LAND MEASUREMENT BIAS: COMPARISONS FROM GLOBAL POSITIONING SYSTEM, SELF-REPORTS, AND SATELLITE DATA

Andrew Dillon and Lakshman Nagraj Rao

NO. 540

March 2018

ADB ECONOMICS WORKING PAPER SERIES

ASIAN DEVELOPMENT BANK

ADB Economics Working Paper Series

Land Measurement Bias: Comparisons from Global Positioning System, Self-Reports, and Satellite Data

Andrew Dillon and Lakshman Nagraj Rao

No. 540 | March 2018

Andrew Dillon (dillona6@msu.edu) is an Assistant Professor at the Department of Agricultural, Food, and Resource Economics, Michigan State University.
Lakshman Nagraj Rao (NagrajRao@adb.org) is a Statistician at the Economic Research and Regional Cooperation Department, Asian Development Bank.

This study was carried out under Regional Technical Assistance (R-CDTA) 8369: Innovative Data Collection Methods for Agricultural and Rural Statistics with the support of the Japan Fund for Poverty Reduction. The authors benefited from the insightful comments of Yasuyuki Sawada, Rana Hasan, Jesus Felipe, Kaushal Joshi, Yi Jiang, Valerie Mercer-Blackman, Zhigang Li, Natalie Chun, Elisabetta Gentile, David Anthony Raitzer, Arturo Martinez Jr., Orlee P. Velarde, Pamela Lapitan, and Lea Rotairo. The authors are also grateful to the Ministry of Agriculture and Forestry (Lao People's Democratic Republic), Philippine Statistics Authority (Philippines), Office of Agricultural Economics (Thailand), and Ministry of Agriculture and Rural Development (Viet Nam) for providing the dataset used in this study. Anna Christine Durante and Rea Jean Tabaco provided excellent research assistance.

ASIAN DEVELOPMENT BANK

6 ADB Avenue, Mandaluyong City, 1550 Metro Manila, Philippines
Tel +63 2 632 4444; Fax +63 2 636 2444
www.adb.org

ISSN 2313-6537 (print), 2313-6545 (electronic)
Publication Stock No. WPS189279-2
DOI: http://dx.doi.org/10.22617/WPS189279-2

Notes:
In this publication, "$" refers to US dollars.
Corrigenda to ADB publications may be found at http://www.adb.org/publications/corrigenda.

CONTENTS

TABLES AND FIGURE

TABLES

FIGURE

ABSTRACT

Agricultural statistics derived from remote sensing data have been used primarily to compare land use information and changes over time. Nonclassical measurement error from farmer self-reports has been well documented in the survey design literature primarily in comparison to plots measured using Global Positioning System (GPS). In this paper, we investigate the reliability of remotely sensed satellite data on nonrandom measurement error and on agricultural relationships such as the inverse land size–productivity relationship and input demand functions. In our comparison of four Asian countries, we find significant differences between GPS and remotely sensed data only in Viet Nam, where plot sizes are small relative to the other countries. The magnitude of farmers' self-reporting bias relative to GPS measures is nonlinear and varies across countries, with the largest magnitude of self-reporting bias of 130% of a standard deviation (2.2-hectare bias) in the Lao People's Democratic Republic relative to Viet Nam, which has 13.3% of a standard deviation (.008-hectare bias). In all countries except Viet Nam, the inverse land size–productivity relationship is upwardly biased for lower land area self-reported measures relative to GPS measures. In Viet Nam, the intensive margin of organic fertilizer use is negatively biased by self-reported measurement error by 30.4 percentage points. As remotely sensed data becomes publicly available, it may become a less expensive alternative to link to survey data than rely on GPS measurement.

Key words: agriculture, land measurement, remote sensing, survey methods

JEL codes: O12, O13, Q12, Q15

I. INTRODUCTION

More than 70% of the world's poor reside in rural areas of developing countries and rely on agriculture as their main source of livelihood (IFAD 2010). Research has shown that lack of access to land could constrain poor households from emerging from poverty (Deininger 2003; Binswanger, Deininger, and Feder 1995), and that productivity gains from increased production per unit of land are central to macro theories of structural transformation. Timely, cost-effective, and high-quality land measurement data through national statistical reporting therefore play an important role in the formulation of policies targeting poverty reduction, agricultural growth, and the welfare of agricultural households.

From an analytical perspective, plot sizes are important because they serve as an input in agricultural production functions, which are used to estimate the return to inputs and factors of production. Standard economic theory predicts that the marginal factor productivity should be the same for both larger and smaller agricultural plots. However, in the empirical literature from different parts of the world, a puzzling relationship observed is the existence of an inverse farm size–productivity relationship (Sen 1962; Mazumdar 1965; Bardhan 1973; Collier 1983; Carter 1984; van Zyl, Binswanger, and Thirtle 1995; Heltberg 1998; Akram-Lodhi 2001; Benjamin and Brandt 2002; Rios and Shively 2005; Kimhi 2003; Barrett, Bellemare, and Hou 2010; Larson et al. 2014).

The literature on the inverse farm size–productivity relationship is extensive with several theoretical explanations. Eswaran and Kotwal (1985) and Feder (1985) theorized that households with larger farms hire labor given their limited endowment of household labor. Hired labor requires supervision costs which may increase more than proportionally as farm size increases, leading to lower production efficiency on larger farms. A second chain of literature focuses on missing markets for land, labor, credit, and insurance markets which leads to differences in land productivity between households (Assunação and Ghatak 2003, Barrett 1996, Carter and Wiebe 1990, Eswaran and Kotwal 1986). Omitted variable bias, such as inability to accurately capture soil quality or farmer ability serves as a third explanation (Barrett, Bellemare, and Hou 2010; Bhalla and Roy 1988; Chen, Huffman, and Rozelle 2011). However, these theories have not been successfully corroborated across different contexts using empirical data.

A fourth explanation, which has recently received attention in the empirical literature due to advancement in land area measurement techniques, is that the inverse relationship is a statistical artefact stemming from a mismeasurement in land size, thereby leading to a spurious correlation (Lamb 2003). Given that land size is an independent variable in econometric estimation of agricultural production functions and that classical measurement error in independent continuous variables could potentially bias parameter estimates (Wooldridge 2008), there is room for misinterpretation of an important and policy-relevant relationship between productivity and land size. While ruling out land measurement error as a spurious correlation has been the prominent focus of many land measurement studies in Africa (for example, Carletto, Savastano, and Zezza 2013; Carletto, Gourlay, and Winters 2015; Dillon et al. 2017), the hypothesis has not been carefully tested in the Asian agricultural context.

The most common land area measurement technique implemented in virtually all agricultural surveys is farmer self-reporting because it is collected inexpensively as a single question within a questionnaire. The compass-and-rope method is a second option where two or three enumerators measure the area of a plot using tools such as calculator, compass, measuring tape, and ranging poles. While it is considered as the gold standard for land measurement (FAO 1982), it is workload intensive from a field implementation perspective. Global Positioning System (GPS) devices have more recently been used in agricultural surveys but still require walking along the boundary of a plot to obtain an area estimate, thereby increasing survey time and costs.

Surveys relying on self-reported land size relative to GPS data and compass-and-rope measurement techniques have established significant effects on levels of landholdings reported by households. Few studies have found statistically significant differences between GPS and self-reported land sizes (Goldstein and Udry 1999; Carletto, Savastano, and Zezza 2013; Carletto, Gourlay, and Winters 2015). Goldstein and Udry (1999), in their data from the eastern region of Ghana found a correlation of 0.15 between GPS and self-reported land size. This finding is attributed to field measurement being historically based on length and not area by the authors.

Carletto, Savastano, and Zezza (2013) report significant differences between self-reported and GPS land size in Uganda which varies by plot size. In their study, self-reported estimates are close to GPS measures for medium-sized plots (between 0.60 and 1.44 hectares) but large for smaller and larger-sized plots. They attribute the differences in GPS and self-reported land size to plot manager and other plot-level characteristics such as age of the household head, whether the plot was in dispute with relatives and rounding off of self-reported production. Similarly, Carletto, Gourlay, and Winters (2015) find that self-reported plot sizes were larger than GPS measures for smaller plots, with an opposite trend for larger plots, suggesting systematic overreporting of plot sizes for smaller plots and underreporting for larger plots. They also find a consistent association between the rounding of farmer estimates and the difference between GPS and self-reported plot sizes in all four countries. Dillon et al. (2017) also find that GPS measurements of land area are similar to compass-and-rope estimates and more reliable than farmer estimates, where self-reported measurement bias leads to overreporting land sizes of small plots by 83% and underreporting of large plots by 21% of the compass-and-rope estimate. Their study in Nigeria finds that the error observed across land measurement methods is nonlinear, is not resolved by trimming outliers, and results in biased estimates of the inverse land size–productivity relationship. A key econometric advance in this paper is the ability to control for plot fixed effects which may bias parameter estimates. They also investigate input demand functions that rely on self-reported land measures and find that these measures significantly underestimate the effect of land on input utilization including fertilizer and household labor. The similarity of estimates between GPS and compass-and-rope methods is also observed by Schøning et al. (2005).

Improved survey methods and technological capacity in the field and remote sensing data are opening new possibilities for agricultural statistics. Agricultural statistics derived from remotely sensed data have been used primarily to compare land use information and changes over time, though applications to yields (Lobell, Cassman, and Field 2009) and economywide outcomes such as food security are becoming more common (Grace, Husak, and Bogle 2014). Lobell, Cassman, and Field (2009); Grace et al. (2012); Grace, Husak, and Bogle (2014); and Husak and Grace (2016) apply remote sensing to the estimation of yields, land use, and total agricultural production for a region, but are limited by their ability to link this data to specific households and other inputs in the agricultural production process.

Carletto et al. (2016b, pp. 28) conclude their analysis of land measurement bias by arguing that, "little research is to date available on the use of remote sensing imagery for area measurement in household surveys. As technology advances and image resolution improves along with affordability, the use of this method becomes more feasible, and is likely to hold promise particularly for the measurement of large plots." While papers such as Carletto, Savastano, and Zezza (2013) and Dillon et al. (2017) have explored the relationship between survey design, land measurement bias, and their implications for econometric specifications, little evidence to date has been provided to draw comparisons across self-reported, GPS, and satellite data. Additionally, the cited surveys have quantified land measurement error across several African countries, though measurement errors may vary across production systems and differences across contexts. External validity of these results in the Asian context merits its own analysis due to differences in how farmer's may perceive land area which could be related to types of crops, farming systems, or cultural norms.

This paper contributes to this literature by presenting the results of a validation study that relied on farmer self-reports, GPS-measured plots, and plots measured using remote sensing data from four pilot provinces of four countries: the Lao People's Democratic Republic (Lao PDR), the Philippines, Thailand, and Viet Nam. We find no differences between remotely sensed data and GPS measures taken by field teams. Given the lower cost of publicly available remotely sensed data relative to GPS data, linking household surveys to these data sources does not induce additional measurement error, particularly for field crops and irrigated areas where plot boundaries are spatially distinguished. We also find that the magnitude of self-reporting bias is nonlinear and varies across countries, with the largest magnitude of self-reporting bias of 130% of a standard deviation (2.2-hectare bias) in the Lao PDR relative to Viet Nam, which exhibits 13.3% of a standard deviation (.008-hectare bias). In all countries except Viet Nam, the inverse land size–productivity relationship is upwardly biased by lower land area self-reported measures relative to GPS measures. In Viet Nam, the intensive margin of organic fertilizer use is negatively biased by self-reported measurement error by 30.4 percentage points.

The next section of the paper describes the study areas, while the third section presents the data used in this study and fieldwork. The fourth section presents the econometric strategy, and the fifth section showcases the key results. The final section discusses the implications of this study and the prospects for integrating remote sensing into national household surveys.

II. STUDY AREA

This study was undertaken in four pilot provinces in four countries: Savannakhet Province (Lao PDR), Nueva Ecija Province (Philippines), Ang Thong Province (Thailand), and Thai Binh Province (Viet Nam). The four countries were selected as part of a technical assistance (TA) project of the Asian Development Bank (ADB), which was designed to promote the use of satellite-based technology in estimating rice area and production.[1] The provinces were chosen in consultation with the counterpart government agencies using the criteria of the existence of substantial extent of contiguous paddy rice area.

Thai Binh Province, located in the northeast coast of Viet Nam, has a land area of 154,200 hectares. It is a key paddy rice production area in the Red River Delta region, with approximately 52% of land in the province dedicated to paddy rice farming.[2] The Red River Delta region also ranks second in terms of total paddy rice production in Viet Nam (FAO 2011a), just behind the Mekong River region. Thai Binh is located in a typical tropical monsoon area, with one key rainy season from May to October. The total rainfall in Thai Binh in the rainy season of 2015 was 1,445 millimeters (mm), accounting for approximately 85% of the total annual rainfall for the same year in the province. The

---

[1] This TA was implemented by ADB in partnership with government agricultural ministries and national statistical offices. The TA has three major components: (i) development of customized software applications and methodology to estimate paddy rice cultivation area and crop production based on data obtained through crop cutting studies at the provincial level; (ii) training of counterpart staff in the four pilot countries; and (iii) development of online training program on the use of satellite data for agricultural and rural statistics (ADB 2013).

[2] ADB estimates are from administrative data provided by the General Statistics Office, Viet Nam.

average temperature ranges from 19°C to 32°C. Paddy rice is grown twice per year: once in the summer (mid-June to end-October) then in the winter (mid-December to end-May).

Nueva Ecija Province, a landlocked province in the Central Luzon region of the Philippines, has a land area of about 575,100 hectares. It is often referred to as the rice granary of the Philippines given that it is the largest producer of rice in the country.[3] Nueva Ecija is in a typical tropical monsoon area, with one key rainy season from May to October. The total rainfall in Nueva Ecija in the rainy season of 2015 was 2,172.89 mm, accounting for approximately 87.6% of the total annual rainfall for the same year. The average temperature ranges from 28°C to 34°C. Paddy rice is grown twice per year: once in the dry season (mid-June to end-October) and then in the wet season (mid-December to end-May). The province was affected by a powerful and devastating typhoon called Koppu (locally known as Lando), which formed on 12 October 2015 and dissipated on 21 October 2015, coinciding with the TA project activities. Administrative data sources indicated a decrease in rice production of approximately 35% in the fourth quarter of 2015 compared to the same reference period in 2014.[4]

Ang Thong Province, located in the central region of Thailand, has a land area of 96,840 hectares. The name "Ang Thong" means "Gold Basin," referring to the color of harvested rice and the basin-like geography of the area. The climate in Ang Thong is characterized by the southwest monsoon that brings heavy rainfall from May to October; by the northeast monsoon that is relatively dry and cool from October to February; and by the transitional period, which brings heavy thunderstorms from March to April. The total rainfall in the Central Plain, where Ang Thong is located, in the rainy season of 2009 was 1,100 mm, accounting for approximately 68% of the total annual rainfall for the same year (FAO 2011a). The average temperature in the Central Plain during the rainy season is 27°C. Paddy rice is grown twice per year: once during the rainy season from May to September and a second time during the dry season of November to April.

Savannakhet, the largest province in the Lao PDR, is located in the southwestern part of the country and has a land area of 2,177,400 hectares. Savannakhet is a key paddy rice production area with a significant proportion of the land in the province allocated to the production of rice (Ministry of Agriculture and Forestry 2014). The climate in Savannakhet is typically tropical with a rainy season from mid-April to mid-October dominated by the humid southwest monsoon. The average annual rainfall is 1,834 mm but ranges from 1,300 mm in the northern valleys to 3,700 mm at high elevations in the south (FAO 2011b). Paddy rice is grown twice per year in the Lao PDR: once during the wet season, and again during the dry season.

III. DATA DESCRIPTION

Crop cutting and farmer recall surveys were implemented in each pilot province. The crop cutting survey was implemented during the harvesting period associated with the rainy season of 2015, while the farmer recall survey was implemented 2 to 3 months after the harvesting was completed to obtain details on crop sales, storage, and postharvest losses.

An area frame was utilized for the crop cutting survey and constructed based on the expected likelihood of finding paddy rice. The sampling frame was constructed using two sources of digitized rice maps to implement the stratification process: rice extent maps using 2015 Moderate Resolution

[3] An average of 8.4% of total annual rice production from 2000 to 2016 comes from Nueva Ecija, based on ADB calculations using Philippines Statistics Authority data.

[4] ADB estimates are from administrative data provided by the Philippine Statistics Authority.

Imaging Spectroradiometer data produced by the International Rice Research Institute;[5] and land use maps produced by the European Space Agency under its GlobCover initiative.[6] Stratification into four categories (high, medium, low, and no probability of rice) was conducted prior to the selection of meshes to improve statistical efficiency and lower fieldwork costs. The primary sampling unit in this study was a 200 m by 200 m square "mesh" that is spatially defined on a digitized satellite image map.

A three-stage stratified sampling methodology was employed in this study in all four study areas. In the first sampling stage, a stratified sample of 120 meshes was selected. A random sample of reserve meshes that could be used for possible replacement was also selected in each stratum. The number of selected meshes was higher in the stratum where the expectation of finding rice growing plots was highest, and lower in areas with low or no likelihood of finding rice growing plots. All sample meshes were checked in the field to determine whether rice was planted in any plot within the mesh boundaries. Only sample meshes with rice were enumerated for the two surveys. For the second sampling stage, a listing of all rice plots identified with at least part of their area within the boundaries of each sample mesh was conducted. All the plots where rice would be harvested during the rainy season of 2015 were eligible to be selected at the second sampling stage.

A high-resolution, detailed, printed Google Earth map of each of the square sample meshes was used to identify the number of plots that fall within each mesh. Landmarks on the printed map were matched to what was observed on the field. The plot boundaries and the respective owners were identified with the help of the village heads and farmers, and delineated on the printed map. Only plots that were either completely or partially inside the sample mesh and were to be harvested in the rainy season of 2015 were included in the listing process. A sample of four plots per mesh was randomly selected for crop cutting from the list of plots that met the selection criterion. For those sample meshes where four or less plots were eligible for selection, crop cutting was done in all plots.

For plots eligible for crop cutting, plot size information was collected using three methods to obtain independent estimates: (i) self-report from farmers; (ii) mapping out the area using a GPS device; and (iii) printing a high-resolution Google Earth satellite image of the study area on paper and requesting farmers to identify plot boundaries, subsequently digitized using geographic information system (GIS) software. Farmers were asked to identify their plot boundaries on the printed paper and provide their own estimates for plot size prior to conducting the GPS mapping of their plots to avoid biases in self-reporting (see appendix). Sampling weights for each of the stages were constructed and utilized for analysis.

Farmer recall surveys were implemented a few months after the conduct of the crop cutting survey. Detailed modules were constructed and adapted to the local context of each country. The questionnaires were translated into local languages and administered on paper in the four countries. In addition to collecting production-related data, ancillary information on the household, plot characteristics, crop variety, etc. were also collected. The questionnaires were verified by field supervisors and subsequently returned to the headquarters of each of the government agencies where double data entry and data cleaning activities were undertaken.

---

5 International Rice Research Institute has been developing remote sensing-based maps of rice systems in Asia as part of its contribution to various projects that need good baseline data on rice (http://irri.org/our-work/research/policy-and-markets/mapping/remote-sensing-derived-rice-maps-and-related-publications).

6 GlobCover began in 2005 in partnership with the Joint Research Center (of the European Commission), United Nations Environment Programme, Food and Agriculture Organization of the United Nations, and other institutions. The aim of the project was to develop a service capable of delivering global composites and land cover maps using as input observations from a sensor onboard the Environmental Satellite mission (http://due.esrin.esa.int/page_globcover.php).

IV. ECONOMETRIC STRATEGY

The paper uses three main econometric specifications. First, we estimate land measurement biases stemming from the different land measurement methods. Establishing these biases, we then estimate the implications of these biases in two other specifications. The second specification estimates the inverse land size relationship to assess the importance of land measurement error, while the third specification estimates the effect of land measurement bias on input demand functions.

In the first econometric specification, we estimate land measurement bias between self-reported (*SR*), *GPS*, and remote-sensed (*Google*) plot observations. In equation (1), land size is measured for each validation sample plot with three observations: one for *SR*, *GPS*, and *Google* using a similar plot fixed effects specification as Dillon et al. (2017). This allows us to directly compare all three measurements in a single regression. In equation (1), L_p is plot size in hectares according to measurement $p = \{SR, GPS, Google\}$, where SR and $Google$ are indicator variables for self-reported and remotely sensed measurement observations, respectively; μ_p represents plot fixed effects; and ε_p is the idiosyncratic error term. The excluded category is *GPS* measurement as we take it as the benchmark plot size measure. Because we have multiple observations for each plot in the validation sample which are stacked by measurement technique, we can estimate equation (1) with plot fixed effects, which will capture the influence of any observed or unobserved plot characteristics on plot size for each measurement. Since land measurement biases have been demonstrated to vary across the land distribution, we also include measurement method by land quartile interactions, denoted by $Quartile$, in the regression to capture potential nonlinearity in land measurement bias.

$$L_p = \beta_1 SR + \beta_2 Google + \beta_3(Quartile \times SR) + \beta_4(Quartile \times Google) + \mu_p + \varepsilon_p \qquad (1)$$

Estimates of this specification have the econometric advantage of controlling for all observable and unobservable characteristics, which might include plot characteristics such as topography or distance to the household, farmer, or household characteristics. The disadvantage of the plot fixed effect specification is that policy recommendations related to improving measurement could benefit from direct estimates of certain plot characteristics on the level of measurement error. If reported plot characteristics are correlated with unobservables, then these estimates would be biased, negating their policy relevance.

In the second and third econometric specifications, we estimate the effect of the land measurement biases on the inverse land size–productivity relationship and input demand functions. The inverse land size–productivity relationship has been well documented by Carter (1984); Barrett (1996); Assunção and Braido (2007); Barrett et al. (2010); Carletto, Savastano, and Zezza (2013); and Carletto, Gourlay, and Winters (2015), among others. Using self-reported plot size and Google measurements, we estimate equation (2) where $yield_{sm}$ is the natural logarithm of total output value of y_{pm} on plot s, in the remotely sensed area mesh m, divided by plot size ($area_{sm}$), where the observations are stacked such that each plot has an observation using *GPS*, *SR*, and *Google* measurement techniques and quartiles by land measurement method interactions are included. The previous inverse land size–productivity relationship already suggests there are nonlinearities in input utilization and efficiency, which may be related to farmer self-reports (Dillon et al. 2017).

$$\begin{aligned} \ln yield_{sm} = {} & \beta_1 \ln area_{sm} + \beta_2(SR \times \ln area_{sm}) + \beta_3(Google \times \ln area_{sm}) + \\ & \beta_4(Quartile \times SR \times \ln area_{sm}) + \beta_5(Quartile \times Google \times \ln area_{sm}) + \mu_m + \varepsilon_{sm} \end{aligned} \qquad (2)$$

In this specification, we also include "mesh" fixed effects, the lowest level of variation across all plot observations to account for unobserved variation such as input or output markets on the inverse land size relationship. In the inverse land size–productivity relationship estimates, we cannot include plot fixed effects, a lower level of aggregation than the mesh, as the key variable of interest is the relationship between plot size and yield. The standard finding in the literature is a negative estimate of β, or decreasing productivity returns to scale in plot size. Previous work on land measurement bias in the inverse land size–productivity relationship (Barrett et al. 2010; Carletto, Gourlay, and Winters 2015; and Dillon et al. 2017) confirm in multiple African contexts that land measurement bias does not explain the inverse land size relationship, but it does bias its magnitude.

The last specification (equation 3) focuses on estimation of the intensive and extensive margin of input demand for organic fertilizer, inorganic fertilizer, and agricultural labor. Plot-level investments may be related to the size of the farm as production technologies change with increasing farm size. Deininger and Jin (2006) find that farmers with more land per capita are less likely to adopt the long-term investment of planting trees on their farm. Marenya and Barrett (2007), Erenstein (2006), and Thuo et al. (2011) found that farmers that cultivate more land were more likely to invest in improved inputs such as fertilizer, herbicides, pesticides, and improved seed varieties. The input demand specification is similar to the inverse land size–productivity relationship specification where the input variable indicates use of fertilizer, herbicide or pesticide, or hired labor on plot as either an indicator or the input quantity of the variable per hectare.

$$\begin{aligned} Input_{pm} &= \beta_1 \ln area_{pm} + \beta_2 (SR \times \ln area_{pm}) + \beta_3 (Google \times \ln area_{pm}) + \\ &\beta_4 (Quartile \times SR \times \ln area_{pm}) + \beta_5 (Quartile \times Google \times \ln area_{pm}) + \mu_m + \varepsilon_{pm} \end{aligned} \tag{3}$$

V. MAIN RESULTS

A. Descriptive Results

Tables 1 and 2 describe household and plot-level characteristics for each sample by country. As we focus analysis on within-country comparisons by plot in this validation study, we do not conduct balancing tests across countries as the samples are not expected to be similar by design. Differences in socioeconomic status and production systems are reflected in differences in descriptive statistics across countries. This is evident by comparing such variables as household size or plots owned per household in Table 1. Household size varies from 5.57 people per household in the Lao PDR relative to 3.68 members per household in Viet Nam. The number of rice plots held per household out of the four countries is the lowest in the Philippines (1.38 per household), and the largest in Viet Nam (2.93 per household). However, the average size of rice plots is the lowest in Viet Nam (0.55 hectares) and largest in Thailand (3.76 hectares).

Plot-level characteristics also reveal interesting differences by country (Table 2). Landownership of plots is high in the Lao PDR (68%) and Viet Nam (82%), but much lower in the Philippines (54%) and Thailand (38%). In the Philippines, the "*buwisan*" system of landownership is prevalent (19%), while land rental is quite frequent in Thailand (45%). Labor allocation across countries also corresponds to differences in production systems and landownership. Hired labor during the agricultural season is low in Thailand (17.29 days), but higher in the Lao PDR (44.31 days) and Viet Nam (53.98 days). A striking difference is found in the Philippines where farmers hire labor for 76 days, primarily for land preparation and planting of rice. Input utilization also varies by country with half the plots using inorganic fertilizer in the Lao PDR with the other half use organic fertilizer. All plots used inorganic fertilizer in the Philippines, Thailand, and Viet Nam. The intensities of inorganic fertilizer use varied considerably by country, with Viet Nam using the highest number of kilograms per hectare (kg/ha) at 986 kg/ha, and the Lao PDR using the lowest amount (361 kg/ha).

Table 1: Household-Level Summary Statistics

	LAO	PHI	VIE	THA
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Average household size	5.57	4.38	3.68	3.76
	(2.22)	(1.93)	(1.44)	(1.32)
Average number of plots owned by household	3.19	1.40	3.00	2.77
	(2.06)	(0.76)	(1.37)	(1.59)
Average number of rice plots owned by household	2.57	1.38	2.93	2.76
	(1.68)	(0.74)	(1.36)	(1.60)
Average size of plots owned by household in hectares	4.00	2.27	0.55	3.78
	(2.50)	(1.68)	(4.68)	(2.99)
Average size of rice plots owned by household in hectares	3.30	2.24	0.55	3.76
	(2.41)	(1.66)	(4.68)	(2.99)
Number of households	94	235	251	117

LAO = Lao People's Democratic Republic, PHI = Philippines, SD = standard deviation, THA = Thailand, VIE = Viet Nam.
Source: Authors' estimates.

Table 2: Plot-Level Summary Statistics

	LAO	PHI	VIE	THA
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Land tenure - Owned or co-owned*	0.68	0.54	0.82	0.38
	(0.47)	(0.5)	(0.39)	(0.49)
Land tenure - Right to use or co-use*	0.02	0.03	0.03	0.01
	(0.15)	(0.18)	(0.17)	(0.10)
Land tenure - Rented-out*	0.00	0.01	0.12	0.45
	(0.00)	(0.12)	(0.33)	(0.5)
Land tenure - Rented-in*	0.04	0.03	0.02	0.16
	(0.19)	(0.18)	(0.13)	(0.37)
Land tenure - Taken in (free)*	0.26	0.00	0.01	0.00
	(0.44)	(0.00)	(0.12)	(0.00)
Land tenure - *Buwisan**	0.00	0.19	0.00	0.00
	(0.00)	(0.4)	(0.00)	(0.00)
Land tenure - Other*	0.00	0.19	0.00	0.00
	(0.00)	(0.39)	(0.00)	(0.00)
Irrigation*	0.03	0.80	0.97	1.00
	(0.18)	(0.40)	(0.17)	(0.02)
Average plot size - Farmer's estimate in hectares	2.54	1.40	0.09	1.18
	(1.68)	(1.07)	(0.06)	(0.77)

continued on next page

Table 2 continued

	LAO	PHI	VIE	THA
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Log (Average plot size - Farmer's estimate)	0.62	0.00	−2.68	−0.03
	(0.95)	(0.93)	(0.69)	(0.64)
Average plot size - GPS in hectares	0.66	1.30	0.08	0.74
	(0.62)	(1.06)	(0.06)	(0.50)
Log (Average plot size - GPS)	−0.88	−0.12	−2.71	−0.50
	(1.07)	(0.99)	(0.69)	(0.64)
Average plot size - Google in hectares	0.64	1.29	0.09	0.75
	(0.59)	(1.06)	(0.05)	(0.50)
Log (Average plot size - Google)	−0.88	−0.13	−2.64	−0.48
	(1.04)	(0.99)	(0.63)	(0.64)
Plot using organic fertilizer*	0.53	0.10	0.15	0.14
	(0.50)	(0.30)	(0.36)	(0.35)
Average use of organic fertilizer (kg/ha)	4,334.37	1,466.55	9,068.54	1,432.16
	(17,165.83)	(3,003.43)	(11,357.65)	(1,192.8)
Log - Average use of organic fertilizer (kg/ha)	6.30	5.11	8.21	6.61
	(2.10)	(2.69)	(1.55)	(1.50)
Plot using inorganic fertilizer*	0.54	1.00	0.96	1.00
	(0.50)	(0.00)	(0.20)	(0.03)
Average use of inorganic fertilizer (kg/ha)	360.82	542.15	985.82	548.67
	(391.57)	(728.53)	(1,448.05)	(1,266.30)
Log - Average use of inorganic fertilizer (kg/ha)	5.38	5.99	6.57	5.88
	(1.08)	(0.68)	(0.78)	(0.85)
Average number of days - Total hired labor	44.31	75.98	53.98	17.29
	(48.26)	(874.10)	(77.15)	(14.37)
Log (Average number of days - Total hired labor)	2.97	3.54	3.48	2.35
	(1.52)	(0.98)	(1.00)	(1.21)
Average number of days - Hired labor for land preparation	3.42	58.23	37.30	2.30
	(3.86)	(1,232.61)	(37.58)	(2.00)
Log (Average number of days - Hired labor for land preparation)	0.59	1.74	3.29	0.62
	(1.24)	(1.16)	(0.81)	(0.61)
Average number of days - Hired labor for planting	48.00	33.95	35.59	6.92
	(39.96)	(53.75)	(34.93)	(2.88)
Log (Average number of days - Hired labor for planting)	3.22	3.17	3.25	1.86
	(1.42)	(0.82)	(0.77)	(0.40)
Average number of days - Hired labor for weeding	1.88	3.46	21.70	7.45
		(4.73)	(21.02)	(3.88)
Log (Average number of days - Hired labor for weeding)	0.63	0.70	2.75	1.90
		(0.98)	(0.79)	(0.46)
Average number of days - Hired labor for nonharvest	0.00	10.88	27.34	6.35
		(14.43)	(27.92)	(2.48)
Log (Average number of days - Hired labor for non-harvest)	0.00	1.66	2.99	1.69
		(1.21)	(0.81)	(0.75)
Average number of days - Hired labor for harvest	15.19	27.08	-	5.21
	(25.96)	(32.08)	-	(4.09)

continued on next page

Table 2 continued

	LAO	PHI	VIE	THA
	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Log (Average number of days - Hired labor for harvest)	1.91	2.74	-	1.41
	(1.19)	(1.14)	-	(0.72)
Average yield (Production/Crop cutting area)	1,515.21	3,799.68	7,164.98	5,676.58
	(1,985.84)	(1,601.05)	(6,109.30)	(3,081.50)
Log (Average yield - Production/Crop cutting Area)	6.73	8.10	8.62	8.44
	(1.04)	(0.63)	(0.80)	(0.84)
Average yield (Production/Area from GPS)	6,979.68	5,348.58	7,124.14	9,258.29
	(15,430.26)	(10,001.74)	(5,621.15)	(8,815.29)
Log (Average yield - Production/Area from GPS)	8.23	8.23	8.61	8.80
	(1.01)	(0.74)	(0.81)	(0.89)
Average yield (Production/Area from Google Earth)	6,723.22	5,409.10	6,920.57	9,172.15
	(13,579.83)	(10,485.96)	(5,374.03)	(8,349.09)
Log (Average yield - Production/Area from Google Earth)	8.23	8.23	8.58	8.81
	(0.99)	(0.74)	(0.81)	(0.88)
Average dollar value of yield (Production/Crop cutting area)	1,862.82	1,112.17	2,164.16	1,108.54
	(8,626.49)	(533.03)	(2,558.41)	(675.35)
Log - Average dollar value of yield (Production/Crop cutting area)	5.39	6.77	7.32	6.81
	(1.69)	(1.08)	(0.88)	(0.71)
Average dollar value of yield (Production/Area from GPS)	6,208.32	1,591.71	2,230.08	1,846.48
	(28,617.17)	(3,198.52)	(3,036.78)	(1,803.26)
Log - Average dollar value of yield (Production/Area from GPS)	6.82	6.90	7.32	7.16
	(1.61)	(1.16)	(0.88)	(0.85)
Average dollar value of yield (Production/Area from Google Earth)	6,358.04	1,614.30	1,981.53	1,833.50
	(28,623.63)	(3,368.17)	(1,982.56)	(1,725.88)
Log - Average dollar value of yield (Production/Area from Google Earth)	6.82	6.90	7.28	7.17
	(1.60)	(1.17)	(0.85)	(0.84)
Number of plots	135	247	253	83

GPS = Global Positioning System, kg/ha = kilogram per hectare, LAO = Lao People's Democratic Republic, PHI = Philippines, SD = standard deviation, THA = Thailand, VIE = Viet Nam.
Notes: *Buwisan* refers to an arrangement where the operator (and his/her family) pays tax or "buwis" to the plot owner. Yield estimates were trimmed at the 95th percentile to remove outliers. * Denotes dummy variables.
Source: Authors' estimates.

Table 3 provides descriptive statistics for the land measurement variables by country and disaggregated by land area quartile. An interesting pattern across all four countries is the similarity between GPS-measured plots and Google Earth estimates. These results have important implications for field methods, particularly because the time and cost of GPS measurement is significantly larger relative to Google Earth estimates. GPS plot measurement not only requires displacement to the plot from the household interviewed, but also circumscribing the plot on foot by an enumerator. This can be time consuming and hazardous for heavily irrigated plots relative to Google Earth estimates, which only require a single GPS coordinate. We discuss cost implications in more detail in the conclusion.

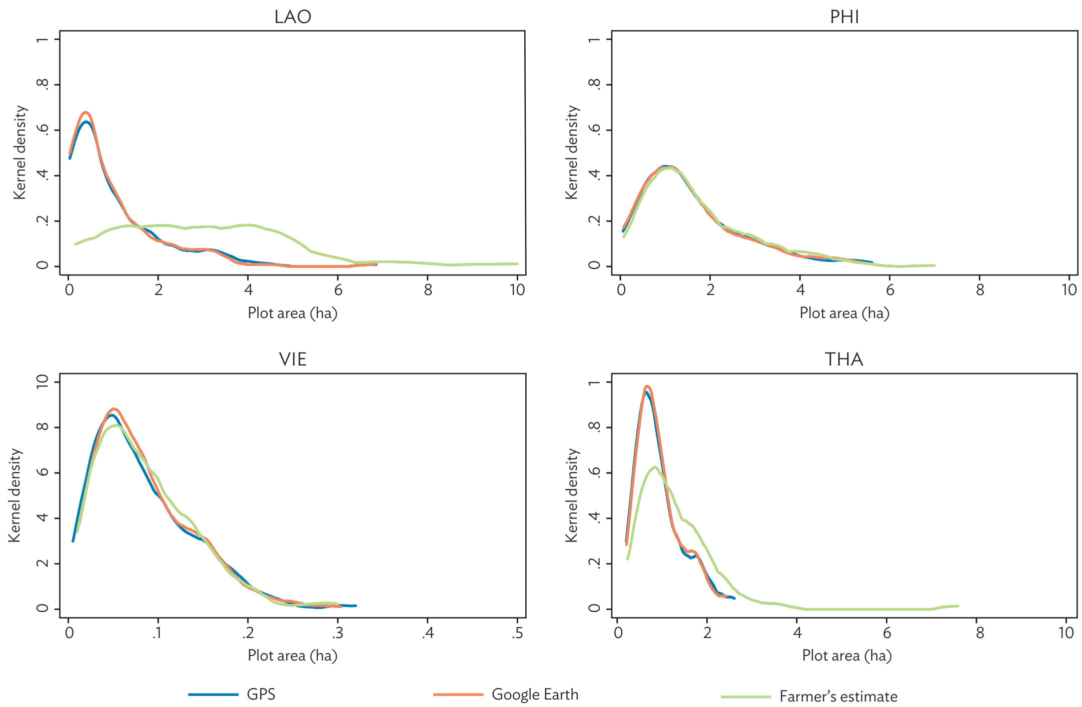
Table 3: Land Area Descriptive Statistics

Area	Quartile	SR	GPS	Google	SR-GPS	(SR - GPS)×100 / GPS	Google - GPS	(Google - GPS)×100 / GPS
LAO		**2.54**	**0.66**	**0.64**	**1.88**	**285.48**	**−0.02**	**−2.54**
	Q1	2.31	0.12	0.13	2.19	1,788.88	0.01	6.67
	Q2	2.70	0.34	0.34	2.36	699.99	0.00	0.26
	Q3	2.10	0.95	0.93	1.16	122.16	−0.02	−2.09
	Q4	3.88	1.95	1.83	1.94	99.49	−0.12	−5.95
PHI		**1.40**	**1.30**	**1.30**	**0.10**	**7.67**	**−0.01**	**−0.43**
	Q1	0.66	0.40	0.40	0.25	63.35	0.00	−1.10
	Q2	1.14	1.04	1.03	0.10	9.94	−0.01	−0.54
	Q3	1.82	1.66	1.66	0.16	9.57	−0.01	−0.35
	Q4	2.98	3.44	3.43	−0.46	−13.33	−0.01	−0.23
VIE		**0.09**	**0.08**	**0.09**	**0.00**	**1.68**	**0.00**	**2.49**
	Q1	0.04	0.03	0.03	0.01	28.94	0.01	17.71
	Q2	0.06	0.05	0.06	0.01	15.56	0.01	10.64
	Q3	0.10	0.10	0.10	0.00	0.02	0.00	1.58
	Q4	0.15	0.17	0.16	−0.01	−7.52	0.00	−2.81
THA		**1.18**	**0.79**	**0.80**	**0.39**	**49.00**	**0.01**	**1.50**
	Q1	1.22	0.33	0.38	0.89	271.87	0.05	15.47
	Q2	0.97	0.61	0.62	0.36	57.80	0.01	1.35
	Q3	0.90	0.86	0.83	0.04	4.44	−0.03	−2.96
	Q4	1.72	1.63	1.64	0.09	5.53	0.00	0.26

GPS = Global Positioning System, LAO = Lao People's Democratic Republic, PHI = Philippines, Q = quartile, SR = self-reporting, THA = Thailand, VIE = Viet Nam.
Source: Authors' estimates.

Descriptive differences between the self-reported and GPS measures are also informative, especially relative to the recent land measurement validation studies in sub-Saharan Africa. In Viet Nam, differences between self-reported and GPS-measured plots are minimal. This is to be expected given the socialist structure of the country with well-documented land records. In the Lao PDR, the Philippines, and Thailand, self-reported land size significantly diverges from GPS-measured land size. Though these differences are nonlinear across the land size distribution, these differences are not uniformly nonlinear in the direction of the reporting bias. For example, in the Lao PDR, self-reported plots diverge significantly from estimates at the two lowest quartiles, 2.2 and 2.4 hectares for quartiles 1 and 2, respectively. A similar pattern is found in Thailand, though with lower magnitudes of divergence between self-reported and GPS measured. Farmers in the lower two quartiles of the land distribution overreport by 0.9 and 0.4 hectares in quartiles 1 and 2, respectively, relative to GPS measures. In the Philippines, farmers underestimate land size for the highest quartile of landholdings by 0.5 hectares. These descriptive statistics are also presented as densities of the land distribution in the figure, disaggregated by measurement method and country, and confirm the trends in the descriptive table. The use of nonstandard measurement units, household and plot manager characteristics (such as education level, age, gender), rounding error, and tenure status could all factor into the divergence between self-reports and GPS (Carletto, Savastano, and Zezza 2013).

Figure 1: Distribution for Differences in Plot Area



GPS = Global Positioning System, ha = hectare, LAO = Lao People's Democratic Republic, PHI = Philippines, THA = Thailand, VIE = Viet Nam.
Source: Authors' estimates.

B. Land Measurement Biases

Descriptive reporting differences and the nonlinearity of these differences are not sufficient to conclude that there is a causal difference between reporting methods. As described in the econometric strategy section, concerns about unobserved land characteristics, which could be correlated with farmer characteristics that influence reporting, may bias estimates. An advantage of this validation study is multiple methodological observations per plot, which permits us to estimate plot fixed effects. Land measurement bias estimates controlling for plot fixed effects are reported in Table 4. Specifying equation (1) in either level or logs of the land area estimates results in consistent upward bias in land reporting when farmers self-report relative to GPS measures. The magnitude of self-reporting bias does vary across countries with the largest magnitude of self-reporting bias of 130% of a standard deviation (2.2-hectare bias) in the Lao PDR relative to Viet Nam, with 13.3% of a standard deviation (.008-hectare bias). As observed with the land size descriptive statistics in Table 3, self-reported land bias is nonlinear across the land distribution. Self-reported landholdings are downward biased relative to GPS measures of land size in the highest quartiles of the land distribution. These results are relatively robust to the specification choice of using either levels or logs of land area.

Table 4: Land Measurement Bias Estimates

	LAO		PHI		VIE		THA	
	Area	Log of Area	Area	Log of Area	Area	Log of Area	Area	Log of Area
SR	2.188***	2.441***	0.255***	0.346***	0.008***	0.192***	0.892***	0.984***
	(0.493)	(0.272)	(0.087)	(0.102)	(0.002)	(0.061)	(0.265)	(0.254)
Google	0.008	0.050	−0.004	−0.005	0.005***	0.164***	0.013	−0.002
	(0.312)	(0.172)	(0.055)	(0.066)	(0.002)	(0.047)	(0.140)	(0.136)
SR × Q2	0.150	−0.468	−0.151	−0.328***	0.000	−0.135	−0.566*	−0.693**
	(0.594)	(0.287)	(0.113)	(0.116)	(0.005)	(0.085)	(0.321)	(0.284)
SR × Q3	−1.031*	−1.799***	−0.095	−0.294***	−0.008*	−0.269***	−0.966***	−1.131***
	(0.546)	(0.310)	(0.120)	(0.107)	(0.004)	(0.089)	(0.279)	(0.273)
SR × Q4	−0.252	−1.834***	−0.713***	−0.532***	−0.021***	−0.285***	−0.811***	−0.957***
	(0.777)	(0.317)	(0.185)	(0.119)	(0.006)	(0.069)	(0.273)	(0.260)
Google × Q2	−0.008	−0.050	−0.001	−0.004	0.001	−0.074	−0.007	0.007
	(0.376)	(0.183)	(0.072)	(0.075)	(0.004)	(0.064)	(0.167)	(0.152)
Google × Q3	-0.028	−0.070	−0.001	0.001	−0.004	−0.155**	−0.048	−0.041
	(0.345)	(0.197)	(0.078)	(0.070)	(0.003)	(0.063)	(0.150)	(0.151)
Google × Q4	−0.124	−0.118	−0.004	0.005	−0.010**	−0.188***	−0.014	0.009
	(0.490)	(0.201)	(0.119)	(0.077)	(0.004)	(0.052)	(0.147)	(0.142)
_cons	6.291***	1.752***	2.780***	1.023***	0.040***	-3.152***	0.987**	−0.187
	(0.680)	(0.223)	(0.078)	(0.029)	(0.003)	(0.031)	(0.402)	(0.328)
Number of observations	405	405	741	741	759	759	248	248
R-squared	0.719	0.912	0.915	0.936	0.930	0.916	0.713	0.813
Adjusted R-squared	0.566	0.865	0.871	0.903	0.893	0.872	0.542	0.702

GPS = Global Positioning System, LAO = Lao People's Democratic Republic, PHI = Philippines, Q = quartile, SR = self-reporting, THA = Thailand, VIE = Viet Nam.
Notes: Standard error in parentheses. Excluded category is GPS land measure taken as benchmark plot size measure. Estimates have plot fixed effects. The dependent variable is plot size in hectares which is stacked according to measurement method: SR, GPS, Google for each plot. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Authors' estimates.

In comparing Google estimates to GPS estimates, we observe few statistically significant differences between these two measures in Table 4. However, a significant difference of 16.4 percentage points is observed between Google and GPS in Viet Nam. These deviations may occur either because of GPS measurement or Google measurement and be of larger magnitude particularly because plot sizes are small. Sources of measurement bias for these two methods are not implausible. GPS measurement bias might include improper tracking of the field's perimeter by enumerators, uncertainty by the farmer in guiding the enumerator around the land surface, or machine measurement errors related to the calibration of the device or the satellite coverage in any given measure. In the case of Google, the accurate demarcation of the plot and its attribution to a given GPS coordinate could result in mismeasured plot sizes. The resolution of the satellite could yield small deviations in land measures, but these are likely to be small.[7]

C. Inverse Land Size–Productivity and Input Demand Results

The land measurement biases estimated in Table 4 may result in biases in agricultural estimates of the inverse land size–productivity and input demand function relationships, specified in equations (2) and (3). These results are presented for the inverse land size–productivity function in Table 5 and by country for the input demand functions in Tables 6–9. For input demand relationships, we estimate input demands for organic and inorganic fertilizer use as well as the total amount of hired labor during the agricultural season.

The inverse land size–productivity relationship results specified in equation (2) are reported in logs for all variables with the yield variables reported in quantities (kilograms) of rice produced as well as value of rice produced. Both sets of results are similar, as expected, since bias in harvest weight relative to dried and sorted granular rice sold is likely low. A distinct result of the inverse land size–productivity relationship estimates across countries is the predicted inverse land size–productivity relationship. Measurement error related to land size reporting does not overturn the direction of the theoretical relationship, but biases due to self-reported measurement do vary, particularly in the largest quartile of the land distribution across countries. In all countries except Viet Nam, the inverse land size–productivity relationship is upwardly biased by lower land area self-reported measures relative to GPS measures. Relative to GPS measures, bias from Google measures are estimated in Table 5 in lower land quartiles in the Lao PDR and Thailand, but no bias in any of the countries in the higher land quartiles (Q2). This is an important result as either the magnitude or the type of the bias in land reporting methods, if measured, does not always imply a bias in agricultural relationships estimated.

Tables 6–9 report biases in the input demands for fertilizer and labor, estimating the effect of land measurement error on both the intensive and extensive margin of input use. In the Philippines (Table 7) and Viet Nam (Table 8), the results indicate a significant effect of self-reported measures relative to GPS measures on input demand, but the direction of the bias differs by country. In Viet Nam, the intensive margin of organic fertilizer use is negatively biased by self-reported measurement error by 30.4 percentage points. The extensive margin of hired labor demand decreases by 10.7 percentage points in response to self-reported measurement error. These biases are nonlinear as we observed in estimating plot measurement bias and the inverse land size–productivity relationship. In the Philippines, this nonlinear bias in input demand is positive in the lower quartiles and negative in the largest quartiles of the land distribution. In Viet Nam, these biases are largest in the lower land quartiles, remaining positive and significant, but much smaller in the larger land quartiles. We do not observe a significant pattern of self-reported land bias in the input demand estimates for the Lao PDR.

[7] Satellite position, signal propagation, and receivers can affect GPS-based coordinates with overall position error ranging from 0.5 meter to 4 meters (Hofmann-Wellenhof, Lichtenegger, and Wasle 2008). While the horizontal accuracy of Google Earth images has not been conducted systematically across the world, studies indicate an average value of 2.18 meters for root-mean-square error (Farah and Algarni 2014).

Table 5: Measurement Error in the Inverse Land Size Relationship

	LAO		PHI		VIE		THA	
	Log of Yield Quantity	Log of Yield Value	Log of Yield Quantity	Log of Yield Value	Log of Yield Quantity	Log of Yield Value	Log of Yield Quantity	Log of Yield Value
log_area	−0.943***	−0.932***	−0.412***	−0.324***	−0.671***	−0.599***	−0.822***	−0.829***
	(0.037)	(0.044)	(0.076)	(0.084)	(0.140)	(0.117)	(0.144)	(0.156)
SR × log_area	−0.063	−0.063	−0.059	−0.107	−0.024	−0.020	−0.190	−0.218
	(0.090)	(0.096)	(0.128)	(0.134)	(0.053)	(0.051)	(0.179)	(0.193)
Google × log_area	−0.015	−0.009	−0.035	−0.076	−0.028	−0.021	−0.053	−0.056
	(0.044)	(0.045)	(0.108)	(0.109)	(0.057)	(0.051)	(0.144)	(0.159)
Q2 × SR × log_area	−0.099	−0.079	−0.069	0.859	0.090	0.052	0.213	0.233
	(0.092)	(0.113)	(0.215)	(0.549)	(0.061)	(0.058)	(0.203)	(0.218)
Q3 × SR × log_area	0.001	−0.007	-0.017	0.164	0.097	0.140	−0.388	−0.418
	(0.082)	(0.082)	(0.185)	(0.244)	(0.067)	(0.105)	(0.397)	(0.463)
Q4 × SR × log_area	0.210**	0.240*	0.267*	0.359**	−0.096	−0.106	0.827**	0.960***
	(0.106)	(0.123)	(0.139)	(0.154)	(0.111)	(0.108)	(0.374)	(0.332)
Q2 × Google × log_area	0.037	0.020	0.707	2.352	0.102	0.056	0.003	0.012
	(0.055)	(0.115)	(0.492)	(1.471)	(0.069)	(0.061)	(0.193)	(0.205)
Q3 × Google × log_area	0.104	0.095	0.174	0.464*	0.123*	0.155	−0.856	−0.979
	(0.085)	(0.089)	(0.197)	(0.282)	(0.070)	(0.113)	(0.716)	(0.836)
Q4 × Google × log_area	0.322**	0.389**	0.104	0.163	−0.089	−0.102	0.902**	0.981***
	(0.154)	(0.193)	(0.129)	(0.144)	(0.121)	(0.113)	(0.364)	(0.354)
_cons	8.913***	4.664***	7.661***	4.562***	6.793***	5.632***	8.925***	7.454***
	(0.207)	(0.092)	(0.100)	(0.134)	(0.388)	(0.353)	(0.081)	(0.079)
Number of observations	399	378	705	693	735	720	213	204
R-squared	0.963	0.975	0.612	0.459	0.393	0.361	0.817	0.783
Adjusted R-squared	0.953	0.969	0.564	0.392	0.327	0.290	0.775	0.731

LAO = Lao People's Democratic Republic, PHI = Philippines, Q = quartile, SR = self-reporting, THA = Thailand, VIE = Viet Nam.
Notes: Standard error in parentheses. Estimates have mesh fixed effects. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.
Source: Authors' estimates.

Table 6: Measurement Error in the Input Demand Functions, Lao People's Democratic Republic

	Use of Organic Fertilizer	Organic Fertilizer Applied per Hectare	Log - Organic Fertilizer Applied per Hectare	Use of Inorganic Fertilizer	Inorganic Fertilizer Applied per Hectare	Log - Inorganic Fertilizer Applied per Hectare	Hired Labor	Total Hired Labor per Hectare	Log - Total Hired Labor per Hectare
log_area	−0.004	1,900.621	−0.050	−0.025	−38.789	−0.107*	0.002	−4.011*	−0.310*
	(0.004)	(1,540.950)	(0.074)	(0.017)	(39.554)	(0.061)	(0.013)	(2.265)	(0.167)
SR × log_area	0.001	1,939.368	0.093	0.035	67.034	0.150	0.022	9.136*	0.707**
	(0.005)	(2,433.737)	(0.170)	(0.022)	(85.206)	(0.144)	(0.019)	(4.672)	(0.344)
Google × log_area	−0.002	427.766	0.008	0.021*	−14.886	−0.007	-0.013	−0.647	−0.057
	(0.004)	(1,381.427)	(0.084)	(0.012)	(40.470)	(0.059)	(0.015)	(1.139)	(0.083)
Q2 × SR × log_area	0.005	−8,389.565	−0.167	0.076	−162.464	−0.102	-0.078*	−2.050	−0.196
	(0.010)	(5,727.047)	(0.193)	(0.069)	(126.220)	(0.133)	(0.046)	(2.011)	(0.138)
Q3 × SR × log_area	−0.013	−3,863.724	−0.072	−0.014	−88.035	−0.226	-0.010	−6.613**	−0.417*
	(0.017)	(2,350.852)	(0.144)	(0.013)	(65.663)	(0.139)	(0.032)	(3.212)	(0.215)
Q4 × SR × log_area	0.003	−3,124.822	−0.272	−0.180*	−42.578	−0.151	-0.010	−6.658**	−0.548**
	(0.006)	(2,274.519)	(0.165)	(0.098)	(68.367)	(0.122)	(0.028)	(3.139)	(0.236)
Q2 × Google × log_area	0.004	−4,740.221	0.028	−0.063*	222.334	0.184	0.049	1.720	0.188
	(0.006)	(5,397.149)	(0.215)	(0.034)	(134.779)	(0.180)	(0.031)	(3.355)	(0.243)
Q3 × Google × log_area	0.052	−1,159.289	0.149	−0.001	82.006	0.110	-0.083	11.817*	0.793**
	(0.072)	(1,407.408)	(0.207)	(0.018)	(64.803)	(0.227)	(0.130)	(7.014)	(0.356)
Q4 × Google × log_area	0.010	−1,258.301	−0.302**	−0.265	19.194	−0.163	0.057	0.995	−0.000
	(0.029)	(1,304.214)	(0.133)	(0.164)	(36.810)	(0.148)	(0.048)	(1.550)	(0.119)
_cons	1.992***	−1,258.731	5.274***	0.973***	126.160***	4.804***	0.987***	9.242***	2.203***
	(0.008)	(1,244.779)	(0.123)	(0.031)	(10.508)	(0.041)	(0.023)	(0.699)	(0.034)
Number of observations	402	261	261	402	324	324	402	111	111
R-squared	0.979	0.673	0.949	0.945	0.773	0.879	0.895	0.992	0.959
Adjusted R-squared	0.973	0.579	0.934	0.930	0.711	0.846	0.867	0.988	0.940

Q = quartile, SR = self-reporting.
Notes: Standard error in parentheses. Estimates have mesh fixed effects. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' estimates.

Table 7: Measurement Error in the Input Demand Functions, Philippines

	Use of Organic Fertilizer	Organic Fertilizer Applied per Hectare	Log - Organic Fertilizer Applied per Hectare	Inorganic Fertilizer Applied per Hectare	Log - Inorganic Fertilizer Applied per Hectare	Hired Labor	Total Hired Labor per Hectare	Log - Total Hired Labor per Hectare
log_area	0.087***	−378.761***	−1.041***	−160.881***	−0.275***	0.002	74.160	−0.198***
	(0.025)	(137.878)	(0.203)	(51.282)	(0.054)	(0.002)	(66.087)	(0.066)
SR × log_area	0.017	81.007	0.253**	101.210	0.082	0.003	48.934	0.115
	(0.032)	(55.803)	(0.125)	(78.778)	(0.083)	(0.003)	(76.532)	(0.088)
Google × log_area	0.010	70.719	0.230	12.312	0.018	0.002	40.415	0.022
	(0.028)	(74.511)	(0.179)	(78.580)	(0.075)	(0.002)	(67.056)	(0.086)
Q2 × SR × log_area	−0.071	502.652***	1.578***	281.871*	0.621***	0.060	−310.275	0.324
	(0.066)	(101.774)	(0.277)	(157.026)	(0.211)	(0.111)	(259.742)	(0.245)
Q3 × SR × log_area	−0.096*	−432.425	−0.453	−79.604	0.010	−0.012**	−188.994	0.176
	(0.057)	(621.886)	(0.368)	(101.503)	(0.141)	(0.006)	(131.036)	(0.167)
Q4 × SR × log_area	−0.024	−79.731	−0.471***	−110.416	−0.088	0.007	−118.692	−0.284*
	(0.053)	(62.367)	(0.166)	(79.266)	(0.107)	(0.011)	(88.563)	(0.168)
Q2 × Google × log_area	−0.121	868.091***	2.577***	73.024	0.070	−0.288	−1,366.079	−0.247
	(0.186)	(240.845)	(0.734)	(186.926)	(0.308)	(0.251)	(1,298.506)	(0.583)
Q3 × Google × log_area	−0.077	−346.438	−0.278	−75.651	−0.077	−0.015*	−221.492	0.222
	(0.069)	(688.530)	(0.358)	(113.301)	(0.145)	(0.008)	(155.156)	(0.196)
Q4 × Google × log_area	−0.014	−26.844	−0.301	−34.550	−0.061	0.005	−113.344	−0.236
	(0.046)	(78.541)	(0.210)	(78.454)	(0.098)	(0.008)	(82.525)	(0.148)
_cons	−0.042**	439.591***	5.721***	270.063***	5.361***	1.004***	55.177	3.351***
	(0.020)	(118.065)	(0.249)	(27.419)	(0.053)	(0.013)	(42.765)	(0.114)
Number of observations	726	96	96	726	726	726	666	666
R-squared	0.514	0.991	0.992	0.765	0.563	0.544	0.046	0.687
Adjusted R-squared	0.453	0.987	0.988	0.736	0.509	0.488	−0.081	0.645

Q = quartile, SR = self-reporting.
Notes: Standard error in parentheses. Estimates have mesh fixed effects. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' estimates.

Table 8: Measurement Error in the Input Demand Functions, Viet Nam

	Use of Organic Fertilizer	Organic Fertilizer Applied per Hectare	Log - Organic Fertilizer Applied per Hectare	Use of Inorganic Fertilizer	Inorganic Fertilizer Applied per Hectare	Log - Inorganic Fertilizer Applied per Hectare	Hired Labor	Total Hired Labor per Hectare	Log - Total Hired Labor per Hectare
log_area	0.028	−6,172.646	−0.357	0.025*	−690.396***	−0.332***	0.056	−47.996**	−0.552***
	(0.030)	(5,544.657)	(0.614)	(0.015)	(235.413)	(0.087)	(0.041)	(24.249)	(0.143)
SR × log_area	−0.003	−3,442.567*	−0.304*	−0.001	−149.736	−0.076**	0.016	−14.820	−0.107*
	(0.013)	(1,897.357)	(0.180)	(0.009)	(92.160)	(0.033)	(0.022)	(9.671)	(0.058)
Google × log_area	−0.004	−3,632.389**	−0.324*	−0.001	−147.749	−0.078**	0.017	−15.915*	−0.115**
	(0.013)	(1,653.903)	(0.171)	(0.009)	(92.097)	(0.033)	(0.021)	(9.351)	(0.047)
Q2 × SR × log_area	0.020	5,869.578**	0.556**	0.011	280.372***	0.120**	−0.026	31.094**	0.166*
	(0.023)	(2,534.815)	(0.237)	(0.015)	(105.172)	(0.049)	(0.028)	(14.688)	(0.090)
Q3 × SR × log_area	−0.031	4,398.206**	0.562**	−0.011	309.420***	0.135**	−0.030	14.881	0.083
	(0.019)	(1,922.634)	(0.242)	(0.013)	(106.470)	(0.056)	(0.030)	(10.371)	(0.071)
Q4 × SR × log_area	0.022	3,823.477*	0.263	−0.002	238.123**	0.237***	−0.033	21.455*	0.294***
	(0.028)	(1,980.995)	(0.267)	(0.014)	(120.886)	(0.069)	(0.043)	(10.953)	(0.097)
Q2 × Google × log_area	0.021	6,298.662***	0.597***	0.012	258.185**	0.103**	−0.024	33.461**	0.181**
	(0.022)	(2,093.541)	(0.207)	(0.015)	(111.904)	(0.051)	(0.028)	(13.797)	(0.074)
Q3 × Google × log_area	−0.031	4,382.864**	0.582**	−0.010	252.792**	0.097*	−0.030	14.820	0.076
	(0.020)	(1,869.996)	(0.248)	(0.014)	(102.187)	(0.051)	(0.031)	(9.681)	(0.061)
Q4 × Google × log_area	0.023	3,624.036**	0.251	−0.000	202.068	0.228***	−0.041	18.068	0.257***
	(0.029)	(1,759.244)	(0.268)	(0.015)	(128.143)	(0.074)	(0.045)	(11.314)	(0.099)
_cons	1.432***	−4,950.194	7.223***	1.088***	−1,574.952**	6.120***	1.433***	−93.448	2.082***
	(0.178)	(6,412.364)	(0.711)	(0.043)	(654.508)	(0.268)	(0.185)	(71.023)	(0.430)
Number of observations	759	108	108	759	735	708	687	222	222
R-squared	0.344	0.763	0.781	0.276	0.410	0.392	0.429	0.642	0.879
Adjusted R-squared	0.275	0.661	0.687	0.200	0.346	0.323	0.362	0.527	0.840

Q = quartile, SR = self-reporting.
Notes: Standard error in parentheses. Estimates have mesh fixed effects. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' estimates.

Table 9: Measurement Error in the Input Demand Functions, Thailand

	Use of Organic Fertilizer	Organic Fertilizer Applied per Hectare	Log - Organic Fertilizer Applied per Hectare	Inorganic Fertilizer Applied per Hectare	Log - Inorganic Fertilizer Applied per Hectare	Hired Labor	Total Hired Labor per Hectare	Log - Total Hired Labor per Hectare
log_area	−0.145*	−1,163.427***	−0.403*	−62.606	−0.314*	0.030	−5.532	−0.628*
	(0.079)	(419.300)	(0.204)	(105.428)	(0.162)	(0.031)	(3.921)	(0.365)
SR × log_area	0.044	-629.911	-0.179	−0.000	−67.562	0.083	−0.031	5.226
	(0.129)	(500.331)	(0.238)	(0.000)	(127.043)	(0.189)	(0.033)	(4.989)
Google × log_area	−0.031	22.216	0.002	−70.711	−0.027	−0.014	4.173	0.349
	(0.085)	(190.138)	(0.092)	(165.175)	(0.170)	(0.020)	(4.444)	(0.247)
Q2 × SR × log_area	0.129	1,183.979	0.431	416.960	0.222	0.082	−10.165	−0.142
	(0.126)	(710.639)	(0.349)	(354.471)	(0.203)	(0.077)	(7.532)	(0.421)
Q3 × SR × log_area	0.050	1,068.035	0.121	−117.444	−0.592	0.011	3.386	0.234
	(0.107)	(868.451)	(0.487)	(205.897)	(0.449)	(0.028)	(6.889)	(0.297)
Q4 × SR × log_area	0.129	1,342.555	0.714	112.964	−0.346	0.034	−12.029*	−1.889***
	(0.140)	(850.094)	(0.480)	(295.790)	(0.559)	(0.044)	(6.975)	(0.685)
Q2 × Google × log_area	0.167	515.571	0.228	532.629	0.484	0.111	-1.098	−0.164
	(0.184)	(309.104)	(0.155)	(330.807)	(0.389)	(0.135)	(7.407)	(0.325)
Q3 × Google × log_area	0.051	164.784	−0.108	−120.712	−1.028	0.006	2.071	0.041
	(0.084)	(561.207)	(0.402)	(415.253)	(1.174)	(0.039)	(8.668)	(0.340)
Q4 × Google × log_area	0.210	417.059	0.335	235.417	−0.378	−0.004	−11.514*	−1.932***
	(0.195)	(426.177)	(0.295)	(481.310)	(0.664)	(0.027)	(6.313)	(0.729)
_cons	−0.033	615.967**	5.198***	565.885***	6.338***	1.006***	41.068***	3.594***
	(0.044)	(282.209)	(0.177)	(142.324)	(0.098)	(0.046)	(3.505)	(0.202)
Number of observations	248	50	50	239	233	219	108	108
R-squared	0.659	0.962	0.993	0.566	0.552	0.932	0.857	0.910
Adjusted R-squared	0.589	0.937	0.989	0.478	0.458	0.917	0.811	0.881

Q = quartile, SR = self-reporting.
Notes: Standard error in parentheses. Estimates have mesh fixed effects. *** p<0.01, ** p<0.05, * p<0.1.
Source: Authors' estimates.

We also find biases in Google relative to GPS measures in the Viet Nam input demand estimates. Google estimates bias in the intensive margin of organic fertilizer demand downward by 32.4 percentage points and in the extensive margin of hired labor demand by 11.5 percentage points (Table 8). These results are consistent with the plot measurement errors found in Table 4 for Viet Nam.

D. Cost Implications

In the preceding analyses, we estimated the effect of survey methods on three dimensions of data quality (focusing on land measures), the implications of land measurement errors on the inverse land size–productivity relationship, and the implications of land measurement errors on input demand functions. Improvements in data quality must be compared with implementation costs when taking a decision to implement any survey method.

While implementing a survey, time is a scarce resource and enumerator's remuneration is often the largest cost item (Carletto et al. 2016b). Thus, any time savings per unit of observation without a compromise in data quality means that more data can be collected and fieldwork can be better streamlined. In this section, we provide our implementation costs to roughly quantify costs per plot using the GPS or Google Earth methods. We cannot estimate enumerator time costs precisely, so some cost components are omitted from this discussion.

The fixed cost associated with procuring GIS software needed to calculate area from GPS instruments or Google Earth images was zero in our study since we used a freely available and open source platform called QGIS (previously known as Quantum GIS). However, variable costs per plot are likely to be different between GPS and Google methods. We discuss four components of variable costs below, namely, plot boundary mapping, printing of paper maps versus procuring GPS instruments, farmer compensation, and consultancy fees. Certain variable cost items such as transportation to the household and to the sample plot are assumed to be the same between Google Earth and GPS methods and not factored into the overall cost comparison.[8]

1. Plot Boundary Mapping

The average time taken to identify the respondent, complete the basic modules of the questionnaire, and reach their plot is roughly 65 minutes per observation. This is the same for both the GPS and Google measurement. The average time taken to walk around the perimeter of plots in our sample was roughly 20 minutes.[9] Assuming an average work day of 8 hours, and full productivity by an enumerator, GPS tracking can be accomplished for five plots a day. In reality, enumerators were only able to cover four plots a day due to either respondent or enumerator fatigue, and prevailing weather conditions. While implementing the Google measurement technique, the enumerator did not have to walk along the boundary of the plot, but only demarcate the same on a paper map, which took about 5 minutes on average per plot. Thus, an efficient enumerator could trace the boundaries of seven plots in a day. Enumerators were paid roughly $25 a day, which makes the cost per plot equal to $8.25 for GPS and $3.60 for Google Earth.

---

8 Transportation costs can drastically increase if the same area has to be visited for a longer duration (more days) to cover the same number of observations, as might be the case with the GPS method. Thus, our estimate is a lower bound on actual cost savings.

9 Based on field survey monitor's management documents.

2. Printing versus Global Positioning System Instrument Costs

High-resolution Google Earth images were printed on A4 size paper with colored ink to facilitate the identification of plot boundaries on the field. The cost of paper and printing was roughly $0.50 per plot. A tablet instrument with a well-functioning GPS application usually costs about $200, including peripherals such as batteries, bags, charging equipment, transport, internet, etc. These instruments are expected to have a lifetime of 600 interview days, which leads to an average per plot cost of $0.08. For future studies, it is possible to load Google Earth images onto the tablets itself to demarcate plot boundaries, which will lead to significant reduction in printing costs.

3. Farmer Costs

In our study, farmers had to be paid to (i) identify plot boundaries and (ii) allow enumerators to traverse the boundaries of their plot in the case of GPS mapping. Given that the dikes for rice plots were very narrow and not well established, farmers were concerned about potential crop losses in case an enumerator fell inside the plot. Farmers also had to walk along the perimeter of their plot with the enumerator in the case of GPS mapping. In our study, a compensation of $2 per plot was given to farmers identifying plot boundaries, and an additional $3 was given to farmers if they had to traverse the plot boundaries. This leads to a cost of $2 for Google Earth mapping and $5 for GPS mapping per plot.

4. Transferring Global Positioning System and Google Earth Boundaries in Geographic Information System Software to Get Precise Area Estimates

In all four countries, most plots were either rectangular or square and even in the case of uneven shapes, clear demarcations existed. However, in the case of GPS data where enumerators had to traverse the plot boundary, enumerators might have avoided a hedge or walked more unevenly. In a few cases, this led to the boundaries not completely closing, thereby making it difficult to compute the area. To correct for the closing of the plot boundary and the uneven walking across the perimeter of the plot, redigitization was required in QGIS. Consultants were able to fix about 32 plots in an 8-hour working period and were paid $100 a day. This translates to $4.69 per plot. In the case of Google Earth, the physical map was scanned and overlaid with the actual Google Earth image, and the plot boundaries were retraced to create a new digitized plot boundary to compute plot area. On average, consultants were able to fix about 24 plots in an 8-hour period and were paid $100 a day. This translates to $4.16 per plot in the case of using Google Earth, which could be cut down further if tablets were used to create digital boundaries.

Given these cost components, the estimated cost in the case of GPS = $8.25 + $0.08 + $5 + $3.13 = $16.46 per plot. The estimated cost in the case of Google Earth = $3.60 + $0.50 + $2 + $4.17 = $10.27 per plot. The average cost per plot was reduced by roughly 37.61% by using Google Earth relative to GPS plot measurement. For a survey with 4,000 plots, which is typical of multi-topic agricultural surveys such as the Living Standards Measurement Study of the World Bank, the cost savings from using Google Earth with our study's cost structure would be $6.19 x 4,000 = $24,760.

VI. CONCLUSION

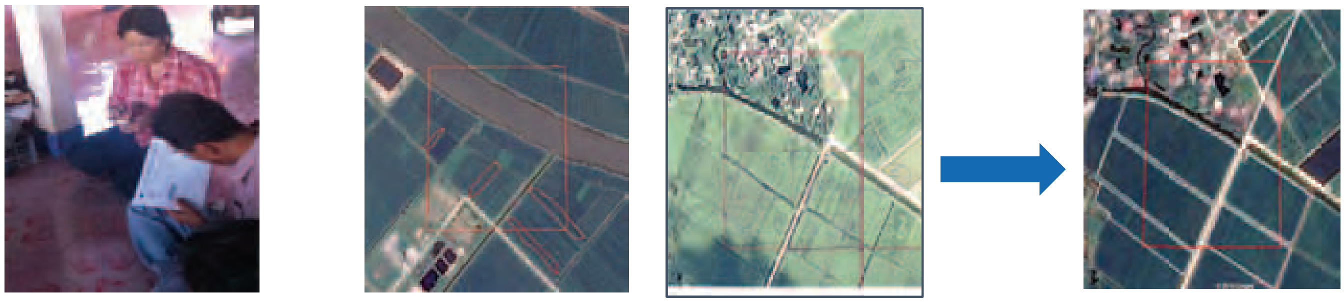
Agricultural statistics using remote sensing have been used primarily to compare land use information and changes over time. This paper investigates the reliability of remote sensing land information in an integrated household survey. Nonclassical measurement error from farmer self-reports has been well documented in the survey design literature (Carletto, Savastano, and Zezza 2013; Dillon et al. 2017, among others), primarily in comparison to GPS-measured plots. In this paper, we investigate the reliability of remotely sensed satellite data on nonclassical measurement error and on agricultural relationships such as the inverse land size relationship and input demand functions. We do this in four Asian countries, contributing to an emerging literature on survey methodology in developing countries, which heretofore has primarily focused on individual countries in Africa.

To summarize our results, we find evidence that the differences between Google and GPS measures are not statistically significant, which validates using Google Earth images in the context of an integrated household survey as an alternative land measurement technique relative to GPS measures. This is an important finding as cost differences between GPS and Google is significant. While remotely sensed data does require a single GPS point to identify the plot, it does not require a full tracing of the field's perimeter by an enumerator if plot boundaries are delineated by irrigation or field boundaries, as is the case with most field crops. In a related literature on compass-and-rope measures relative to self-reporting, Keita and Carfagna (2009) find that on small plots, compass-and-rope can take up to 17 times longer than GPS, though GPS measurement still requires a survey team going to the plot and taking time to trace the field's perimeter.

The nonlinearity of self-reported bias varies across countries, with the largest magnitude of self-reporting bias at 130% of a standard deviation (2.2-hectare bias) in the Lao PDR relative to Viet Nam, which has 13.3% of a standard deviation (.008-hectare bias). In all countries except Viet Nam, the inverse land size–productivity relationship is upwardly biased by lower land area self-reported measures relative to GPS measures. In Viet Nam, the intensive margin of organic fertilizer use is negatively biased by self-reported measurement error by 30.4 percentage points. The extensive margin of hired labor demand decreases by 7.6 percentage points in response to self-reported measurement error. These differences across countries could be explained by at least two factors. Production systems diverge in important ways among countries as our descriptive statistics illustrate. Observed differences and the role of nonclassical measurement error may be correlated with production system characteristics. An alternative explanation may be related to input market differences that could bias estimates of input demand or be correlated with landholdings, potentially due to wealth effects and access to markets, in different contexts.

As established by a growing literature on land measurement bias due to survey methods (Carletto, Gourlay, and Winters 2015; Dillon et al. 2017), we provide evidence in four Asian countries of the persistence of self-reported error relative to GPS measures, though the magnitude of these biases differs considerably by context as noted above. The policy implications of these results are significant for agricultural policy makers. Biases in the inverse land size–productivity relationships may provide false justification for input or land redistribution on the grounds of productivity gains. Fertilizer demand estimates could be biased, affecting the targeting of fertilizer subsidies or the emphasis on input market development. There is still much to be learned about measurement error in land reporting, particularly across different farming and crop systems where plot sizes may be nonsymmetrical. Further exploration of the sources and determinants of these biases will improve causal estimates of these relationship by researchers, and data-driven policy making by agricultural statisticians and agricultural policy makers.

APPENDIX: LAND VALIDATION TECHNIQUES IMPLEMENTED IN THE STUDY



(a) (b) (c)

Notes: Image (a) shows how farmer estimates for plot area were collected through a questionnaire. Image (b) shows plot area estimates derived using Global Positioning System (GPS), where enumerators walked around the plot with a GPS instrument. Image (c) displays how plot boundaries marked on a digitized Google Earth Image were traced onto a digitized map to obtain a third set of plot area estimates.

Sources: Images captured by the authors during the Farmer Recall Survey (ADB R-CDTA 8369) in Ang Thong, Thailand, March 2016; Google Earth. http://www.earth.google.com (accessed 26 August 2016), based on the following specifications: Thai Binh, Viet Nam. 20°37'19.27"N, 106°22'47.46"E, eye alt 710m.

BIBLIOGRAPHY*

Akram-Lodhi, A. Haroon 2001. "Vietnam's Agriculture: Is There an Inverse Relationship?" The Hague: Institute of Social Studies Working Paper Series. No. 348.

Asian Development Bank (ADB). 2013. Innovative Data Collection Methods for Agricultural and Rural Statistics. https://www.adb.org/projects/46399-001/main.

Assunação, Juliano J., and Luis H. B. Braido. 2007. "Testing Household-Specific Explanations for the Inverse Productivity Relationship." *American Journal of Agricultural Economics* 89 (4): 980–90.

Assunação, Juliano J., and Maitreesh Ghatak. 2003. "On the Inverse Relationship between Farm Size and Productivity." *Economics Letters* 80 (2): 189–94.

Bardhan, Pranab K. 1973. "Size, Productivity, and Returns to Scale: An Analysis of Farm-Level Data in Indian Agriculture." *Journal of Political Economy* 81 (6): 1370–86.

Barrett, Christopher B. 1996. "On Price Risk and the Inverse Farm Size-Productivity Relationship." *Journal of Development Economics* 51 (2): 193–215.

Barrett, Christopher B., Marc F. Bellemare, and Janet Y. Hou. 2010. "Reconsidering Conventional Explanations of the Inverse Productivity–Size Relationship." *World Development* 38 (1): 88–97.

Benjamin, Dwayne, and Loren Brandt. 2002. "Property Rights, Labour Markets, and Efficiency in a Transition Economy: The Case of Rural China." *The Canadian Journal of Economics* 35 (42): 689–716.

Bhalla, Surjit S., and Prannoy L. Roy. 1988. "Mis-specification in Farm Productivity Analysis: The Role of Land Quality." *Oxford Economic Papers* 40 (1): 55–73.

Binswanger, Hans P., Klaus Deininger, and Gershon Feder. 1995. "Power, Distortions, Revolt, and Reform in Agricultural Land Relations." In *Handbook of Development Economics, Volume 3 Part B,* edited by Jere Behrman and T. N. Srinivasan, 2467–3047. Elsevier.

Carletto, Calogero, Sydney Gourlay, Siobhan Murray, and Alberto Zezza. 2016a. "Cheaper, Faster, and More Than Good Enough: Is GPS the New Gold Standard in Land Area Measurement?" World Bank Policy Research Working Paper No. 7759.

———. 2016b. *Land Area Measurement in Household Surveys: A Guidebook.* Washington, DC: World Bank.

Carletto, Calogero, Sydney Gourlay, and Paul Winters. 2015. "From Guesstimates to GPStimates: Land Area Measurement and Implications for Agricultural Analysis." *Journal of African Economies* 24 (5): 593–628.

* ADB recognizes "China" as the People's Republic of China, "Lao" as the Lao People's Democratic Republic, and "Vietnam" as Viet Nam.

Carletto, Calogero, Sara Savastano, and Alberto Zezza. 2013. "Fact or Artifact: The Impact of Measurement Errors on the Farm Size–Productivity Relationship." *Journal of Development Economics* 103: 254–61.

Carter, Michael. 1984. "Identification of the Inverse Relationship between Farm Size and Productivity: An Empirical Analysis of Peasant Agricultural Production." *Oxford Economic Papers* 36 (1): 131–45.

Carter, Michael, and Keith Wiebe. 1990. "Access to Capital and Its Impact on Agrarian Structure and Productivity in Kenya." *American Journal of Agricultural Economics* 72 (5): 1146–50.

Chen, Zhuo, Wallace E. Huffman, and Scott Rozelle. 2011. "Inverse Relationship between Productivity and Farm Size: The Case of China." *Contemporary Economic Policy* 29 (4): 580–92.

Collier, Paul 1983. "Malfunctioning of African Rural Factor Markets: Theory and a Kenyan Example." *Oxford Bulletin of Economics and Statistics* 45 (2): 141–72.

Deininger, Klaus 2003. "Land Policies for Growth and Poverty Reduction." World Bank Policy Research Report No. 1548.

Deininger, Klaus, and Songqing Jin. 2006. "Tenure Security and Land-Related Investment: Evidence from Ethiopia." *European Economic Review* 50 (5): 1245–77.

Dillon, Andrew, Sydney Gourlay, Kevin McGee, and Gbemisola Oseni. 2017. "Land Measurement Bias and its Empirical Implications: Evidence from a Validation Exercise." *Economic Development and Cultural Change.* Forthcoming.

Erenstein, Olaf. 2006. "Intensification or Extensification? Factors Affecting Technology Use in Peri-urban Lowlands along an Agro-ecological Gradient in West Africa." *Agricultural Systems* 90 (1–3): 132–58.

Eswaran, Mukesh, and Ashok Kotwal. 1985. "A Theory of Contractual Structure in Agriculture. *American Economic Review* 75 (3): 352–67.

———. 1986. "Access to Capital and Agrarian Production Organization." *The Economic Journal*. 96 (382): 482–98.

European Space Agency. GlobCover. http://due.esrin.esa.int/page_globcover.php.

Farah, Ashraf, and Dafer A. Algarni. 2014. "Positional Accuracy Assessment of Google Earth in Riyadh." *Artificial Satellites* 49 (2): 101–106.

Feder, Gershon. 1985. "The Relation between Farm Size and Farm Productivity: The Role of Family Labor, Supervision and Credit Constraints." *Journal of Development Economics*. 18 (2–3): 297–313.

Food and Agriculture Organization of the United Nations (FAO). 1982. *Estimation of Crop Areas and Yields in Agricultural Statistics.* Rome.

———. 2011a. AQUASTAT Country Profile: Lao People's Democratic Republic, 2011. http://www.fao.org/nr/water/aquastat/countries_regions/LAO.

———. 2011b. AQUASTAT Country Profile: Thailand, 2011. http://www.fao.org/nr/water/aquastat/countries_regions/THA.

Goldstein, Markus, and Christopher Udry. 1999. "Agricultural Innovation and Resource Management in Ghana." Final Report to IFPRI under MP17. http://aida.econ.yale.edu/~cru2/pdf/finalrep.pdf.

Google Earth. http://www.earth.google.com (accessed 26 August 2016).

Grace, Kathryn, Greg Husak, and Seth Bogle. 2014. "Estimating Agricultural Production in Marginal and Food Insecure Areas in Kenya Using Very High Resolution Remotely Sensed Imagery." *Applied Geography* 55: 257–65.

Grace, Kathryn, Greg Husak, Laura Harrison, Diego Pedreros, and Joel Michaelsen. 2012. "Using High Resolution Satellite Imagery to Estimate Cropped Area in Guatemala and Haiti." *Applied Geography* 32 (2): 433–40.

Heltberg, Rasmus. 1998. "Rural Market Imperfections and the Farm Size-Productivity Relationship: Evidence from Pakistan." *World Development* 26 (10): 1807–26.

Hofmann-Wellenhof, Bernhard, Herbert Lichtenegger, and Elmar Wasle. 2008. *GNSS – Global Navigation Satellite Systems.* New York: Springer-Verlag.

Husak, Greg and Kathryn Grace. 2016. "In Search of a Global Model of Cultivation: Using Remote Sensing to Examine the Characteristics and Constraints of Agricultural Production in the Developing World." *Food Security* 8 (1): 167–77.

International Fund for Agricultural Development (IFAD). 2010. *Annual Report 2010.* Rome.

International Rice Research Institute. Remote Sensing Derived Rice Maps and Related Publications. http://irri.org/our-work/research/policy-and-markets/mapping/remote-sensing-derived-rice-maps-and-related-publications.

Keita, Naman, and Elisabetta Carfagna. 2009. "Use of Modern Geo-Positioning Devices in Agricultural Censuses and Surveys: Use of GPS for Crop Area Measurement." Bulletin of the International Statistical Institute, the 57th Session, 2009, Proceedings, Special Topics Contributed Paper Meetings (STCPM22). Durban.

Kimhi, Ayal. 2003. "Plot Size and Maize Productivity in Zambia: The Inverse Relationship Re-examined." The Hebrew University of Jerusalem, The Center for Agricultural Economic Research, and The Department of Agricultural Economics and Management Discussion Paper No. 10.03.

Lamb, Russell L. 2003. "Inverse Productivity: Land Quality, Labor Markets, and Measurement Error." *Journal of Development Economics* 71 (1): 71–95.

Larson, Donald F., Keijiro Otsuka, Tomoya Matsumoto, and Talip Kilic. 2014. "Should African Rural Development Strategies Depend on Smallholder Farms? An Exploration of the Inverse-Productivity Hypothesis." *Agricultural Economics* 45 (3): 355–67.

Lobell, David B., Kenneth G. Cassman, and Christopher B. Field. 2009. "Crop Yield Gaps: Their Importance, Magnitudes, and Causes." *Annual Review of Environmental Resources* 34: 179–204.

Marenya, Paswel, and Christopher Barrett. 2007. "Household-Level Determinants of Adoption of Improved Natural Resources Management Practices among Smallholder Farmers in Western Kenya." *Food Policy* 32 (4): 515–36.

Mazumdar, Dipak. 1965. "Size of Farm and Productivity: A Problem of Indian Peasant Agriculture." *Economica* 32 (126): 161–73.

Ministry of Agriculture and Forestry. 2014. *Lao Census of Agriculture 2010/11: Analysis of Selected Themes*. Vientiane.

Rios, Ana R., and Gerald E. Shively. 2005. "Farm Size and Nonparametric Efficiency Measurements for Coffee Farms in Vietnam." Paper presented at the American Agricultural Economics Association Annual Meeting, Providence, Rhode Island. 24–27 July 2005.

Schøning, Per, J. B. M. Apuuli, E. Menyha, and Elijah S. K. Muwanga-Zake. 2005. *Handheld GPS Equipment for Agricultural Statistics Surveys: Experiments on Area Measurements Done during Fieldwork for the Uganda Pilot Census of Agriculture*, 2003. Oslo–Kongsvinger: Statistics Norway.

Sen, Amartya Kumar 1962. "An Aspect of Indian Agriculture." The Economic Weekly, February, 243–46.

Thuo, Mary, Boris E. Bravo-Ureta, Ibrahima Hathie, and Patrick Obeng-Asiedu. 2011. "Adoption of Chemical Fertilizer by Smallholder Farmers in the Peanut Basin of Senegal." *African Journal of Agricultural and Resource Economics* 6 (1): 1–17.

van Zyl, Johan, Hans Binswanger, and Colin Thirtle. 1995. "The Relationship Between Farm Size and Efficiency in South African Agriculture." World Bank Policy Research Working Paper. No. 1548.

Wooldridge, Jeffrey M. 2008. *Econometric Analysis of Cross Section and Panel Data*. Cambridge: MIT Press.

Land Measurement Bias: Comparisons from Global Positioning System, Self-Reports, and Satellite Data

Traditionally, data on agricultural land size is collected through farmer self-reports in surveys, which has been shown to vary significantly from more accurate estimates derived from Global Positioning System (GPS). However, using GPS introduces significant time and financial costs. This paper proposes using Google Earth for land area measurement and compares estimates with GPS and farmer self-reports. Results show that Google Earth-based land area estimates are very similar to GPS measures, but reduce fieldwork costs by nearly 38%. As remotely sensed data becomes publicly available, it may become a less expensive alternative to link to survey data than rely on GPS measurement.

About the Asian Development Bank

ADB's vision is an Asia and Pacific region free of poverty. Its mission is to help its developing member countries reduce poverty and improve the quality of life of their people. Despite the region's many successes, it remains home to a large share of the world's poor. ADB is committed to reducing poverty through inclusive economic growth, environmentally sustainable growth, and regional integration.

Based in Manila, ADB is owned by 67 members, including 48 from the region. Its main instruments for helping its developing member countries are policy dialogue, loans, equity investments, guarantees, grants, and technical assistance.

ADB

ASIAN DEVELOPMENT BANK
6 ADB Avenue, Mandaluyong City
1550 Metro Manila, Philippines
www.adb.org