Global Navigation Satellite System (GLONASS), which works seamlessly with the United States' GPS network, became globally operational with 24 satellites. Augmentation systems can improve the accuracy and speed of GPS measurement in the field. The Wide Area Augmentation System (WAAS), a real-time correction based on ground stations, has been proven to increase position accuracy by as much as five times according to a leading manufacturer. The WAAS system is only operational in North America, while Europe and Asia have their own regional solutions (Euro Geostationary Navigation Overlay Service (EGNOS) and Japanese Multi-Functional Satellite Augmentation System (MSAS), respectively). India's regional augmentation system (GAGAN) was cleared for navigational use in early 2014.

Despite the great potential of GPS technology, GPS-based coordinates are subject to known types of measurement error stemming from satellite position, signal propagation, and receivers. Approximate contributions of these factors to the overall position error are significant, ranging from 0.5 to 4 meters (Hofmann-Wellenhof, Lichtenegger, & Wasle, 2008). The number of satellites, in particular, can cause the distribution of position error to be elliptical, rather than spherical, and therefore not exactly randomly distributed around the true point (Van Diggelen, 2007). Additional factors that may be expected to influence the quality of GPS measures include the presence of dense tree canopy or cloud cover, which may interfere with the signal. The quality of the GPS device used also has non-negligible impact on the magnitude and distribution of measurement error (Palmegiani, 2009). Although position estimates are subject to a certain level of inaccuracy and may be distributed in a non-spherical manner, in theory the error associated with area measurement should be random – that is, the factors that cause non-spherical position error are largely macro level factors that are unlikely to change in the short period of time required to pace the perimeter of a plot, rendering the position error distribution consistent at all points along the perimeter. A study by (Bogaert, Delincé, & Kay, 2005) using simulated coordinates and European Geostationary Navigation Overlay Service (EGNOS) augmentation concluded that the position error can be reasonably assumed to be normally distributed.

The literature suggests some concern that errors in GPS measures may vary systematically with key plot characteristics, namely plot size, slope, and shape. Few published studies have tested the use of GPS measurement against the gold-standard measure, the traditional compass and rope method. Recent research by FAO points out possible effects of slope on the accuracy of GPS-based area measurement (Keita, Carfagna, & Mu'Ammar, 2010). Slope-related effects on area measurement are rooted in the fact that the actual area should be the horizontal projection of the plot, as opposed to the plot area itself (Muwanga-Zake, 1985). The difference between actual area and projection appears to be particularly important for slopes greater than 10 degrees (Fermont & Benson, 2011).

Bogaert et al. (2005), based on modeling and simulations conclude that "for GPS/EGNOS measurements made by an operator moving along the border of a field, area measurement error is linked both to the operator speed and to the acquisition rate of the GPS device. For typical field sizes found in the European Union, ranging from 0.5 ha to 5 ha, the coefficient of variation (CV) for area measurement errors is about 1 percent to 5 percent. These results depend on the field area, but they can be considered to be insensitive with respect to the field shape. They also show that field area measurement errors can be limited if an appropriate combination of operator speed and GPS acquisition rate is selected."

Fasbender and Lucau (2012) also find that plot shape as well as plot size affects GNSS area measurement error. In their synthetic simulation of four distinct parcel shapes (square, rectangular, elongated narrow rectangle, and irregular polygon), with simulations for areas from 1 m² to 10 ha, they find that the variance of the measurement on the elongated rectangle and irregularly shaped polygon are the most amplified. Specifically, they suggest that the error on such irregular parcels, which are common amongst low-income regions" small-holder farmers, is primarily attributable to operator (enumerator) error (Fasbender & Lucau, 2012).

One concern with GPS measures in large scale surveys, which does not apply to self-reported measures, is the rate of missingness in the data. Missingness rates of 20-30 percent are not uncommon in existing datasets, and the pattern of missingness is not random but tends to be correlated with both plot and respondent characteristics. Kilic, Zezza, Carletto, and Savastano (2017) show, with national data for Uganda and Tanzania, how plot distance from the interviewed household is the main factor determining what plots get measured, as field protocols normally include a provision not to measure plots beyond a given distance. Partly due to that, the plots that are not measured also differ systematically from those for which a GPS measure is taken in a number of (self-reported) characteristics, such as self-reported plot size, level of input use, and titling. Furthermore, some respondent characteristics are associated with higher missingness rates: plots belonging to older, less educated, poorer household heads, owning fewer plots are more likely to be measured than other plots. This is a drawback of GPS data that raises concerns about possible biases introduced by relying on observed GPS plot measures alone. Utilizing the compass and rope method in place of GPS would not alleviate these missingness problems, as it, too, requires physical travel to the plot.

In the presence of rates of missingness this high, imputations are often necessary for analysts to be able to work with complete case datasets. Self-reported land areas measures have been shown to be an important predictor of GPS area measure (Kilic et al., 2017). For that reason it is recommended that GPS measures be taken in addition to, not instead of, self-reported ones.

3 Data: The LSMS Methodological Validation Program

In order to address the gaps in the area measurement literature and extend the applicability of studies to the plot conditions common to developing countries, the Living Standard Measurement Study – Integrated Surveys on Agriculture (LSMS-ISA) of the World Bank has prioritized land area measurement in its research agenda. The Global Strategy to Improve Agricultural and Rural Statistics has also identified improving the measurement of crop productivity, and by

necessity farm area measurement, as a top priority (World Bank, FAO, United Nations, 2010). Because agricultural statistics are often marred by controversy over methods and overall quality, stringent validation of the available measurement methodologies is essential. With financial support from UK Aid, the Living Standards Measurement Study (LSMS) has partnered with national statistical offices in the design and implementation of methodological validation studies. The methodological studies completed through the LSMS have a particular focus on the feasibility of implementation in large-scale household surveys, thus the recommendations on best practices are made in consideration for both the highest data quality and practicality of implementation under the constraints common in this type of survey. To date, methodological validation studies on land area measurement have been conducted in Tanzania (Zanzibar), Ethiopia and Nigeria. This paper uses the data collected within these studies, which are briefly described in what follows.

Data for Zanzibar, Tanzania come from the Measuring Cassava Productivity study. This study focused on testing several methods for measuring cassava production, including crop-cutting, harvest diary, various means of assisted harvest diary, and various recall periods. To complement the measurement of cassava production, cassava plots were also measured using three methods of area measurement. Fieldwork extended from June 2013 to May 2014, with area measurement completed from August 2013 to January 2014. The study was conducted in two districts, one on Unguja and one on Pemba Island, Zanzibar. The sample consisted of 1,247 households, with 1,932 cassava plots measured for area. Only 1.1 percent of selected households failed to participate in the study, rendering non-response negligible (98.9 percent household response rate). Partners in the study included the Ministry of Agriculture and Natural Resources, Zanzibar, the Office of the Chief Government Statistician, Zanzibar, and the World Bank. The handheld GPS Unit used in the study was a Garmin eTrex 30.

The second data set used in this paper comes from the Ethiopia Land and Soil Experimental Research (LASER) study. The LASER study involved methodological validation of plot area measurement, soil fertility testing, and measurement of maize production. Area measurement and soil fertility testing was conducted on up to two randomly selected plots per household (where applicable, one pure-stand maize plot was selected for crop-cutting). The questionnaires were administered using computer-assisted personal interviewing. Fieldwork was conducted in multiple waves. Post-planting activities were conducted from September to December 2013. Post-harvest activities were conducted from January to early March 2014. Crop-cutting was conducted at any point during this period when the maize was deemed ready for harvest by the respondent. Area measurement was conducted in the post-planting visit. The data collection for LASER was

conducted in 3 zones of the Oromia region in Ethiopia. In total, 85 enumeration areas (EAs) were randomly selected using the Central Statistical Agency of Ethiopia's Agricultural Sample Survey as the sampling frame. Within each EA, 12 households were randomly selected from the household listing completed September 2013. Non-response was not a problem, as only 2 of the 1020 selected households refused to participate in the study (99.8 percent household response rate). Partners in the study include the Central Statistical Agency of Ethiopia, the World Agroforestry Centre, and the World Bank. This study also used Garmin eTrex 30 units to collect GPS land area data. Data for the Ethiopia LASER study is available on the LSMS website (Ethiopia Land and Soil Experimental Research (LASER) data, 2016).

The last batch of data used in this analysis comes from the Nigeria Area Measurement Validation Study. The primary focus of this study was validation of area measurements. Extraordinary differences between GPS and farmer self-reported areas were observed in the first wave of the Nigeria General Household Survey, invoking the need to validate the methodologies. This study was conducted on a subsample of the General Household Survey panel households. After the measurement conducted in the second wave of the national survey, a special team was deployed to re-measure a subsample of plots using three area measurement methods. Fieldwork for the area measurement validation study ran from March to May 2013. Four states were selected for inclusion in the study based on safety, location, and previous performance of farmer self-reported area and GPS area. The plot selection was stratified on plot size to ensure a complete range of plot sizes included[6]. In total, 211 households were selected, including 518 plots. Nine households failed to participate in the study, totaling 23 plots, either due to farmer refusal (4 plots), land disputes (5 plots), or other reasons (14 plots) (95.7 percent household response rate). The study was implemented by the National Bureau of Statistics, Nigeria, and the World Bank. The GPS unit utilized for this study was the Garmin GPS Maps 62.

In each of the three studies, agricultural plots were measured first by farmer self-reported estimate, then by compass and rope, and finally by GPS. The order of measurements was deliberate and great attention was paid to this in the field. Farmer estimation must be recorded prior to any objective

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[6]The stratification on plot size has the potential to bias results, as larger plots were more heavily sampled relative to the population. In order to evaluate this possibility, all analysis was run with and without sample weights. The conclusions of the paper were not altered by the inclusion of sample weights. This, coupled with the fact that using unweighted analysis allows for greater comparability with the pooled analysis, led to the presentation of unweighted results throughout. Sample weights were not computed for Tanzania or Ethiopia, as household selection was random within the selected enumeration areas and not stratified on plot size.

measurement so as not to influence the farmer. Enumerators were instructed in all studies not to influence the farmer's estimate. Consistent with the evidence found in the national level studies discussed above, data from each of the three methodological studies reveals rounding of self-reported area estimates on common fractions, such as 0.25 and 0.5, and integers.

Although in each of the three studies the training of methods was conducted in the same way, with the same LSMS staff present at each training, there were two differences in implementation worth noting. First, in each survey, enumerators were required to repeat the compass and rope measurement if the closing error was 5 percent or more. However, in the Ethiopia experiment the closing error calculation was done on the spot by the enumerators, possible because of the use of computer-assisted personal interviewing. In Tanzania and Nigeria, the closing error was calculated by the supervisors (in some instances the supervisors in Nigeria were present at the plot at the time of measurement). This may influence the comparison of compass and rope with GPS measurement if, for example, an enumerator had to re-visit the plot in order to take the new compass and rope measurement and unintentionally identified the borders differently during the second visit. In Ethiopia, on the other hand, all re-measurements were completed at the same time of the initial measurement as the closing error was calculated before leaving the plot. The instance of closing error greater than 5 percent, however, was rare and therefore not expected to influence the analysis (in the Ethiopia experiment, only 5 percent of fields were measured more than once).

Second, the skill level of the enumerators varied. In Tanzania, the enumerators were the agricultural extension officers for the local area. These enumerators were very familiar with the agricultural practices but generally inexperienced in survey administration and the use of the particular measurement tools. These enumerators also happened to be significantly older and several had poor vision (requiring the purchase of glasses in order to read the compass and GPS). Because of the ongoing and intensive nature of the cassava measurement component of the Tanzania experiment, the extension officers were the preferred enumerators for the existing infrastructure and established relationships within the community. In Ethiopia, professional enumerators were hired based on past performance with the Central Statistical Agency and previous experience with computer-assisted personal interviewing. In this particular study the enumerators all held bachelor's degrees and were relatively young. In Nigeria, staff from the head office of the National Statistics Bureau were trained and sent to the field rather than the enumerators used to conduct the national panel survey. In each of these studies the health, education, and skill level varied, as did the incentive structure and duration of fieldwork. Rather than discredit the comparability of the data collected

from each of these studies, the consistency observed in the comparison of methods should lend confidence in the applicability across survey environments.

4 Methods

Before comparing the various measurement methods, the integrity of the compass and rope method is first examined, as well as a descriptive analysis of the time required to complete the measurements. A simple OLS model is employed with the aim of identifying the determinants of closing error, a proxy for measurement error in the compass and rope measurement. Recall that the closing error reflects the error in constructing a full polygon only, and does not account for cases in which enumerators may misidentify plot corners or simplify plot shapes. The following model is estimated:

$$C_i = \gamma + \alpha_1 L_i + \alpha_2 S_i + \alpha_3 T_i + \alpha_4 W_i + \varepsilon_i \quad , \qquad (1)$$

where C is the percent closing error on plot i, L is the measure of the plot taken using CR, S is a vector of proxies for the complexity of plot shape (the number of corners and plot slope, where available), T is a vector of dummy variables related to tree canopy cover (the reference being no canopy cover), W is a dummy variable indicating mostly cloudy, all cloudy, or rainy weather conditions at the time of the measurement, and ε is a random error with the usual desirable characteristics. Parameters to be estimated include α_1, α_2, α_3 and α_4 and the constant term, γ. Had plots been randomly assigned to enumerators, enumerator effects could have been used to control for enumerator skill level and other idiosyncrasies, but plots were assigned primarily based on geographic proximity and thus enumerators often measured plots with very similar geographic properties, rendering enumerator effects inappropriate.[7]

After examining the potential determinants of error in compass and rope measurement, comparisons of the various measurements are made. To that end we construct two measures of deviation between the GPS and CR measures, defined as follows:

$$\text{Bias} = \text{GPS} - \text{CR} \quad ,$$

and

$$\text{Relative Bias} = \frac{\text{GPS} - \text{CR}}{\text{CR}} \cdot 100$$

The bias is the simple difference between the GPS measure and the CR measure, expressed in acres. The relative bias is the simple difference between the GPS measure and the CR measure, in acres, divided by the CR measure, expressed in percentage terms. The absolute value of both measures is also used in the analysis.

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[7]The inclusion of enumerator fixed effects did not improve the fit of the models, likely due to the correlation of enumerator assignment and geographic identifiers.

Although the main focus on what follows will be on the deviation of the GPS from the CR measure, we will occasionally employ measures of deviation of the self-reported (SR) from the CR measure, employing a terminology analogous to the one just described for the deviation of GPS from CR measures[8].

The analysis will be based initially on a bivariate comparison of the means of the above variables for particular portions of the sample cross-tabulated with a broad range of variables of interest. The second part of the analysis will explore the determinants of the different measures of bias. We will estimate two main regression models. The first model is an OLS regression specified as:

$$Y_i = \gamma + \beta_1 L_i + \beta_2 C_i + \beta_3 SAT_i + \lambda S_i + \delta T_i + \eta W_i + \varepsilon_i \quad , \quad (2)$$

where Y is one of the four measures of bias defined above (bias, relative bias, absolute bias and absolute relative bias), L is the measure of the plot taken using CR, C is the closing error of the CR measure, S is a vector of proxies for the shape of the plot (including the number of corners and the ratio of the perimeter/area, SAT is the number of satellites the GPS device was fixed on at the time of measurement, T is a vector of dummy variables related to tree canopy cover (the reference being no canopy cover), W is a vector of dummy variables related to weather conditions at the time of the measurement (the reference being clear or partly cloudy sky), and ε is a random error term with the usual desirable characteristics. β_1, β_2, and β_3 are parameters to be estimated, as are vectors λ, δ, and η, and constant, γ.

To focus specifically on plots for which large deviations are observed between GPS and CR, we then estimate a probit model to capture the factors likely to increase the probability that a plot be measured with a relative bias larger than ten percent (in absolute value). We estimate three versions of this model for each country dataset, so as to investigate whether under- and over-estimation by large margins are driven by different factors. The model is specified as follows:

$$\Pr(i = 1|X_i) = \Phi(X_i\beta) \quad , \quad (3)$$

where $X_i = (C_i, S_i, SAT_i, T_i, W_i)$ and Φ is the standard cumulative distribution function and β is a vector of estimated parameters. In equation (3), Y_i is one of three outcomes: a plot having absolute relative bias greater than 10 percent; a plot having relative bias greater than 10 percent; a plot having relative bias smaller than -10 percent.

5   Results

5.1   Compass and rope: How golden is the gold standard?

Closing error is (weakly) associated with plot characteristics.   The error associated with the compass and rope

measurement is to some degree observable through the closing error. The average closing error in our data across all measurements is around 2 percent, with the range going from 1.6 percent in Nigeria to 2.2 percent in Ethiopia.

Regression analysis aimed at determining the factors that contribute to closing error is presented in Table 1. At the individual country level, only in Tanzania is there a significant negative relationship between plot area and closing error, implying that closing error is smaller on larger plots. When the data from three experiments are pooled, plot size has no significant effect on the closing error. The number of corners on the plot (as measured by the number of vertices captured in the compass and rope measurement) exhibits a negative and significant coefficient in Ethiopia and the pooled data – contrary to the expectation that more corners lead to higher closing error. Tree cover proves to have little effect on the closing error, as none of the individual experiments exhibit significant coefficients. Ultimately, there seems to be little evidence that closing error is systematic. This is comforting for the analysis that follows, as we move to explore systematic sources of error in other area measures, namely deviation from the CR method.

Compass and rope is significantly more time consuming that GPS measurement.   From the perspective of survey practitioners and national statistical offices, considerations about accuracy need to be accompanied by considerations related to time (and hence cost) of each methods' implementation. The reason why the choice of method should matter for survey practitioners is compellingly conveyed by Figure 1, which shows the measurement time for GPS and compass and rope measurements by plot size classes, moving from small plots on the left to large plots on the right. Compass and rope requires significantly more time than GPS, with time increasing exponentially with plot size, while the additional time required for GPS measurement for plots of the size included in these studies is negligible. In both the Ethiopia and Tanzania experiments, the compass and rope measurement took approximately four times the time required for GPS[9]. In Ethiopia, GPS required 13.9 minutes on average, while the compass and rope measurement on the same plots required an average of 57 minutes. In Tanzania, the duration averages were 7.4 minutes and 29.3 minutes for GPS and compass and rope respectively. These findings are

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[8]To limit the influence of outliers, 78 observations which fell in the top 1 percent in terms of absolute value of relative bias (for GPS vs CR and SR vs GPS) of the individual country data sets were dropped. The majority of identified outliers are smaller plots (as measured by CR), where small discrepancies in area estimates result in very high absolute value of relative bias figures (in percentage terms). The exclusion of outliers results in conservative estimates of the bias between CR and subjective measurements, but has little impact on the comparison of GPS and CR measurements.

[9]Data on measurement duration are not available for Nigeria.

Table 1
Determinants of Closing Error

OLS Regression	Ethiopia	Tanzania	Nigeria	Pooled
CR Area (acres)	0.020	−0.291[*]	0.096	−0.032
CR Area^2	0.166	-	−0.005	-
CR Area^3	−0.039[*]	-	-	-
Number of Corners	−0.032[**]	0.006	−0.004	−0.013[**]
Slope (clinometer)	0.014[**]	-	-	-
Treecover (Ref. Categ.: None)				
Partial	−0.003	−0.052	−0.128	−0.143[**]
Heavy	0.183	−0.163	0.331	0.021
Weather (Ref. Categ.: Partly Cloudy or Clear)				
Mostly Cloudy, All Cloudy, or Rainy	−0.014	−0.128[*]	0.036	−0.048
Constant	2.298[**]	2.118[**]	1.597[**]	2.238[**]
N	1765	1908	485	4158
R2	0.015	0.007	0.019	0.008

[*] p <.05;　[**] p < .01

consistent with previous studies such as Keita and Carfagna (2009), Schøning (2005) who find that compass and rope takes approximately 3.5 times as long as GPS on average.

To put the time considerations into context, given the sample size and average measurement durations in Ethiopia, the field teams spent a total of 416 hours measuring plots with GPS (1797 plots * 13.89 minutes) and 1,707 hours measuring with compass and rope. Using GPS instead of compass and rope, therefore, saved 1,291 hours of labor – over 160 person/days (at 8 hours per day). This estimate of time savings is for a relatively small-scale methodological experiment; savings in nationally representative household surveys would be proportionally larger. Minimizing the amount of time required to collect quality land area data can significantly reduce costs and improve the flow of fieldwork.

5.2 Comparison of competing measurements

Compass and Rope vs. Self-Reported Estimations. Before examining the comparability of GPS and compass and rope measurements, we first explore the difference in subjective (self-reported) and objective (CR) measurement[10]. Table 2 presents mean plot areas as measured by farmer self-reported estimation and compass and rope for all three methodological experiments. The data is grouped by compass and rope plot size class. While the mean plot areas as measured by GPS and compass and rope differ by only as much as 3 percent on average (explored further below), the mean self-reported and compass and rope measurements differ by as much as 143 percent on average (Tanzania). The mean difference is smaller in Ethiopia and Nigeria, at 23 percent and 5 percent respectively, but still considerably larger than the divergence observed between the objective measurements.

Self-reported measures result not only in higher average deviations, but in dramatic systematic error as the size of small plots is overestimated by anywhere from 30 percent (Nigeria) up to a factor of six (Tanzania), with the over-estimation declining almost monotonically as plot size increases and eventually results in under-estimation in the larger plot size classes in Nigeria and Ethiopia. These results comparing objective and subjective area measures are in line with findings of previous literature (Carletto et al., 2015; De Groote & Traoré, 2005). The scatter plots on the right side of Figure 2 convey the same message in graphic form.

Compass and Rope vs. GPS. In the literature, the main reservation regarding the use of GPS measurement in surveys is its performance on small plots. Furthermore, Keita and Carfagna (2009), Palmegiani (2009), Schøning (2005) all found that GPS tends on average to err on the negative side, i.e. to understate the area with respect to compass and rope.

Table 3 presents descriptive statistics on the GPS and compass and rope area measurements completed as part of the methodological studies. Mean plot size is small in all countries, ranging from 0.27 acres in Tanzania to 1.31 acres in Nigeria. The mean difference between compass and rope and GPS measurement is very small. The sample mean bias in all three countries is plus or minus 0.01 acre, which translates in a 1 to 3 percent difference when expressed in relative terms (note that the values are not expressed in absolute value and as such negative and positive figures are averaged). Mean GPS and CR measurements are significantly different at the

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[10]Comparing self-reported to GPS yields exactly the same results, even when analyzed using data from the nationally representative LSMS surveys in Malawi (2010/11) and Tanzania (2010/11), therefore we limit the comparison to self-reported and CR.

Average Measurement Duration
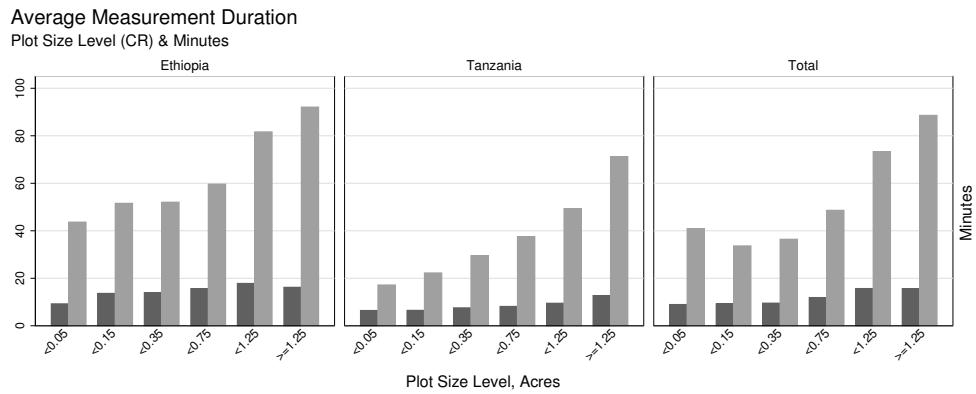Plot Size Level (CR) & Minutes

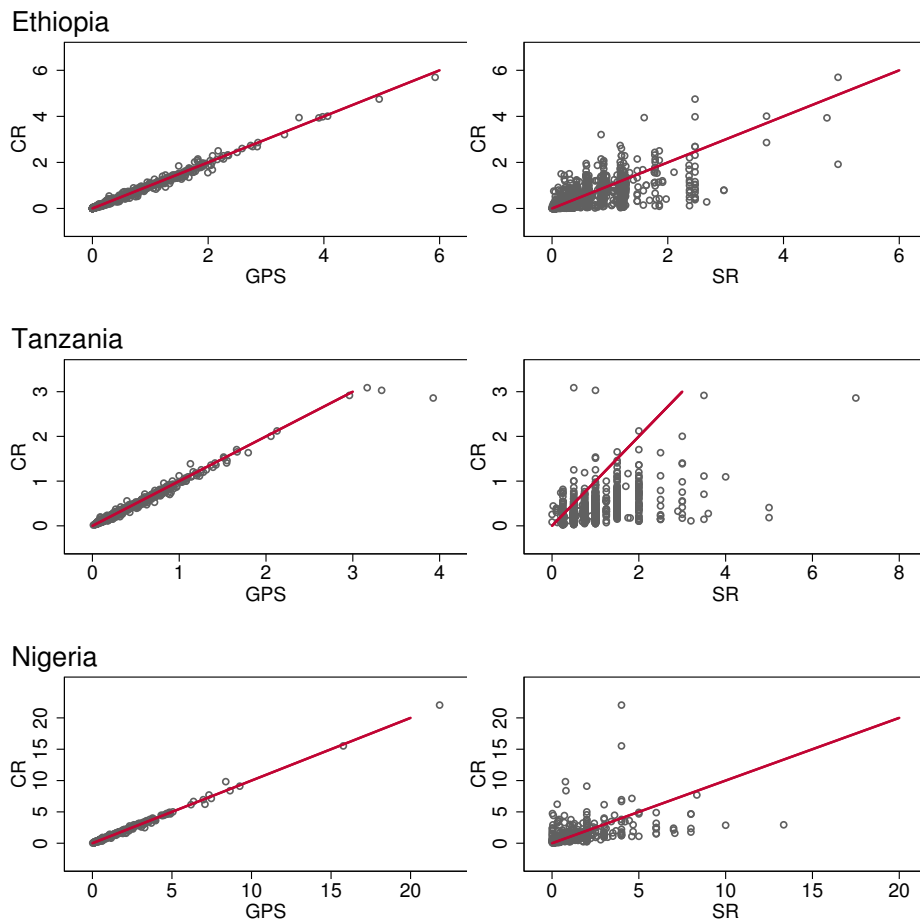*Figure 1.* Time taken for GPS and CR measurement by plot size (minutes)

Figure 2. Scatter plots of Compass and Rope vs GPS (left) and Self-Reported (right) land area measures, acres (Note: red line is line of equality between measurements.)

Table 2
Comparison of Self-Reported and CR measures

Level (CR)	N	SR	CR	Bias	Mean Bias /Mean CR (in %)	Difference in means
Ethiopia						
1 (<0.05 acres)	352	0.09	0.02	0.07	307	**
2 (<0.15 acres)	392	0.27	0.09	0.18	188	**
3 (<0.35 acres)	351	0.40	0.23	0.17	72	**
4 (<0.75 acres)	316	0.66	0.51	0.15	29	**
5 (<1.25 acres)	179	0.95	0.97	−0.02	−2	-
6 (≥1.25 acres)	99	1.42	1.90	−0.47	−25	**
Total	1689	0.47	0.38	0.09	23	**
Tanzania						
1 (<0.05 acres)	44	0.32	0.04	0.28	661	**
2 (<0.15 acres)	622	0.41	0.11	0.31	288	**
3 (<0.35 acres)	816	0.62	0.23	0.39	173	**
4 (<0.75 acres)	323	0.98	0.49	0.49	100	**
5 (<1.25 acres)	63	1.53	0.92	0.61	66	**
6 (≥1.25 acres)	20	2.05	1.81	0.24	13	-
Total	1888	0.65	0.27	0.38	143	**
Nigeria						
1 (<0.05 acres)	-	-	-	-	-	-
2 (<0.15 acres)	21	0.15	0.11	0.03	30	-
3 (<0.35 acres)	73	0.39	0.25	0.14	55	**
4 (<0.75 acres)	129	0.79	0.53	0.26	50	**
5 (<1.25 acres)	108	1.31	0.99	0.32	33	**
6 (≥1.25 acres)	153	2.56	2.87	−0.30	−11	-
Total	485	1.38	1.31	0.07	5	-
Pooled						
1 (<0.05 acres)	397	0.12	0.03	0.09	371	**
2 (<0.15 acres)	1035	0.35	0.10	0.25	247	**
3 (<0.35 acres)	1240	0.55	0.23	0.32	136	**
4 (<0.75 acres)	768	0.82	0.50	0.31	62	**
5 (<1.25 acres)	350	1.16	0.96	0.20	21	**
6 (≥1.25 acres)	272	2.11	2.44	−0.32	−13	*
Total	4062	0.66	0.44	0.22	51	**

* p <.05; ** p < .01

1 percent level in Ethiopia, Tanzania, and the pooled data. In Nigeria, GPS and CR area measurements are significantly different at the 10 percent level. Furthermore, in Nigeria the GPS and compass and rope measurements are significantly different at the 5 percent level for all plot size levels reported in Table 3 except for the largest plots (level 6), in which the measurements are not significantly different. Notably, GPS and CR measurements on the smallest plots (level 1) are not found to be significantly different in Ethiopia, Tanzania or the pooled data.

The data do not exhibit any clear trends in terms of GPS underestimating plot size compared to CR. In Nigeria, GPS under-estimates plot size compared to CR, but only slightly, while in Tanzania and Ethiopia GPS averages are somewhat larger than compass and rope measurements. Moreover, the magnitude as well as the sign of the error seem both to be un-related to plot size, being small in all of the plot size classes.

The concern of GPS accuracy at small plot sizes is also discounted, particularly when looking at group means. While some literature suggests that plots smaller than 0.5 hectares

Table 3
GPS vs Compass and Rope (CR) measures, by plot size classes

Level (CR)	N	SR	CR	Bias	Mean Bias /Mean CR (in %)	Difference in means
Ethiopia						
1 (<0.05 acres)	390	0.02	0.02	0.00	0	-
2 (<0.15 acres)	400	0.10	0.09	0.00	2	**
3 (<0.35 acres)	365	0.24	0.24	0.01	3	**
4 (<0.75 acres)	328	0.52	0.51	0.01	2	**
5 (<1.25 acres)	182	0.98	0.96	0.02	2	**
6 (≥1.25 acres)	100	1.91	1.89	0.02	1	-
Total	1765	0.38	0.38	0.01	2	**
Tanzania						
1 (<0.05 acres)	45	0.04	0.04	0.00	−3	-
2 (<0.15 acres)	631	0.11	0.11	0.00	2	**
3 (<0.35 acres)	823	0.23	0.23	0.01	2	**
4 (<0.75 acres)	326	0.51	0.49	0.02	4	**
5 (<1.25 acres)	63	0.94	0.92	0.02	2	**
6 (≥1.25 acres)	20	1.91	1.81	0.09	5	-
Total	1908	0.28	0.27	0.01	3	**
Nigeria						
1 (<0.05 acres)	-	-	-	-	-	-
2 (<0.15 acres)	21	0.11	0.11	−0.01	−7	**
3 (<0.35 acres)	73	0.24	0.25	−0.01	−4	**
4 (<0.75 acres)	129	0.52	0.53	−0.01	−2	*
5 (<1.25 acres)	108	0.97	0.99	−0.02	−2	**
6 (≥1.25 acres)	153	2.86	2.87	−0.01	0	-
Total	485	1.30	1.31	−0.01	−1	*
Pooled						
1 (<0.05 acres)	436	0.02	0.02	0.00	−1	-
2 (<0.15 acres)	1052	0.10	0.10	0.00	2	**
3 (<0.35 acres)	1261	0.24	0.23	0.01	2	**
4 (<0.75 acres)	783	0.51	0.50	0.01	2	**
5 (<1.25 acres)	353	0.97	0.96	0.01	1	-
6 (≥1.25 acres)	273	2.44	2.43	0.01	0	-
Total	4158	0.44	0.44	0.00	1	**

Note: Results for categories in which there are fewer than 20 observations are not reported. The same is true for all tables presented in the paper.
* p <.05;   ** p < .01

(1.24 acres) have significantly different GPS and compass and rope measurements with much lower correlation (Schøning, 2005), results from the methodological validation experiments suggest otherwise. In the pooled data, the difference between the average GPS measurement and average compass and rope measurement for plots ranging from 0.05 – 0.15 acres was less than 0.002 acres or 2 percent of the average

compass and rope area. Even for the smallest plots, those less than 0.05 acres (202.3 square meters or 0.02 hectares), the average measurements are extremely consistent. In Ethiopia, the average GPS measurement of 390 plots in this size range is 0.0216 while the average compass and rope measurement for the same plots is 0.0215 acres.

The differences in mean plot areas do not appear to bear

Table 4
Correlation Coefficient (GPS & CR)

Level (CR)	Ethiopia	Tanzania	Nigeria	Pooled
1 (<0.05 acres)	0.95	0.81	-	0.95
2 (<0.15 acres)	0.91	0.92	0.91	0.92
3 (<0.35 acres)	0.90	0.95	0.90	0.93
4 (<0.75 acres)	0.91	0.96	0.87	0.92
5 (<1.25 acres)	0.93	0.95	0.91	0.92
6 (≥1.25 acres)	0.98	0.96	1.00	1.00
Total	0.996	0.993	0.997	0.997

any clear trend with plot size. In Tanzania, the smallest and largest plot classes have the smallest and largest average relative bias, but the figures are not large, and the number of observations in these two classes fairly small. The correlation coefficients between GPS and CR are in excess of 0.99 in all three studies, and 0.87 or larger in all classes with *n* larger than 50 (Table 4).

The results presented here suggest that *average* GPS measures are not much different from compass and rope even for very small plots, and even from a fairly small *n*, and that is despite the difference in enumerator skill levels and plot characteristics of the different studies. This is confirmed by an inspection of the scatter plots in the left side of Figure 2, where GPS measures are plotted against compass and rope with measures tightly clustered around the equality line. This all lends support to the argument that GPS is an acceptable substitute of compass and rope measures across the range of plot sizes in our samples, at least if the goal is that of estimating average plot size for groups with sufficient numerosity. While this section examines mean differences, the regression analysis in subsequent sections delves deeper into differences in measurements on individual observations.

GPS measures: Exploring deviations from the gold-standard. Previous studies have also raised the issue of how factors other than plot size may affect the quality of GPS measures, as was recalled earlier in this paper. None of the studies have provided compelling, conclusive evidence on the impact of these factors on measurement quality. Some have explicitly called for further research to systematically investigate this matter. Our data allow for analysis on a number of factors including plot shape, slope, and tree cover, weather conditions, and number of GPS satellites acquired at the time of measurement, via a comparison of the GPS measurement to the "gold standard" of CR measurement.

Satellite acquisition, canopy cover, weather conditions, and plot slope. The global navigation system requires, at a minimum, the acquisition of four satellites to triangulate the 3D position of the GPS receiver. The acquisition of additional satellites can improve position error[11]. Enumerators in both the Tanzania and Ethiopia experiments recorded the

number of satellites fixed at the start of the GPS measurement. In training, enumerators were instructed to wait until at least four satellites were acquired, with further instruction that they must wait until the "GPS accuracy" figure on the GPS device stabilized (thereby allowing time for maximum satellite acquisition). Descriptive statistics (Annex 1) suggest that the difference between GPS and CR measurement tends to decline the higher the number of satellites, but average difference remains small across all the distribution of plot areas. In Ethiopia, the difference between measurements is 1.6 percent (but not statistically significant) on the plots with fewer than 16 satellites and 1.2 percent on plots with 20 or more satellites, though the trend is not linear as the middle category has an average of 1.8 percent bias. In Tanzania, the differences are 2.9 percent and 2.6 percent, respectively.

Various geographic and atmospheric conditions can impact the satellite acquisition and signal quality. Dense canopy cover and weather conditions at the time of measurement have been found or argued to impair the precision of the GPS measurement. Contrary to expectations, descriptive analysis reveals that the relative difference between the GPS and CR measurements was slightly higher on plots with *no* tree cover, with the level of bias decreasing with increasing canopy density. In Ethiopia and Nigeria, there was no statistically significant difference in measurements found on plots reported with partial or heavy tree cover. The lack of statistical significance in the groups with canopy cover is also likely linked to the smaller sample size for these groupings. This could also be attributable to plot size, enumerator characteristics or other factors, which are not controlled for in these simple descriptive statistics. The sections below will further explore the influence of tree cover on measurement.

The literature on GPS measurements points to weather conditions as a potential source of error. In all three methodological studies, no clear trend emerges in terms of systematic association of the differences between the two measures and weather conditions. In Ethiopia, the relative bias in measurements hovers around 2 percent for plots measured in conditions "mostly clear" or better, and the difference in mean measurements is only significantly different on plots measured in clear or mostly clear conditions. Similarly, in Nigeria differences in GPS and CR measurements are only observed on plots measured in "clear/sunny" conditions. The descriptive statistics from Nigeria and Tanzania provide little evidence that weather conditions have an adverse effect on GPS area measurement. It should be noted that the majority of plots were measured in conditions "partly cloudy" or clearer.

Keita et al. (2010), and Muwanga-Zake (1985) explain that plot slope can influence the difference between GPS and compass and rope measured areas, as the GPS measures the horizontal plane and compass and rope measures the sur-

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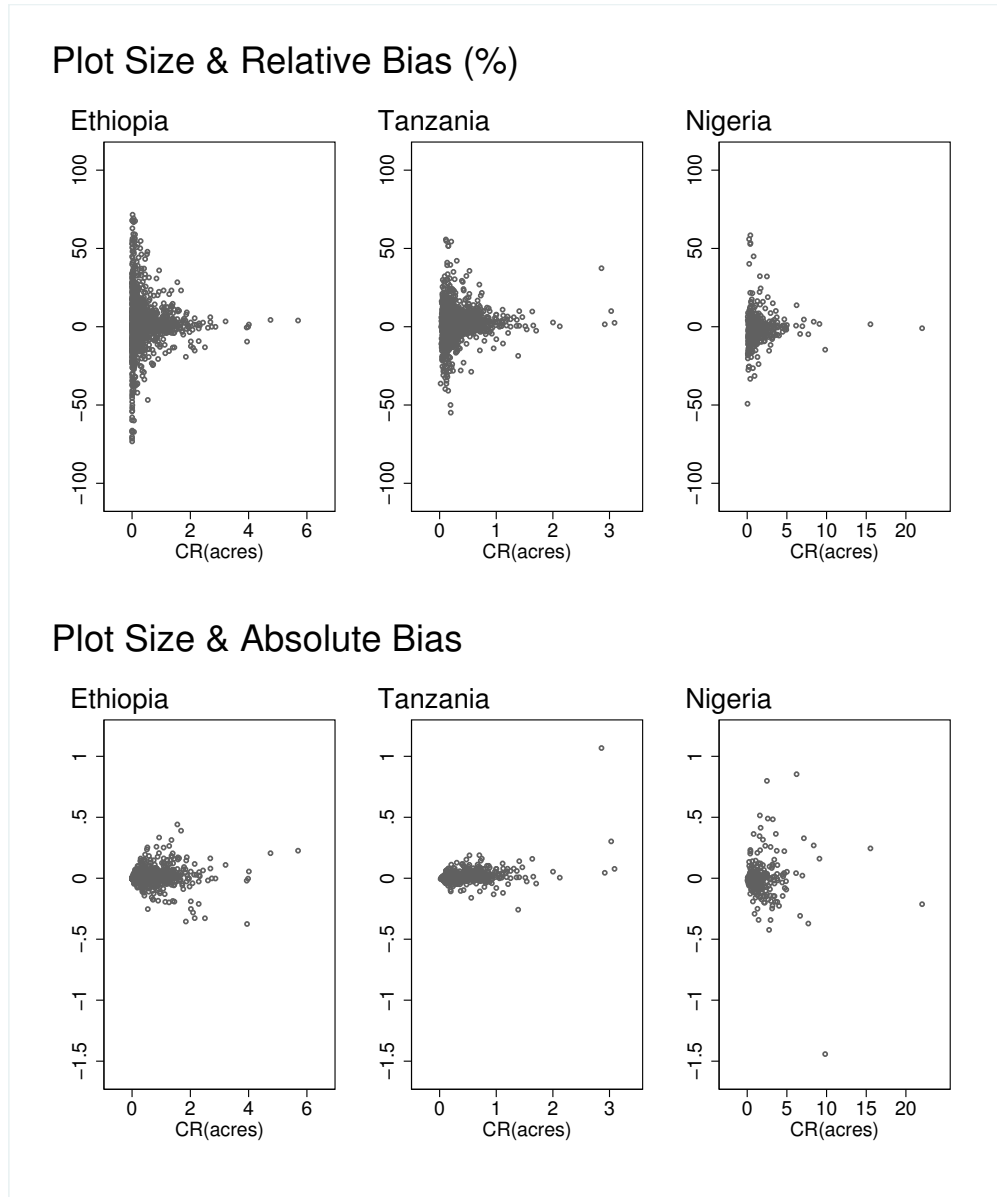[11] http://www8.garmin.com/aboutGPS/

Figure 3. Scatter plots of relative (percent) and absolute (acres) bias over plot size (acres)

face area. Fermont and Benson (2011) note that plot slopes greater than 10 degrees will result in significantly different measurements. The LASER study incorporated the use of clinometers for slope measurement. For plots of slope 5 degrees or less, the mean relative difference is 1.3 percent whereas for plots of 6 – 15 degrees in slope it is 2.2 percent and for plots of slope greater than 15 degrees it is 2.4 percent.

High bias observations.   Having ascertained that the average difference between GPS and CR is small does not rule out that for individual measurements, there may be observations with errors of significant magnitude. To investigate this aspect we plot the percentage and absolute differences between GPS and CR measures over plot area (Figure 3).

A number of considerations emerge from a visual analysis of these graphs. First, the GPS measurement error in percentage terms is often far from negligible, in some instances larger than plus or minus 50 percent. Second, large percentage errors appear to be roughly equally distributed above or below the zero line, which explains why we do not observe differences in the means for the two measures. Thirdly, the magnitude of the percentage errors is much larger for the small size classes, and decreases rapidly as plot size increases. Those trends are clearly mirrored by the graphs with the absolute bias, which show no clear correlation with plot size and fairly constant dispersion both sides of the zero line, with most values within the plus/minus 0.5 acre range. That seems to sug-

Table 5
Descriptive statistics for high-bias observations

	Relative Bias >10%	GPS *over-* reported by >10%	GPS *under-* reported by >10%	Relative Bias <10%	All Plots	Diffenrence in Means (>10% Bias vs.<10%)
Ethiopia						
Average:						
CR Area (acres)	0.22	0.23	0.20	0.45	0.38	**
GPS Area (acres)	0.23	0.28	0.16	0.45	0.38	**
Bias (GPS - CR)	0.01	0.05	−0.03	0.00	0.01	**
|% Bias|	22.74	23.18	22.18	3.41	9.34	**
Closing Error (%)	2.24	2.31	2.14	2.22	2.23	-
Number of Corners	5.94	5.98	5.89	6.48	6.32	**
Per: Area Ratio (GPS)	0.41	0.27	0.59	0.20	0.26	**
Number of Satellites	17.00	17.10	16.80	17.40	17.30	**
Walking Speed (m/min)	37.00	37.80	36.10	43.50	41.50	**
Treecover:						
Partial (n)	139	77	62	292	431	
(%)	26	25	26	24	24	-
Heavy (n)	39	20	19	50	89	
(%)	7	7	8	4	5	**
N	542	305	237	1223	1765	
% of Total Plot Sample	31	17	13	69	100	
Tanzania						
Average:						
CR Area (acres)	0.21	0.23	0.17	0.28	0.27	**
GPS Area (acres)	0.22	0.27	0.14	0.29	0.28	**
Bias (GPS - CR)	0.02	0.04	−0.03	0.01	0.01	**
|% Bias|	16.95	16.61	17.57	4.13	6.74	**
Closing Error (%)	2.09	2.21	1.86	1.97	2.00	
Number of Corners	8.09	8.25	7.80	8.35	8.30	-
Per: Area Ratio (GPS)	0.19	0.16	0.24	0.15	0.16	**
Number of Satellites	16.50	16.60	16.40	16.80	16.70	*
Walking Speed (m/min)	42.10	42.40	41.60	44.30	43.90	**
Treecover:						
Partial (n)	207	132	75	739	946	
(%)	53	53	55	49	50	
Heavy (n)	26	16	10	78	104	
(%)	7	6	7	5	5	-
N	388	251	137	1520	1908	
% of Total Plot Sample	20	13	7	80	100	

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	Relative Bias >10%	GPS *over-*reported by >10%	GPS *under-*reported by >10%	Relative Bias <10%	All Plots	Diffenrence in Means (>10% Bias vs.<10%)
Nigeria						
Average:						
CR Area (acres)	0.94	1.31	0.72	1.38	1.31	*
GPS Area (acres)	0.96	1.56	0.61	1.37	1.30	
Bias (GPS - CR)	0.02	0.25	−0.11	−0.02	−0.01	*
|% Bias|	18.96	23.60	16.33	3.93	6.50	**
Closing Error (%)	2.05	2.68	1.69	1.54	1.62	**
Number of Corners	9.17	9.50	8.98	10.24	10.06	-
Per: Area Ratio (GPS)	0.13	0.08	0.15	0.09	0.09	**
Number of Satellites	-	-	-	-	-	-
Walking Speed (m/min)	58.60	67.50	53.30	61.80	61.30	
Treecover:						
Partial (n)	50	18	32	228	278	
(%)	60	60	60	57	57	-
Heavy (n)	9	3	6	48	57	
(%)	11	10	11	12	12	-
N	83	30	53	402	485	
% of Total Plot Sample	17	6	11	83	100	
Pooled						
Average:						
CR Area (acres)	0.27	0.29	0.25	0.49	0.44	**
GPS Area (acres)	0.29	0.34	0.21	0.49	0.44	**
Bias (GPS - CR)	0.01	0.05	−0.04	0.00	0.00	**
|% Bias|	20.21	20.39	19.97	3.82	7.82	**
Closing Error (%)	2.16	2.29	1.99	2.01	2.05	**
Number of Corners	7.03	7.13	6.89	7.87	7.66	**
Per: Area Ratio (GPS)	0.30	0.21	0.42	0.16	0.20	**
Number of Satellites	-	-	-	-	-	-
Walking Speed (m/min)	40.70	41.30	39.90	46.00	44.70	**
Treecover:						
Partial (n)	396	227	169	1259	1655	
(%)	39	39	40	40	40	-
Heavy (n)	74	39	35	176	250	
(%)	7	7	8	6	6	*
N	1013	586	427	3145	4158	
% of Total Plot Sample	24	14	10	76	100	

* $p < .05$; ** $p < .01$

gest that it is the inherent imprecision of GPS devices that causes percentage error to matter much more for very small plots. We therefore turn to investigating more in depth the extent and nature of the discrepancy for observations with an arbitrary set value of plus or minus 10 percent.

Table 5 reports on some key the characteristics of the plots and the measurements, slicing the sample according to whether the bias is below or above the 10 percent threshold, and splitting the latter portion of the sample in observations where GPS over- or under-reports land area. The number of observations with such large errors is far from negligible, ranging from 17 percent in Nigeria to 31 percent in Ethiopia. Again, no strong systematic bias emerges in terms of GPS over- or under-reporting: differences in average acreage between GPS and CR are small, yet statistically significant, even for the high-error portion of the sample in all countries. In two of the three experiments (Ethiopia and Tanzania) there are more GPS observations with large percentage over-reporting compared to under-reporting, in Nigeria the opposite is true. Desiere and D'Haese (2015) present more optimistic results in their robust sample of over 50,000 parcel-level observations in Burundi, as 90 percent of plots greater than 550m^2 were measured with less than 10 percent absolute value of relative error.

Table 5 also reports the average values for several of the variables that are expected to influence the quality of GPS measurement. We do not observe any substantial difference for some of the factors that are often cited as important for GPS measurement, such as number of plot corners, number of satellites and tree canopy cover. In Ethiopia there is no statistically significant difference in closing error between plots measured with high bias versus those not measured with high bias, while the number of plot corners is not significantly different in Tanzania or Nigeria. We do, however, observe some difference in the perimeter/area ratio, which approximates the complexity of a plot shape. In all three experiments, this ratio is higher in plots that are substantially underestimated by the GPS measure, compared to the plots that are measured with greater accuracy. Ethiopia is the only country for which such a difference, albeit of much smaller magnitude, is also observed for plots with size over-reported by more than 10 percent. Shape complexity therefore does seem to affect GPS precision, resulting mostly in under-reporting of the plot size.

Some differences are observed also for the walking speed of the enumerators, but with results that are more difficult to interpret. In Ethiopia, the walking speed is lower on the plots measured with larger errors. In Tanzania we observe no sizeable difference. In Nigeria, plots that are under-estimated by more than 10 percent are associated with lower average walking speed, while plots that are over-estimated tend to record higher average walking speed. We are not able to draw any conclusions from this mixed evidence.

One last variable for which we do observe systematic dif-ferences is the magnitude of the CR closing error, although differences are not significantly different across high-bias and non-high bias plots in Ethiopia. In both Ethiopia and Tanzania there is a gradient between plots that are underestimated by a large margin (which have the smallest closing error), plots with error below 10 percent (which have moderate closing error), and plots with large GPS over-estimate (with the largest closing error). In Nigeria the plots with larger over-estimates are also the ones with the largest closing error, but the ranking of the other two groups is inverted. What we conclude from these observations is that for the cases in which we observe substantial deviations between GPS and CR measures, part of the explanation is likely to rest in noise in the CR measures. In that sense the inaccuracy in the GPS measures may be somewhat less serious than if one just looked at the prevalence of high bias cases, and that as observed earlier the gold standard is also bound to be imperfect.

5.3 Regression analysis of the differences between competing measures

Comparison of SR and Objective Measurements. While Table 2 illustrates the degree to which farmer self-reported estimates differ from compass and rope measurements, it does not offer any explanation as to why the two systematically diverge. For this we turn to regression analysis. Table 6 presents the results of four specifications per dataset, the difference among them being the dependent variable, which is: (i) bias (self reported estimate – CR), (ii) absolute value of bias, (iii) relative bias (bias as a percentage of the CR area), and (iv) absolute value of relative bias.

The claim of plot area affecting the direction and degree of error associated with self-reported area estimates is supported by the regression results. The results from the first two specifications (on bias and its absolute value), indicate an increase in the bias with plot size. When looking at the relative bias and the absolute value of the relative bias, the linear term is negative and the quadratic term positive in all countries, indicating that in percentage terms the bias declines steeply with plot size.

The distance from the plot to the dwelling holds significant explanatory power in the Ethiopia data, but not in Tanzania. The results from Ethiopia suggest that self-reported estimates of area diverge more from compass and rope measurements on those plots that are further from the household. This could be theoretically explained by assuming the farmer spends less time on plots more distant from the household and does not have the opportunity to view these plots to make his/her area estimate, should he/she prefer to do so. Consistent with Carletto et al. (2015), the existence of property rights (proxied here by the possession of a title or certificate of ownership or the ability to sell or use the plot as collateral) has a significant, negative relationship with the relative

Table 6
Determinants of Bias (SR - CR)

Dependent Variable	Ethiopia				Tanzania			
	SR-CR	|SR-CR|	$\frac{\text{Bias}}{\text{CR}} \cdot 100$	$\frac{\|\text{Bias}\|}{\text{CR}} \cdot 100$	SR-CR	|SR-CR|	$\frac{\text{Bias}}{\text{CR}} \cdot 100$	$\frac{\|\text{Bias}\|}{\text{CR}} \cdot 100$
CR Area (acres)	0.046	0.282**	−776.727**	−725.699**	−0.070	0.805**	1213.335**	−1177.100**
CR Area²	−0.246**	-	426.154**	409.271**	-	−0.844**	972.639**	948.049**
CR Area³	0.037**	-	−56.191**	−54.582**	-	0.259**	−210.863**	−203.417**
Number of Corners	−0.011**	0.001	−10.050**	−8.630**	0.027**	0.022**	7.696**	7.450**
Distance from dwelling	0.011**	0.012**	4.966**	4.782**	0.000	0.000	−0.145	−0.154
Number cultivated plots in HH[a]	−0.015**	−0.012**	−5.354	−4.204	−0.002	0.000	2.190	2.082
Slope (dinometer)	0.000	0.001	−1.869	−1.682	-	-	-	-
Cash Crops Grown[b]	0.066	0.081*	−11.352	−6.089	-	-	-	-
Soil Quality (SR):								
Fair	−0.088**	−0.073*	−70.382**	−67.414**	−0.030	−0.021	2.996	3.965
Poor	−0.049	−0.056	−132.101**	−124.020**	0.124	0.107	44.642	44.402
Property Rights[c]	−0.011	−0.023	−32.928	−33.150	0.011	−0.001	−1.816	−3.371
Treecover:								
Partial	0.120**	0.081**	126.055**	118.517**	0.062**	0.037	5.273	2.810
Heavy	0.136**	0.133**	79.802*	76.089*	−0.022	−0.026	−12.579	−13.393
HH Head Characteristics:								
Female	−0.027	−0.015	−26.496	−26.907	−0.021	−0.011	18.273	18.209
Years education	0.010**	0.004	7.246*	6.324*	−0.005*	−0.004*	−2.560*	−2.523*
Age	−0.001	0.000	−0.236	−0.207	0.001	0.001	0.728	0.760
Constant	0.294**	0.204**	454.268**	449.767**	0.136*	0.034	331.901**	329.174**
N	1689	1689	1689	1689	1737	1737	1737	1737
R2	0.227	0.273	0.205	0.183	0.071	0.149	0.169	0.160

Continued from last page

Dependent Variable	Nigeria				Pooled[d]			
	SR-CR	|SR-CR|	$\frac{Bias}{CR}\cdot 100$	$\frac{\|Bias\|}{CR}\cdot 100$	SR-CR	|SR-CR|	$\frac{Bias}{CR}\cdot 100$	$\frac{\|Bias\|}{CR}\cdot 100$
CR Area (acres)	0.051	0.2432**	-26.586**	-12.078**	-0.013	0.341**	-225.641**	-229.641**
CR Area²	-0.116**	0.018**	1.047**	0.624**	-0.101**	0.022**	42.165**	39.891**
CR Area³	0.004**	-	-	-	0.003**	-	-1.457**	-1.392**
Number of Corners	0.039*	0.010	1.203	0.970	0.026**	0.014**	-0.108	-0.157
Distance from dwelling	-	-	-	-	-	-	-	-
Number cultivated plots in HH[a]	0.066	0.094**	1.225	3.295	-0.016**	-0.007**	-2.727	-1.749
Slope (dinometer)	-	-	-	-	-	-	-	-
Cash Crops Grown[b]	0.835*	0.661*	70.005**	51.146**	-	-	-	-
Soil Quality (SR):								
Fair	-	-	-	-	-	-	-	-
Poor	-	-	-	-	-	-	-	-
Property Rights[c]	0.070	-0.135	7.457	-8.180	0.017	-0.033	-9.782	-12.982
Treecover:								
Partial	-0.297**	-0.130	-41.158**	-22.624*	0.030	0.045**	46.040**	45.204**
Heavy	0.151	0.113	-41.168*	-25.973	0.244**	0.171**	47.739**	43.484*
HH Head Characteristics:								
Female	0.298	0.110	5.325	-6.550	-0.011	-0.020	-5.035	-6.297
Years education	0.041**	0.000	2.332*	0.373	0.007**	-0.002	-0.170	-0.661
Age	0.008	0.002	0.339	0.027	0.001	0.000	-0.106	-0.126
Constant	-0.858*	-0.160	32.965	80.102**	-0.060	0.049	254.079**	269.850**
N	485	485	485	485	3931	3931	3931	3931
R2	0.536	0.635	0.126	0.050	0.386	0.510	0.114	0.090

[a] In Tanzania , number of plots owned or cultivated.
[b] Binary variable. Cash crops of Ethiopia include coffee, cotton, sugar cane, and chat. Cash crops for Nigeria include coffee, cotton, sugar cane, palmiol, cocoa, and rubber.　[c] Property rights defined here as: HH has title or certificate. HH has ability to sell land, or HH can use land as collateral.　[d] Includes country dummies
* p <0.05;　** p < 0.01

bias in Ethiopia and the pooled data, suggesting that on plots where the household has some form of property rights they are better able to estimate the area. The presence of cash crops on the plot exhibits a significant relationship with measurement bias in both Ethiopia and Nigeria, but to differing degrees. In Ethiopia, the effect of cash crops is minimal, with a small positive significance in the absolute bias specifications but no significance in the relative bias specifications. The effect of cash crops is much more pronounced in Nigeria, where both absolute and relative biases are higher for plots on which cash crops are cultivated. This finding comes contrary to expectation, as one might expect farmers to have more precise knowledge of cash crop plots.

Household characteristics such as the gender, age, and education of the household head play out differently across countries. Results from Nigeria and Tanzania (but not Ethiopia) suggest that measurement bias is slightly greater in households with older household heads. The education of the household head significantly increases the measurement bias in Ethiopia and in some Nigeria specifications, but has a negative effect on bias in Tanzania. One can speculate that, education may be associated with increasing opportunity cost of time or decreasing involvement in agriculture, which could make the respondent less attentive or knowledgeable regarding the measurement or reporting of plot area.

Finally, one key decision point when collecting self-reported area data is whether to allow respondents to use non-standard units, or to force them (or enumerators) to convert responses from traditional to standard units at the moment of the interview. In Table 7, we compare deviations between self-reported and GPS data separately splitting the sample between observations where respondents used traditional and standard units in the Ethiopia and Nigeria sample. When land area is collected using non-standard units, as opposed to forcing respondents or enumerators to perform a conversion to standard units at the time of the interview, data from self-report appears to approximate the preferred GPS measures much better. This finding supports the idea that it is best to allow non-standard units to be used at interview time, while organizing complementary collection of adequate conversion factors to translate all the data into a common metric at the data processing stage (refer to Oseni, Durazo, and McGee (forthcoming) for information on the use of non-standard units).

Comparison of CR and GPS . The descriptive statistics presented above are aimed at comparing the two primary objective area measurement options, GPS and compass and rope. In this section, regression analysis is used to explore the determinants of measurement bias, defined here as the difference between GPS measured area and compass and rope measured area, which is used as the benchmark.

The results in Table 8 include four regression models as in the preceding section: the first on the measurement bias

(GPS minus CR measured area), the second on the absolute value of this bias, the third on the relative bias, and the fourth on the absolute value of the relative bias (in percentage terms). Recall from the descriptive statistics that the observed error is generally small, and little evidence of systematic variation with many of the factors that are *a* priori expected to influence GPS measurement precision was found. It is therefore not surprising that the explanatory power of these regressions (as captured by their R^2 values) is low, and that the majority of the estimated coefficients are not statistically significant.

The main variables of interests are the set of terms (levels, quadratic, cubic) related to the plot size itself, as measured by CR. In the first specification, there appears to be a relationship between plot size and measurement error in Ethiopia, where the shape of the relationship is that of an inverted U, with the predicted bias being positive on very small plots, peaking at about 0.7 acres, and becoming negative for plots larger than about 1.7 acres. The coefficients are small, so that the predicted error is in the plus/minus 0.02 acres range. In Tanzania, a linear relationship is exhibited in which larger plot size results in larger bias (in terms of acres). In Nigeria there is no statistically significant relationship between bias and plot size, and in the pooled data there is very little, controlling for other factors.

When the absolute level of bias is considered the relationship with plot size becomes monotonically positive, with a small curvature only in Nigeria and the pooled data. Values are somewhat larger, up to about 0.2 acres in the observed plot size range, but still small.

When the percentage bias is considered (third specification) the relationship with plot size becomes an L-shaped quadratic curve (the cubic term is significant only in Ethiopia and the pooled data, tilting the curve up around the 2 acres mark). The last specification has the absolute bias expressed in percentage terms as the dependent variable, with the relationship with plot size being again best characterized as L-shaped. Nigeria is an exception in that no statistically significant relationship with plot size is revealed by these two specifications.

These results are in line with the earlier descriptive analysis in that the overall distribution of the bias does not seem to bear much relationship with plot size, as they are largely equally distributed on the positive and negative side. The absolute magnitude of the error does, however, increase somewhat with plot size but less than proportionally. For that reason, in percentage terms the bias actually declines fairly rapidly as plot size increase, stabilizing as plot size reaches the 1-2 acres range.

Of the covariates reflecting physical characteristics that are expected to affect the quality of GPS measures (cloud and canopy cover, plot slope) hardly any are consistently significant across country. What appears to matter most are closing

Table 7
Standard and Non-Standard Area Units

| Level (GPS) | Standard Units | | | | Non-Standard Units | | | | |
	N	SR	GPS	Mean Bias/ Mean GPS (%)	N	SR	GPS	Mean Bias/ Mean GPS (%)	Difference in Bias^
Ethiopia									
1 (<0.05 acres)	-	-	-	-	375	0.09	0.02	276.1	-
2 (<0.15 acres)	31	0.67	0.09	643.6	356	0.24	0.10	150.0	**
3 (<0.35 acres)	24	1.02	0.25	302.4	349	0.36	0.23	53.6	**
4 (<0.75 acres)	20	1.32	0.52	152.4	309	0.60	0.52	16.3	**
5 (<1.25 acres)	-	-	-	-	163	0.87	0.96	−9.8	-
6 (≥1.25 acres)	-	-	-	-	93	1.19	1.71	−30.3	-
Total	120	1.16	0.63	84.2	1645	0.42	0.37	12.9	**
Nigeria Experiment									
1 (<0.05 acres)	-	-	-	-	-	-	-	-	-
2 (<0.15 acres)	-	-	-	-	25	0.15	0.11	38.1	-
3 (<0.35 acres)	-	-	-	-	69	0.33	0.25	33.9	-
4 (<0.75 acres)	28	1.49	0.53	181.4	112	0.67	0.54	24.4	**
5 (<1.25 acres)	25	2.24	1.01	121.2	71	1.06	0.99	7.3	**
6 (≥1.25 acres)	76	3.51	3.24	8.4	76	1.61	2.51	−35.9	*
Total	131	2.80	2.19	28.2	354	0.85	0.97	−12.2	**

^ Testing difference in mean bias across plots reported with standard units and non-standard units.
* p <.05; ** p < .01

error and the perimeter/area ratio. The former reflects inaccuracy in the CR measure, while the latter is a proxy for the complexity of the plot shape which is likely to affect the accuracy of GPS measures, but can in principle also be capturing noise in the CR measure besides what is captured by the closing error. In Ethiopia and Tanzania (as well as in the fourth specification of the pooled sample regression), there is evidence that heavy canopy cover does increase relative bias. An unsystematic comparison of plot outlines computed from the CR method and collected in the GPS also suggests that it may often be the case that enumerators may tend to simplify the shape of the plot more when collecting CR than GPS data (Figure 4, for additional evidence see Carletto et al., 2016).

Although the difference between the two objective measurements is relatively small on average, it is worth digging into the problem cases in which the deviation is much larger. Table 9 reports results of a probit model (see equation 3) estimating the probability of a plot being a "problem plot" – defined here as having a relative bias greater than 10 percent (in absolute value). In all countries, we find evidence that the plots with the highest probability of large measurement error are the very small plots. The regressions unveil a cubic relationship between the probability of GPS measures being overestimated by more than 10 percent of plot size. That translates into the probability being highest for very small plots, and decreasing fast as plot size increases, before flat-

tening fairly quickly (and eventually tilting up somewhat) for larger plot sizes. The same relationship is found for plots underestimated by GPS in Ethiopia, but not in the other two experiments. As in the OLS regression, in the probit model the other covariates that appear to be playing a role are closing error and perimeter/area ratio. Tree canopy cover appears to play more of a role in these regressions, implying that the effects of canopy cover are not felt equally throughout the distribution of the bias variable, but that they kick-in in particular regions of the distribution. Weather at the time of GPS measurement has a more limited effect. In Tanzania, plots that are measured during "mostly cloudy", "all cloudy", or "rainy" weather, aggregated into a single dummy variable, are slightly more likely to be over-stated by the GPS by 10 percent or more (compared to plots measured during "partly cloudy" or clearer weather). In all other countries and specifications the weather conditions do not have a statistically significant effect on the probability of area being measured with high bias.

6 Conclusions

Several important findings emerge forcefully from this analysis, which translate into clear implications for future survey design and implementation. The first result is that our experimental data confirm what we already knew about the

Table 8
Determinants of Bias (GPS − CR)

Dependent Variable	Ethiopia				Tanzania			
	SR-CR	|SR-CR|	$\frac{Bias}{CR}\cdot 100$	$\frac{\|Bias\|}{CR}\cdot 100$	SR-CR	|SR-CR|	$\frac{Bias}{CR}\cdot 100$	$\frac{\|Bias\|}{CR}\cdot 100$
CR Area (acres)	0.049**	0.040**	−9.186**	−9.013**	0.055*	0.069**	−8.169**	−5.421**
CR Area²	−0.037**	-	4.025**	4.557**	-	-	3.057*	2.406*
CR Area³	0.006**	-	−0.447*	−0.589**	-	-	-	-
Closing Error (%)	0.003*	0.001	0.862**	0.156	0.002	0.002*	0.494**	0.282*
Number of Corners	0.001	0.001	−0.048	0.026	0.000	0.000	0.056	0.090*
Per: Area Ratio (GPS)	0.002	−0.002	−13.927**	10.551**	−0.003	0.036	−38.537**	12.955**
Number of Satellites	0.000	−0.001	0.107	−0.114	0.000	0.000	0.027	−0.004
Slope (clinometer)	0.000	0.000	0.018	0.045	-	-	-	-
Treecover:								
Partial	−0.005*	0.000	−0.074	0.318	−0.001	0.002	−0.729	0.779*
Heavy	−0.006	0.009	−1.019	3.804*	−0.006	0.001	−1.339	1.116
Weather:								
Mostly Cloudy - Rainy	−0.005*	0.003	−0.085	1.206	0.001	0.000	0.569	0.527
Constant	−0.009	0.007	3.897	9.213**	−0.007	−0.021	8.317**	3.867*
N	1765	1765	1765	1765	1908	1908	1908	1908
R2	0.046	0.262	0.117	0.199	0.151	0.263	0.071	0.051

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Dependent Variable	Nigeria				Pooled[a]			
	SR-CR	|SR-CR|	$\frac{Bias}{CR} \cdot 100$	$\frac{\|Bias\|}{CR} \cdot 100$	SR-CR	|SR-CR|	$\frac{Bias}{CR} \cdot 100$	$\frac{\|Bias\|}{CR} \cdot 100$
CR Area (acres)	−0.005**	0.055**	−0.331	−0.015	0.011	0.050**	−1.898**	−3.344**
CR Area²	-	−0.002**	-	-	−0.001**	−0.002**	0.352*	0.507**
CR Area³	-	-	-	-	-	-	−0.012*	−0.017***
Closing Error (%)	0.006	0.019**	1.327**	1.260**	0.003	0.004**	0.762**	0.370**
Number of Corners	−0.001	0.000	−0.101	−0.009	0.000	0.000	−0.002	0.055
Per: Area Ratio (GPS)	−0.130	0.109	−58.831**	43.445**	−0.006	0.001	−13.442**	11.534**
Number of Satellites	-	-	-	-	-	-	-	-
Slope (clinometer)	-	-	-	-	-	-	-	-
Treecover:								
Partial	0.013	−0.004	0.126	0.721	−0.001	0.001	−0.217	0.692*
Heavy	0.023	−0.012	−1.237	0.560	−0.002	0.004	−0.870	2.170**
Weather:								
Mostly Cloudy - Rainy	−0.029	0.016	−0.274	−0.773	−0.004	0.003	0.219	0.772*
Constant	0.000	−0.033	2.856	0.107	−0.002	−0.008	3.979**	5.731**
N	485	485	485	485	4158	4158	4158	4158
R2	0.017	0.304	0.127	0.136	0.026	0.316	0.095	0.162

[a] Includes country dummies.
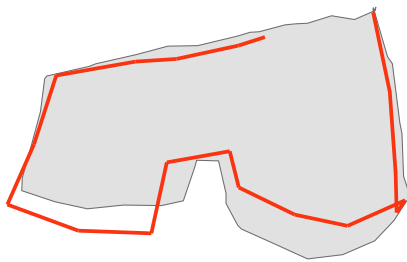* $p < .05$;   ** $p < .01$
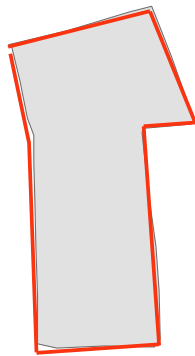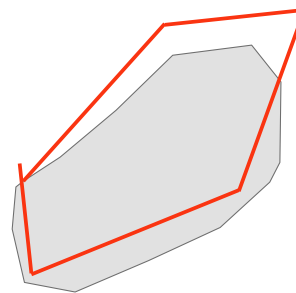
(a) Not high bias plot (included for reference)　　　(b) Not high bias plot (included for reference)
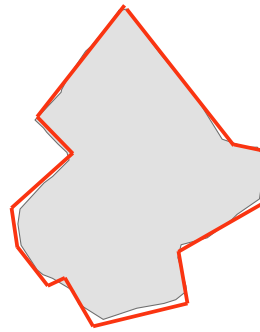
(c) 19 sides and obvious closing error　　　(d) CR shape simplification – number of vertices in GPS is twice the number of CR corners

(e) Apparently an enumerator/field delineation error, with CR shape simplification　　(f) Apparently an error in CR bearing (front and back bearings were likely switched)
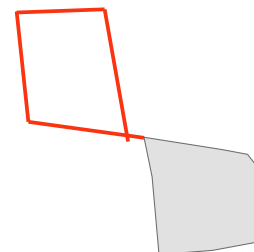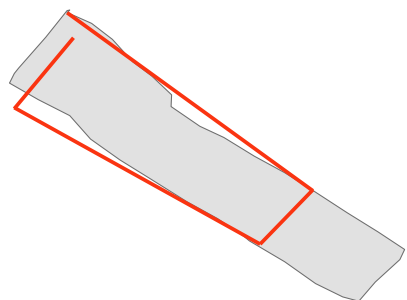
Figure 4. GPS and Compass and Rope Plot Outlines. Red outlines were constructed from compass and rope measurements. Gray shapes are GPS plot outlines.

Table 9
Determinants of High Bias

	Ethiopia			Tanzania		
	Percent Bias >10%	GPS *over-* reported by >10%	GPS *under-* reported by >10%	Percent Bias >10%	GPS *over-* reported by >10%	GPS *under-* reported by >10%
CR Area (acres)	−0.899**	−0.941**	−0.339**	−0.674**	−0.871**	−0.036
CR Area²	0.794**	1.056**	0.281**	0.555*	0.642**	-
CR Area³	−0.198**	−0.349**	−0.059*	−0.117	−0.129*	-
Closing Error (%)	0.003	0.010	−0.007	0.014	0.018	−0.005
Number of Corners	0.006	0.002	0.004	0.005	0.006	0.001
Per. Area Ratio (GPS)	0.173**	−0.144*	0.175**	0.428**	−0.911**	0.558**
Number of Satellites	−0.003	0.001	−0.004	−0.007	−0.003	−0.003
Slope (clinometer)	0.002	0.002	0.000	-	-	-
Treecover:						
Partial	0.002	0.005	0.003	0.043	0.014	0.027
Heavy	0.111	0.042	0.078*	0.080	0.031	0.045
Weather:						
Mostly Cloudy - Rainy	0.026	0.009	0.016	0.044	0.035	0.012
Pseudo-R2	0.096	0.047	0.128	0.050	0.036	0.120
N	1765	1765	1765	1908	1908	1908

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	Nigeria			Pooled		
	Percent Bias >10%	GPS *over-* reported by >10%	GPS *under-* reported by >10%	Percent Bias >10%	GPS *over-* reported by >10%	GPS *under-* reported by >10%
CR Area (acres)	0.006	−0.193**	0.008	−0.275**	−0.257**	−0.119**
CR Area²	-	0.060**	-	0.069**	0.100**	0.023**
CR Area³	-	−0.005**	-	−0.004**	−0.010**	−0.001**
Closing Error (%)	0.053**	0.038**	0.015*	0.017*	0.021**	−0.004
Number of Corners	−0.001	−0.001	0.000	0.004	0.002	0.002
Per. Area Ratio (GPS)	1.700**	−1.435**	1.696**	0.254**	−0.072*	0.191**
Number of Satellites	-	-	-	-	-	-
Slope (clinometer)	-	-	-	-	-	-
Treecover:						
Partial	0.052	0.016	0.044	0.029	0.012	0.019
Heavy	0.047	−0.017	0.060	0.081*	0.026	0.055*
Weather:						
Mostly Cloudy - Rainy	−0.026	0.007	−0.019	0.035	0.023	0.012
Pseudo-R2	0.106	0.152	0.172	0.076	0.039	0.111
N	485	485	485	4158	4158	4158

Standard errors clustered at enumerator level.

* p <.05;   ** p <.01

presence of large, systematic measurement error in farmers' self-reported estimates of land area, and on its direction, correlates and determinants (which include land area itself, introducing potentially large biases at the data analysis stage). While not a novel finding, this is a useful reminder of the urgency to find alternative measures that are both accurate and usable in the context of large scale household surveys, specifically in the developing country context where non-traditional units of measure are common, land titling (with area measurement) is limited, and plots are small and irregularly shaped. GPS measurement is the obvious candidate.

Much of the focus of the paper has, therefore, been on assessing the fitness for purpose of GPS measures. In this respect, an important finding of the study is that on average GPS measures return very accurate estimates of plot size, even for very small plots, and even for reasonably small samples. The small differences between GPS and CR measurements are primarily driven by factors that cannot necessarily be addressed by survey practitioners, such as complexity of plot shape. Yet, even with these errors in GPS measurement, the method offers dramatic improvement over SR estimates. We also do not detect any evidence that GPS systematically under-reports land size, as is the case in earlier studies. That should suffice to make GPS an attractive method for land area data collection for most household survey practitioners. This conclusion becomes even more forceful when taken together with the comparison of the time required for GPS compared to CR measurement, with our data showing GPS to lead CR by several orders of magnitude.

This strong message in support of the adoption of GPS in survey fieldwork is, however, mediated by a number of considerations regarding outstanding challenges with GPS measurement. One that emerges from the analysis is that while the GPS measurement error is almost universally small in magnitude (only 5 percent of observations recording a discrepancy with CR of more than 0.09 acre), in relative terms a discrepancy of plus or minus 10 percent is not uncommon. However the CR method itself is not immune to measurement error thus some of the problematic cases could be attributable to noise in the CR data. Complementing data collection with information that can aid in identifying those problem cases, as well as enforcing sound field implementation protocols, can significantly reduce both bias and missingness in GPS measures.

Despite the evidence that subjective measurements can be riddled with problems, farmer self-reported estimates of area should still be included in household surveys, though not as the primary measurement method. Objective measurements come with their own challenges, including time and equipment requirements, questions of accuracy at small-plot levels, and feasibility of full plot sample measurement (a large scale dataset of GPS plot measurements could be plagued by as much as 50 percent problem cases). Subjective measurements have negligible fieldwork costs, and, more importantly, they can serve as a baseline for imputation where objective measurements may be missing (Kilic et al., 2017). Therefore, we recommend GPS measurement (where feasible) complemented by farmer self-reported estimated area (for all plots).

An ancillary story emerging from the data concerns self-reported data. While confirming all the known issues with measurement error in self-reported land data, the analysis presented here provides at least one suggestion for limiting the scope of this error in the future. When land area is collected using non-standard units, as opposed to forcing respondents or enumerators to perform a conversion to standard units at the time of the interview, data from self-report appears to be a better approximation of the benchmark preferred measure.

Furthermore, our analysis casts some shadows on the benchmark compass and rope measurement. It appears that a good deal of what we labeled, for simplicity, as measurement error in the GPS measurement, may in fact be linked to noise in the CR data. This result is hardly surprising since CR does in fact require a good deal of precision that, no matter how careful the training, will be hard to reach for survey enumerators who are not professional land surveyors. In terms of specific suggestions for CR measurements, we do observe an increase in discrepancy between CR and GPS when the CR closing error is above 3 percent. Translated into recommendations for survey work, this means that 3 percent offers a good rule of thumb for instructing enumerators to re-take CR measurement.

Finally, little research is currently available on the use of remote sensing imagery for area measurement in household surveys. As technology advances and image resolution improves along with affordability, the use of this method becomes more feasible, and is likely to hold promise particularly for the measurement of large plots. Future research on how to effectively integrate remote sensing and household survey data for plot area measurement, including fieldwork challenges and respondent ability to identify plots, is highly encouraged.

Acknowledgement

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Appendix

(Appendix tables on next page)

Table A1

Summary Statistics on Weather Conditions, Satellite Acquisition, and Canopy Cover

	N	GPS	CR	Bias	Mean Bias/ Mean CR (%)	Difference in means
Ethiopia						
Weather Conditions at Measurement						
Clear/Sunny	576	0.50	0.49	0.01	1.9	**
Mostly Clear	733	0.33	0.33	0.01	2.0	**
Partly Cloudy	334	0.32	0.31	0.00	0.6	-
Mostly Cloudy	94	0.34	0.34	0.00	−0.1	-
Completely Cloudy	-	-	-	-	-	-
Rainy	-	-	-	-	-	-
Tree Canopy Cover						
None	1245	0.40	0.39	0.01	2.0	**
Partial	431	0.35	0.35	0.00	0.7	-
Heavy	89	0.28	0.28	0.00	1.0	-
GPS Satellites Acquired						
≤15	305	0.23	0.22	0.00	1.6	-
16-19	1204	0.40	0.39	0.01	1.8	**
≥20	256	0.49	0.48	0.01	1.2	*
Total	1765	0.38	0.38	0.01	1.7	**
Tanzania						
Weather Conditions at Measurement						
Clear/Sunny	800	0.30	0.29	0.01	3.3	**
Mostly Clear	217	0.28	0.27	0.00	1.3	*
Partly Cloudy	705	0.25	0.24	0.01	2.8	**
Mostly Cloudy	76	0.22	0.21	0.01	3.1	*
Completely Cloudy	41	0.26	0.25	0.00	2.0	*
Rainy	69	0.29	0.28	0.01	2.7	**
Tree Canopy Cover						
None	858	0.27	0.26	0.01	3.2	**
Partial	946	0.28	0.27	0.01	2.8	**
Heavy	104	0.34	0.33	0.01	1.6	
GPS Satellites Acquired						
≤15	488	0.31	0.30	0.01	2.9	**
16-19	1266	0.27	0.26	0.01	2.9	**
≥20	154	0.24	0.24	0.01	2.6	**
Total	1908	0.28	0.27	0.01	2.9	**

Continued from last page

	N	GPS	CR	Bias	Mean Bias/ Mean CR (%)	Difference in means
Nigeria						
Weather Conditions at Measurement						
Clear/Sunny	317	1.31	1.32	−0.01	−0.9	*
Mostly Clear	101	1.35	1.34	0.01	0.5	-
Partly Cloudy	62	1.13	1.16	−0.03	−2.6	-
Mostly Cloudy	-	-	-	-	-	-
Completely Cloudy	-	-	-	-	-	-
Rainy	-	-	-	-	-	-
Tree Canopy Cover						
None	150	0.92	0.94	−0.02	−2.1	-
Partial	278	1.42	1.43	−0.01	−0.6	-
Heavy	57	1.66	1.66	0.00	−0.1	-
GPS Satellites Acquired						
≤15	NA	NA	NA	NA	NA	NA
16-19	NA	NA	NA	NA	NA	NA
≥20	NA	NA	NA	NA	NA	NA
Total	485	1.30	1.31	−0.01	−0.9	
Pooled						
Weather Conditions at Measurement						
Clear/Sunny	1693	0.56	0.55	0.01	1.0	**
Mostly Clear	1051	0.42	0.41	0.01	1.5	**
Partly Cloudy	1101	0.32	0.32	0.00	1.0	
Mostly Cloudy	174	0.30	0.30	0.00	0.5	-
Completely Cloudy	54	0.25	0.25	0.00	1.3	-
Rainy	85	0.34	0.33	0.01	2.1	
Tree Canopy Cover						
None	2253	0.38	0.38	0.01	1.6	**
Partial	1655	0.49	0.48	0.00	0.7	*
Heavy	250	0.62	0.62	0.00	0.4	-
GPS Satellites Acquired						
≤15	NA	NA	NA	NA	NA	NA
16-19	NA	NA	NA	NA	NA	NA
≥20	NA	NA	NA	NA	NA	NA
Total	4158	0.44	0.44	0.00	1.1	**

* p <.05;   ** p < .01