POLICY RESEARCH WORKING PAPER 11363

In Tablets We Trust?

Validation of the Use of Tablet-Based Tools for Land Area Measurement in Household Surveys

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April 2026

Abstract

Accurate and scalable methods for land area measurement are essential for estimating key agricultural indicators, such as crop yields, as well as understanding agricultural relationships. A significant body of literature has demonstrated systematic bias in farmer estimates of land area, the most inexpensive option, and at the same time provided evidence supporting the use of handheld GPS units for objective measurement. Despite the successful adoption of handheld GPS measurement in many survey operations, new tablet-based tools offer potential for smoother, more cost-effective measurement of land area. Using data collected in a methodological experiment in Uganda, this study evaluates the accuracy and operational trade-offs of tablet-based area measurement tools, both with and without the support of GPS-boosting devices, relative to handheld Garmin GPS units. The findings demonstrate that both tablet-based approaches are highly correlated with handheld GPS measurements, with relatively small but statistically significant differences in means. On average, the boosted and unboosted tablet measures exhibit absolute percentage errors of approximately 11 and 12 percent, respectively, with underestimation more pervasive than overestimation. Importantly, the findings highlight that even small differences in land area measurement can lead to substantial variations in yield and production estimates, underscoring the critical role of the measurement method for agricultural productivity analysis and policy. From an implementation perspective, the tablet-based approach offers clear advantages, with a significantly reduced burden of data cleaning and processing compared to handheld GPS data and enumerators facing few technical challenges.

This paper is a product of the Development Data Group, Development Economics. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at http://www.worldbank.org/prwp. The authors may be contacted at sgourlay@worldbank.org. A verified reproducibility package for this paper is available at http://reproducibility.worldbank.org, click **here** for direct access.

Produced by the Research Support Team

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JEL Codes: C83, O12, Q15, C88, Q12, Q24

Keywords: household surveys, agriculture, land measurement, CAPI technology

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CRediT Authorship Contribution Statement.
Federica Petruccelli: Data curation, Formal analysis (lead), Methodology, Writing - original draft (lead); **Sydney Gourlay:** Conceptualization, Formal analysis, Investigation, Methodology, Project administration, Supervision, Writing - original draft**;** **Adriana Paolantonio:** Conceptualization, Investigation, Methodology, Project administration, Supervision, Writing – Review & Editing; **Emanuele Clemente**: Data curation, Investigation; **John Ilukor**: Conceptualization, Funding acquisition, Project administration.

Acknowledgments

This paper was produced with financial support from the Korea Green Growth Trust Fund, the FoodSystems2030 Umbrella MDTF, and the 50x2030 Initiative to Close the Agricultural Data Gap, a multi-partner program that seeks to bridge the global agricultural data gap by transforming data systems in 50 countries in Africa, Asia, the Middle East and Latin America by 2030. For more information on the Initiative, visit 50x2030.org. The authors would like to thank Siobhan Murray (World Bank) for her valuable support in processing the geospatial data used in this study. We are also grateful to the participants of the 32nd International Conference of Agricultural Economists (ICAE) for their insightful comments and suggestions on an earlier version of this work, as well as Dramane Bako (FAO), Yakob Seid (FAO), Talip Kilic (World Bank) and Wondu Yemanebirhan Kassa (World Bank).

1. Introduction

Accurate land area measurement is critical for agricultural productivity analysis, land inequality assessments, and the formulation of evidence-based agricultural policies (Carletto et al., 2013; Dillon et al., 2016). Developing a comprehensive understanding of agricultural systems, as well as designing and assessing the impacts of agricultural interventions, requires significant enhancements in the availability, timeliness, and quality of data accessible to researchers and policy makers. With more than 75 percent of the world's extreme poor residing in rural areas (World Bank, 2024) where agriculture remains the primary source of livelihood, data on land plays a pivotal role in designing and evaluating policies aimed at poverty alleviation and sustainable agricultural development.

Land acts as a critical determinant of both absolute and relative farmer wealth, a key resource in agricultural production, and a central variable for standardizing the use of inputs and measuring outputs. Often underestimated, the accuracy of land area measurement can have profound implications for the reliability of agricultural statistics, economic assessments, and the development of informed policies (Carletto et al., 2013, 2015; Dillon et al., 2016). Despite its importance, obtaining accurate and reliable land area data has been a persistent challenge in household and agricultural surveys. Many surveys rely on farmer self-reports of land area, which are inexpensive and easy to implement but are often prone to significant measurement error.

Previous studies have highlighted systematic biases in respondent estimates of plot size across multiple countries (Carletto et al., 2013, 2015, 2017; Dillon et al., 2016). Farmers tend to overestimate the size of small plots and underestimate larger ones, leading to systematic errors that distort productivity estimates and land inequality measures. Research conducted by the Living Standards Measurement Study (LSMS) of the World Bank (Carletto et al., 2016) has validated the use of handheld Global Positioning System (GPS) devices for land area measurement, using the traditional compass-and-rope method as a benchmark. This method has been shown to drastically reduce measurement error relative to that in self-reported estimates (by over 90 percent for the smallest plots; see Carletto et al., 2017) while also cutting implementation time compared to the compass-and-rope approach, which can take about 3.5 times longer than GPS-based measurement (Keita & Carfagna, 2009; Schøning, 2005). Despite the great advancements in data quality made possible by the proliferation of GPS devices available and their increasing affordability, the use of handheld GPS devices still comes with challenges that hinder their widespread adoption in some cases. The primary challenge is high acquisition costs, which can be prohibitive for large-scale surveys where numerous devices are needed, budgets are limited, and procurement processes burdensome. Additionally, data integration remains an issue, as data collected and stored on separate GPS devices often require extensive post-processing and cleaning to allow for integration with survey microdata. These challenges highlight the need for further innovation in land measurement tools to ensure broader accessibility and seamless integration into survey workflows.

To address the limitations of handheld GPS-based methods, the LSMS team, under the 50x2030 Initiative, supported the development of an area measurement feature in the World Bank's Survey Solutions Computer-Assisted Personal Interviewing (CAPI) software.[1] While this tool, and other similar tools on the market, offers a streamlined approach to land area measurement that has the potential to bypass the need for external equipment and the integration of data from multiple sources, validation against established measurement tools with verified accuracy is needed, especially given concerns around the accuracy of the GPS technology embedded in tablets vis-à-vis that of dedicated handheld GPS devices. In addition to their utility for measuring area, these tools can serve as effective georeferencing instruments, enabling the integration of spatial data collection into fieldwork activities.

Leveraging data collected in a methodological study in Uganda designed for this particular objective, this research aims to test and validate the use of innovative, tablet-based tools for land area measurement in smallholder agricultural contexts, both with and without the use of a GPS signal boosting device**.** The accuracy of these methods is evaluated by systematically comparing them against measurements taken with handheld Garmin GPS devices, assessing their relative performance, and exploring whether GPS boosting devices are needed to obtain sufficiently accurate area measurements using the tablet. Furthermore, this study seeks to examine the trade-offs associated with different approaches, considering multiple factors such as data quality, implementation costs, and scalability in diverse agricultural settings. Finally, to highlight the broader implications of land measurement for official statistics and agricultural policy, estimates of agricultural productivity leveraging the various area measurement approaches are explored.

Findings demonstrate that both GPS-unboosted and boosted tablet-based measurements are highly correlated with benchmark measurements taken with a handheld GPS device, with

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[1] For more information on Survey Solutions, visit: https://mysurvey.solutions/en/.

relatively small but statistically significant differences in means. The boosted and unboosted measures exhibit absolute percentage errors of approximately 11 and 12 percent on average, respectively, relative to handheld GPS measurements, with underestimation more pervasive than overestimation. The use of a GPS booster appears to produce plot outlines more in line with those collected using the handheld GPS and reduce measurement error, particularly for more irregularly shaped plots, but mean measurements with and without the booster are not statistically different in the sample overall. Importantly, results point to specific conditions under which measurement errors are more likely to occur, such as on plots with complex shapes and when conducted with excessively slow walking speeds. The implications for agricultural productivity analysis and policy are significant, however, as even small differences in land area measurement can lead to substantial variations in yield and production estimates. From an implementation perspective, advantages of the tablet-based approach were observed, as enumerators faced very few technical challenges using the tablet-based tool and the burden of data cleaning and processing was significantly reduced relative to data collected through the handheld GPS.

The remainder of the paper is organized as follows. Section 2 reviews the menu of land area measurement methods available, including those traditionally used as well as the relatively new tablet-based tools that this study sets out to validate. Section 3 describes the data and fieldwork design, while Section 4 discusses the methodology. Section 5 presents the results, and Section 6 concludes with a discussion on policy implications.

2. Land measurement methods

Accurately measuring land area in household surveys—especially under tight timelines and limited resources—poses logistical and methodological challenges. Choosing the right approach requires considering not only the accuracy of the measurement but also transportation to plots, questionnaire length, and the safety of field teams and equipment. The literature identifies several methods, each with specific advantages and limitations, which must be weighed against survey objectives, plot characteristics, and the feasibility of implementation at scale (Carletto et al., 2016, 2017; Dillon et al., 2016).

The compass-and-rope (or traversing) method is widely considered the “gold standard” for accuracy when properly applied (FAO, 1982). It offers benchmark-quality measurements for validating alternatives like the use of handheld GPS devices. However, it is labor- and time-intensive (Schøning et al., 2005; Keita and Carfagna, 2009), and often unfeasible for large surveys (Carletto et al., 2016). The method involves visiting plots, clearing boundaries, marking corners, and taking compass bearings—tasks that are especially difficult for irregularly-shaped plots, where human judgment and skill can introduce error. A key quality check is the closing error—the gap between starting and ending points—which, if too large, requires repeating the measurement. Small errors across multiple plot corners can accumulate, reducing overall accuracy (Carletto et al., 2016).

An alternative approach widely used in household surveys is relying on self-reported land area estimates, which are low-cost and require only a few additional survey questions. While relatively easy to implement and yielding high response rates, there is strong evidence of bias in self-reports associated with respondent characteristics, land tenure systems, and the use of non-standard area units, among others (Carletto et al., 2013, 2015, 2017; Dillon and Rao, 2021). In many settings, informal or undocumented land holdings make accurate estimates difficult. Systematic biases in self-reported estimates are well-documented. Studies in Malawi, Tanzania, Niger, and Uganda, for example, show that small plots are often overestimated—sometimes by 90 percent or more—while large plots are underestimated, distorting productivity analysis and policy (Carletto et al., 2015; Dillon et al., 2016). Accuracy also varies by respondent, with more educated farmers reporting more accurately, and absentee landlords, part-time farmers, and older household heads tending to misreport to a greater degree. Irregular plot shapes further reduce reliability (Carletto et al., 2013).

The use of portable GPS devices for land area measurement has become increasingly prevalent among survey practitioners worldwide, providing a practical solution to objective area measurement (Kelly and Donovan, 2008; Carletto and Gourlay, 2019). Research by the World Bank's Living Standards Measurement Study (LSMS) (Carletto et al., 2016, 2017) and other institutions has validated the use of handheld Global Positioning System (GPS) devices for measuring land area, using the traditional compass-and-rope method as a reference standard. This research has led to the widespread adoption of GPS technology in many national survey operations, significantly improving the accuracy of land area estimates. Despite these advancements, the use of handheld GPS devices is not without challenges; they are still subject to certain biases, particularly in sloped terrains where angles may affect accuracy (Dillon and Rao, 2021), and they may be less accurate on small plots, though there is mixed evidence on the latter with some studies finding greater measurement error on plots smaller than 0.5 hectare (Schøning et al., 2005; Keita and Carfagna, 2009), while others find GPS and compass and rope measurements to be statistically similar, on average, even for plots smaller than 0.05 hectare (Carletto et al., 2017).

The relatively high unit cost of the devices, averaging approximately $300, can pose a financial barrier to their adoption in large-scale surveys (Carletto et al., 2017). Additionally, integrating data collected with a handheld GPS device into survey datasets can require extensive data cleaning, as it involves manual entry of plot areas into the questionnaire and naming and saving of plot outlines, both of which are subject to data entry errors. Other challenges associated with this approach include the inability to measure plots that are inaccessible to survey staff either due to survey protocols aimed at managing fieldwork duration and costs, safety-related constraints, or respondent refusal—resulting in missing data.

With the aim of providing an alternative to the use of handheld GPS units, given the barriers to adoption and implementation costs noted above and the increasing affordability and quality of GPS-enabled tablets, the 50x2030 Initiative contributed to the development of an advanced feature for area measurement in the World Bank's Survey Solutions CAPI software (referred to henceforth as the "SuSo" or tablet method for brevity).[2] The new feature allows for the collection and storage of plot boundaries (or polygons) directly in the CAPI software, thereby bypassing the need for external GPS devices as well as any need for manual entry of plot areas or polygon track names. Contrary to the handheld GPS devices, the SuSo area measurement tool is already integrated into the software platform and runs on the same tablets used for regular household survey data collection. As a result, there are no additional hardware or software costs for implementing area measurement beyond what survey operations would already need for implementing a CAPI-based survey. The feature can be implemented in automatic and semi-automatic modes, enabling interviewers to record waypoints while walking along the perimeter of the plot, holding a tablet. In the automatic mode, coordinates are automatically recorded at predefined intervals (e.g., every five seconds). In the semi-automatic mode, coordinates are collected when instructed by the enumerator as they pace the perimeter. The application then calculates the plot's area and perimeter based on these coordinates and allows for the export of these variables as well as a string of ordered coordinates that can be easily converted into polygons. Additionally, when deployed within a roster, the software detects overlaps between multiple plots, alerting interviewers to potential double-counting issues.

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[2] For more details on the Survey Solutions feature, visit: https://docs.mysurvey.solutions/release-notes/version-22-12/.

Similar tools have been developed by other initiatives, most notably through open-source platforms such as Open Data Kit (ODK).[3] This example illustrates a growing trend toward integrating geospatial and area measurement functionality into digital survey platforms, reducing reliance on external GPS devices and improving data quality. Despite the availability of these tools, however, to the best of our knowledge there is no published evidence on the accuracy of the measurements conducted using these features benchmarked against validated methods such as the use of handheld GPS devices.

3. Data and Implementation

This study leverages data collected through a methodological study, the Uganda Climate, Land Area, and Soil Study (CLASS), designed specifically for validating the use of tablet-based tools for area measurement, along with the objectives of validating innovative tools for measuring soil health and weather at the local level. The Uganda CLASS was led by the World Bank's LSMS team under the aegis of the 50x2030 Initiative, in partnership and with complementary financial support from the World Bank's Agriculture and Food Global Practice. This section outlines the Uganda CLASS design and sample and details the implementation of the various land area measurement methods.

3.1 Data Description

The Uganda CLASS study included data collection in five districts in the Eastern and Northern regions of Uganda, with a target sample of 900 maize-growing households. Households were randomly selected from 75 Enumeration Areas (EAs), with 15 selected from each of the five districts based on a listing exercise that identified whether the household was cultivating maize in the July to December 2023 agricultural season.[4] Data collection was facilitated through Computer-Assisted Personal Interviewing (CAPI) using the World Bank's Survey Solutions software. The experiment was conducted in four phases between August 2023 and March 2024,

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[3] ODK supports geospatial question types like geoshape, which allow enumerators to walk the perimeter of a plot while GPS coordinates are automatically recorded at regular intervals. These coordinates can then be used to compute land area directly within the digital form. For more information on the ODK tool, visit: https://docs.getodk.org/form-question-types/#geoshape.

[4] The five districts are: Apac, Dokolo, Kamuli, Kaliro, and Buyende. These districts were chosen based on several key criteria, including the proportion of households engaged in maize cultivation, climatic variability, the presence of weather stations managed by the Uganda National Meteorological Authority, and the availability of network connectivity. Households that are included in the sample for agriculture-related national surveys, including the Uganda Harmonised Integrated Survey (UHIS), the Uganda National Panel Survey (UNPS), or the Annual Agricultural Survey (AAS), were exempt from selection into the CLASS sample.

namely the listing phase, the post-planting (PP) phase, the crop-cutting (CC) phase, and the post-harvest (PH) phase.

During the PP phase, a questionnaire was administered to collect data primarily on the plots cultivated by the household and planting activities. As part of this phase, one maize plot was randomly selected for objective land area measurement, soil health assessment, and crop cutting of maize. Selection of the plot was made directly in the CAPI program to avoid any selection bias in the sample of plots selected for measurement. All available methods for measuring land area were conducted on the randomly selected plot to allow for direct comparison of the methods. For crop-cutting, an 8x8 meters crop-cutting subplot was demarcated. Where plot size or shape did not allow for the demarcation of an 8x8 meter subplot, crop cutting was to be conducted on the entire plot.[5]

The CC visit took place when the maize was ready for harvest. During this visit, the crop cut subplots were harvested and weighed. The moisture content of the maize harvest was also measured using a moisture meter, which allowed for a standardization of moisture content when computing yield estimates (yield estimates used in the subsequent analysis are standardized to 12 percent moisture content). A total of 894 interviews were successfully completed during the CC phase, accounting for 99 percent of the targeted households. The remaining six households were repeatedly tracked by the field team but could not be surveyed. Among the 894 households visited, 654 had an 8x8 meter subplot established during the post-planting visit, while the remaining 240 were classified as full-plot crop-cutting households due to the plot dimensions not allowing for 8x8 meter subplot placement.

The fourth and final visit (PH) involved the administration of a post-harvest questionnaire which collected self-reported information on harvest activities and production.

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[5] Crop-cutting is a widely recognized method for estimating total crop production by measuring yield from a small, randomly selected section of a plot and extrapolating it based on the plot's total area. This approach is considered the gold standard for assessing agricultural productivity due to its objectivity and accuracy. The designated "subplot" refers to an 8x8 meters area within the plot where crop-cutting will take place. This subplot was further divided into four quadrants, each measuring 4x4 meters, to facilitate systematic yield assessment and allow for analysis of heterogeneity in yields within the 8x8 meter subplot. If the selected plot was smaller than 8x8 meters or its shape did not allow for the demarcation of an 8x8 meters subplot, the crop-cutting exercise was conducted on the entire plot instead. A local crop cut monitor was employed to periodically visit sampled households between the PP and CC visits to ensure the subplots were not harvested by the households prior to crop-cutting by the survey teams.

3.2 Land Area Measurement in the Uganda CLASS

As mentioned above, the Uganda CLASS study was designed to allow for direct comparison of area measurements collected using various methods on one randomly selected maize plot per household. Three objective methods were deployed: (i) use of a handheld GPS-device, (ii) use of a tablet with the Survey Solutions built-in area measurement feature, and (iii) use of the same tablet approach in point (ii) but with the support of a GPS signal-boosting device. The GPS measurements were collected using handheld Garmin devices, specifically the Garmin eTrex 30.[6] For simplicity, the approach using the handheld Garmin GPS device is henceforth referred to as GPS. In all methods, enumerators walked the perimeter of each plot to record geospatial data, from which land area was calculated. In addition to these objective measures, self-reported estimates of plot size were also collected. Consistent with previous studies, self-reported estimates exhibit systematic errors—typically overestimating smaller plots and underestimating larger ones (see Figure A1, Appendix). These self-reports are not used in the analysis that follows but are included for descriptive comparison.

To ensure consistency and comparability in land area measurements, all objective measurements were conducted simultaneously, ensuring that the same plot boundaries were walked for each method and that they were walked at the same pace. This was achieved by placing all measurement devices on a tray, oriented in the same direction, which was carried by the enumerator as they paced the perimeter of the plot. Before conducting the measurement, enumerators were instructed to walk the perimeter of the plot together with the respondent to identify and, if necessary, clear the boundaries, ensuring a clear path for measurement.

The Garmin-based GPS area used for the analysis that follows is extracted from the polygon constructed based on the .gpx tracks stored on the Garmin devices and serves as the benchmark for evaluating the tablet-based measures. It is important to emphasize that obtaining this measure requires a thorough extraction and processing procedure. Although the enumerators also manually recorded the area as measured by the GPS device into the survey at the time of measurement, this manually entered variable is often affected by inconsistencies and errors, stemming primarily from data entry errors and incorrect decimal locations. Relying on the manually entered GPS measures that are available directly in the survey data, without processing the .gpx tracks to extract area estimates from the resulting polygons or at a minimum

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[6] The cost of each of these devices was approximately USD 300.

utilizing those figures to identify significant errors in the manually entered areas, could lead to the use of unreliable and internally inconsistent data.[7]

By contrast, the tablet-based area measures conducted using the Survey Solutions feature are not entered manually by enumerators and are therefore not prone to data entry errors, nor do they require cleaning to identify and correct for these errors.

For the tablet-based measurements, each enumerator was provided with two tablets: a standard version—“unboosted”—and a “boosted” version. The boosted tablet was connected to a Garmin GLO2[8] external GPS receiver. The use of the booster has the potential to negate concerns about the accuracy of the GPS technology embedded in tablets relative to that of handheld GPS devices and the implications for area measurement, as it serves to effectively override the tablet’s embedded GPS sensor and apply a Garmin-grade receiver to the tablet. While both tablets function identically in terms of software, including the use of Survey Solutions, the key distinction lies in the source of the GPS technology and the improved GPS accuracy offered by the booster. The tablet model used for both the unboosted and boosted measurements was the Samsung Galaxy T580. Results, therefore, are valid for this tablet model but may not be valid for other tablet models, especially older devices which may have inferior embedded GPS technology.

The implementation of the Survey Solutions tablet-based tool and GPS booster faced minimal technical challenges, with only 5.9 percent of users reporting issues when using the tablet without the booster and an even lower 2.7 percent when using the boosted tablet. Among the challenges encountered, the most common issue with the unboosted tablet was that the shape did not resemble the actual plot shape (2.7 percent), followed by accuracy being too low for measurement (1.8 percent), and the time required to reach accuracy (1.5 percent). The boosted tablet showed fewer issues, with only 0.3 percent of cases reporting unexpected plot shapes, 0.8 percent citing insufficient accuracy, and 1 percent noting a long time to achieve the required accuracy. A minor connectivity issue with the booster was reported by 0.1 percent of users.

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[7] As shown in Table A1 in the Appendix, the raw Garmin Survey data include several extreme outliers, with a mean of over 378,000 m² and a maximum exceeding 330 million m²—clearly implausible figures for plot size. To address this, we construct a cleaned version of the Garmin Survey variable by removing obvious outliers and entry errors—such as misplaced decimal points or extra digits. The cleaned Garmin Survey data closely match the Garmin Extracted values, with a correlation of 0.99, compared to –0.017 for the raw values.

[8] The Garmin GLO 2 receiver, which costs about USD 120, combines GPS and GLONASS satellite signals with Bluetooth wireless technology. By accessing both satellite constellations, it connects to up to 24 more satellites than GPS-only devices, resulting in faster satellite lock-on (about 20 percent quicker) and improved tracking, even at high speeds. The device updates position data 10 times per second, significantly more frequently than standard mobile GPS receivers, ensuring real-time, high-accuracy location information on compatible iOS and Android devices.

The descriptive statistics of the key variables used in the analysis are reported in Table A2 in the Appendix.

The higher rate of reported challenges with the unboosted tablet, especially those related to the plot shapes and time to reach required accuracy, are in line with priors that the GPS technology embedded in the tablets is inferior to the booster. In the SuSo tool, a predetermined accuracy threshold must be met in order for coordinates to be collected as the enumerator paces the perimeter of a plot. In the Uganda CLASS this threshold was set to 10 meters, which implies that coordinates were not collected during the pacing of the perimeter when the accuracy obtained by the tablet was more than 10 meters (the point was simply skipped and the next point was collected when the accuracy requirement was met). Figure 1 illustrates a comparison of plot outlines obtained from the unboosted and boosted tablets, as well as the Garmin GPS, for three illustrative examples. Across all examples, the SuSo without booster (blue) often deviates more from the Garmin reference (red), sometimes distorting the plot shape (as in Plot A and Plot C). The SuSo with booster (green) aligns more closely with the Garmin outline.

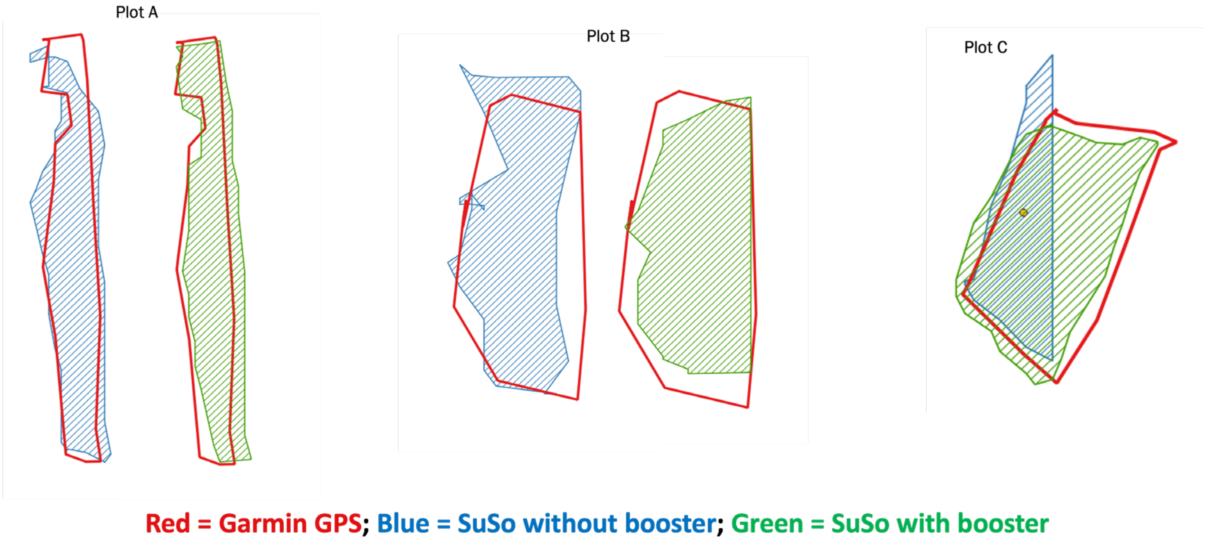

Figure 1. Comparison of plot boundaries measured using Garmin GPS, SuSo without booster, and SuSo with booster.

4. Methods

To compare the SuSo tablet-based methods with the standard GPS, we construct two main measures of deviation. The first is the simple bias, calculated as the difference between the tablet-based measure—either unboosted or boosted—and the GPS-derived area:

$$Bias\ unboosted\ (boosted)\ = SuSo\ unboosted\ (boosted)\ -\ GPS$$

The second is the relative bias, expressed as a percentage of the GPS area:

$$Relative\ Bias\ unboosted\ (boosted) = \frac{SuSo\ unboosted\ (boosted)\ -\ GPS}{GPS}\ x\ 100$$

In addition to these raw bias measures, we also consider their absolute values to better capture the magnitude of discrepancies regardless of direction.

The analysis unfolds in four distinct stages. First, we conduct a descriptive exploration by comparing average values across different segments of the sample. This helps to highlight key differences and potential sources of variation.

In the second stage, we investigate the factors that account for discrepancies between the tablet-based and GPS-based area measurements. To this end, we estimate a standard Ordinary Least Squares (OLS) specification designed to quantify the relationship between observed biases and various explanatory variables. The specification is as follows:

$$Y_i\ =\ \alpha\ +\ \beta_1 GPS_i\ +\ \beta_2 R_i\ +\ \beta_3 P_i\ +\ \beta_4 E_i\ +\ \beta_5 O_i\ +\ \beta_6 D_i\ +\ \varepsilon_i \qquad (1)$$

where the unit of observation is plot *i*. α is the constant, the dependent variable Y represents one of the four bias measures defined above (bias, absolute bias, relative bias, absolute relative bias). GPS_i denotes the Garmin-extracted GPS area. R_i represents the perimeter-to-area ratio,[9] which serves as a proxy for the geometric complexity or irregularity of plot shapes where a higher ratio reflects a more irregular plot shape (Carletto et al., 2017). P_i includes implementation-related factors like the dummy variables for a walking speed that is too slow and sun exposure. In our sample the average walking speed is very low, likely due to training protocols that we employed encouraging a slow pace, ranging between 0.08 and 2 meters per second using the perimeter and duration estimated with the unboosted tablet.[10] According to

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[9] To compute the perimeter-to-area ratio we use the perimeter and area from the benchmark Garmin to best reflect the true complexity of the plot shape.

[10] Walking speeds as measured with the boosted tablet are slightly different, ranging from 0.003 and 1 meter per second. Given the construction of the walking speed – computed as *perimeter ÷ duration* using each device's own perimeter estimate and time stamps – the implied walking speed will differ if perimeter estimates are different,

Bogaert et al. (2005), for parcels up to 4 hectares, the optimal walking speed for operators on foot ranges between 0.5 and 2 meters per second (1.8–7.2 km/h). Based on this benchmark, and considering the generally slow speed in the sample, we define walking speed to be “too slow” if it is below 0.3 meters per second. The sun exposure variable captures whether the measurement began during midday hours (between 11:00 AM and 2:00 PM), when direct sunlight could plausibly interfere with the tablet’s visibility. E_i is a vector of proxies capturing environmental and topographic characteristics (including Terrain Roughness Index (TRI), Topographic Position Index (TPI), slope, elevation and a dummy variable indicating whether any rainfall occurred on the day of measurement). The vector O_i includes variables reflecting potential obstacles encountered during the measurement, such as a variable indicating different levels of tree canopy cover (with the absence of canopy cover serving as the reference category) and built-up area. Finally, D_i includes georeferenced variables capturing spatial context, namely the distance to the nearest main road and the distance to the nearest cell tower (based on OpenCelliD data; OCI), which may be related to remoteness and strength of GPS satellite signal.[11] ε_i is the random error term.[12]

In the third stage, we explore the conditions under which tablet-based measurements may be less reliable. To do this, we estimate a probit model aimed at identifying the factors associated with a higher likelihood that a plot is measured with a relative bias exceeding 10 percent in absolute terms.

We define three binary outcome variables for the analysis: whether a plot exhibits an absolute relative bias greater than 10 percent; whether the relative bias exceeds +10 percent (overestimation); and whether it falls below -10 percent (underestimation). The model is specified as follows:

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

where X_i includes the GPS_i, R_i, P_i, E_i, O_i, D_i as defined above, Φ is the cumulative distribution function and β a vector of estimated parameters.

Finally, in the fourth stage, we assess how alternative land measurement approaches affect the estimation of plot-level maize production and agricultural yields, shedding light on the

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even if the actual duration of measurement was the same (as is expected in the vast majority of cases given the protocol to measure the area with all devices simultaneously).

[11] For more on OpenCelliD, visit opencellid.org.

[12] Table A2 in the Appendix reports the descriptive statistics of these variables.

practical consequences of measurement choice for productivity analysis and official statistics. To do so, we reshape the data to long format such that each plot appears in multiple rows—one for each measurement method—with the corresponding method identifier and associated area estimate. This transformation enables us to compare, within the same plot, how different methods affect derived outcomes. By leveraging within-plot variation and holding physical plot characteristics constant, this structure supports fixed effects regression analysis that isolates the impact of measurement method on agricultural output.

Equations (3) and (4) model the relationship between measurement methods and agricultural outcomes, specifically maize production (Y_i) and yield ($\frac{Y_v}{L_i}$), respectively. In both specifications, the key explanatory variables are indicators for two alternative land measurement methods—SuSo unboosted and SuSo boosted—relative to the Garmin GPS baseline. Plot fixed effects are included to control for time-invariant plot-level heterogeneity. As specified in Section 2, maize production is estimated for a subset of plots that are relatively small and regularly shaped—specifically, those suitable for 8x8 meter crop-cutting segments (8x8 Sample). For these plots, total production on the plot is obtained by multiplying the yield measured on the 8x8 meter segment by the total plot area as measured by each method, under the assumption that yield is homogeneous across the full plot. In contrast, yield is calculated for a different subset of plots for which full plot crop cutting was implemented, either because they are smaller than 8x8 meters or irregular in shape such that they were unsuitable for standard 8x8 meter crop-cutting segments (referred to as the Fullplot Sample). In this case, total production (Y_v) is directly measured during harvest, and yield is computed by dividing this production by the corresponding plot area measurement (L_i). As a result, the production and yield regressions are estimated on different samples, reflecting the underlying heterogeneity in plot geometry and ensuring that each outcome is constructed using the most reliable approach given the available data.

$$Y_i = \alpha + \beta_1 SuSo\ unboosted_i + \beta_2 SuSo\ boosted_i + Plot_i + \varepsilon_i \tag{3}$$

$$\frac{Y_v}{L_i} = \alpha + \beta_1 SuSo\ unboosted_i + \beta_2 SuSo\ boosted_i + Plot_i + \varepsilon_i \tag{4}$$

5. Results

This section presents a comprehensive assessment of the performance of tablet-based land measurement methods (SuSo) relative to the Garmin GPS benchmark. We begin by comparing SuSo measurements—with and without booster support—to GPS-based estimates, using visual and descriptive statistics to assess systematic patterns of bias across methods and plot size categories. We then examine the determinants of measurement error through regression analysis. In the third part, we examine the likelihood of excessive bias—defined as deviations exceeding 10 percent—and assess the conditions under which such large errors are most likely to occur. Finally, we explore the consequences of measurement discrepancies for key agricultural outcomes by analyzing how different land measurement methods affect reported maize production and yield.

5.1 Bias Comparison between SuSo Methods and the Garmin GPS

Figure 2 displays three scatter plots comparing plot size measurements derived from three methods: Garmin GPS, SuSo without booster, and SuSo with booster. Each subplot shows a pairwise comparison of methods. The left panel compares Garmin with SuSo without booster, the middle compares Garmin with SuSo with booster, and the right panel compares SuSo with and without booster. The reported correlation coefficients are 0.98 for Garmin vs. SuSo without booster, 0.98 for Garmin vs. SuSo with booster, and 0.99 for SuSo with vs. without booster. Nonetheless, some minor discrepancies are observed, particularly in the SuSo without booster method, which appears to have slightly more variation when compared with the other two.

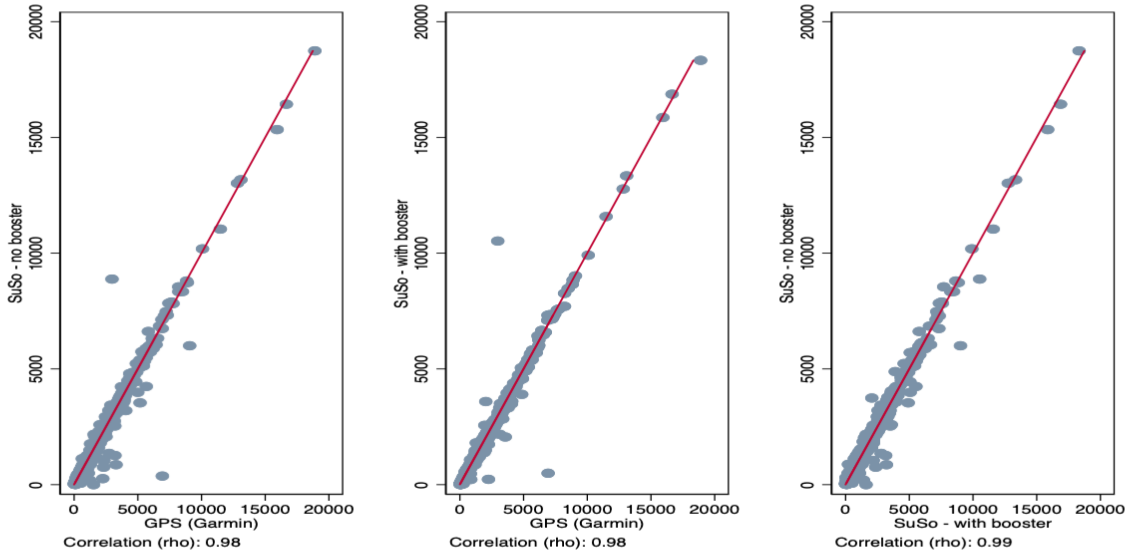

Figure 2. Scatter plots of different land area measurements: SuSo – unboosted and GPS (left), SuSo boosted and GPS (middle), and SuSo unboosted and SuSo boosted (right), in square meters. (Note: the red line is the line of equality between measurements.)

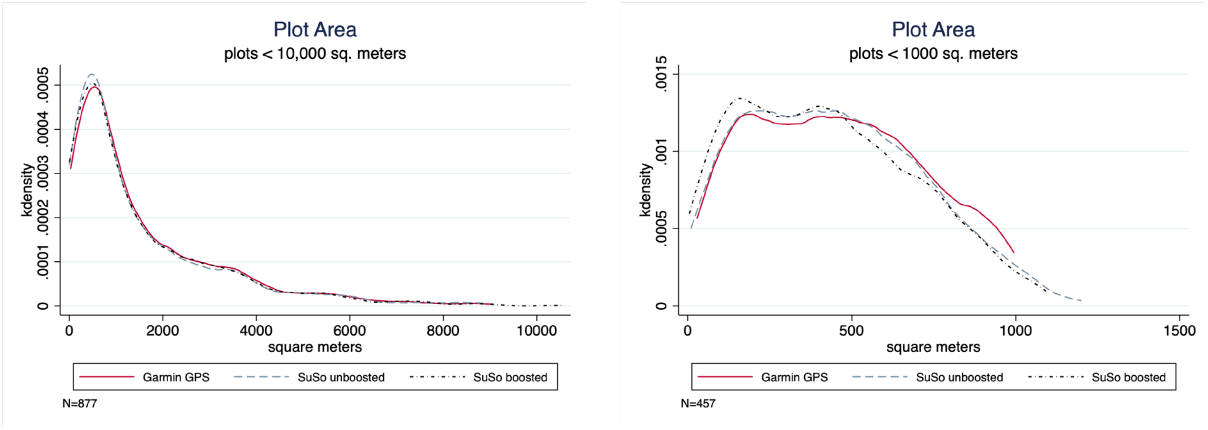

Figure 3. Distribution of plot area measurements by method and plot size

Figure 3 presents kernel density estimates of plot area measurements obtained using the three different methods: Garmin GPS, SuSo without booster, and SuSo with booster. The left-hand side panel shows the distribution for all plots smaller than 10,000 square meters, while the right-hand side panel focuses on those below 1,000 square meters. Across both panels, the distributions are broadly similar in shape but exhibit differences in density levels and tail behavior, particularly among smaller plots. In the <1,000 m² subsample, the SuSo methods—especially without booster—tend to produce slightly higher density mass at lower area values compared to the GPS benchmark. However, the tablet-based measures, with and without the booster, are not statistically different from each other overall, as shown in Table 1.

Table 1. Comparison of SuSo methods (without and with the booster), by plot size

		SuSo unboosted		SuSo boosted		
GPS Level	Obs.	Mean	SD	Mean	SD	Difference in Means
Smallest	177	190.753	102.020	163.743	89.611	***
Small	177	502.279	131.830	473.119	111.149	***
Medium	176	920.934	237.669	916.400	210.849	-
Large	177	1897.281	505.358	1888.202	476.192	-
Largest	177	4699.406	2490.072	4702.161	2517.842	-
Total	884	1642.947	1994.129	1629.531	2006.908	-

Note: This table compares average plot area measurements using SuSo (Survey Solutions) without and with the booster tool, across five plot size categories based on GPS quintiles. The “Difference in Means” column indicates whether the difference between the two methods is statistically significant within each plot size group.

**** p<.01, ** p<.05, * p<.1*

Table 2. Comparison of SuSo methods (without and with booster) and Garmin GPS measures, by plot size

				(1)	(2)	(3)	(4)	
GPS Level	Obs.	GPS	SuSo	SuSo - GPS	|SuSo - GPS|	Bias/GPS*100	|Bias|/GPS*100	Difference in Means
SuSo without booster								
Smallest	177	191.907	190.753	-1.154	33.706	-1.245	20.120	-
Small	177	514.301	502.279	-12.021	69.099	-2.334	13.592	*
Medium	176	958.109	920.934	-37.174	103.347	-3.981	10.825	***
Large	177	1939.030	1897.281	-41.748	155.791	-2.097	8.209	*
Largest	177	4771.381	4699.406	-71.974	301.860	-0.976	7.075	-
Total	884	1675.756	1642.947	-32.809	132.794	-2.125	11.965	**
SuSo with booster								
Smallest	177	191.907	163.743	-28.164	35.769	-16.332	21.187	***
Small	177	514.301	473.119	-41.181	63.173	-8.023	12.407	***
Medium	176	958.109	916.400	-41.708	77.482	-4.647	8.286	***
Large	177	1939.030	1888.202	-50.828	133.435	-2.647	7.150	***
Largest	177	4771.381	4702.161	-69.219	226.192	-1.031	5.454	-
Total	884	1675.756	1629.531	-46.225	107.244	-6.538	10.900	***

Note: This table compares average plot area measurements from Garmin GPS with those from SuSo (with and without the booster), across plot size categories. The columns show the raw, absolute and relative differences between SuSo and GPS, capturing both the direction and magnitude of bias. Negative values in the “SuSo - GPS” and “Bias/GPS*100” columns indicate underestimation by SuSo relative to GPS. Statistical significance in the “Difference in Means” column refers to paired t-tests comparing SuSo and GPS measures within each quintile.

**** p<.01, ** p<.05, * p<.1*

Table 2 compares Garmin area measurements to those collected using the SuSo without booster (top) and with booster (bottom) methods across different plot size categories and reveals that, despite the strong correlation, the area estimates of the tablet-based measures are similar but statistically different from those obtained using the handheld Garmin across most of the plot size distribution.

Results show a systematic underestimation by the SuSo without booster. The average discrepancy, Column (1), ranges from -1.15 m² for the smallest plots to -71.97 m² for the largest. Relative bias, Column (3), is most pronounced for medium-sized plots (-3.98 percent). Statistically significant differences are observed for all the plot sizes except for the smallest and largest plot size categories. On average, the SuSo without booster method underestimates area by approximately 33 m² (-2 percent), and this difference is statistically significant at the 5 percent level.

On the other hand, the SuSo with booster method exhibits larger average biases than the unboosted method, particularly for smaller plots. The smallest category shows a substantial bias of -28.16 m², amounting to a -16.33 percent underestimation, and all categories except the largest exhibit statistically significant differences at the 1 percent level. While the absolute percentage error declines with increasing plot size, the average total underestimation remains considerable at -46.23 m² or -6.54 percent. Measurements taken with support of the booster do have, on average, a lower absolute value of error, measured both in square meters and percentage terms, than those taken without a booster.

Though the unboosted method exhibits a lower bias in percentage terms relative to the boosted method, that metric looks only at average bias, where overestimation and underestimation can be netted out to reflect a lower level of bias. When looking at the primary metric of interest—absolute percentage error, Column (4)—the booster exhibits a lower level of error (10.9 percent) relative to the unboosted configuration (11.97 percent). This metric is of critical importance as it presents the total deviation from the benchmark, regardless of direction. Given this, we consider the booster as ‘better’ in terms of average accuracy.

The patterns described above are further illustrated in Figure 4, which presents the distribution of percentage bias between SuSo and Garmin area estimates across plot size categories, separately for the unboosted and boosted tablet. The boxplots confirm the presence of greater underestimation by both tablet-based methods, particularly in smaller plots. Overall, measurement error, in percentage terms, is smaller on larger plots and when booster support is used.

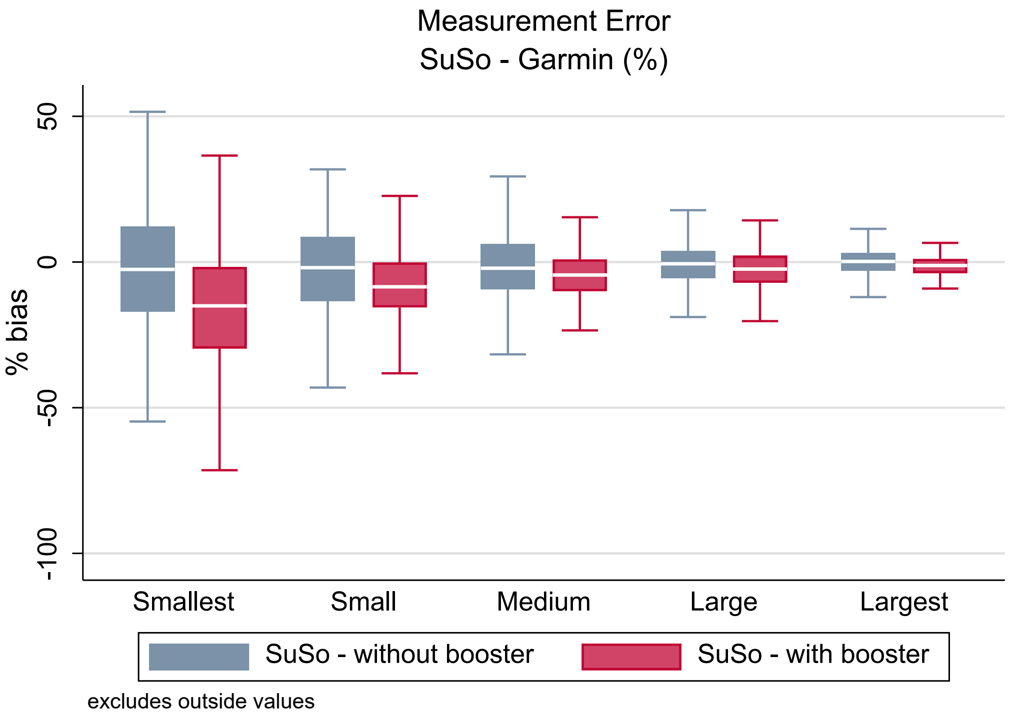

Figure 4. Distribution of measurement error between SuSo and Garmin by plot size

To unpack the source of the observed bias in tablet-based land area measurements, we also examine the role of enumerator performance. Figure 5 presents the percentage measurement error (SuSo minus Garmin GPS) by enumerator, comparing outcomes between the SuSo method without and with booster support. The results highlight substantial heterogeneity in performance: while some enumerators consistently exhibit high bias regardless of booster use, others demonstrate clear improvements when supported by the booster. For instance, enumerators 4 and 14 show reduced error with booster assistance. In contrast, some enumerators such as 6 and 11 record higher bias when using the booster. These patterns suggest that enumerator behavior, such as their handling of the equipment or how they pace the perimeter of plots, plays a critical role in shaping measurement accuracy. Formal ANOVA tests assessing the variation in measurement error across enumerators are reported in Table A3 of the Appendix.

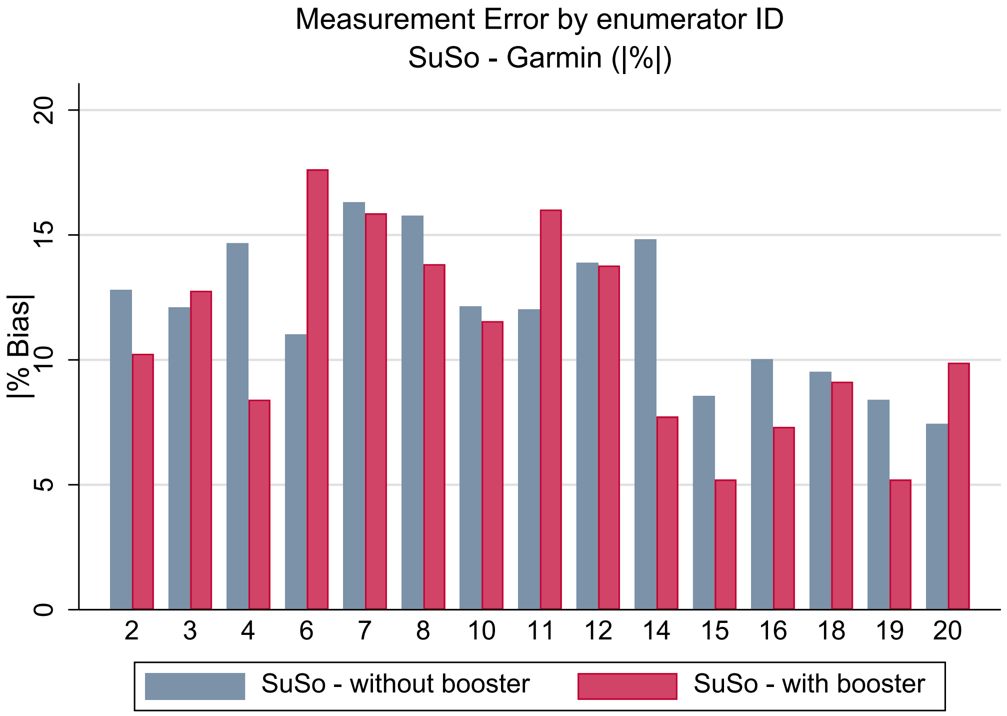

Figure 5. Enumerator-specific measurement error in SuSo relative to Garmin GPS

5.2 Determinants of Measurement Bias

The regression results presented in Table 3 examine the determinants of absolute percentage error in area measurements between SuSo and Garmin, comparing unboosted and boosted tablet configurations.[13] Across both models, the perimeter-to-area ratio emerges as a strong and consistent predictor of measurement error, suggesting that more geometrically irregular plots are associated with significantly higher bias. Notably, walking pace appears to play a larger role when using the booster, with walking too slowly being significantly associated with greater error (in percentage terms), possibly reflecting sensitivity of the GPS signal to pace when booster support is implemented. Environmental features such as elevation and built-up areas also exhibit differential effects across the two configurations: higher elevation is associated with lower absolute value of error in the unboosted model, which is not the case using the boosted tablet, and proximity to built-up areas is related to higher percent bias in the boosted model but not in the unboosted one. Partial tree canopy cover is linked to increased error only when using the booster. The implementation of the booster seems to enhance the

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[13] Complete results for all bias measures presented in Section 4 for both the unboosted and boosted configurations are reported in the Appendix in Tables A4 and A5, respectively.

sensitivity of the device to such variables. Rather than eliminating bias, the booster appears to change the way measurement conditions translate into error—potentially offering advantages in predictability and signal performance. Moreover, the inclusion of the booster improves model fit considerably (R^2 increases from 0.127 to 0.214), suggesting that less of the error in unboosted measurements is explained by the observable factors considered.

Table 3: Determinants of Bias - SuSo (without and with booster) - GPS

Method	SuSo unboosted	SuSo boosted
Dependent Variable	|Bias|/GPS*100	|Bias|/GPS*100
Garmin GPS area (m^2)	0.000	0.000
	(0.000)	(0.000)
Per: Area Ratio (GPS)	36.02***	34***
	(10.404)	(6.849)
Sun Exposure	-0.304	0.624
	(1.08)	(0.915)
Too-slow walking speed	5.495	6.545***
	(3.778)	(1.998)
Topographic Position Index (TPI)	-0.51	0.743
	(1.032)	(0.854)
Terrain Roughness Index (TRI)	-0.523	-2.175
	(1.93)	(1.998)
Elevation	-0.048**	0.001
	(0.024)	(0.021)
Slope	0.591	0.415
	(1.000)	(0.919)
Any rainfall	0.496	0.448
	(1.013)	(0.781)
Built-up (buffer zone)	-2.714	4.762**
	(1.955)	(2.351)
Tree cover:		
Partial	0.25	1.676**
	(1.054)	(0.821)
Heavy	1.611	2.372
	(1.602)	(1.679)
Distance to the main road (Km)	-0.007	0.038
	(0.027)	(0.024)
Distance to OCI	0.011	-0.107*
	(0.074)	(0.06)
Constant	55.842**	1.243
	(26.122)	(23.131)
Observations	884	884
R-squared	0.127	0.214

Note: This table reports OLS regressions where the dependent variable is the absolute percentage error between SuSo (without (first column) and with booster (second column)) and Garmin GPS area measurements.

Standard errors, clustered at the EA level, are reported in parentheses. *** *p<.01,* ** *p<.05,* * *p<.1*

5.3 Determinants of Excessive Bias

In this section, we investigate the key factors associated with large discrepancies between tablet-based and GPS-based land area measurements. Specifically, we model the likelihood that the measurement error exceeds 10 percent in absolute terms, separately for the SuSo unboosted and boosted methods. Our goal is to identify the plot-level, environmental, and behavioral characteristics that systematically predict excessive bias in land area measurement to shed light on the conditions under which tablet-based methods are most prone to failure, and to assess whether booster support meaningfully reduces such errors.

Table A6 in the Appendix presents key descriptive statistics for plot characteristics and measurement conditions, disaggregated by whether the absolute value of measurement bias exceeds 10 percent, and further distinguishing between cases of over- and under-estimation. The share of high-bias observations is considerable across both protocols: 37 percent of plots in the SuSo unboosted group and 35 percent in the SuSo boosted group exhibit absolute relative bias above 10 percent. Under-reporting is the dominant direction of these large errors, especially in the boosted case, where nearly 30 percent of all high bias plots are underestimated, compared to just 5 percent that are overestimated. Differences in plot size are substantial: plots with high bias are significantly smaller than those with low bias, with average Garmin-measured area below 700 m^2 for high-bias cases in the boosted sample, compared to over 2,200 m^2 for low-bias plots. Similarly, both the boosted and unboosted methods show elevated perimeter-to-area ratios in the high-bias group, indicating greater plot shape irregularity. Several environmental and implementation-related factors differ systematically across the bias threshold. For instance, slow walking speed is markedly more common in the high-bias group, particularly in the boosted protocol, and rougher terrain and steeper slopes also correlate with greater measurement error. Tree cover and distance to the main road appear more relevant: higher bias is associated with more remote locations and slightly denser coverage.

Table 4 reports marginal effects from probit regressions estimating the determinants of excessive bias—under both SuSo unboosted and boosted protocols.[14] Several covariates emerge as significant predictors of high bias, although the strength and consistency of their associations vary across models. Smaller plots, as defined by the Garmin area, are more prone to large bias across all specifications, with the marginal effect consistently negative and statistically significant. Perimeter-to-area ratio, an indicator of plot shape complexity, is positively associated with higher measurement error in both unboosted and boosted protocols suggesting that more irregularly shaped plots are measured with less accuracy using the tablets.

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[14] Table A7 in the Appendix reports the standard coefficients.

Table 4: Determinants of excessive Bias - SuSo (without and with booster) – GPS – Marginal effect

Method	SuSo unboosted			SuSo boosted		
Dependent Variable	|Bias|>10%	Bias>10%	Bias<-10%	|Bias|>10%	Bias>10%	Bias<-10%
Garmin GPS area (m²)	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Per: Area Ratio (GPS)	0.798**	0.404***	0.192	0.443**	0.135*	0.145
	(0.312)	(0.141)	(0.137)	(0.193)	(0.076)	(0.182)
Sun Exposure	-0.008	0.009	-0.020	0.031	0.001	0.031
	(0.032)	(0.020)	(0.026)	(0.023)	(0.014)	(0.023)
Too-slow walking speed	0.078	-0.078	0.140**	0.136***	-0.023	0.145***
	(0.078)	(0.051)	(0.055)	(0.045)	(0.026)	(0.048)
Topographic Position Index (TPI)	0.019	0.005	0.010	0.059**	0.011	0.048*
	(0.035)	(0.022)	(0.032)	(0.029)	(0.013)	(0.028)
Terrain Roughness Index (TRI)	-0.062	0.034	-0.108*	-0.053	-0.004	-0.049
	(0.069)	(0.048)	(0.060)	(0.069)	(0.033)	(0.070)
Elevation	-0.001	-0.001	0.001	0.000	-0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Slope	0.033	-0.008	0.045*	0.029	-0.006	0.035
	(0.033)	(0.024)	(0.026)	(0.029)	(0.013)	(0.029)
Any rainfall	-0.034	-0.009	-0.030	-0.002	-0.030**	0.027
	(0.030)	(0.024)	(0.025)	(0.030)	(0.014)	(0.028)
Built-up (buffer zone)	-0.043	-0.023	-0.014	0.100*	-0.003	0.089*
	(0.050)	(0.037)	(0.044)	(0.055)	(0.023)	(0.052)
Tree cover (base: None):						
Partial	-0.016	-0.016	0.001	0.035	-0.004	0.039
	(0.028)	(0.023)	(0.026)	(0.029)	(0.016)	(0.028)
Heavy	0.126	0.049	0.090	0.110	0.008	0.095
	(0.080)	(0.061)	(0.071)	(0.083)	(0.043)	(0.083)
Distance to the main road (Km)	0.000	-0.001**	0.002**	0.002**	-0.001	0.002***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.001)
Distance to OCI	-0.001	0.002	-0.002	-0.002	-0.000	-0.002
	(0.003)	(0.002)	(0.002)	(0.003)	(0.001)	(0.003)
Observations	884	884	884	884	884	884
Pseudo R-squared	0.149	0.114	0.089	0.226	0.089	0.208

Note: This table presents marginal effects from probit regressions analyzing the likelihood of significant measurement bias—defined as an error greater than 10% or less than -10%—in SuSo area measurements (with and without booster) relative to Garmin GPS. The dependent variables are binary indicators capturing whether the absolute bias exceeds 10%, and whether the bias is positive or negative. Pseudo R-squared values are reported from the underlying probit models, as the marginal effect estimates themselves do not produce R-squared statistics.

Standard errors, clustered at the EA level, are reported in parentheses. *** *p<.01,* ** *p<.05,* * *p<.1*

Slow walking speed significantly increases the probability of underestimation in both models, with the effect being stronger under the boosted configuration, where it increases the likelihood of high negative bias by more than 14 percentage points. Rainfall during measurement day has a weak effect, while greater distance to main roads slightly increases the chance of large errors. The pseudo R-squared values (coming from the normal regression without margins) indicate that the models for boosted data generally explain more variation than those for unboosted.

5.4 Impact of Measurement Method on Agricultural Output Estimates

In this section, after having examined the determinants of measurement bias across methods, we now assess how different land measurement approaches affect estimates of key agricultural outcomes—namely maize production and yield. Accurate land measurement is critical for estimating these outcomes, as both production and yield are highly sensitive to the accuracy of plot area data (Carletto et al., 2015). A growing body of evidence highlights how systematic land measurement errors can bias yield estimates and lead to incorrect inferences, especially in smallholder settings (Abay et al., 2019; Carletto et al. 2013, 2015; Dillon et al., 2016; Dillon & Rao, 2021).

Table 5 presents fixed effects regression estimates comparing SuSo with and without booster methods to Garmin GPS measurements, which serve as the benchmark. We analyze two distinct and non-overlapping samples: (i) production measured on the 8×8 subsample of plots for plots in which that was available, and (ii) yield (kg/ha) computed on the Fullplot sample. Because the samples differ by design—particularly given that the Fullplot sample is formed by fewer and much smaller plots—results are not directly comparable across the two panels.[15] We estimate both raw levels and log-transformed values of production and yield.

All specifications include plot fixed effects, which control for any unobserved characteristics of the plot that could influence maize production or yield. The results show that production and yield estimates differ significantly when measured with SuSo—either with or without a booster—compared to the Garmin GPS benchmark. Specifically, the SuSo without booster method is linked to a statistically significant underestimation of maize production, in logged terms, by approximately 6 percent for the 8x8 sample. Using the booster reduces this gap somewhat, with production underestimated by approximately 5 percent. Inverse patterns are seen in the yield data for the Fullplot sample, where use of SuSo without booster results in a substantial upward bias (188.6 kg/ha) in yield, while the booster version leads to an even larger increase (475.3 kg/ha). Importantly, since yields are calculated using plot area as the denominator, these results suggest that the degree of area underestimation—more pronounced for smaller plots—drives the magnitude of the yield inflation. These results are consistent with existing literature emphasizing the need for high-quality area measurement in smallholder settings to reduce bias in agricultural statistics (Carletto et al., 2013, 2015; Gourlay et al., 2017, Kilic et al., 2017a, 2017b).

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[15] See Section 3.1 for more information about the samples.

Table 5: Effect of Land Measurement Methods on Maize Production and Yield (Levels and Log-Transformed Outcomes)

Sample	8x8		Fullplot	
Dependent Variable	Maize production (kg)	Log of Maize production	Yield (kg/ha)	Log of Yield
Land Measurement methods (Base: Garmin GPS):				
SuSo without booster	-3.06	-.06***	188.648***	0.074***
	(2.41)	(0.02)	(63.182)	(0.024)
SuSo with booster	-4.702**	-0.052***	475.342***	0.203***
	(2.289)	(0.007)	(168.992)	(0.025)
Constant	273.706***	4.423***	988.802***	6.22***
	(1.443)	(0.007)	(68.316)	(0.013)
PLOT FE	YES	YES	YES	YES
Observations	1881	1881	669	669
R-squared	0.004	0.012	0.027	0.12
Garmin GPS (mean)	2137.99		399.19	
SuSo without booster (mean)	2100.38		379.64	
SuSo with booster (mean)	2090.12		357.53	

Note: This table presents regression estimates of maize production and yield using different land measurement methods, with Garmin GPS serving as the reference category. The outcomes are shown both in levels and in natural log form, separately for the 8x8m and Fullplot samples. Plot fixed effects are included in all specifications. The 'Garmin GPS (mean)' and 'SuSo (mean)' entries report the mean plot area (m^2) in the corresponding estimation sample (not mean outcomes).

Standard errors, clustered at the plot level, are reported in parentheses. *** *p<.01,* ** *p<.05,* * *p<.1*

6. Implications and Conclusions

This study provides empirical validation of tablet-based land area measurement tools developed within the World Bank's Survey Solutions Computer-Assisted Personal Interviewing (CAPI) software. Drawing on a carefully designed methodological experiment conducted in Uganda, we assess the accuracy of SuSo tablet-based area measurement (using Samsung Galaxy T580 tablets)—both with and without an external GPS booster device—relative to benchmark measurements obtained through Garmin eTrex 30 handheld GPS units.

The analysis demonstrates that the relatively new Survey Solutions feature for automated plot area measurement via perimeter pacing, both with and without a GPS boosting device, delivers area estimates that are highly correlated with those generated by Garmin GPS devices, with small but statistically significant average bias. Importantly, while the use of an external GPS booster slightly improves measurement accuracy—especially on plots with irregular shapes—the differences between boosted and unboosted tablet-based measurements are modest.

These results carry several important implications for survey design and agricultural data systems. First, the successful deployment of the Survey Solutions tablet tool points to a low-cost, scalable alternative to handheld GPS devices for land area measurement. Different from the handheld GPS, the Survey Solutions tool is integrated directly into the survey platform, eliminating the need for separate data entry and the costs of time-consuming data cleaning efforts. Although our benchmark comparisons rely on shapefiles extracted from Garmin and processed before analysis, many field operations rely solely on interviewers reading the area from the handheld device and recording it manually in the survey instrument, allowing room for significant entry error. The marked benefits offered by the tablet-based approach in terms of eliminating these data-entry errors— an issue likely to be broadly prevalent in surveys – as well as related post-processing efforts, ought to be considered alongside the degree of measurement accuracy presented here. Ultimately, use of a tablet-based approach can modernize fieldwork, improve data consistency, and reduce overall implementation costs— challenges that have previously limited the broader uptake of GPS-based land measurement (Carletto et al., 2017; Dillon et al., 2016).

Second, while the booster improves GPS signal stability and accuracy, the marginal gain may not justify the added procurement and logistical costs in all settings. As such, national statistical offices and survey implementers may adopt a differentiated strategy; the unboosted tablet-based method may serve as a suitable and cost-effective alternative to handheld GPS in settings where budgets are constrained**,** while the boosted configuration should be considered when higher measurement accuracy is required, particularly in complex environments or for very irregularly shaped plots.

However, the study also highlights important implementation risks. Measurement errors, although generally limited, are more likely in specific conditions such as irregular plot geometry, dense tree cover, and excessively slow walking speeds. These findings suggest that while tablet-based tools are robust overall, survey designers should incorporate clear field protocols and enumerator training modules to minimize error under challenging field conditions. Relatedly, the conclusions made in this paper may not be valid for all tablet models, with greater uncertainty particularly for older tablet models that may not have the same quality of embedded GPS technology, implying that additional validation work may be needed prior to a field operation utilizing a different tablet model.

From a policy perspective, these findings have significant implications for survey programs seeking to modernize land area measurement practices. Given their ease of use, integration within standard survey platforms, and reduced cost, tablet-based tools may represent a viable alternative for land measurement in household and agricultural surveys. However, this study also stresses that measurement choice has non-trivial consequences for key agricultural statistics. In line with earlier research (Carletto et al., 2015; Dillon and Rao, 2021), we demonstrate that discrepancies in land area measurement translate directly into differences in plot-level yield and production estimates. Even small differences in land area measurement can lead to substantial variations in yield estimates, which can have consequences on the understanding of agricultural productivity and the evaluation of agricultural interventions.

Transitioning toward integrated, tablet-based land measurement tools represents a critical step for more efficient, accurate, and scalable agricultural data collection. While the use of GPS boosters may further improve performance in select contexts, the baseline utility of unboosted tablet-based measurement may be sufficiently high to warrant adoption, depending on the accuracy requirements of specific operations.

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Appendix Tables

Table A1: Descriptive statistics of Garmin based measures

	Obs	Mean	Std. Dev.	Min	Max	Correlation with Garmin Extracted
Garmin Extracted	884	1675.756	1997.664	27.567	18895.55	
Garmin Survey	884	378365.7	11172004	0.31	3.32E+08	-0.017
Garmin Survey Cleaned	875	1696.552	2029.449	27.5	18876	0.991

Note: “Garmin Extracted” refers to values derived from georeferenced polygons. “Garmin Survey” shows the raw values directly reported by the Garmin device. “Garmin Survey Cleaned” represents the same data after removing clear outliers and correcting evident measurement errors. The correlation values reflect the relationship with Garmin Extracted area. All statistics are based on the full sample of 884 plots, except for Garmin Survey Cleaned, which includes 875 observations.

Table A2: Descriptive statistics of key variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Garmin GPS area (m^2)	884	1675.756	1997.664	27.567	18895.55
SuSo without booster (m^2)	884	1642.947	1994.129	0.016	18740.44
SuSo with booster (m^2)	884	1629.531	2006.908	4.883	18330.75
Per: Area Ratio (GPS)	884	0.194	0.131	0.018	1.306
Sun Exposure	884	0.454	0.498	0	1
Too-slow walking speed (unboosted)	884	0.066	0.248	0	1
Too-slow walking speed (boosted)	884	0.141	0.349	0	1
Topographic Position Index (TPI)	884	-0.002	0.46	-2	3
Terrain Roughness Index (TRI)	884	0.821	0.425	0.1	3.3
Elevation	884	1066	21.604	1035	1141
Slope	884	1.539	0.913	0.1	6.1
Any rainfall	884	0.614	0.487	0	1
Built-up (buffer zone)	884	0.105	0.275	0	1
Tree cover (mean)	884	1.643	0.566	1	3
None (%)	356	40.27	-	-	-
Partial (%)	488	55.2	-	-	-
Heavy (%)	40	4.52	-	-	-
Distance to the main road (Km)	884	35.118	18.543	0.8	70.9
Distance to OpenCelliD (OCI)	884	9.294	6.942	0.1	30.6

Table A3. ANOVA Test - SuSo (without and with booster) biases compared to Garmin GPS - By Enumerator ID

	SuSo - GPS	|SuSo - GPS|	Bias/GPS*100	|Bias|/GPS*100
SuSo without booster				
N	884	884	884	884
F	2.340	2.273	3.262	1.847
p	0.004***	0.005***	0.000***	0.029**
r2	0.036	0.035	0.050	0.029
rmse	385.927	364.480	19.414	15.757
SuSo with booster				
N	884	884	884	884
F	1.418	1.260	5.191	4.142
p	0.138	0.227	0.000***	0.000***
r2	0.022	0.020	0.077	0.063
rmse	367.322	354.860	16.916	14.770

Note: This table reports ANOVA test statistics from models estimating measurement bias in SuSo data (without and with booster), using Enumerator ID fixed effects. The dependent variables reflect raw, absolute and relative bias measures compared to Garmin GPS.

**** p<.01, ** p<.05, * p<.1*

Table A3 reports tests of enumerator fixed effects in measurement bias for the SuSo methods with and without booster. The results suggest significant enumerator effects on measurement bias. The F-tests and p-values confirm that differences across enumerators are statistically significant for most outcomes. While in the unboosted method, enumerators significantly influence both the raw measurement bias and its percentage form, the boosted method exhibits less variation in raw or absolute error, but stronger differences in percentage-based bias. Absolute and raw bias levels are not statistically different across enumerators (p-values: 0.138 and 0.227), percentage-based bias measures are strongly influenced by enumerator identity, with p-values < 0.001.

Table A4: Determinants of Bias - SuSo without booster – GPS

Dependent Variable	SuSo - GPS	|SuSo - GPS|	Bias/GPS*100	|Bias|/GPS*100
Garmin GPS area (m^2)	-0.022	0.035**	0.000	0.000
	(0.015)	(0.014)	(0.000)	(0.000)
Per: Area Ratio (GPS)	88.824	-214.584**	20.208*	36.02***
	(76.269)	(85.389)	(11.024)	(10.404)
Sun Exposure	-13.269	2.057	0.856	-0.304
	(25.558)	(24.853)	(1.21)	(1.08)
Too-slow walking speed (Unboosted)	-42.176	44.065	-16.125***	5.495
	(37.88)	(34.012)	(5.321)	(3.778)
Topographic Position Index (TPI)	-41.561**	7.213	-2.075	-0.51
	(17.508)	(15.212)	(1.61)	(1.032)
Terrain Roughness Index (TRI)	77.775**	-34.773	6.102**	-0.523
	(37.29)	(31.034)	(3.024)	(1.93)
Elevation	-0.903	0.472	-0.079**	-0.048**
	(0.827)	(0.679)	(0.033)	(0.024)
Slope	-37.963*	3.645	-2.588*	0.591
	(19.463)	(17.373)	(1.341)	(1.000)
Any rainfall	-1.164	21.286	1.003	0.496
	(22.079)	(19.004)	(1.404)	(1.013)
Built-up (buffer zone)	11.604	-27.119**	-0.375	-2.714
	(16.693)	(12.313)	(2.907)	(1.955)
Tree cover:				
Partial	24.885	-5.406	-0.724	0.25
	(28.021)	(22.958)	(1.433)	(1.054)
Heavy	22.287	-7.27	-1.263	1.611
	(45.437)	(47.628)	(2.495)	(1.602)
Distance to the main road (Km)	-1.342**	-0.35	-0.083**	-0.007
	(0.56)	(.511)	(0.036)	(0.027)
Distance to OCI	0.58	0.336	0.008	0.011
	(1.643)	(1.622)	(0.099)	(0.074)
Constant	980.304	-367.078	80.354**	55.842**
	(884.933)	(733.532)	(34.709)	(26.122)
Observations	884	884	884	884
R-squared	0.022	0.065	0.051	0.127

Note: This table presents OLS regression results using different formulations of bias between SuSo without booster and Garmin GPS area measurements as dependent variables.

Standard errors, clustered at the EA level, are reported in parentheses. *** *p<.01,* ** *p<.05,* * *p<.1*

Table A5: Determinants of Bias – SuSo with booster – GPS

Dependent Variable	SuSo - GPS	|SuSo - GPS|	Bias/GPS*100	|Bias|/GPS*100
Garmin GPS area (m^2)	-0.014	0.022*	0.000	-0.000
	(0.012)	(0.011)	(0.000)	(0.000)
Per: Area Ratio (GPS)	112.881	-206.847***	-20.579*	34***
	(67.972)	(69.659)	(10.878)	(6.849)
Sun Exposure	-37.999*	21.917	-0.815	0.624
	(21.737)	(22.836)	(1.102)	(0.915)
Too-slow walking speed (Boosted)	-13.378	17.935	-7.954***	6.545***
	(16.168)	(13.861)	(2.7)	(1.998)
Topographic Position Index (TPI)	-19.681	-6.21	-1.784	0.743
	(18.327)	(17.118)	(1.122)	(0.854)
Terrain Roughness Index (TRI)	36.56	-1.984	3.543	-2.175
	(39.623)	(37.713)	(2.538)	(1.998)
Elevation	-0.921	0.241	-0.047*	0.001
	(0.711)	(0.709)	(0.024)	(0.021)
Slope	-27.703	-8.675	-1.968*	0.415
	(21.203)	(20.229)	(1.084)	(0.919)
Any rainfall	-24.45	38.919**	-0.771	0.448
	(20.075)	(17.927)	(1.006)	(0.781)
Built-up (buffer zone)	-7.346	-20.036	-4.998*	4.762**
	(16.805)	(13.356)	(2.941)	(2.351)
Tree cover:				
Partial	13.367	19.399	-1.115	1.676**
	(17.048)	(15.577)	(1.001)	(0.821)
Heavy	26.181	15.041	-1.824	2.372
	(41.337)	(38.655)	(2.031)	(1.679)
Distance to the main road (Km)	-0.887	-0.401	-0.113***	0.038
	(0.61)	(0.56)	(0.032)	(0.024)
Distance to OCI	1.993*	-2.427*	0.083	-0.107*
	(1.189)	(1.259)	(0.086)	(0.06)
Constant	988.678	-140.938	53.999**	1.243
	(772.184)	(769.3)	(26.475)	(23.131)
Observations	884	884	884	884
R-squared	0.018	0.04	0.146	0.214

Note: This table presents OLS regression results using different formulations of bias between SuSo with booster and Garmin GPS area measurements as dependent variables.

Standard errors, clustered at the EA level, are reported in parentheses. *** *p<.01, ** p<.05, * p<.1*

Table A6: Descriptive statistics for high bias observations (SuSo without and with booster)

Variable	|Bias| >10%	|Bias| ≤ 10%	Bias >10%	Bias <-10%	Diff. in Means (>10% Bias vs. ≤ 10%)
SuSo without booster					
Share of the sample (%)	36.312	63.688	14.480	21.833	
Observations	321	563	128	193	
Average:					
Garmin GPS area (m²)	843.823	2150.091	721.544	924.919	***
SuSo without booster	749.239	2152.503	899.135	649.827	***
SuSo with booster	808.637	2097.572	782.258	826.133	***
Per: Area Ratio (GPS)	0.261	0.155	0.275	0.252	***
Sun Exposure	0.449	0.456	0.461	0.440	-
Too-slow walking speed	0.131	0.028	0.086	0.161	***
Topographic Position Index (TPI)	0.011	-0.009	0.040	-0.009	-
Terrain Roughness Index (TRI)	0.864	0.796	0.865	0.863	**
Elevation	1066.121	1065.931	1063.305	1067.990	-
Slope	1.626	1.490	1.573	1.662	**
Any rainfall	0.589	0.629	0.609	0.575	-
Built-up (buffer zone)	0.145	0.082	0.149	0.142	***
Tree cover (mean)	1.592	1.671	1.555	1.617	**
None (%)	46.417	36.767	49.219	44.560	-
Partial (%)	47.975	59.325	46.094	49.223	-
Heavy (%)	5.607	3.908	4.688	6.218	-
Distance to the main road (Km)	38.611	33.127	36.205	40.206	***
Distance to OCI	8.403	9.802	9.236	7.851	***
SuSo with booster					
Share of the sample (%)	35.181	64.819	5.317	29.864	
Observations	311	573	47	264	
Average:					
Garmin GPS area (m²)	687.090	2212.362	763.300	673.522	***
SuSo without booster	652.754	2180.381	901.308	608.504	***
SuSo with booster	605.086	2185.556	1072.457	521.880	***
Per: Area Ratio (GPS)	0.270	0.152	0.270	0.270	***
Sun Exposure	0.476	0.442	0.447	0.481	-
Too-slow walking speed	0.299	0.056	0.191	0.318	***
Topographic Position Index (TPI)	0.036	-0.022	0.053	0.033	*
Terrain Roughness Index (TRI)	0.901	0.777	0.804	0.918	***
Elevation	1067.685	1065.086	1062.638	1068.583	*
Slope	1.675	1.466	1.447	1.715	***
Any rainfall	0.608	0.618	0.489	0.629	-
Built-up (buffer zone)	0.182	0.063	0.144	0.189	***
Tree cover (mean)	1.621	1.654	1.553	1.633	-
None (%)	43.408	38.569	48.936	42.424	-
Partial (%)	51.125	57.417	46.809	51.894	-
Heavy (%)	5.466	4.014	4.255	5.682	-
Distance to the main road (Km)	40.184	32.369	34.221	41.245	***
Distance to OCI	7.935	10.032	8.768	7.786	***

Note: This table presents descriptive statistics of the key variables used in the probit regressions for high bias observations both for the unboosted and boosted models. Column 1 includes observations where the absolute relative bias is greater than 10%, while Column 2 includes those where the absolute bias is 10% or less. Column 3 shows averages for plots where SuSo over-reported area, and Column 4 for those where it under-reported area. The reported difference in means and associated significance levels refer to a t-test comparing Columns 1 and 2. The table also includes the share of plots falling into each category. **** p<.01, ** p<.05, * p<.1*

Table A7: Determinants of excessive Bias: SuSo (without and with booster) – GPS (Probit model, standard coefficients)

Method	SuSo unboosted			SuSo boosted		
Dependent Variable	|Bias|>10%	Bias>10%	Bias<-10%	|Bias|>10%	Bias>10%	Bias<-10%
Garmin GPS area (m^2)	-0.000***	-0.000**	-0.000***	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Per: Area Ratio (GPS)	2.502**	1.99***	0.717	1.556**	1.357*	0.528
	(1.015)	(0.67)	(0.511)	(0.665)	(0.757)	(0.656)
Sun Exposure	-0.024	0.042	-0.074	0.109	0.015	0.111
	(0.1)	(0.099)	(0.097)	(0.081)	(0.142)	(0.083)
Too-slow walking speed	0.245	-0.382	0.524**	0.477***	-0.228	0.529***
	(0.243)	(0.254)	(0.209)	(0.16)	(0.26)	(0.179)
Topographic Position Index (TPI)	0.061	0.026	0.036	0.208**	0.112	0.174*
	(0.111)	(0.11)	(0.121)	(0.099)	(0.128)	(0.102)
Terrain Roughness Index (TRI)	-0.193	0.168	-0.403*	-0.185	-0.044	-0.179
	(0.215)	(0.238)	(0.223)	(0.242)	(0.334)	(0.255)
Elevation	-0.002	-0.005	0.002	0.001	-0.006	0.003
	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.002)
Slope	0.103	-0.04	0.167*	0.102	-0.06	0.126
	(0.104)	(0.12)	(0.095)	(0.102)	(0.131)	(0.104)
Any rainfall	-0.107	-0.046	-0.111	-0.008	-0.304**	0.099
	(0.094)	(0.116)	(0.093)	(0.107)	(0.137)	(0.1)
Built-up (buffer zone)	-0.134	-0.115	-0.054	0.351*	-0.029	0.325*
	(0.157)	(0.183)	(0.163)	(0.192)	(0.234)	(0.188)
Tree cover:						
Partial	-0.049	-0.082	0.002	0.125	-0.042	0.142
	(0.088)	(0.115)	(0.098)	(0.103)	(0.159)	(0.105)
Heavy	0.377	0.211	0.307	0.38	0.077	0.338
	(0.238)	(0.247)	(0.226)	(0.281)	(0.384)	(0.286)
Distance to the main road (Km)	0.001	-0.007*	0.007**	0.006**	-0.007	0.009***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)
Distance to OCI	-0.002	0.009	-0.008	-0.007	-0.001	-0.006
	(0.008)	(0.01)	(0.008)	(0.009)	(0.013)	(0.01)
Constant	1.433	4.453	-3.238	-1.796	4.847	-4.36*
	(2.29)	(3.573)	(2.719)	(2.731)	(4.218)	(2.611)
Observations	884	884	884	884	884	884
Pseudo R-squared	0.149	0.114	0.089	0.226	0.089	0.208

Note: This table presents the coefficients of probit regressions analyzing the likelihood of significant measurement bias—defined as an error greater than 10% or less than -10%—in SuSo area measurements (with and without booster) relative to Garmin GPS. The dependent variables are binary indicators capturing whether the absolute bias exceeds 10%, and whether the bias is positive or negative.

Standard errors, clustered at the EA level, are reported in parentheses. *** *p<.01,* ** *p<.05,* * *p<.1*

Appendix Figure

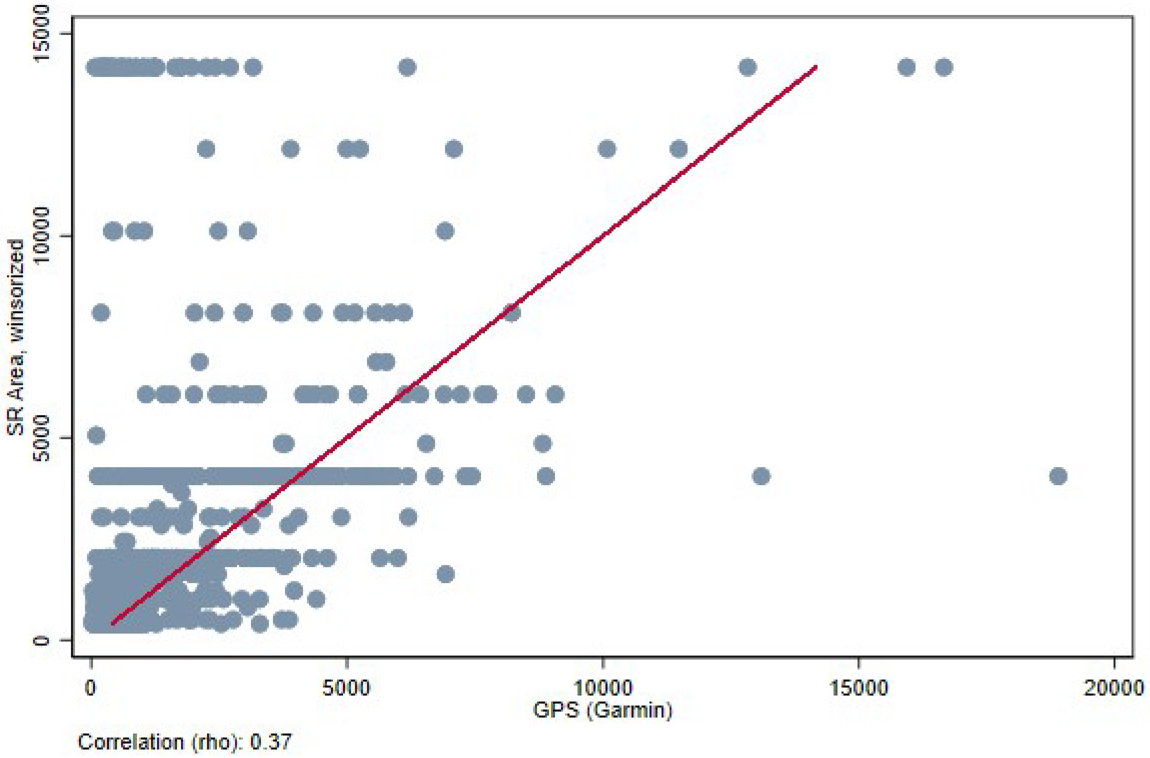

Figure A1. Scatter plot of Self-Reported vs GPS (Garmin) land area measures, in square meters (Note: the red line is the line of equality between measurements.)