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Cheaper, Faster and More Than Good Enough: Is GPS the new gold standard in land area measurement?

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ABSTRACT

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: traversing (accurate, but cumbersome), and farmers self-report (cheap, but marred by measurement error). Recently, the advent of cheap handheld GPS devices has held promise of 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. Results largely point to the support of GPS measurement, with simultaneous collection of farmer self-reported areas.

Keywords: Land, Agriculture, Measurement, Surveys.

PAPER

1. Introduction

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. 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. For the analysis of household level processes and outcomes 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. 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 the three primary methodological options: farmer estimate, GPS measurement, and the traditional compass and rope method.

2. Methods

The first step in analyzing the different methods is comparing the measurements obtained. To that end we construct two measures of deviation between the GPS and CR measures, defined as follows:

$$Bias = GPS - CR$$

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

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. 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.

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:

$$(1) \qquad Y_i = L_i + C_i + S_i + SAT_i + T_i + W_i + e_i$$

Where *Y* is one of the four measures of bias defined above, 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 e is a random error with the usual desirable characteristics.

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 arelative bias larger than ten percent (in absolute value). The model is specified as follows:

$$(2) \Pr(Y_i = 1 | X_i) = \Phi(X_i \beta)$$

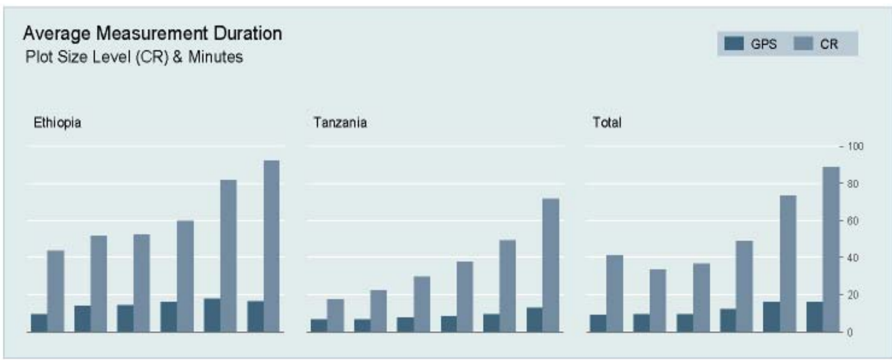
where $X_i = (C_i, s_i, SAT, T, W_i)$ and Φ is the standard cumulative distribution function. In equation (2), Y_i is one of three outcomes: a plot having absolute relative bias greater than 10%; a plot having relative bias greater than 10%; a plot having relative bias smaller than -10%.

3. Results

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 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 consistent with previous studies such as Schoning et al.(2005) and Keita and Carfagna (2009) 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 urations 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).

Figure 1 - Time taken for GPS and CR measurement



A. Comparison of competing measurements

1.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. Table 1 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 0.38 acres in Ethiopia to 1.30 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). 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. While some literature suggests that plots smaller than 0.5 hectares (1.24 acres) have significantly different GPS and compass and rope measurementswith much lower correlation (Schoning et al., 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 acreswas less than 0.001 acres or 3% 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 that are recorded do not appear to bear 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 1 - GPS vs Compass and Rope (CR) measures, by plot size classes

Means; Acres

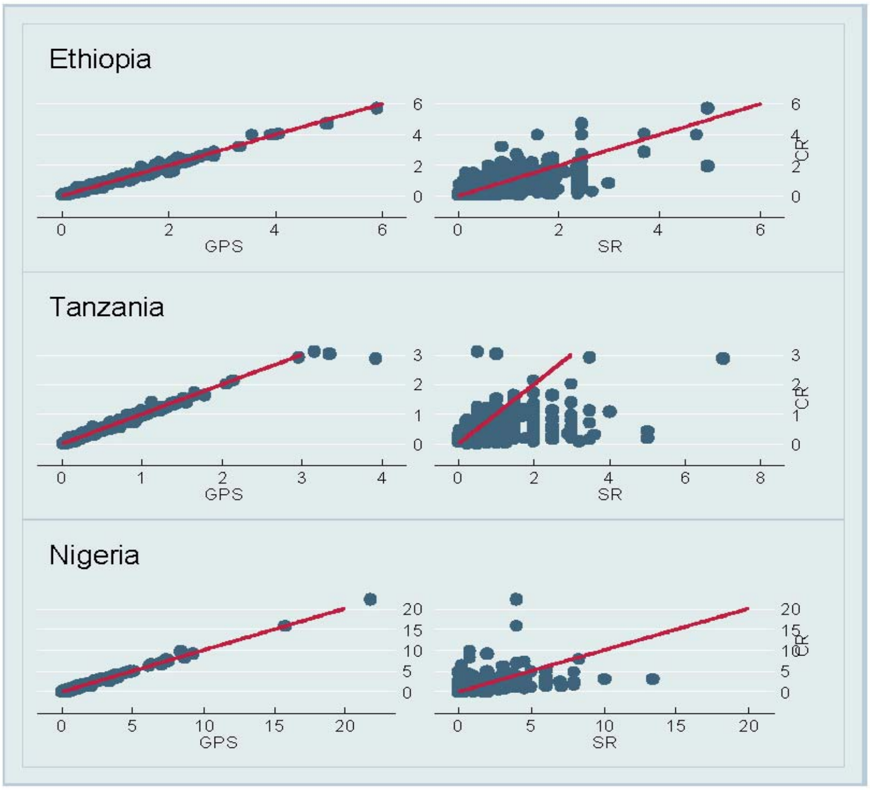
Level (CR)	Ethiopia						Tanzania					
	N	GPS	CR	Bias	Mean Bias / Mean CR	Difference in means	N	GPS	CR	Bias	Mean Bias / Mean CR	Difference in means
1 (< 0.05 acres)	390	0.02	0.02	0.00	0%	-	45	0.04	0.04	0.00	-3%	-
2 (< 0.15 acres)	400	0.10	0.09	0.00	2%	***	631	0.11	0.11	0.00	2%	***
3 (< 0.35 acres)	365	0.24	0.24	0.01	3%	***	823	0.23	0.23	0.01	2%	***
4 (< 0.75 acres)	328	0.52	0.51	0.01	2%	***	326	0.51	0.49	0.02	4%	***
5 (< 1.25 acres)	182	0.98	0.96	0.02	2%	***	63	0.94	0.92	0.02	2%	***
6 (>= 1.25 acres)	100	1.91	1.89	0.02	1%	-	20	1.91	1.81	0.09	5%	-
Total	1765	0.38	0.38	0.01	2%	***	1908	0.28	0.27	0.01	3%	***

Level (CR)	Nigeria						Pooled					
	N	GPS	CR	Bias	Mean Bias / Mean CR	Difference in means	N	GPS	CR	Bias	Mean Bias / Mean CR	Difference in means
1 (< 0.05 acres)	-	-	-	-	-	-	436	0.02	0.02	0.00	-1%	-
2 (< 0.15 acres)	21	0.11	0.11	-0.01	-7%	***	1052	0.10	0.10	0.00	2%	***
3 (< 0.35 acres)	73	0.24	0.25	-0.01	-4%	***	1261	0.24	0.23	0.01	2%	***
4 (< 0.75 acres)	129	0.52	0.53	-0.01	-2%	**	783	0.51	0.50	0.01	2%	***
5 (< 1.25 acres)	108	0.97	0.99	-0.02	-2%	***	353	0.97	0.96	0.01	1%	-
6 (>= 1.25 acres)	153	2.86	2.87	-0.01	0%	-	273	2.44	2.43	0.01	0%	-
Total	485	1.30	1.31	-0.01	-1%	*	4158	0.44	0.44	0.00	1%	***

*p<.1; ** p<.05; *** p<.01

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 allends 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.

Figure 2 - Scatter plots of Compass and Rope vs GPS (left) and Self-Reported (right) land area measures, acres

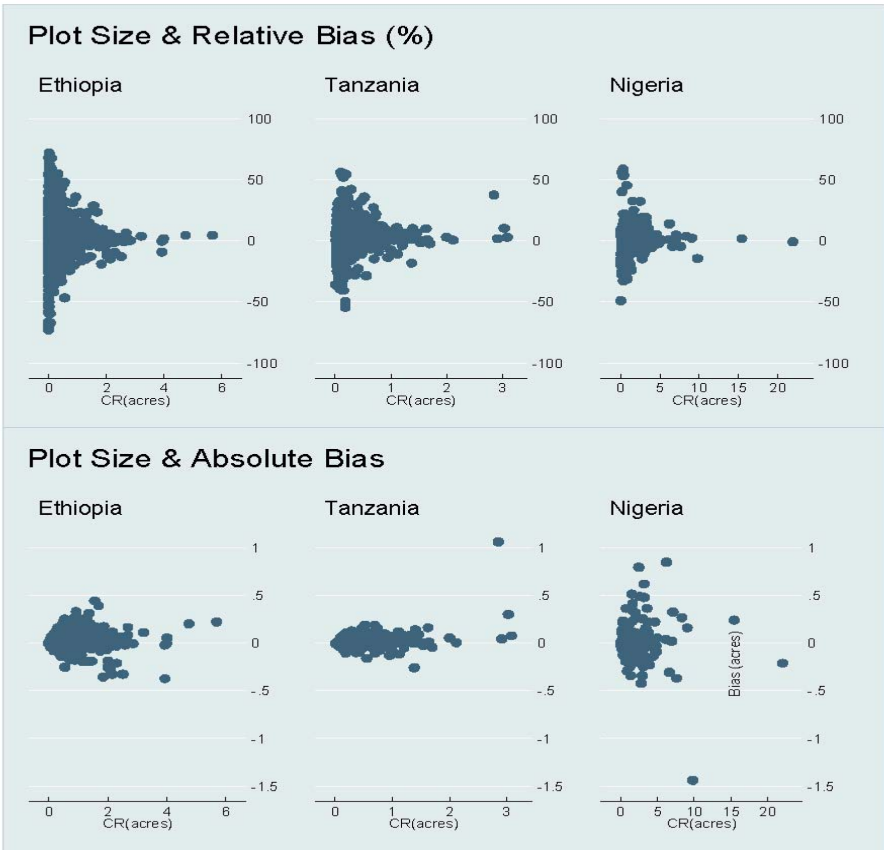


2.GPS measures: Exploring deviations from the gold-standard

Previous studies have also raised the issue of how factors other than plot size may affect the quality of GPS measures. 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.

The global navigation system requires, at a minimum, the acquisition of four satellites to triangulate the 3D position of the GPS receiver. Descriptive statistics suggest that the difference between GPS and CR measurement tends to decline the higher the number of satellites, but average difference remain small across all the distribution of plot areas. In Ethiopia, the difference between measurements is 1.6% (but not statistically significant) on the plots with less than 16 satellites and 1.2% on plots with the 20 or more satellites, though the trend is not linear as the middle category has an average of 1.8% bias. In Tanzania, the differences are 2.9% and 2.6%, respectively.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.No clear trend emerges in terms of systematic association of the differences between the two measures and weather conditions.
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 increase. 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 acres range. That seems to suggest 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 errors for observation with an arbitrary set value of plus or minus 10 percent.

Figure 3 - Scatter plots of relative (%) and absolute (acres) bias over plot size (acres)



3. Compass and Rope vs. Self-Reported Estimations

With an understanding of the comparability of GPS and compass and rope objective measurements, we now explore the difference in subjective (self-reported) and objective (CR) measurement. While the mean plot areas as measured by GPS and compass and rope differ by only as much as 3% on average, the mean self-reported and compass and rope measurements differ by as much as 143% on average (Tanzania). The mean difference is smaller in Ethiopia and Nigeria, at 23% and 5% 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% (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. The scatter plots on the right side of Figure 2 convey the same message in graphic form.

B. Regression analysis of the differences between competing measures

1. Comparison of CR and GPS

The results in Table 2include four specifications(only pooled model shown), the difference among them being the dependent variable, which is: (i) bias (GPS – CR), (ii) absolute value of bias, (iii) relative bias (bias as a percentage of the CR area), and (iv) absolute value of relative bias. 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 R2 values) is low, and that the majority of the estimated coefficients are not statistically significant.

The main variables of interest 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.

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.

Table 2 - Determinants of Bias (GPS – CR)

OLS Regression
Bias = GPS - CR (acres)

Dependent Variable:	Bias	|Bias|	Pooled {Bias/CR} * 100	{|Bias|/CR} * 100
CR Area (acres)	0.011	0.050***	-1.898***	-3.344***
CR Area^2	-0.001***	-0.002***	0.352**	0.507***
CR Area^3	-	-	-0.012**	-0.017***
Closing Error (%)	0.003*	0.004***	0.762***	0.370***
Number of Corners	0.000	0.000	-0.002	0.055*
Per : Area Ratio (GPS)	-0.006	0.001	-13.442***	11.534***
Number of Satellites	-	-	-	-
Slope (clinometer)	-	-	-	-
Treecover:				
Partial	-0.001	0.001	-0.217	0.692**
Heavy	-0.002	0.004	-0.870	2.170***
Weather:				
Mostly Cloudy - Rainy	-0.004	0.003	0.219	0.772**
Constant	-0.002	-0.008*	3.979***	5.731***
Includes Country Dummies	Yes	Yes	Yes	Yes
N	4158	4158	4158	4158
R2	0.026	0.316	0.095	0.162

*p<.1; ** p<.05; *** p<.01

What appears to matter most are closing 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. 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.

2. Comparison of SR and Objective Measurements

The models run above for the comparison of objective measures are ran again in an attempt to explain the difference between self-reported estimates and compass and rope measurements. The claim of plot area affecting the direction and degree of error associated with self-reported area estimates is supported by the regression results. In the first specification (on bias) the coefficient on plot area is negative quadratic and positive in the cubic term in Ethiopia, Nigeria and the pooled data. In the second specification (on absolute value of bias), the coefficients on plot area are positive suggesting that as plot size increases the degree of farmer over-reporting shrinks while at the same time the absolute value of the bias increases. In this second specification, the Tanzania data exhibits a negative quadratic term and positive cubic term. When looking at the relative bias and absolute value of relative bias, the linear term is negative and the quadratic term positive in each country but at very different magnitudes, potentially driven by the difference in average plot size observed across the countries. 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. 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 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. Household characteristics such as the gender, age, and education of the household head play out differently across countries.

4. 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 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). 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.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.

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