Toward Efficient Land-Use Decisions: Impact of Economic Incentives on Ecosystem Services

A DISSERTATION
SUBMITTED TO THE FACULTY OF
UNIVERSITY OF MINNESOTA
BY

Suhyun Jung

IN PARTIAL FULFILLMENT OF THE REQUIREMENTS
FOR THE DEGREE OF
DOCTOR OF PHILOSOPHY

Stephen Polasky, Advisor

December, 2015

Acknowledgements

The past six years have been a blessing and an invaluable journey for me both academically and personally. I would not have been able to complete this journey without the help of my advisor, other professors, family, and friends. I am so thankful that they have shared this journey with me and I will never forget what they have done for me.

I would like to thank my advisor, Stephen Polasky, who has been a role model as a scholar who enjoys his work more than anything else. Your clear thinking and logic along with excitement and energy for research have always challenged and inspired me. I also thank professors Elizabeth Davis, Paul Glewwe, Terry Hurley, and Timothy Smith for their insightful comments and encouragement for my research and career.

My research has been financially supported by various organizations/programs at the University of Minnesota: the Graduate School's Interdisciplinary Doctoral Fellowship with Institute on the Environment, Consortium on Law and Values in Health, Environment, and the Life Sciences' Intramural Research Award, Interdisciplinary Center for the study of Global Change's Global Food Security Fellowship, and Center for International Food and Agricultural Policy. The support from these fellowships has provided me with the resources and connections with people that were essential for my research.

I am indebted to my family and friends who have continually supported me through my graduate study in the US. Thank you my father (Joohee Jung), mother (Jeongrae Kim), sisters (Heehyun and Jahyun), father-in-law (Youngso Chang), mother-in-law (Jungjae Lee), and brothers and sisters in-law (Sunghee Lee, Kyunghyun Sung, Sungwook Chang, Jaejin Shin) for your prayers, support, and belief in me throughout the process. I also want to thank my friends Jongwoo Choi, Youngeun Chu, Ribuga Kang, Kiwook Ha, Milda, Irhamni, Bhagyashree Katare, Andrew Larson, Chihyun Lee, Jongwook Lee, Kiyoung Lee, Wonfy Lee, Younghwan Lee, William Meland, Keeseon Nam, Corey Risch, Martha Rogers, Jaehyun Shin, and others who have endured Minnesota's brutal winter with me and encouraged me along the way. I am thankful to my pastor Seungeun Kim and his wife Ohsook Kim at The Lord's Church of Minnesota who have led me with words and prayers, and counseled me for mental and spiritual growth.

Lastly, I could not have finished it without the support of my lovely wife, Sunmi Chang, who has laughed and cried with me in great and less great moments of our lives in Minnesota. It was such a blessing to meet you here in Minnesota and I look forward to living our after-PhD life together holding our hands throughout the yet-unknown but exciting journey.

Dedication

To my heavenly Father who knows me and works for the good.
You have done it through me (2 Corinthians 10:5).

Abstract

In this dissertation, I investigate the impact of economic incentives to provide ecosystem services, and discuss potential policies and research methods to increase the net value of ecosystem services. The first two chapters evaluate the impact of economic incentives on deforestation rates and resulting tradeoffs between agricultural production and carbon sequestration in the Brazilian Amazon. I found that the opening of a port facility in Santarém in the Brazilian Amazon resulted in an immediate increase in the deforestation rate, 5.48% increase in 2003, and 11.70% in 2004. The value of carbon released was over $100 million, which exceeds the value of agricultural production within the deforested area. Deforestation rates decreased starting in 2005 with the beginning of the Responsible Soy Project, a joint collaboration between agricultural multinational, Cargill, and an environmental NGO, The Nature Conservancy (TNC). It is less clear whether the decline in the deforestation rate in 2005 and thereafter was due to the project or a reversion to more normal rates of deforestation after the initial burst of land clearing with the port opening. These results emphasize the importance of timing. To be effective, environmental conservation projects should be in place prior to economic development activities that encourage deforestation. The third chapter discusses the importance of including agricultural production cost to calculate economic rent and constructs a globally consistent agricultural production cost data set. Omitting production cost results in overestimates of value from agricultural production and a failure to correctly identify areas with negative profit. Using the correct measure of economic rent is important in making land-use decisions and arriving at efficient land-use patterns. In summary, this dissertation shows that we can use land more efficiently and maximize net value of ecosystem services if we plan in advance and consider the correct value of multiple ecosystem services.

Table of Contents

List of Tables

List of Figures

Chapter 1. Environmental Evaluations of Agricultural Multinational's Deforestation Mitigation Efforts in the Amazon

I. Introduction

There often is a tradeoff between economic development and environmental conservation. Agricultural expansion in many developing countries has contributed to economic development through increased production of agricultural commodities but has also caused environmental degradation including widespread deforestation. For example, Brazil's economic growth increased the country's per capita real gross domestic product (GDP) 1.4 times from 1988 to 2014 while 407,511 km^2 (8%) of the Legal Amazon was deforested during the same period (World Bank 2015; INPE 2015), an area comparable to the size of the state of California (423,967 km^2). Deforestation leads to the release of carbon into the atmosphere and the loss of biodiversity, which have generated concerns from the international community about the consequences of agricultural expansion.

Typically governments are responsible for monitoring economic activities and enforcing regulations to maintain environmental quality because many valuable ecosystem services such as carbon sequestration are under-provided by markets. The government can use various ways to provide ecosystem services, including direct regulation, permit systems, taxes, or subsidies. Brazil has one of the most stringent set of environmental laws in the world. The Forest Code, enacted in 1965, strengthened in 1995 and modified in 2012, requires 80% of each property in the Amazon be preserved as primary forest. Despite the strict law, however, rapid deforestation continued during much of this period until 2004, highlighting ineffective government monitoring and enforcement. Brazil cleared an average area of 17,633 km^2 of forest per year from 1990 to 2003. In 2004, 27,772 km^2 of forest were cleared, the second highest annual total since 1988 when annual record keeping began. Deforestation declined significantly in subsequent years. By 2010 deforestation was 7,000 km^2. Part of the success in reducing deforestation is an improved monitoring system and Brazilian government's increased enforcement of the environmental regulations (INPE 2015). However, deforestation has continued and it remains a problem in much of the Amazon area because of the region's high value of carbon and other ecosystem services compared to the value of income generated from agricultural production or logging.

An alternative route to monitoring and enforcement is a market-oriented approach that engages multinational companies and non-governmental organizations (NGOs). The desires of consumers for sustainable products as well as commitments to corporate social responsibility may give corporations an incentive to enforce environmental regulations. The buying power of corporations can force farmers and other suppliers to comply with environmental laws. Environmental NGOs can provide assurance that environmental standards are upheld as well as technical expertise on environmental monitoring using remote sensing and other tools.

In this paper, I investigate the performance of the Responsible Soy Project, a joint collaboration between Cargill, a multinational company, and The Nature Conservancy, an international conservation NGO. The Responsible Soy Project is an example of a new type of market-oriented approach to monitor and enforce environmental regulations, and in particular to reduce deforestation. More generally, I investigate conditions when economic incentives, enforced by multinational agricultural companies and monitored by NGOs, are effective in monitoring and enforcing environmental laws.

In 2005, Cargill began working with The Nature Conservancy (TNC) on the Responsible Soy Project, a pilot project in the municipality of Santarém located near where the Tapajós River joins the Amazon River (Figure 1-1). Cargill opened a port facility in Santarém in 2003 to export soybeans. TNC tracked deforestation through a satellite monitoring system and Cargill agreed to buy soybeans only from farmers who had not deforested their land from the time of the start of the project. The project contributed to the establishment of the Soy Moratorium in 2006, where all major agricultural companies agreed not to buy soybeans from farmers who had deforested their land. NGOs, such as TNC, World Wildlife Fund (WWF), and Greenpeace, were responsible for oversight of the Soy Moratorium.

While there are many prior studies on the impact of market-oriented environmental projects undertaken by businesses, governments, and NGOs, none of these studies, to the authors' knowledge, quantitatively evaluate the impact of conservation efforts by private companies and NGOs. Studies in the political science and business literatures conduct qualitative analyses of the causes and consequences of collaborations for environmental conservation among different stakeholders, including private companies, NGOs, government, and civil society (Büthe 2010; Fuchs and Kalfagianni 2010; Mayer and Gereffi 2010). There are studies in the conservation and economics literature that quantitatively estimate the impact of market-oriented approaches such as payment for ecosystem services (PES) and sustainability certification system (Arriagada et al. 2010; Blackman and Rivera 2011; Landell-Mills and Porras 2002; Miteva et al. 2012; Pattanayak et al. 2010; Wunder et al. 2008). But these studies did not specifically evaluated the environmental impact of a project initiated by a private company and an NGO.

I develop a simple model of a profit maximizing farmer to predict farmers' deforestation and production decisions under the conditions of the Responsible Soy Project. I use a unique data set from the project to empirically test the hypothesis that the Responsible Soy Project significantly decreased deforestation. I use nearest neighbor covariate matching, difference-in-differences (DID), and matching-DID methods to compare deforestation rates between properties enrolled in the project (the treatment group) and properties not enrolled in the project (the control group) before and after the implementation of the Responsible Soy Project in 2005.

The model and empirical estimation show consistent results. The model suggests that farmers who can take advantage of higher prices by selling soybeans to Cargill once the port opened in 2003 would engage in deforestation. However, once this deforestation is accomplished farmers would have little incentive to clear more land in subsequent years. Therefore, a ban on deforestation that is imposed *after* the opening of the port would likely be ineffective. Empirical estimates support these results. There was an increase in deforestation after the opening of the soybean export facility in 2003, especially for farmers who sold soybeans to Cargill. Deforestation was reduced after the Responsible Soy Project began in 2005. Whether the reduction in deforestation was a result of intended deforestation already occurring or because of the initiation of the project is unclear. Both results from the model and empirical estimation highlight the importance of timing: for environmental regulations to be effective they should be put into place before there are economic incentives for environmentally destructive activities.

II. Background

Brazilian Amazon and Deforestation in the Santarém Area

The Amazon rainforest is the largest rainforest in the world and is globally important for the carbon cycle and for its rich biodiversity. The modern history of deforestation in the Amazon begins in the late 1800s and early 1900s. The forest land in the Santarém region was cleared for rubber plantations and for the production of rice, corn, and other crops. The "Rubber Boom" accelerated after 1900 with the development of the automobile industry. The Brazilian rubber boom, however, was short-lived because of competition from Asian rubber suppliers and the invention of synthetic rubber. Many rubber plantations were subsequently abandoned. Some rubber plantations reverted to secondary forest while farmers grew corn and rice on other abandoned plantation land. In the 1970s black pepper plantations were developed and the federal government started to make investments in transportation infrastructure. This increase in economic activity caused renewed deforestation. Extraction of mineral resources in the 1980s brought additional population and economic activity to the Santarém region (Moraes 2010). By 2000, the cumulative deforestation rate in Santarém was 16% (3,756 km^2) and as of 2010 the cumulative deforestation rate had reached 20% (4,586 km^2).

The Responsible Soy Project

Cargill opened a grain terminal at the port of Santarém, located on the confluence of the Amazon and Tapajós Rivers in northern Brazil, in 2003 (see Figure 1-1). Cargill built the facility because of increased congestion in southern Brazilian ports and to have an Amazonian port closer to European markets. Santarém is a regional center for trade and finance with waterway, road, and air transportation links. The Santarém port exports mostly soybeans from the state of Mato Grosso; 95% of the soybean production exported through the Cargill facility comes from Mato Grosso. The opening of the Santarém port also made soybean production in the Santarém area more attractive.

In 2004, shortly after the grain terminal at Santarém opened, Cargill and TNC began discussions about how to ensure that Cargill operations did not increase deforestation. Though it was illegal to deforest more than 20% of land area in each property under the Forest Code, Cargill did not have a way to distinguish between farmers who were in compliance with the Forest Code and those had violated the law. Cargill and TNC had substantive discussions about the impact of road construction from the state of Mato Grosso to the Santarém municipality and a possible compliance tracking scheme for soybeans (Cleary 2004). This initial meeting led to the creation of the Responsible Soy Project, which was launched in December 2004. Between December 2004 and June 2005, TNC and Cargill had meetings with farmers to explain the deforestation monitoring system and the reasons for such a system. In June 2005 Cargill informed farmers that they would only purchase soybeans from farmers who participated in the monitoring system.

Cargill and TNC staff agreed on four main compliance criteria for farmers in order to receive financing and sell soybeans to the Cargill grain terminal in Santarém: i) no deforestation on their property; ii) legal compliance with the Forest Code; iii) compliance with ecological economic zoning (EEZ); and iv) registration in the rural environmental registration (CAR) system. Legal compliance with the Forest Code criterion includes restoration of Areas of Permanent Preservation (APP), which was one of the key elements of the Responsible Soy Project because of the ecological importance of APP for water resources and biodiversity. TNC, working with the Forest Ecology and Restoration Laboratory (LERF) from the University of São Paulo, trained farmers on how to restore APP. Farmers participating in the project are required to participate in or to make plans for restoration of APP. The third criterion of the Responsible Soy Project mandates that soy areas be located within areas identified for consolidation or expansion of agricultural areas according to the EEZ, which establishes protected areas within a state. Farmers are prohibited from undertaking agricultural activities in these protected areas. The fourth criterion requires farmers to register their properties' spatial boundary information with the CAR system to monitor and control farmers' economic activities in their fields.

Cargill was the only major buyer of soybeans in Santarém area and this gave Cargill considerable leverage in enforcing compliance with these criteria. The compliance criteria provided clear and simple standards for soy sourcing. Any observed deforestation from 2005 would exclude farmers from being able to sell to Cargill. For example, there were 15 properties (out of 383) in the project that did not meet the compliance criteria and were excluded from the project in 2008.

To monitor whether farmers were satisfying zero deforestation and APP restoration requirements, TNC monitored properties every year by satellite imagery and field inspection. Yearly observation allows TNC to compare the differences in forest cover on the property. The first version of the database was established in June 2005. It covered the municipalities of Santarém and Belterra (S&B). These two municipalities have a combined area of 27,285km^2. The database was later extended to the neighboring municipalities outside of S&B (96,256 km^2) in order to cover farmers outside of S&B that supply soybeans to the Santarém terminal (Cleary 2007). The initial assessment was used to create a map showing stands of primary forest in S&B as well as farm locations. Updated maps were completed in May 2007 and December 2008. Since then the map has been updated annually.

III. Model

In this section, I develop a simple three period profit maximization model to explain farmers' production and deforestation decisions for a case like that in the Santarém area.

Let $d_i^t \geq 0$ denote the proportion of land deforested by farmer *i* in period *t* and let D_i^t represent the cumulative deforestation in period *t*: $D_i^t = \sum_{t=1}^{t} d_i^t$. Assume initial deforestation is given by D_i^0. I assume there is a constant cost of deforestation per unit area, C_D. Farmer *i*'s agricultural production function in period *t*, $f_i(A_i^t)$, is a function of the proportion of area in cultivation, $A_i^t \leq D_i^t$. The production costs of farmer *i* in period *t* is given by $C_i(A_i^t)$. Assume that both the production function and cost function are twice differentiable with:

Assumption 1. $f_i(.)$ is increasing and concave ($f' > 0, f'' < 0$)

Assumption 2. $C_i(.)$ is increasing and convex ($C' > 0, C'' \geq 0$)

As long as net revenue of agricultural production does not decline through time, a profit maximizing farmer will set the proportion of area of cultivation equal to the cumulative amount of deforestation, $A_i^t = D_i^t$. I assume this condition holds in what follows.

In period 1, farmers can only sell agricultural output to firm 1. Firm 1 may be thought of as a local buyer that pays a low price and does not impose environmental standards on farmers. Let P_1 be the price paid by firm 1 per unit of production. Firm 2 enters in period 2. Firm 2 may be thought of as a multinational company that exports agricultural output. In period 3, firm 2 introduces a strict environmental standard and will only buy from farmers who do not engage in deforestation in period 3 (deforestation that occurs before the standard is put in place in period 1 and 2 is not restricted). Let P_2 be the price paid by firm 2 per unit of production, with $P_2 > P_1$. The transportation cost per unit of agricultural products sold by farmer *i* to firm *j* is C_{ij}. Depending on price and transport cost farmer *i* will sell to firm 1 if $P_1 - C_{i1} \geq P_2 - C_{i2}$, and sell to firm 2 otherwise. Let δ be the discount factor between time periods. Suppose that farmers do not anticipate future entry of firm 2 or strict environmental standards, either because they are myopic or because they do not have access to information about such future changes. The case with fully informed farmers generates qualitatively similar results in terms of the pattern of deforestation across periods and will not be discussed here. In period 1 each farmer expects to sell agricultural products in periods 1, 2, and 3 with production and cost functions defined above. A farmer solves the following profit maximization problem to decide how much forest to clear and how much to produce:

$$\max_{D_i^1} E\sum_{t=1}^{3} \delta^{t-1}\,[(P_1 - C_{i1})f_i(D_i^t) - C_i(D_i^t) - C_D d_i^t]$$

With constant marginal costs of deforestation, a farmer will plan on clearing land for production in period 1 and not in periods 2 and 3 since clearing in period 1 allows production in all periods while clearing later foregoes production in earlier periods. Let $D_i^{1^*}$ represent the profit maximizing choice of deforestation for farmer *i*. The farmer will produce on all cleared land with production of $f_i(D_i^{1^*})$ and anticipated net revenue in each period of $E\{(P_1 - C_{i1})f_i(D_i^{1^*}) - C_i(D_i^{1^*}) - C_D d_i^1\}$, with $d_i^1 = D_i^{1^*}, d_i^2 = d_i^3 = 0$.

In period 2, farmers now realize they have the option of selling to firm 2. Farmers now solve the following problem:

$$\max_{D_i^t} \sum_{t=2}^{3} \delta^{t-2}\,[(P_j - C_{ij})f_i(D_i^t) - C_i(D_i^t) - C_D d_i^t]$$

Farmers will find it profitable to clear more land in period 2 as long as expected marginal profit from selling to firm 2, evaluated at $D_i^{1^*}$ is positive:

$$E\sum_{t=2}^{3} \delta^{t-2}[(P_2 - C_{i2})\frac{\partial f_i(D_i^{1^*})}{\partial D_i^1} - \frac{\partial C_i(D_i^{1^*})}{\partial D_i^1} - C_D] > 0$$

Farmers selling to firm 2 may find it profitable to deforest in period 2 because $P_2 - \mathrm{C_{i2}} > P_1 - \mathrm{C_{i1}}$. Farmers selling to firm 1 will not engage in deforestation. In period 3, farmers cannot deforest to sell to firm 2 and there will be no further deforestation. However, even without a ban on deforestation, neither farmers selling to firm 1 nor to firm 2 would find it profitable to engage in further deforestation in period 3. The environmental standard imposed by firm 2 in period 3 to prevent further deforestation has no impact on deforestation behavior of farmers.

Based on this simple model, I would expect that farmers enrolled in the Responsible Soy Project (those who sell to Cargill) would engage in deforestation after the port opens (period 2) and cease to deforest after the project begins (period 3). Farmers who do not enroll in the project (those who sell produce locally) would not be expected to deforest in either time period 2 or 3. The environmental standard imposed in period 3 has no impact on the pattern of deforestation.

IV. Empirical Model

The Responsible Soy Project is a non-randomized experiment because farmers choose whether to register their properties in the project. Farmer and property characteristics that make a farmer more likely to enroll in the project may be correlated with the deforestation rate on the property. Unobservable characteristics that are correlated with the participation decision and deforestation rates, such as a farmer's attitudes towards the environment, or the profitability of growing soybeans for export, can bias regression results (Imbens and Wooldridge 2009). I use matching, difference-in-differences (DID), and matching-DID methods to deal with the endogeneity problem and estimate the impact of the project on deforestation. Matching, DID, and the combination of those two methods have been widely used in recent years to evaluate the impact of environmental policies and projects (e.g., Andam et al. 2008; Honey-Roses et al. 2011; Nelson and Chomitz 2011; Robalino and Pfaff 2013).

One of the challenges in using matching and DID methods in the context of the Responsible Soy Project is that there are two events that have impact on deforestation rates: the opening of the port in 2003 and the start of the project in 2005. I first estimate whether there was an impact of the opening of the port facility on deforestation rates in 2003 and 2004. I then estimate the impact of the Responsible Soy Project on deforestation rates in 2005 – 2012. I assume that the deforestation rates in 2003 and 2004 were not affected by the project announcement. The Brazilian National Institute for Space Research (INPE) annually records deforestation in the Amazon starting from

August of that year to July of the following year. The announcement of the Responsible Soy Project in June 2005 might have impacted deforestation in June and July of 2005, which were recorded as deforestation in 2004 by INPE. However, I assume that the amount of deforestation in those two months would be minimal compared to deforestation in other months given that the months of June and July belong to the wet season and farmers burn down the forest to deforest in many cases within the study area.

Nearest Neighbor Covariate Matching Method

In matching methods, each observation in the treatment group is matched with one or more observations in the control group that have similar observable characteristics. I match each observation in the treatment group ($\mathrm{P} = 1$) to observations in the control group ($\mathrm{P} = 0$) based on an observed set of variables, Z. I first use four matching covariates to measure the impact of the port facility opening on deforestation of the treatment group between 2003 and 2004. The four matching covariates are distance to the nearest major roads, distance to the soybean delivery facility, soil quality, and total property area. These four covariates are chosen based on the theoretical model ad availability of the data. Given there is no price difference among farmers selling to the same firm in this region, each farmer's production and deforestation decisions depend on factors affecting yield and cost. Distance variables and total property area affect transportation and production costs and soil quality affects yield of crops. I then use the same four covariates plus the deforestation rates in 2003 and 2004 to measure the impact of the Responsible Soy Project on deforestation between 2005 and 2012. These six variables are used to find the nearest neighbors to match each property in the treatment group to one or more properties in the control group.

I match properties in the treatment group based on observed variables both to their single nearest neighbor and to their four[1] nearest neighbors (Abadie and Imbens, 2011). The inverse of the variances of each element in Z is used for the distance metric. I

---

[1] Abadie and Imbens (2011) suggest using four nearest neighbors because the model with four neighbors performed better with less mean-squared error in their simulation.

correct for bias that remains after matching by adjusting the differences in matched control and treatment properties for the differences in covariates (Abadie and Imbens 2011; Abadie et al. 2004). I estimate heteroskedastic-robust asymptotic variance (Abadie and Imbens 2006; Abadie et al. 2004) because the bootstrap standard error method is not valid for nearest neighbor matching using a fixed number of neighbors with replacement (Abadie and Imbens 2008). The heteroskedasticity assumption relaxes the assumption of constant variance conditional on treatment and covariates, Z.

Difference-in-Differences (DID) Method

The DID method is useful for disentangling the impacts of a specific project that affects only those participating in a project from more general trends that affect everyone. The DID estimator controls for unobserved time-invariant farmer characteristics that affect selection in the project participation by double differencing. It takes differences in the pre- and post-project deforestation rates within control and treatment groups, and takes differences again between control and treatment groups. The DID is estimated using the following regression (Imbens and Wooldridge 2009):

$$Y_{it} = \alpha + \beta D_t + \gamma_1 G_i + \tau_{DID} D_t G_i + \delta X_{it} + \varepsilon_i$$

where Y_{it} is the deforestation rate of property *i* at time period *t*; D_t is a time dummy variable which is 1 if $\mathrm{t} \geq 2005$ and 0, otherwise; G_i is a participation dummy variable equal to 1 if the property is eventually in the project and 0 otherwise; X_{it} is a vector of other control variables that affect the deforestation rate in property *i* including land quality, previous year's average revenue per hectare from crop production, total property area, distance to the soybean delivery facility, and distance to major roads; and ε_i is an error term that is assumed to be independent of both *G* and *D*. The initial time period $2001 \leq t \leq 2004$ and control group of $G_i = 0$ coefficients have implicitly been normalized to zero. This model assumes that the policy effect is the same for all years.

The resulting coefficient, τ_{DID}, estimates the difference in the average outcome of the treatment group before and after the treatment minus the difference in the average outcome of the control group before and after the treatment. This double-differencing method controls for the time trend and differences in Y_i caused by time-invariant characteristics and thus isolates the effect of project participation on deforestation.

I use a robust clustered variance-covariance matrix. Bertrand et al. (2004) show that serial autocorrelation can lead to overestimated t-statistics and significance levels. The robust clustered variance-covariance matrix clusters all observations in different years by property and corrects for serial autocorrelation.

Matching-DID method

I combine matching and DID estimation methods to control for both observable and time-invariant unobservable characteristics that can affect project participation decisions (Heckman et al. 1997,1998). I use kernel-based propensity score matching-DID. I first estimate the probability of participating in the project, i.e., the propensity score, which is used as a weight to account for the relative proximity of the control group to the treatment group. The weighted average of deforestation rates of the control group using the relative propensity score of the control group to that of the treatment group as a weight is compared to that of the treatment group by double differencing as explained in the *DID Method* section. I perform DID on the common support of the propensity score after matching and use clustered robust standard errors as I have used them for the covariate matching method.

In using the DID and matching-DID estimators, I control for the opening of the port facility. Ignoring the opening of the port might cause bias in evaluating the impact of the project and violate the “parallel trend” assumption that needs to be satisfied in using the DID method. I estimate the DID estimator using all years as well as excluding the years 2003 and 2004 when there is a significant difference in deforestation rates between control and treatment groups (Ashenfelter 1978). I assume that 2003 and 2004 is when the effect of the opening of the port facility might have had different effects on the treatment and control groups. Matching-DID method estimates DID using only matched observations based on all covariates including deforestation rates in 2003 and 2004. This approach also controls for the different effect of the port facility opening on treatment and control groups before the start of the Responsible Soy Project.

V. Data

Constructing Variables

The deforestation rate in each year is calculated for the properties in the control and treatment groups. Data on deforestation from 2001 to 2012 come from the Brazilian National Institute for Space Research (INPE). The deforestation rate on each property is defined as the percentage of deforested area during time t over the remaining forest cover at time $t-1$. In this dataset, only properties with more than 6.25 hectares of forest cover are recorded as having forest cover, which is the minimum area that can be detected through satellite imagery system.

ArcMap GIS software was used to create property polygons from property boundary information and to calculate the other control variables, including the total area of each property, distance to soybean delivery facility, distance to the nearest major roads, and land quality variables. Data on individual property boundaries come from TNC for the treatment group, and from the Environmental Registry System (CAR) of the Pará State Environmental Agency (SEMA) for the control group (SEMA 2012). Distance to Cargill's soybean delivery facility and distance to the nearest major roads are calculated from the coordinates of Cargill's soybean delivery facility and from road shape files from Brazilian Agricultural Research Corporation (Embrapa 2013). Distances are measured as the length of a straight line from a point to the nearest edge of a feature. Land quality is calculated for each farm by assigning proportional area weights using data from Embrapa (Embrapa 2013). The description of variables used in the model and summary statistics are given in Table 1-1.

The average revenue from crop production is represented as 2010 US dollar values calculated by using data from Brazilian Institute of Geography and Statistics (IBGE 2015) adjusted by GDP deflator and purchasing power parity from World Bank

(World Bank 2012a 2012b). Total revenue from temporary crops, which are sown and harvested during the same agricultural year, is divided by total temporary crop harvested area to calculate the average per hectare revenue from crop production. I use previous year's average revenue in each year assuming that farmers use previous year's information on prices for their current decisions on deforestation and crop production.

Constructing Treatment and Control Groups

The treatment group is defined as properties participating in the Responsible Soy Project, while the control group is defined as properties not participating in the project but within the municipalities of Santarém and Belterra (S&B).

I exclude properties with zero recorded forest cover in any given year because the focus of this study is on deforestation (with no forest there is no possible deforestation). In the treatment group, 65 of 383 properties had no forest cover. I also excluded 15 properties after 2008 and 8 properties after 2010 that were dropped from the project because they failed to meet project criteria. Finally, I restrict the analysis to farms that were in the project since its implementation in 2005 which results in an additional 40 farms being dropped because they did not join the project until 2011-2012. To check the robustness of the results, I also run the analysis including the 23 properties that were dropped from the project and the 40 properties that entered the project in 2011-2012 and found that the main findings were robust to different inclusion and exclusion assumptions.

For the control group, I downloaded boundary files of farms in S&B, located east of the Tapajós and south of Amazon rivers, where the farms in the treatment group are located to minimize bias that can occur because of geographic mismatch (Heckman et al 1997; 1998). In addition, I used only farms that have been reviewed and confirmed by SEMA. There are 235 properties in the control group.

I test for covariate balance before and after matching and find that matching improves covariate balance between control and treatment groups. Table 1-2 shows the mean of covariates, significance of the differences in the mean of covariates, and percentage of the bias between control and treatment groups before and after matching. On average, properties in the treatment group tend to be closer to the soybean delivery facility and to major roads, have larger total area, and have better land quality compared to the properties in the control group. The differences between the means of covariates in the treatment and control groups are all significant at 10% level of significance except the total area variable. The significant differences between the mean of covariates in the treatment and control groups disappear after matching. The results in Table 1-2 also show that the percentage of the bias is reduced significantly, which indicates an improvement in balance between the treatment and control groups. The percentage of the bias is calculated as the percentage difference of the sample means in the treatment and control sub-samples as a percentage of the square root of the average of the sample variances in the treatment and control groups (Rosenbaum and Rubin 1985).

VI. Results

The main environmental question of interest is the effect of the Responsible Soy Project on deforestation. I first present evidence using descriptive statistics and then present econometric estimates using DID and matching methods.

Evidence from Descriptive Statistics

The descriptive statistics show that deforestation increased dramatically in 2003 and 2004 following the opening of the port facility and then fell dramatically in 2005 at the time of start of the Responsible Soy Project and have remained low since (Figure 1-2).

The opening of the port in 2003 appeared to push deforestation rates higher in the S&B region, especially for the treatment group, and to increase the production of soybeans in the region. Deforestation rates increased dramatically in 2003 and 2004, the period after the port opened but before the project began. The average deforestation rate of the treatment group increased 311% from 2002 to 2003 and 170% from 2003 to 2004. The average deforestation rate of the control group increased 145% from 2002 to 2003 and 38% from 2003 to 2004. Figure 1-3 shows the percentage of land planted with soybeans over total cropland area for S&B, the surrounding municipalities,[2] Pará state, and Brazil, from 2001 to 2011. The percentage of crop land planted with soybeans in S&B increased from just 0.9% in 2002 to 28.1% in 2005. In Brazil as a whole, the percentage of crop land planted with soybeans increased from 30% in 2002 to 36.4% in 2005. The significant increase in land planted with soybeans in S&B between 2003 and 2005 is consistent with the fact that the new port opened up opportunities for producing and exporting soybeans from the area. Following 2005, soybean percentages have stayed relatively unchanged in both S&B and in Brazil as a whole.

Deforestation rates decreased significantly in 2005 for both control and treatment groups with a greater decrease in the treatment group. With the beginning of the Responsible Soy Project in 2005, the rate of deforestation in the treatment group dropped and has remained relatively low thereafter; the average deforestation rate dropped from 17.8% in 2004 to 1.7% in 2005. However, deforestation rates also dropped in the control group starting in 2005 though the decline was not as dramatic as in the treatment group (from 5.8% in 2004 to 2.3% in 2005). Since 2006, the average deforestation rate has been relatively steady with a decreasing trend for both the treatment and control groups. The average deforestation rate was slightly higher in the treatment group than in the control group between 2007 and 2010. Since 2011, the deforestation rate in the treatment group has been lower compared to that of the control group.

It is not clear whether the large decrease in deforestation rates after 2005 in the treatment group shows the positive impact of the Responsible Soy Project in reducing deforestation or whether it is a reversion to a more typical deforestation following elevated deforestation rates as a result of the opening of the port facility. It is possible that without the project there would have been continued high rates of deforestation after 2005 because of profitable opportunities to produce soybeans given the existence of the port facility. Yet this evidence is also consistent with the view that the deforestation that

---

[2] Surrounding 10 municipalities include Alenquer, Aveiro, Curuá, Juruti, Monte Alegre, Óbidos, Placas, Prainha, Rurópolis, and Uruará. The total area of these 10 municipalities is 136,443 km^2, making it 5 times larger than the combined area of S&B.

was going to occur with the opening of the port largely occurred in 2003 and 2004 and would have dropped in any event soon thereafter. The decline in deforestation after 2005 may also have been the result of changes in federal policies, such as increased enforcement of the Forest Code by the government, or changes in international agricultural markets, such as the drop in the price of soybeans in 2005. The real price of soybeans dropped by 13%, and that of maize dropped by 14%, from 2004 to 2005 (World Bank 2013). However, prices of crops increased in the years following without an increase in deforestation rates.

The following subsection further investigates which hypothesis best describes the impact of the port and the project by using matching, DID and matching-DID methods.

Evidence from empirical models

Results from DID and matching methods show positive impact of the port facility opening on deforestation but ambiguous impact of the Responsible Soy Project.

The matching estimator results from Table 1-3 shows that the treatment group had higher deforestation rates in 2004 while there is not much significant differences in deforestation rates between control and treatment groups between 2005 and 2012 after the Responsible Soy Project started. The positive and significant parameters of 7.9% and 8.5% using one and four nearest neighbors, respectively, indicate that the treatment group had significantly higher deforestation rates than the control group in 2004. After 2005 when the Responsible Soy Project began both treatment and control groups had similar deforestation rates, i.e., no significant differences, except for the year 2008 and 2011, where there were statistically significant positive and negative coefficients, respectively.

The DID and matching-DID methods also show similar results for the impact of the Responsible Soy Project. The key coefficient in the DID regression is the coefficient on the Project time period*Treatment variable (shown in Table 1-4). This variable measures the difference in the effect of the project on deforestation rates of the treatment and control groups. A negative coefficient indicates that the project is correlated with a decrease in deforestation. The results using data from all years indicate a negative and significant coefficient of Project time period*Treatment variable (Column 2 of Table 1-4). However, when the DID regression is run without 2004, which is the year that deforestation rates are significantly different between control and treatment groups after the port facility opening, the significant impact of the project disappears (Project time period*Treatment variable in Column 3 of Table 1-4). The insignificant impact of the project after exclusion of 2004 observations from DID shows that the negative and statistically significant coefficient is due almost entirely to the high rates of deforestation in the treatment group in 2004 (as shown in Figure 1-2).

Similar results are found using the matching-DID method. The significant impact of the project disappears when I use deforestation in 2003 and 2004 as matching covariates along with other observable characteristics (Project time period*Treatment variable in Column 4 and 5 of Table 1-4). The sign of the variable is negative but it is not significant either at 5% or at 10%. Matching-DID method compares control and treatment groups that have similar distance to the soybean delivery facility and major roads, total area, land quality, and deforestation rate in 2003 and 2004 and difference out time-invariant factors that affect deforestation and program participation decisions. Specifically, the inclusion of deforestation rate in 2003 and 2004 as matching covariates supports the parallel trend assumption and enables us to compare control and treatment groups that are likely to have similar deforestation rates in 2003 and 2004. This allows us to assume that this matched control group would have had similar deforestation rates as the treatment group had there not been the Responsible Soy Project. The negative sign shows that there may have been some impact from the project. However, this coefficient is not statistically significantly different from no effect.

The regression results from the DID method in Table 1-4 also show how physical characteristics and crop prices affect deforestation rates. Properties that are closer to the soybean delivery facility, have higher quality land, and with larger total area tend to have higher deforestation rates. Previous year's higher average revenue from crop production is associated with high deforestation rates. It is intuitive that properties closer to the soybean delivery facility or with high quality land would tend to have higher deforestation rates as this makes agricultural production more profitable, but it is less clear why large properties also tend to have higher deforestation rates. The total area variable was included for consistency between the DID estimator and matching estimators. The main results do not change with exclusion of the total area variable. The distance to a major road is statistically insignificant. Most of the properties in the region are fairly close to federal and state roads, which may explain why this variable does not appear to be much of a factor. These results hold using data from all years and excluding the year 2004.

VII. Conclusion

Thoughtful economic development coupled with enforcement of environmental laws to protect natural capital offers the best hope for achieving a decent standard of living for all people while maintaining the natural capital on which future prosperity depends. Often some type of government regulation is needed to achieve an efficient level of development and conservation because of environmental externalities. In many cases, however, especially in developing countries, governmental regulations fail to achieve desired goals due to lack of monitoring and enforcement. An alternative route to monitoring and enforcement is to engage the private sector and NGOs to help with enforcement. In this paper, I used data from The Responsible Soy Project, a pilot project between Cargill and TNC to prevent deforestation from soybean production, to evaluate whether this type of partnership can have a positive impact on environmental outcomes.

I found that there was a spike in deforestation in 2003-2004 when the port facility opened, especially in the treatment group. There was also an extensive expansion of soybean planted area during these years. After the Responsible Soy Project was implemented, deforestation rates declined, especially in the treatment group, but it is not clear whether or not this is a result of the Responsible Soy Project. Just comparing the period after 2005 with the period before 2005 (including 2004), I find that there is a statistically significant negative effect of the project on deforestation rates. However, when 2004 is dropped from the analysis, the effect of the project is still negative but it becomes statistically insignificant. The larger decline in deforestation rates after 2005 in the treatment group compared to the control group may be simply a reversion to more typical deforestation rates following elevated deforestation in 2004. The nearest neighbor matching methods showed that deforestation rates of the treated group are not statistically significantly different from the control group after the implementation of the Responsible Soy Project, with exceptions in 2008 and 2011. The matching-DID method suggested that there may have been positive impact of the project on decreasing deforestation, as shown by the negative sign, but it is not statistically significant.

What is clear from these results is the importance of timing. To prevent environmentally unsustainable activities from occurring, projects to monitor and enforce environmental laws must be in place prior to proceeding with economic development that presents opportunities for environmentally destructive outcomes rather than being put in place after such activity is already underway. The simple theoretical model showed that a project such as the Responsible Soy Project will not have a beneficial environmental impact if it is implemented after opportunities for environmentally destructive activities have occurred in the field. Land owners adjust their production decisions when they are given economic incentives to do so. Enforcing strict regulation to prevent deforestation only after deforestation has occurred is too late.

In other respects, there is some evidence of positive effects of the project but these may be harder to quantify. Through a visit to the project properties and a series of semi-structured interviews with farmers, governmental officials, and TNC and Cargill staffs, I found that the project increased farmers' knowledge of the Forest Code and improved the means for compliance. The project has had success in forging relationships among important stakeholder groups and in demonstrating techniques for registering land, monitoring and enforcement of the Forest Code. The amount of deforestation in Brazil as a whole has declined significantly after 2004 when deforestation was the second highest it had been since 1988 when the annual record began. While it is unclear how much this project can claim as success it is clear that enforcement and monitoring have improved and deforestation has declined in recent years.

The business environment in Brazil and other countries has been changing significantly, with governments' increased efforts to enforce environmental regulations and consumers who are increasingly willing to purchase environmentally sustainable products (Pickett-Baker and Ozaki 2008). Multinational businesses and local farmers respond to changes in the market. A partnership such as that between Cargill and TNC, demonstrated in the Responsible Soy Project, can change incentives and produce results on the ground. The project provides an example of how a multinational corporation and an international conservation NGO can address the issue of environmental degradation in the process of economic development using market incentives and involving all stakeholders. With further attention to issues of timing as well as other important details of the project design, such projects have the potential to achieve both economic development and environmental conservation goals.

Table 1-1. Variable descriptions, means, and standard deviations (S.D.)

Variable	Description	Mean (S.D.)		
		Total	Control group	Treatment group
		(N=553)	(N=235)	(N=318)
Deforestation rate in each year between 2001 and 2012 (%)	The percentage of deforested area over remaining forest cover			
Deforestation in 2003 (%)	The percentage of deforested area over remaining forest cover in 2003	5.56 (15.29)	4.17 (12.41)	6.58 (17.06)
Distance to the soybean delivery facility (km)	Euclidean distance from a property to Cargill's soybean delivery facility	49.22 (25.04)	52.20 (23.37)	47.01 (26.02)
Distance to a major road (km)	Euclidean distance from a property to the nearest federal or state road	4.37 (5.47)	6.45 (7.07)	2.84 (3.10)
Total area (ha)	Total area of a property	379.48 (676.35)	369.68 (447.87)	386.72 (805.22)
Land quality	Area-weighted land quality based on the classification of Ramalho and Pereira (1995). Scores range from 0 (no production capability) to 7 (most productive soil)	5.23 (1.89)	4.60 (2.09)	5.70 (1.58)
Average revenue per hectare from crop production (2010 US $/ha)	Total revenue from temporary crop production divided by total harvested area in the municipalities of Santarém and Belterra	1,447.25 (370.57)	1,447.25 (370.57)	1,447.25 (370.57)

Table 1-2. Covariate balance and bias between treatment and control groups before and after matching

Variable	Unmatched				Matched			
	Mean				Mean			
	Treatment group	Control group	t-test	% bias	Control group	t-test	% bias	Change in % bias (%)
Deforestation rate in 2003 (%)	6.58	4.17	1.84*	16.2	5.54	0.80	6.3	-61
Deforestation rate in 2004 (%)	17.78	5.76	5.58***	49.8	15.88	0.82	6.5	-87
Distance to the soybean delivery facility (km)	47.01	52.20	-2.42**	-21	46.46	0.28	2.2	-110
Distance to a major road (km)	2.84	6.45	-8.11***	-66.1	2.46	1.59	12.6	-119
Total area (ha)	386.72	369.68	0.29	2.6	315.17	1.31	10.4	300
Land quality	5.70	4.60	7.08***	59.7	5.68	0.14	1.1	-98

***, **, and * indicate 1% and 5% level of significance, respectively

Table 1-3. The nearest neighbor matching estimator results on the impact of the port facility and of the Responsible Soy Project

Year	Average Effect on the Treated			
	Impact of the Port Facility		Impact of the Project	
	one neighbor (S.E)	four neighbors (S.E)	one neighbor (S.E)	four neighbors (S.E)
2003	-0.35	0.89		
	(1.83)	(1.48)		
2004	7.89***	8.53***		
	(2.92)	(2.46)		
2005			0.27	-0.27
			(1.28)	(1.12)
2006			-3.33	-1.36
			(2.39)	(1.61)
2007			0.63	0.96
			(0.67)	(0.59)
2008			1.42**	1.00
			(0.65)	(0.73)
2009			-2.12	-1.90
			(1.59)	(1.73)
2010			-1.86	-2.05
			(2.66)	(1.78)
2011			-5.20*	-5.39**
			(2.79)	(2.11)
2012			-0.93	-0.69
			(1.23)	(1.01)

***, **, and * indicate 1%, 5%, and 10% level of significance, respectively, using standard errors adjusted for individual property

Table 1-4. Difference-in-differences (DID) and matching-DID regression results for the effect of the Responsible Soy Project on deforestation with all years and without 2004 observations

Variables	DID		Matching-DID
	2001-2012 (S.E)	Without 2004 (S.E)	2001-2012 (S.E)
Intercept	-3.46*** (0.84)	1.29*** (0.69)	
Distance to the soybean delivery facility	-0.04*** (0.01)	-0.02*** (0.00)	
Distance to a major road	0.00 (0.02)	0.00 (0.02)	
Total area (100ha)	-0.05*** (0.01)	-0.04*** (0.01)	
Land quality	0.37*** (0.08)	0.21*** (0.06)	
Average revenue from crop production ($100)	0.57*** (0.06)	0.12** (0.05)	
Project time period	-2.96*** (0.50)	-1.22** (0.54)	
Treatment	2.82*** (0.68)	0.22 (0.56)	
Project time period*Treatment	-3.65*** (0.70)	-0.73 (0.61)	-1.48 (1.08)

***, **, and * indicate 1% and 5% level of significance, respectively

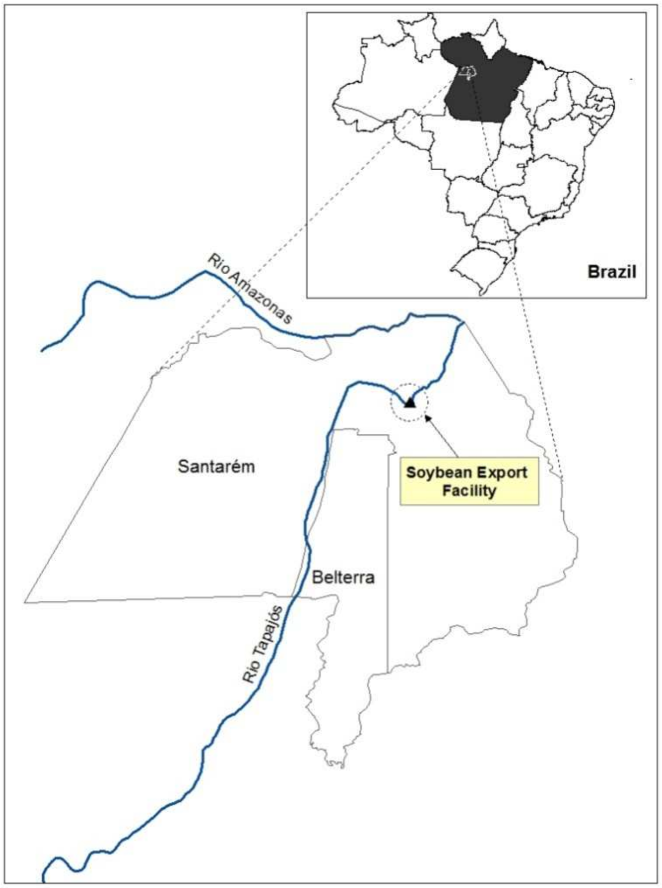
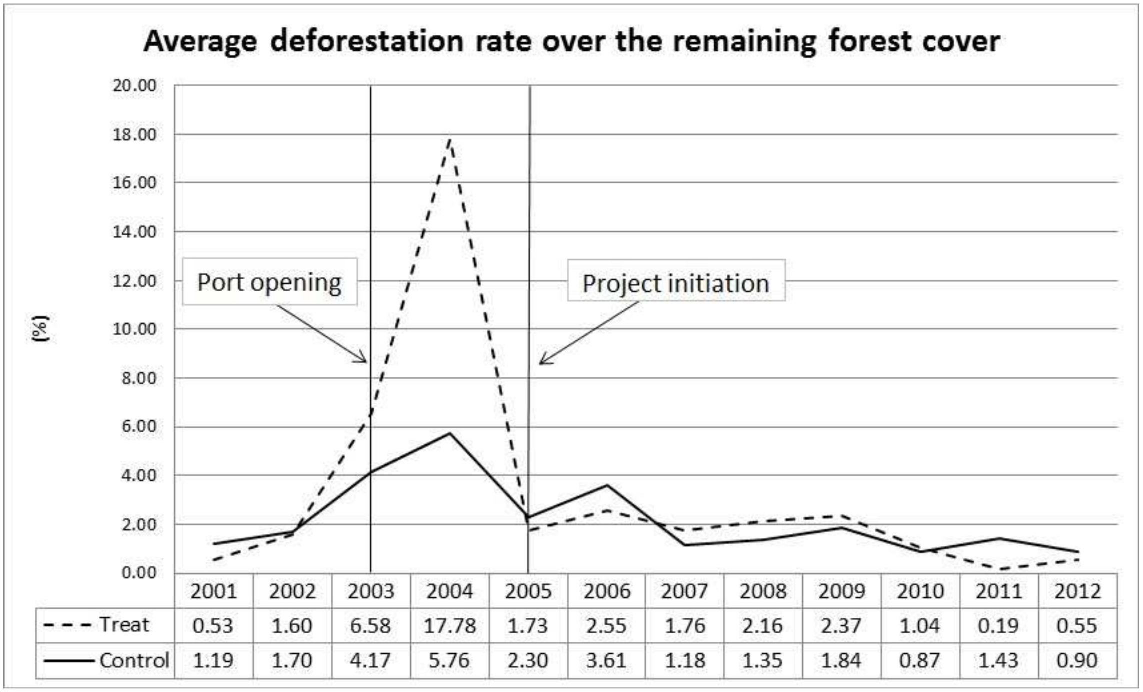
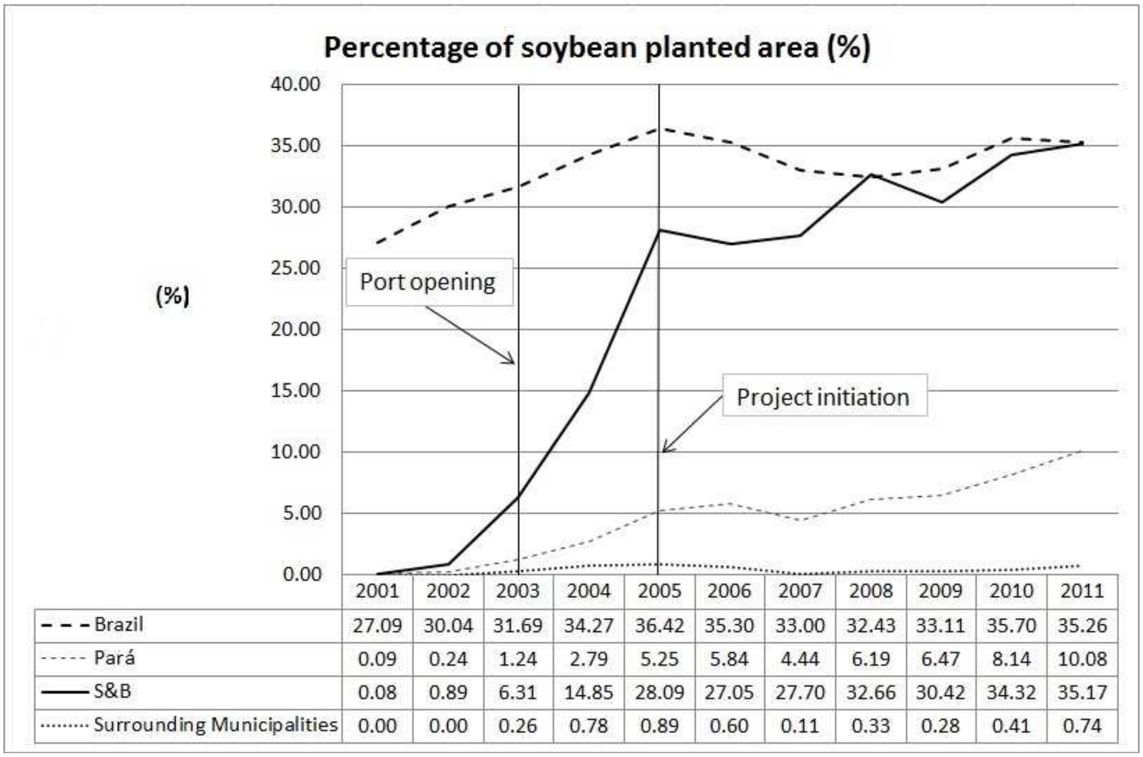


Figure 1-1. The location of Cargill soybean export facility in Santarém near the confluence of the Amazon and Tapajós Rivers in northern Brazil



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
- - - Treat	0.53	1.60	6.58	17.78	1.73	2.55	1.76	2.16	2.37	1.04	0.19	0.55
—— Control	1.19	1.70	4.17	5.76	2.30	3.61	1.18	1.35	1.84	0.87	1.43	0.90

Figure 1-2. Comparison of the average percentage of deforested land over the remaining forest area in the control group and in the treatment group by year from 2001 to 2012



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
- - - Brazil	27.09	30.04	31.69	34.27	36.42	35.30	33.00	32.43	33.11	35.70	35.26
----- Pará	0.09	0.24	1.24	2.79	5.25	5.84	4.44	6.19	6.47	8.14	10.08
—— S&B	0.08	0.89	6.31	14.85	28.09	27.05	27.70	32.66	30.42	34.32	35.17
········ Surrounding Municipalities	0.00	0.00	0.26	0.78	0.89	0.60	0.11	0.33	0.28	0.41	0.74

Figure 1-3. Percentage of soybean planted area over total cropland area in Brazil, Pará, S&B, and surrounding municipalities

Chapter 2. How Much Did We Lose/Gain As A Result of Soybean Export Facility Opening in the Amazon?

I. Introduction

The Brazilian Amazon is important for both conservation and development. The region has rich biodiversity and carbon storage that are of global significance, and at the same time it has the highest poverty rate of any region in Brazil. The Amazon is the largest tropical rainforest in the world and stores vast amounts of carbon. However, as of 2013 about 15% of total legal Amazon area had been deforested through agricultural expansion, leading to a massive release of carbon and loss of biodiversity. Agricultural expansion in the Brazilian Amazon has generated income and employment and has contributed to the economic development of the region. Still, many people remain in poverty: the average poverty rate in Pará state between 2011 and 2013 was 24% (IPEA 2015).

Efficient land-use planning requires estimation of the impacts from new economic incentives and the resulting tradeoffs among ecosystem services. The estimation of impacts and tradeoffs can be used for benefit/cost analyses to find efficient practices that maximize net benefits from conservation and/or development. Failure to estimate the impacts of changes in economic incentives and resulting tradeoffs will likely lead to inefficient land use decisions. Many past development strategies have generated inefficient results because they have not utilized accurate values of ecosystem services (Balmford et al. 2002; MEA 2005). The estimation of impacts and tradeoffs is particularly important in many developing countries because they have high value of ecosystem services and people depend directly on natural resources for food and income. Impact assessments of new economic incentives and estimation of the resulting tradeoff value of ecosystem services will contribute to efficient land use decisions that can provide both income for the local people as well as a variety of ecosystem services, such as carbon sequestration.

In this paper, I investigate the impact of the opening of a new soybean export facility on the amount of deforestation and the resulting tradeoff between agricultural production and carbon sequestration in the Santarém area. In 2003, the agricultural multinational company Cargill opened a soybean export facility in Santarém, located on the confluence of the Amazon and Tapajos Rivers (Figure 2-1) within the northern region of the Brazilian Amazon. I first estimate the impact of the opening of the port facility opening on deforestation. I then construct a counterfactual land-use land-cover map using estimation results to compare the tradeoff between agricultural production and carbon sequestration. I also calculate the break-even price of carbon needed to compensate farmers for their lost profit from agricultural production if the land were preserved.

I find that the average deforestation rate increased from 1.52% in 2002 to 5.48% in 2003 and 11.70% in 2004. The increase in deforestation is equivalent to 164 km^2. The comparison of the value of the reduction in carbon storage to increased agricultural production depends on the discount rate and the social cost of carbon (IWG 2015). Using a 3% discount rate and a social cost of carbon of \$40 per ton of CO_2, the value of the lost carbon in the study area exceeds the value of the increased agricultural production. At a 5% discount rate, the value of the loss in carbon storage is less than the agricultural value. I also find that the break-even price of carbon to compensate farmers for their loss of agricultural profit is \$92.4 and \$55.4 per ton of carbon, assuming 3% and 5% discount rates, respectively. The results suggest that careful consideration of benefits and costs prior to the opening of the port facility might have increased the net benefits from these ecosystem services. Considering other ecosystem services, such as water purification, would increase the value of conservation relative to development. These estimates of the break-even price of carbon provide quantitative estimates of how much farmers should be compensated if Brazil were to preserve those lands to increase net benefits from various ecosystem services.

In the conservation and land-use planning literature, impact evaluation studies have used program evaluation methods to quantitatively measure the amount of avoided deforestation as a result of conservation programs. Blackman (2013) provides a good review of *ex-post* analyses of the impact of various forest conservation policies such as protected areas (PA) and payment for ecosystem services (PES). However, most of these studies do not consider other associated costs or benefits from conservation programs such as the cost of implementing the conservation project or the benefits of conservation on ecosystem services. Ignoring the associated costs and benefits from conservation programs can be misleading because the marginal costs and benefits of additional forest cover spatially vary significantly (Vincent 2015).

This study contributes to the land use planning literature by evaluating the impact of the opening of a port facility on deforestation and the resulting tradeoff between agricultural production and carbon sequestration. It bridges the gap between the impact evaluation and the tradeoff of ecosystem services' analysis (e.g., Koh and Ghazoul 2010; Goldstein et al. 2012) literature by translating the change in deforestation resulting from the port facility opening into the change in the value of carbon and agricultural production.

This study can inform policies for efficient land use that promote both economic development for the poor and the provision of ecosystem services. It will lead to better land-use decisions not only for governments but also for other stakeholders, including private companies and global initiatives such as United Nation's program on Reducing Emissions from Deforestation and Forest Degradation. The following sections proceed with background of the deforestation in the Santarém and Belterra region, empirical estimation methods, and regression estimation results, followed by conclusions.

II. Background

Deforestation in the Brazilian Amazon and in the municipalities of Santarém and Belterra

The cumulative cleared forest area in the Brailian Amazon in 2010 was 742,782 km^2, which is about 14% of the total Legal Amazon area in Brazil and is bigger than the size of Texas (696,241 km^2). The history of major deforestation goes back to 1970s and 1980s, when there were both land speculation and tax and subsidy incentives to clear forest for large-scale cattle ranching (Fearnside 2005). The deforestation rate peaked in 1995. The peak in land clearing occurred during an economic recovery following a successful currency reform, Plano Real, in 1994. The deforestation rate declined from 1995 to 1997 but increased from 1997 to 2004 largely due to increased deforestation in the states of Mato Grosso, Rondônia, and Pará (Macedo et al. 2012) for cattle ranching and crop production. Since 2004 the deforestation rate has been declining as a result of various factors such as a stronger Brazilian currency, increased enforcement of regulations from the Brazilian government, and increased engagement of private companies in reducing deforestation. Focusing on Santarém, the history of major deforestation dates from the 1970s, when black pepper plantations were developed and the government started to construct transportation infrastructure. The cumulative deforestation rate in the municipality of Santarém was 16% (3,756 km^2) in 2000, and it had reached 20% (4,586 km^2) in 2010.

To a certain extent the pattern of deforestation around Santarém and Belterra (S&B) area is reflected in the patterns for Amazon as a whole as is shown in the Figure 2-2. This figure presents the annual deforestation rate over the remaining forest cover in the Amazon, in Pará state, and in the two municipalities of S&B and the surrounding 10 municipalities[3]. The Amazon, Pará state, and S&B and the surrounding municipalities all have decreasing trends, with some fluctuations from 2001 to 2011. It appears that the deforestation patterns of Amazon and Pará state were similar. Pará state has had the highest deforestation rate compared to other regions during this period. The deforestation rate pattern in the S&B and surrounding 10 municipalities was different from that of the other regions between 2002 and 2004, which is around the time when Cargill opened the soybean export facility in 2003. The rate increased by 145% in the S&B and surrounding 10 municipalities, which is more than four times and seven times higher than that increase in Pará state (32%) and in the Amazon area (20%), respectively. The differences

---

[3] The surrounding 10 municipalities are Alenquer, Aveiro, Curuá, Juruti, Monte Alegre, Óbidos, Placas, Prainha, Rurópolis, and Uruará, which surround the municipalities of S&B. The total area of these 10 municipalities is 136,443 km^2, making it 5 times larger than the combined area of S&B.

in these deforestation rates have become smaller in more recent years, while the deforestation rates have become relatively higher in S&B and the surrounding 10 municipalities relative to other regions after 2006.

Soybean Export Facility Opening in the municipality of Santarém

The soybean expansion in the municipality of Santarém is primarily due to the soybean export facility opening in 2003 by Cargill. Cargill opened a soybean export facility at the port in Santarém (Figure 2-1) to avoid congestion in the southern port of Santos and to decrease transportation cost. Since then, production of soybeans has increased in the region; the percentage of soybean planted area over total crop planted area changed from 1% in 2002 to 28% in 2005 in Santarém and Belterra (IBGE 2015).

III. Methods

I model changes in two ecosystem services, i.e., agricultural production and carbon sequestration, as a result of the opening of the soybean export facility in Santarém in 2003. The analysis is composed of two parts: 1) Regression analysis on the impact of the soybean export facility opening on deforestation and 2) Estimation of the tradeoff between the value of agricultural production and carbon sequestration using the results from the regression analysis.

I estimate a regression to measure the impact of the new soybean export facility opening on deforestation in the region of S&B using two different estimation methods. The first method, year specific effects on deforestation, estimates whether there is any year between 2001 and 2010 that has higher deforestation than the other years. The results from this first regression give a general idea of which years the port opening potentially had a significant impact on deforestation. Then, I run difference-in-diffearences (DID) regression to measure the impact of the port facility opening on deforestation. I measure the specific impact of the port facility opening on deforestation by dividing and comparing impacted (treatment) and non-impacted (control) groups of properties by the port facility opening using the same data.

Secondly, I estimate the tradeoff between the value of agricultural production and carbon sequestration by projecting the land use and land cover (LULC) if there had not been the opening of the soybean export facility in 2003 using the regression estimation results. The projected LULC is compared to the actual LULC to estimate the tradeoffs.

Year Specific Effects on Deforestation

The first regression estimation method is often used in event analyses to evaluate the impact of a certain event on a response variable. The deforestation rate regression is estimated as follows:

$$Y_{it} = \alpha_i + \sum_{t=2001}^{2010} \beta_t T_t + \sum_{t=2001}^{2010} \delta_t T_t X_i + u_{it} \tag{1}$$

where Y_{it} is the deforestation rate, which is the percentage of area of deforestation in property *i* relative to the remaining forest cover at time period *t* and α_i is an individual fixed effect to control for the farmers' and properties' characteristics that affect deforestation rates. T_t is a vector of time dummy variables for the years 2002 to 2010, year 2001 being the base year. X_i is a set of physical characteristics that are time invariant including distance to the soybean unloading facility and soil quality that may affect farmers' deforestation behaviors, and u_{it} is an error term.

The parameters β_t and δ_{t} in equation (1) jointly indicate time-specific effects in each year. They account for the impacts of possible shocks on deforestation in each year such as change in the degree of governmental enforcement of environmental regulations or economic shock from changes in prices of agricultural products. Therefore, the significance of the coefficients β_t and δ_t will reflect whether the impact of the port opening is significant in each year. It is expected that the coefficient β_t will be positive and significant for the years following the opening of the port facility in 2003, showing the immediate effect of the port facility opening on deforestation. The standard errors for the total effects of single time and physical characteristic variables, which include both their direct effect and interaction effects, are estimated using the delta method, which uses a first-order Taylor approximation to estimate the standard error of the transformed parameters.

Constructing Control and Treatment Groups

I construct control and treatment groups to evaluate the impact of the soybean export facility opening on deforestation. Setting up a control group is challenging given that this is not a randomized control trial and the soybean export facility opening might have affected all the properties in the region.

In order to construct a control group not affected by the facility, I find a variable that can be used to divide the properties into two groups: relatively higher deforestation after 2003 (treatment group) and little change in deforestation after 2003 (control group). Among other variables, the distance to the soybean unloading facility is a significant factor that determines whether a property is affected by the new soybean export facility opening. The farther a property is from the port, the less likely there will be an increased deforestation of the property as a result of the port facility opening. The variables measuring the distance from the places where major economic activities occur such as major city and market place are one of the significant variables that are included in most deforestation regressions (see the Table 1A in Blackman 2013).

I define all the properties that are farther than 80 km from the soybean unloading facility as the control group while the properties within 80 km from the soybean unloading facility are defined as the treatment group. Figure 2-3 shows scatter plots of each property's percentage of deforestation by distance to the soybean unloading facility from 2001 to 2004. On average, the properties that are more than 80 km away from the soybean unloading facility have lower deforestation rates than those that are closer than 80 km throughout all years. The pattern of deforestation in the figure shows that there had been an increased deforestation in the properties that are closer to the port since 2003, when the port facility opened in the region. Note in particular that the rate of deforestation did not change much after 2003 for the properties that are more than 80 km away from the soybean unloading facility. To check the sensitivity of the results, I also did the analysis with threshold values from 60 km to 100 km.

The statistics of each group using the 80 km threshold indicate that both groups have similar land quality, yet treatment group properties are located nearer from major roads. Table 2-1 shows the comparison of the mean of each variable used between control and treatment groups as defined by the distance to the soybean unloading facility. The properties in the treatment group are less than half distance away from the soybean unloading facility and have higher average deforestation rates by 2.2% compared to the properties in the control group. The land quality is similar for both of the groups with the average difference of 0.6.

Impact of the Port Opening on Deforestation

I use the difference-in-differences (DID) regression method to evaluate the impact of the port opening on deforestation because it can eliminate time-invariant characteristics that affect both control and treatment groups by double differencing. Instead of dividing the period to two periods of before and after the port facility opening, I estimate the DID estimator in each year to estimate the effect of the port facility opening on deforestation in each specific year. I estimate the following regression (Imbens and Wooldridge 2009).

$$Y_{it} = \alpha_i + \sum_{t=2002}^{2010} \beta_t T_t + \gamma G_i + \sum_{t=2002}^{2010} \tau_{DIDt} T_t G_i + \delta X_i + u_{it} \tag{2}$$

where T_t is a vector of time dummy variable from the year 2002 to 2010, which is equal to one when t is the corresponding year; G_i is a group dummy variable equal to 1 if the property i is in a treatment group and 0 otherwise; X_i is a set of physical characteristic variables, including distance to federal and state roads and soil quality, which affect the deforestation rate; and u_{it} is an error term that is assumed to be independent of both T and G.

The main parameter of interest is the set of τ_{DIDt} coefficients, which indicate the difference in deforestation rates between the control ($G_i=0$) and treatment groups ($G_i=1$) in a given year t ($T_t=1$); they indicate the marginal effect of the port opening on deforestation in a given year *t*. I expect the value of τ_{DIDt} for the years in or immediately after 2003 (i.e., *t=2003* and *t=2004*) to be positive and significant, indicating that the opening of the port facility increased deforestation. A vector of coefficients, β_t, represent the year-specific effects on deforestation for the control group.

Land Use Land Cover (LULC) Maps

I compare the actual LULC map with the projected LULC map under the scenario that the new soybean export facility did not open in the S&B region. Comparing the projected map and the original map, I evaluate the impact of the port facility opening on tradeoffs between agricultural production and carbon sequestration. The projected LULC map is created by changing the deforestation rates of the treatment group using the estimation results from equation (2). The total area of deforestation that happened as a result of the port facility opening at time period t, $\mathrm{Def}_{\mathrm{t}}^{\mathrm{port}}$, is estimated by multiplying τ_{DIDt} from equation (2) and the total remaining forest cover in all properties. The properties that have high predicted value of deforestation $\widehat{\mathrm{y_{it}}}$ from equation (2) for property *i* within the treatment group are reforested until the sum of the total reforested areas reaches the estimated total area of additional deforestation from opening of the port in a given year *t*.

Tradeoffs Between Agricultural Production and Carbon Sequestration

I calculate the change in the value of agricultural production and carbon sequestration by using the actual and projected LULC maps. Comparing the change in the total value of both carbon storage and agricultural production can show whether net benefits increased or decreased with land-use change associated with the opening of the port facility. In addition to total benefits, the distribution of net benefits also matters. Some of the benefits of increased agricultural expansion accrue locally with increased income to farmers. Carbon storage, however, generates global benefits. Unless there are payments for carbon storage there will likely be a mismatch in who benefits from agricultural expansion and who benefits from carbon storage.

I calculate the per hectare profit of planting soybeans in the S&B area by using crop price and yield data from Instituto Brasileiro de Geografia e Estatistica (IBGE 2015), and cost data for soybean production from Huerta and Martin (2002), which includes both variable and fixed costs. Given data limitations, I assume that all farms are identical, including physical characteristics and input levels, for both yields and production costs. The estimated profit per hectare from soybean production in 2004 was $336 given a soybean price of $288.5 per ton in 2004, an average yield of soybeans of 2.7 ton per hectare, and a cost of soybean production of $443 per hectare. I assume that farmers grow soybeans on land that is deforested because it is one of the four major crops in terms of hectares planted, and it has a higher value of crop production per hectare than other crops and the planted area increased dramatically in 2004 (IBGE 2015).

I calculate the change in the amount of above-ground biomass carbon using the current and counterfactual LULC maps and the average storage amount of carbon per hectare for each LULC from Baccini et al. (2012), which is shown in Table 2-5. I consider changes in biomass under the assumption that the change in the soil organic carbon is zero between current and counterfactual LULC maps. I calculate the change of carbon sequestration by estimating the area change for each classification of LULC going from original to projected LULC to be multiplied by the amount of carbon sequestered per hectare for each LULC classification.

I calculate the lost values of carbon storage and increased value of agricultural production as a result of the port facility opening by using the discount rate and social cost of carbon from the literature. The social cost of carbon is a key element in the benefit/cost analysis and has been a topic of discussion and debate among economists. I set the social cost of carbon to $40 per ton of carbon dioxide in 2014 US dollar value ($32.9 in 2004 US dollars) and set the corresponding constant discount rate to 3% from the Interagency Working Group (IWG) on the Social Cost of Carbon, released in 2013 and updated in 2015 (IWG 2015). These rates are calculated averages based on socio-economic and emission trajectories using three models: the Dynamic Integrated model of Climate and the Economy (DICE) (Nordhaus 2014), the Framework for Uncertainty, Negotiation and Distribution (FUND) (Anthoff and Toll 2013), and the Policy Analysis of the Greenhouse Effect (PAGE) (Hope 2013).

IV. Data

Land Use Land Cover

I use maps of deforestation from the Brazilian National Institute for Space Research (INPE) between 2001 and 2010 (INPE 2015) to calculate the deforestation rates in each property in the study area. The actual and counterfactual LULC maps in 2004 are constructed using the LULC map in 1999 from Lu et al. (2013) and INPE's deforested area map from 2001 to 2003 in the S&B area. I use the same six land use classifications as those in Lu et al. (2013), which are forest, savanna, other vegetation (secondary succession and plantation), agro-pasture, impervious surface, and water.

Constructing Variables

The deforestation rate, distance, and land quality variables are calculated using ArcMap software. The deforestation rate from 2001 to 2010 is calculated as the percentage of deforested area over the remaining forest cover in each property in a given year. The remaining forest cover is used to calculate the deforestation rate to give a relatively higher deforestation rate for the properties with less remaining forest cover. The distances to the soybean unloading facility and to the major road variables are calculated as the shortest Euclidean distance between a point or a line and an edge of a property. The location of the port is identified as a point using spatial coordinates and road shape files downloaded from Brazilian Agricultural Research Corporation (Embrapa 2013). The land quality variable is calculated for each property by using area weighted average of agricultural aptitude in each property. The original data were downloaded from Embrapa (Embrapa 2013). The definition and statistics of each variable used in the model are given in Table 2-1.

Control and Treatment Groups

The property boundary data of the control and treatment groups come from two sources: SIMLAM system (SEMA 2012), which is the Environmental Registry System (CAR) of the Pará State Environmental Agency (SEMA) and the Responsible Soy Project, which is a joint collaboration between Cargill and The Nature Conservancy (TNC). I downloaded all available property boundaries from CAR. CAR was a voluntary property registration system of the state government before the change in the Forest Code in 2012. Currently, every farmer is required to be registered in the CAR. Although not all properties in the region of S&B have been registered in the system, it is the only publicly available data for most properties. I also use property boundary data from the Responsible Soy project that was started in 2005 by Cargill and TNC to prevent increased deforestation as a result of the soybean export facility opening in the region. Through the project TNC recorded the property boundary of all properties registered with the project to monitor deforestation in each property. Combining all properties in both data sets, the total number of properties is 529.

The area of all properties in the data set does not represent all properties in the S&B region, but it is equivalent to about half of the total area of agricultural establishments in S&B region. The total area of all properties in the data set is 178,273 ha, while the total area of agricultural establishments was 353,840 ha in S&B (IBGE 2006). The properties in the data set might represent a mix of commercial farmers and farmers that are more environmentally conscious. The properties from TNC's data might represent a group of producers that are more commercial as opposed to being subsistent because they are selling their products to Cargill. The properties from the CAR data set might represent a group of producers that are more conscious about the environment. Therefore, the combined data set represents both potentially high deforesting and low deforesting producers.

V. Results

The main question of interest is how the opening of the new soybean export facility has changed deforestation in the S&B area and the resulting impact of LULC change on the value of agricultural production and carbon sequestration. In this section, I first present the results from two regressions on the impact of the opening of the port facility on deforestation. Then I present estimates of the monetary benefits and costs that have been incurred from the port facility opening.

Evidence from Empirical Models

The year specific effect and DID regressions both suggest that there was a positive and significant impact of the opening of the port facility on deforestation(Table 2-2 and 2-3). Table 2-2 from the year specific effect regression shows that there was a large increase in the deforestation rate in 2003 and 2004 after the port opened in 2003. The year alone effects excluding interaction terms' effects in the second column suggest that the year alone effects on deforestation rates during 2003 (8.8%) and 2004 (15.3%) were the highest among all the years. In 2005 the deforestation rate was not statistically significant while it becomes statistically significant again in 2006 and 2007. The calculated average year specific effect in the third column shows a similar trend, with high deforestation rates in 2003 (5%) and 2004 (12.3%) compared to other years. It is notable that the values of the average year specific effect for the years 2003 and 2004 are more than twice those of any other years. The interaction effect of the year dummies and the distance to soybean unloading facility variable shows that it has negative and significant effect on deforestation, which means that the properties closer to the soybean unloading facility tend to have higher deforestation rates. The land quality variables are not significant in most of the years.

The positive year-specific effects in 2003 and 2004 and the absence of a statistically significant effect of year on deforestation in 2005 suggest a deforestation-increasing effect of the port facility opening in 2003. It is likely that farmers increased deforestation in their properties to increase soybean production around the year 2003, when the port facility opened. The lower effects in following years might reflect mixed effects of increased governmental enforcement of environmental regulations and a diminishing impact of the port facility opening as time progresses.

The DID estimation results using control and treatment groups from Table 2-3 indicate that the opening of the new soybean export facility increased deforestation in the treatment group by 5.5% in 2003 and 11.7% in 2004. Table 2-3 shows the average marginal effect of port opening on deforestation by comparing control and treatment groups using data between 2001 and 2010. The year specific effects for the control group indicate no significant effects in all years, while the treatment group had higher deforestation rates compared to the control group in 2002-2004, 2006, and 2009. Similar to the results shown in Table 2-2, the deforestation rates in the treatment group were the highest in 2003 (5.5%) and 2004 (11.7%) and the significant effect of the year disappears in 2005. The effects of physical characteristics also show that closer proximity to a major road and higher land quality are associated with higher deforestation rates.

The high deforestation rates in the treatment group in 2003 and 2004 compared to those in the control group are distinct from any other years between 2002 and 2010. The rates of difference between control and treatment groups in 2003 (5.5%) and 2004 (11.7%) are 89% and 303% higher than the third highest difference in deforestation rates between the control and treatment groups, that for 2006 (2.9%). These significantly high differences in deforestation rates between control and treatment groups, along with no significant difference between them in 2005 is credible evidence of the port facility opening's immediate impact on deforestation.

To check the robustness of the results, I change the threshold value that divides properties into control and treatment groups. The results, shown in Table 2-4, suggest that the change of the value of the threshold variable (distance to the soybean unloading facility) that defines the treatment and control groups does not affect the positive and significant impact of the port opening on deforestation in 2003 and 2004. The magnitude of the coefficient changes slightly, but there is not much variation in the coefficients of the impacts of the port facility both in 2003 and 2004 as the threshold value changes. The change of the threshold by 5 km from between 70 km and 90 km changes the values less than 10% from 5.2% to 5.6% and 11.1% to 11.8% for the impacts in 2003 and 2004, respectively. Further change in the values down to 60 km or up to 100 km changes the value a little more than the changes within the 70 km to 90 km range, but the values are still less than 20% of the values from the middle value at the 80 km threshold. This means that the impact of the port opening on deforestation is robust to changes in the threshold value.

Change in LULC

Using the regression results from the empirical models, I predict the amount of forest land that would exist in the counter-factual case without the port. The total area of forest in the treatment group was 99,010 ha and 93,594 ha in 2003 and in 2004, respectively. The area that was deforested as a result of the port facility opening is 16,369 ha calculated as the sum of 5.5% (5,421 ha) of the total forested areas in 2003 and 11.7% (10,948 ha) of total forested areas in 2004. I reforest those deforested areas in each property until the sum of the predicted area of deforestation becomes 16,369 ha. The counter-factual case map in 2003 and 2004 are combined with the LULC map of 1999 along with deforested areas in 2001 and 2002 to construct an original map with the port facility opening and a counter-factual map without it. Figure 2-4 shows an example from original and counter-factual LULC maps.

The conversion reveals that total area of 8,359 ha, which is composed of 5,874 ha of primary forest and 2,486 ha of secondary forest, had been converted to Agropasture as a result of the port facility opening. Table 2-5 shows calculated areas of each LULC map between original map and projected LULC map without the port facility opening.

Tradeoffs Between Agricultural Production and Carbon Sequestration

The comparison between the total increased value of agricultural production and the value of released carbon differs depending on the discount rate that is used. Table 2-6 shows how agricultural production and carbon values compare to each other using a 3%

discount rate. The per year profit from soybean production is \$335.95/ha. Assuming an infinite stream of benefits using the discount rate of 3% makes the profit from soybean production \$11,198/ha. Multiplying the total area converted to agropasture and the infinite stream of profit per hectare yields a total gained value of agricultural production of \$93,606,868. The table also shows that 770,438 tons of carbon had been lost due to the conversion from forest and other vegetation to agropasture land after the port facility opening. Using 3% discount rate, a social cost of carbon in 2015 from the IWG estimate is \$120.8 per ton of carbon in 2004 US dollars (\$32.9 per ton of carbon dioxide). Using this value makes the total lost value of carbon \$122,369,979, which makes the dollar value of released carbon greater than the gained value of agricultural production.

Using a 5% discount rate makes the value of agricultural production higher than the value of carbon. Using a 5% discount rate changes the infinite stream of gained value of agricultural production to \$56,164,121, while social cost of carbon changes to \$36.2 per ton of carbon in 2004 US dollars using the estimates by IWG. This makes the lost value of carbon \$36,710,994.

The break-even price of carbon that can compensate farmers for their loss of agricultural production under an infinite stream of profit would be \$92.4 and \$55.4 per ton of carbon, assuming 3% and 5% discount rates, respectively. The current social cost of carbon estimates from IWG is higher when using the 3% discount rate (\$120.8) while it is lower when using the 5% discount rate (\$36.2) in 2004 US dollars. The current social cost of carbon may not outweigh the lost value of agricultural production, depending on the discount rate used in the northern Brazilian Amazon. The high cost of carbon in the Amazon area is consistent with other recent studies, which indicate a high value of carbon in the Amazon (Johnston et al. 2014; O’Connell et al. 2015).

The quantitative estimates of agricultural production and carbon values provide information on the increased income of farmers and on the lost value of carbon due to increased agricultural production within the deforested area. The results showed that the values are comparable to each other and that the break-even price of carbon is lower than the estimated social cost of carbon at a 3% discounting rate but higher than that at a 5%

discount rate. These results imply that the net benefit of expanding soybean production in the Amazon is close to the value of released carbon, and one would have to pay the break-even prices that are comparable to the social cost of carbon estimates from IWG to keep farmers from clearing land.

VI. Discussion

Land use planning requires estimation of the impacts of alternative land uses and the resulting tradeoffs among different ecosystem services to be able to find the best land use that maximizes net benefits from conservation and development. In this paper, I measured the impact of the opening of a new soybean export facility on deforestation and resulting tradeoffs between agricultural production and carbon sequestration in the S&B region, located in the northern Brazilian Amazon.

The results showed that the opening of the new soybean export facility increased average deforestation rates by 5.5% and 11.7% in 2003 and 2004, respectively, which implies a 16,369 ha conversion of forest land into agricultural land. It increased the income of local farmers from additional agricultural profit but released significant amounts of carbon into the atmosphere. Overall, the increased value in agricultural production is approximately equal to the lost value of carbon, although the comparison between them varies depending on the discount rate used for the calculation. The break-even price of carbon for farmers to forgo their agricultural profit in the study area is estimated to be $92.4 and $55.4 per ton of carbon, assuming 3% and 5% discount rates, respectively.

These quantitative estimates of the change in deforestation rates and of the tradeoff values between agricultural production and carbon sequestration provide useful information about whether the impact of the new soybean export facility opening in the S&B area has increased net value. The increased in agricultural income shows that there is an increase in net benefits locally. This result is beneficial given high poverty rates in the area. The poverty rates were 43.1% and 28.4% in 2003 in the municipalities of

Santerém and Belterra, respectively (IBGE 2006). Even though the net benefit overall from the opening of the port facility is close zero when carbon losses are factored in, the opening of the port facility may be justified because it provided an additional income source for local people many of whom are poor.

On the other hand, an argument against the opening of the port facility can be made because of the significant volume of lost carbon that has a value that may well exceed the value of increased agricultural production. Carbon sequestration is a global public good. In addition to carbon losses, agricultural expansion may result in declines in other ecosystem services, such as water quality. Considerations of other ecosystem services will likely increase the loss in value of ecosystem services and make it more likely to outweigh the increased value of agricultural production.

If we assume that the port facility needs to be built in the area to generate additional income opportunities for the poor local people, society would want to maximize net benefits from ecosystem services including agricultural production, carbon sequestration, and others such as water purification. An efficient land use planning that maximizes the net value of ecosystem services prior to the opening of the port facility would require more spatially explicit information. This study was restricted to do the analysis at a municipality level because the information on carbon storage and agricultural production such as the price of crops, yields, and production costs are based on simple assumptions and are not spatially explicit. Further, detailed data on actual carbon storage per pixel by LULC in this region, variation of yields, and costs of producing different crops would make it possible to plan land use in a way that maximizes the net values of ecosystem services. It will identify areas with high values of ecosystem services and enable targeted development and conservation strategies for efficient use of land.

With increasing concerns for degrading the environment and its impact on ecosystem services, it is becoming more important to quantitatively measure the impact of economic development on values of ecosystem services to reflect them in the future land-use decisions. Despite some caveats such as coarse spatial resolution of the data, this study shows how one can measure the impact of new economic incentives on the environment and the resulting tradeoff between carbon storage and agricultural production. This type of impact assessment and quantification of tradeoffs would be helpful for similar land use planning decisions in the Amazon. It will ultimately help in generating higher net gains from new land use decisions by applying/modifying methods presented in this study and by using spatially explicit data during the planning process.

Table 2-1.Variable descriptions, means, and standard deviations (S.D.)

Variable	Description	Mean (S.D.) Control N=52	Mean (S.D.) Treat N=477	Mean (S.D.) Total N=529
Deforestation rate in each year between 2001 and 2010 (%)	The percentage of deforested area over remaining forest cover	1.34 (4.84)	3.51 (13.66)	3.30 (13.07)
Distance to the soybean unloading facility (km)	Euclidean distance from a property to Cargill's soybean delivery facility	92.11 (10.86)	41.52 (15.80)	46.49 (21.52)
Distance to a major road (km)	Euclidean distance from a property to the nearest federal or state road	7.53 (8.47)	4.14 (4.98)	4.47 (5.50)
Land quality	Area-weighted land quality based on the classification of Ramalho and Pereira (1995). Scores range from 0 (no production capability) to 7 (most productive soil)	5.75 (1.58)	5.15 (1.91)	5.21 (1.89)

Table 2-2. Regression results for the year specific effects on deforestation

Variables	Coefficient (Standard error)	Average year specific effects (Standard error)
Average individual fixed effect	0.84*** (0.27)	
Year Specific Effects		
T_{2002}	3.61*** (1.08)	
T_{2002} × Dist. to soy unloading place	-0.04*** (0.01)	0.86** (0.40)
T_{2002} × Land quality	-0.21 (0.18)	
T_{2003}	8.82*** (1.91)	
T_{2003} × Dist. to soy unloading facility	-0.15*** (0.03)	4.96*** (0.65)
T_{2003} × Land quality	0.60 (0.31)	
T_{2004}	15.30*** (2.74)	
T_{2004} × Dist. to soy unloading facility	-0.36*** (0.04)	12.27*** (1.10)
T_{2004} × Land quality	2.65*** (0.49)	
T_{2005}	-0.01 (0.96)	
T_{2005} × Dist. to soy unloading facility	-0.02 (0.02)	1.03** (0.47)
T_{2005} × Land quality	0.34 (0.22)	
T_{2006}	7.49*** (1.95)	
T_{2006} × Dist. to soy unloading facility	-0.09*** (0.02)	2.28*** (0.62)
T_{2006} × Land quality	-0.17 (0.29)	
T_{2007}	3.39** (1.43)	
T_{2007} × Dist. to soy unloading facility	-0.02** (0.01)	0.68 (0.43)
T_{2007} × Land quality	-0.31 (0.21)	
T_{2008}	2.92* (1.53)	
T_{2008} × Dist. to soy unloading facility	-0.04** (0.02)	1.06** (0.46)
T_{2008} × Land quality	0.03 (0.26)	
T_{2009}	2.89*** (1.07)	
T_{2009} × Dist. to soy unloading facility	-0.06*** (0.02)	1.33*** (0.51)
T_{2009} × Land quality	0.27 (0.22)	
T_{2010}	1.55* (0.92)	
T_{2010} × Dist. to soy unloading facility	-0.03*** (0.01)	0.14 (0.36)
T_{2010} × Land quality	0.01 (0.18)	

***, **, and * indicate 1%, 5%, and 10% level of significance, using standard errors adjusted for individual property. Standard errors for the average year specific effects were calculated using the delta method.

Table 2-3. Average marginal effects of the port opening on deforestation using data from 2001 and 2004

Variables	Equation (2) Coefficient (Standard error)	
Treat	-0.06	(0.56)
Year Specific Effects – Control group		
T_{2002}	-0.51	(0.36)
T_{2003}	0.02	(0.52)
T_{2004}	1.72	(1.19)
T_{2005}	1.54	(1.38)
T_{2006}	-0.32	(0.47)
T_{2007}	0.58	(0.82)
T_{2008}	1.11	(0.84)
T_{2009}	-0.31	(0.56)
T_{2010}	-0.35	(0.62)
Year Specific Effects – Treatment group		
T_{2002}	1.52***	(0.57)
T_{2003}	5.48***	(0.90)
T_{2004}	11.70***	(1.76)
T_{2005}	-0.57	(1.47)
T_{2006}	2.90***	(0.83)
T_{2007}	0.12	(0.94)
T_{2008}	-0.06	(0.98)
T_{2009}	1.83**	(0.80)
T_{2010}	0.55	(0.73)
Physical Characteristics (X_i)		
Distance to a major road	-0.07***	(0.03)
Land quality	0.58***	(0.10)

***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. Standard errors are calculated using the delta method.

Table 2-4. The sensitivity of the port facility opening effect by different distance threshold that is used to distinguish control and treatment groups

	Port Facility Opening Effect – treatment group	
Distance to the soybean delivery facility (km)	T_{2003}	T_{2004}
60	6.06***	14.13***
	(1.02)	(1.79)
65	5.07***	12.49***
	(1.01)	(1.88)
70	5.19***	11.80***
	(1.02)	(1.97)
75	5.55***	11.21***
	(1.06)	(2.21)
80	5.48***	11.70***
	(0.90)	(1.76)
85	5.16***	11.65***
	(1.07)	(2.16)
90	5.58***	11.11***
	(1.26)	(2.74)
95	5.08***	12.18***
	(1.49)	(2.07)
100	4.45**	11.37***
	(1.80)	(2.46)

***, **, and * indicate 1%, 5%, and 10% level of significance, respectively. Standard errors are calculated using the delta method.

Table 2-5. The land use and land cover (LULC) composition in 1999 and change in LULC with and without port facility opening in 2004 and the amount of carbon storage in each land use and land cover (LULC) classification

LULC	1999	2004	2004 -No port facility	Increase
Agropasture (ha)	82,438	110,843	102,483	-8,359
Forest (ha)	922,569	899,140	905,014	5,874
Impervious Surfaces (ha)	9,207	9,207	9,207	0
Other Vegetation (ha)	167,531	162,622	165,108	2,486
Savanna/Cerrado (ha)	5,149	5,081	5,080	0
Water (ha)	20,870	20,870	20,870	0

Table 2-6. The amount of carbon sequestration in each land use and land cover (LULC) classification and the value of carbon and soybean production change as a result of port facility opening

LULC	Area (ha)	Carbon Storage[a] (ton/ha)	Total Carbon Storage (ton)	Total Carbon Storage Value[b] ($)	Agricultural Value[c] ($)
Agropasture	8,359	29	242,425		93,606,868
Forest	-5,874	139	-816,478	-122,369,979	
Other Vegetation	-2,486	79	-196,385		

[a] Baccini et al. 2012

[b] Assuming $120.8 per ton of carbon value in 2004 US dollars (IWG 2015)

[c] Assuming $335.95 per hectare of profit from soybean production (Huerta and Martin 2002; IBGE 2015)

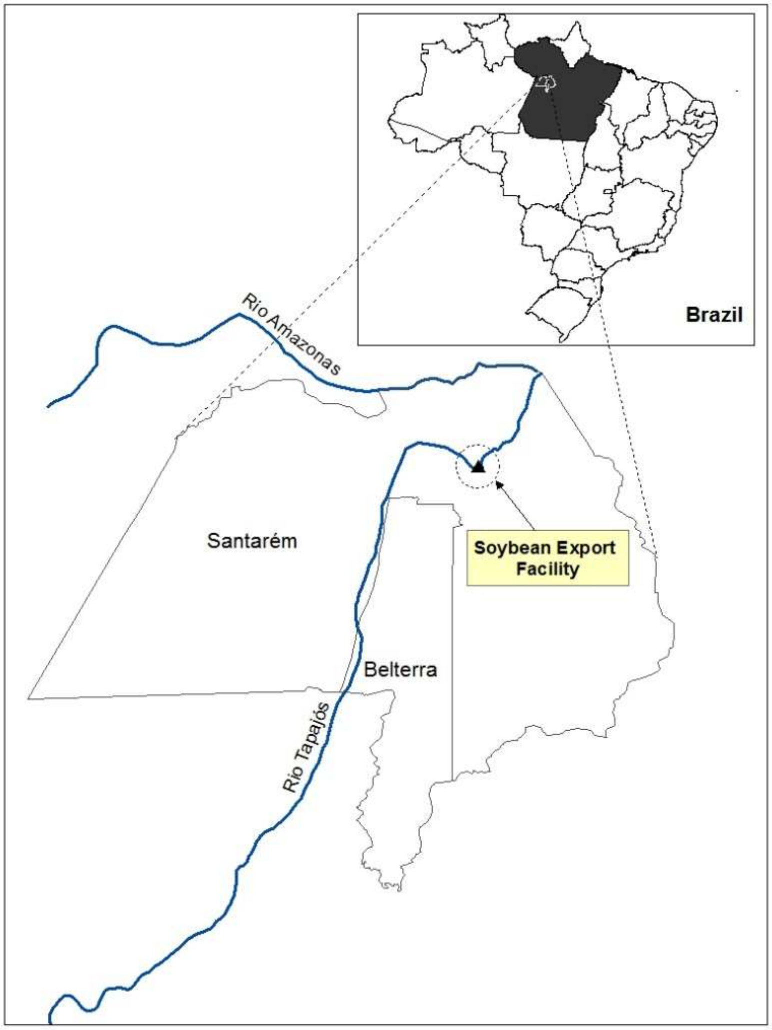
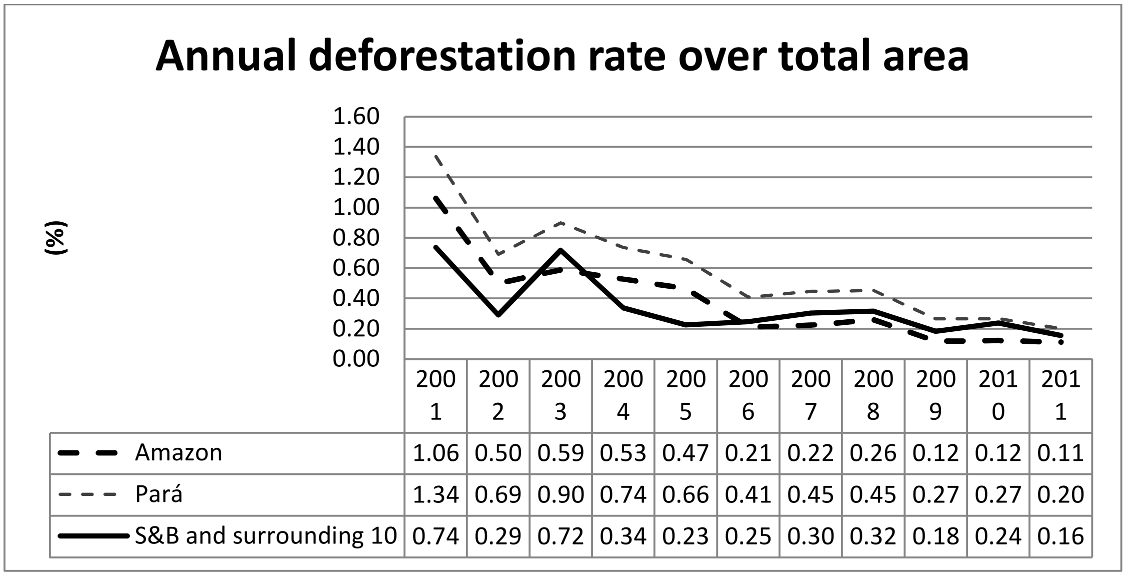


Figure 2-1. The location of Cargill soybean export facility in Santarém near the confluence of the Amazon and Tapajos Rivers in northern Brazil



	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011
Amazon	1.06	0.50	0.59	0.53	0.47	0.21	0.22	0.26	0.12	0.12	0.11
Pará	1.34	0.69	0.90	0.74	0.66	0.41	0.45	0.45	0.27	0.27	0.20
S&B and surrounding 10	0.74	0.29	0.72	0.34	0.23	0.25	0.30	0.32	0.18	0.24	0.16

Figure 2-2. Comparison of the annual percentage of deforested land over the remaining forest area in Amazon, Pará, Santarém and Belterra (S&B) and surrounding 10 municipalities

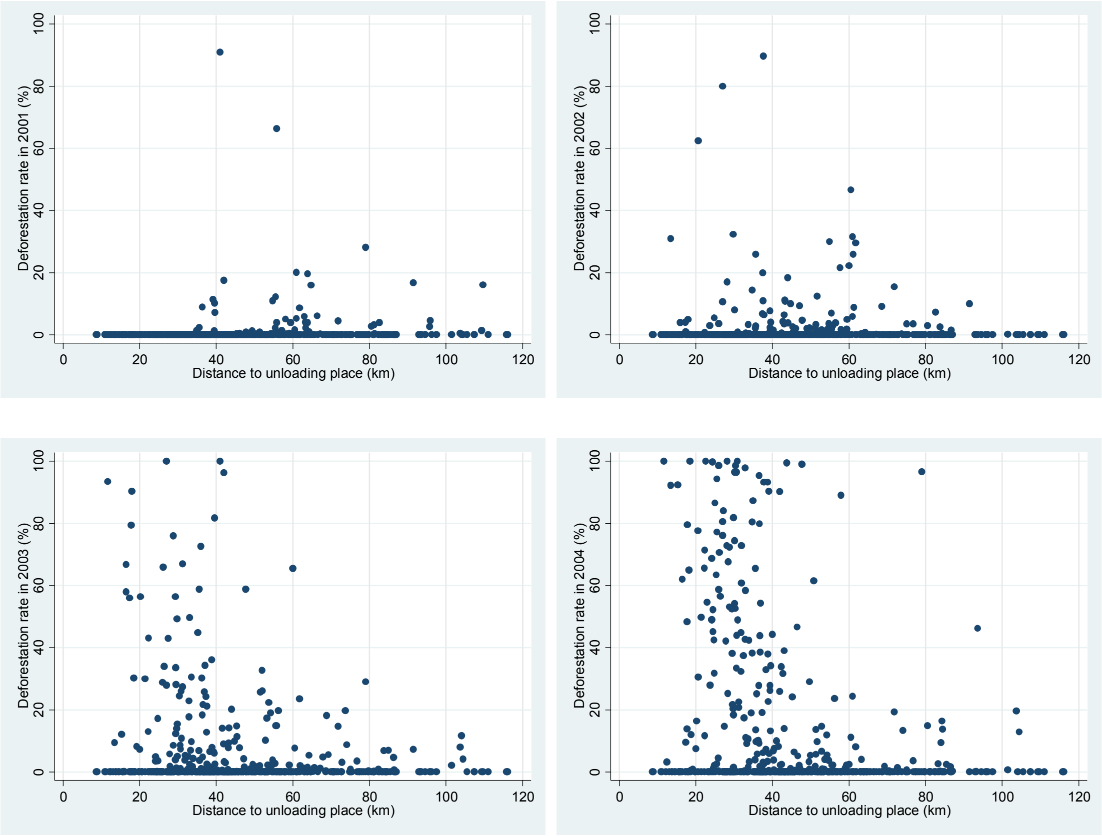


Figure 2-3. Scatter plots of each property's percentage of deforestation by distance to the soybean unloading facility place from 2001 to 2004

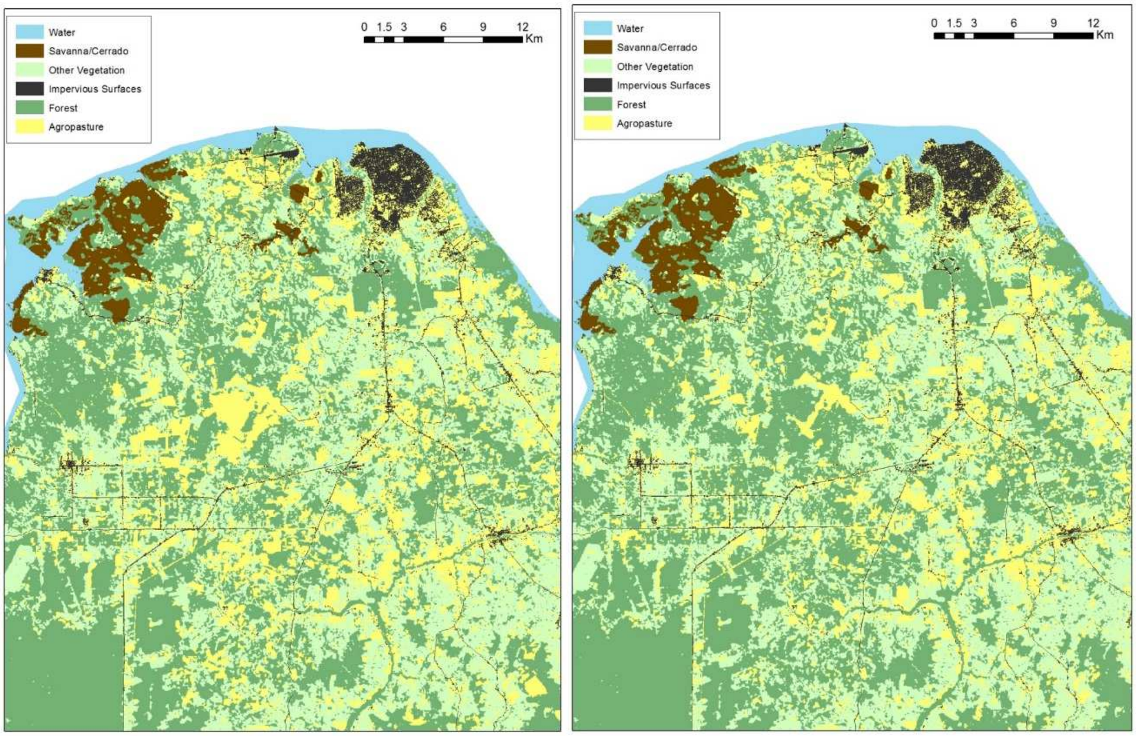


Figure 2-4. Original LULC (left) and projected LULC without opening of a new soybean export facility in 2004

Chapter 3. Global Agricultural Production Cost: A Missing Component in Calculating Economic Rent for Land-Use Decisions

I. Introduction

Land use affects the provision of many goods and services including the production of marketed commodities and non-marketed ecosystem services. Conversion of forest into agricultural land increases agricultural production that can help feed increasing populations but also releases carbon into the atmosphere that contributes to climate change. In order to efficiently manage land and to increase the net value of the provision of food and other ecosystem services, information is needed on all benefits and costs of alternative land uses. Failure to obtain such information will lead to land-use decisions that will generate inefficient results.

Economic rent (profit) from crop production is an important determinant of land use. In addition, estimates of economic rent from crop production are necessary for calculating the opportunity cost of taking land out of crop production and putting it to other land uses such as protected areas or urban development. Economic rent per unit area of crop production is equal to revenue from crop production (price x yield per unit area) minus production cost (per unit area). Despite the fact that 38% of total land area in the world is used for agricultural production (FAOSTAT 2015), no globally consistent data set exists for production cost. Globally consistent data do exist for prices and yields. Providing data on agricultural production costs, therefore, fills an important gap and allows for the generation of a globally consistent data set on economic rent from agricultural production. Consideration of such economic rents is a necessary component for analyzing the full costs and benefits of various land-use scenarios and, ideally, will lead to more efficient land-use decisions.

In this study, I construct a globally consistent production cost data set for ten major crops. I construct the data set in each country by piecing together data on particular components of costs from a number of existing global data sets such as FAOSTAT, which is compiled by the Food and Agriculture Organization (FAO). When there are no existing global data sets available for a particular cost item, I use data sets from individual countries (e.g., production cost data in the US published by the US Department of Agriculture) and adjust for differences in various factors such as labor productivity, unit prices of inputs, and yields. After constructing the data set, I validate the constructed production cost data set by comparing constructed wheat production cost data and wheat production cost data from the International Wheat and Maize Improvement Center (CIMMYT) and the Farm Accounting Data Network (FADN) of the European Commission. Then, I show how much difference it makes to include production costs when calculating economic rent compared to using only revenue, which has been used as an alternative to profit.

In the production economics literature, there are many global-scale agricultural productivity comparison studies that utilize some agricultural input price and quantity information (e.g., Alston et al. 2009; Avila and Evenson 2010; Coelli and Rao 2005; Hayami and Ruttan 1985; O'Gorman and Pardey 2010). However, none of these studies provide crop-specific globally consistent production cost estimates. For example, Avila and Evenson (2010) compute total factor productivity growth in developing countries by calculating input and output growth rates and input cost shares to investigate the factors that cause productivity growth. They calculate input cost shares for the whole agricultural sector (i.e. not crop specific) in developing countries. They use national data on input cost shares from Brazil and India and adjust this for other countries by using input quantity to crop land ratios in each country relative to those in Brazil and India. There are many local level productivity or profitability analyses providing production cost data for some crops (e.g., Ajayi et al. 2009 in Zambia; Jin et al. 2010 in China; Singh et al. 2013 in India). However, the definitions of the costs differ across studies and the geographic coverage of each study is limited, so these studies are of limited use in a assembling a consistent profit comparison at a global scale.

As a result of the lack of a globally consistent agricultural production cost data, many local and global land-use studies have used revenue as a measure of economic rent. Naidoo and Iwamura (2007) constructed a global map of economic rent using revenue while ignoring production cost. Many subsequent studies (e.g., Busch et al. 2012; McCarthy et al. 2012; Wedland et al. 2010; Wünscher et al. 2008) have used their data set as an approximation of the opportunity cost of land. For example, McCarthy et al. (2012) used the data set as a proxy for the cost of compensation for land preservation to reduce extinction risk of certain bird species on a global scale. Wedland et al. (2010) extracted the Madagascar data from Naidoo and Iwamura (2007) and used it to identify areas where a payment for ecosystem services (PES) scheme would increase net benefits taking into consideration biodiversity, carbon, and water services in Madagascar. Using revenue as an estimate of the opportunity cost of land assumes that there is no cost of production and ignores spatial variation in socioeconomic factors.

There have been other efforts to provide guidelines for constructing standardized global agricultural production costs, but none provides actual cost data on a global scale. The *Handbook on Agricultural Cost of Production Statistics* by the FAO (2014) is the most recent initiative to provide guidelines for designing and implementing standardized cost of production data. The handbook provides recommendations for methods to collect production cost data using experiences from countries that already have national systems to collect them. There are other similar guidelines such as *Commodity Costs and Returns Estimation Handbook* by AAEA (2000) and the *Sustainability and Production Costs in the Global Farming Sector* by the European Commission (2012). They provide methodologies and possible data sources for production costs but do not provide actual crop production cost data that are globally consistent.

Another group that focuses on collecting standardized cost of agricultural production is Agri Benchmark. It is an organization of various institutions and individuals that has a network of agricultural economists and producer groups around the world that aims to construct an internationally standardized agricultural production data set. As of June 2014, they have ongoing research to cover multiple cash crops in two countries in Africa, six countries in Asia, eight countries in Europe, two countries in North America, and three countries in Latin America. Much of their data are not publicly available and they do not cover all regions of the world.

In what follows, I describe the data sources, assumptions, and methods I used to develop a globally consistent data set of agricultural production costs. I then summarize the results by showing regional weighted averages of production costs for each crop, provided in the Appendix.

I compare wheat production cost from the constructed data set to data from the International Maize and Wheat Improvement Center (CIMMYT) to check on the validity of the constructed data. I find some significant differences (greater or less than 50% of the constructed values) in the comparison of the regional average wheat production cost with the CIMMYT data. The significant differences in regional average wheat production cost between the constructed data set and CIMMYT data set exist in 4 out of 11 regions for fertilizer costs, 4 out of 10 regions for labor costs, 1 out of 7 regions machinery costs, and 7 out of 13 regions for seed costs. The results from validation of the constructed cost data set using methods in this paper indicate that the regional weighted average values of wheat production cost match with those of other data sets relatively better than the individual country values. At a country level, significant differences exist in 8 out of 21 for fertilizer costs, 8 out of 14 for labor costs, 4 out of 14 for machinery costs, and 18 out of 31 countries for seed costs.

Lastly, using the wheat production cost data, I show how much difference it makes to use profit instead of revenue to estimate economic rent. The comparison of revenue and profit maps from wheat production suggests not only that some areas with high revenue appear to have negative profit values but also that the regions with high economic rent per hectare change significantly when using profit instead of revenue as a measurement of economic rent. For example, the central U.S., many European countries, and most of western China have high revenues from wheat production but profit is negative in these regions because of high production costs[4]. The results also show that regions with high profits from wheat production match areas with a high fraction of wheat harvested area over total area better than the areas with high revenue. The major

---

[4] Central US' profit is negative without consideration of distortion factors such as subsidies from the government, which are covered in the "Discussion" section.

countries that produce wheat include India, eastern China, and the western U.S. These regions show higher profits from wheat production compared to other regions, while the revenue map does not differentiate these regions as having higher revenue compared to other regions. These results further validate the constructed cost data.

These results suggest potential problems in using revenue as a proxy for economic rent. Using revenue as a proxy for economic rent overestimates the value of agricultural returns, which effectively underweights the value of other ecosystem services such as carbon sequestration. Using revenue as a proxy for economic rent may also result in a distorted picture of where agriculture should be a priority and where conservation should be a priority.

II. Construction of the Global Production Cost Data

The constructed data set on production costs includes the costs for fertilizer, labor, machinery, and seed. I define production costs per hectare as the amount of the input required per hectare times the unit cost of the input. For example, fertilizer cost is the sum over all types of fertilizer of the amount of a specific type of fertilizer applied per hectare times the cost per unit of that specific fertilizer. I calculate crop-specific per hectare production cost for 10 major crops: barley, maize, potato, rapeseed, rice, rye, soybean, sugar beet, sunflower, and wheat. Further, I define cost for three different production intensity levels: actual, low intensity, and high intensity production.

It should be noted at the outset that this is a first attempt to provide a uniform global data set for agricultural production cost. The numbers reported here should be viewed as providing a rough approximation of production costs rather than precise estimates. I have been forced to make a number of assumptions because of the limited data that are globally available. Better estimates of production cost can be done in particular countries (e.g., the U.S.) where more data are readily available. I have ignored a number of details that may be quite important in determining production costs for particular crops in particular regions. It is my hope that by putting together these numbers in a clear and transparent fashion I will make it easier for others to improve upon my efforts.

Data Sources

While good production cost data exist for some individual countries (e.g., production cost data in the US published by the Economic Research Service (ERS) of the US Department of Agriculture (USDA)), uniform cost data across all countries do not exist. Here I calculate production costs for all countries constructed by piecing together data on particular components of cost from a number of existing global data sets. To build a uniform global data set on agricultural production cost I use data in FAOSTAT compiled by the Food and Agriculture Organization (FAO) of the United Nations (UN), the International Labor Organization (ILO), the World Bank, the U.S. National Bureau of Economic Research (NBER), ERS of the USDA, the International Seed Federation (ISF), and several other country and sub-national statistics. In Table 3-1 I provide a brief description of the data available on input unit costs and input amounts used per hectare for each major component of cost: fertilizer, labor, machinery, and seed. For some inputs, namely machinery and seed, I have cost data that combine unit cost and quantity rather than data on unit cost and quantity separately.

General Methods

Unit cost conversion method

I adjust all unit costs both temporally and spatially to convert nominal unit costs in a given year measured in local currency to 2010 US dollars. To convert unit costs in a given year to 2010 unit costs in local currency I use the GDP deflator for each country from the World Bank (World Bank 2012a). I then convert 2010 local currency to 2010 US dollars using Purchasing Power Parity (PPP) from the World Bank (2012b). PPP conversion has advantages relative to actual exchange rates because it increases the comparability among unit costs in different countries (Alston et al. 2009; Pardey et al. 1992). The unit cost is calculated as follows:

$$P_k^i = LC_{kt}^i \left(\frac{1}{Def_t^i}\right)\frac{1}{PPP^i} \tag{1}$$

where P_k^i is the unit cost of item k in country i in 2010 US dollars; LC_{kt}^i denotes unit cost of item k in country i in year t in local currency unit (LC); Def_t^i is the GDP deflator of country i with the base year of GDP deflator in 2010 being normalized to 1; PPP^i is the PPP conversion factor (LCU per US dollar) of country i in 2010. I adjusted deflation factors for individual countries that underwent currency reform using the notes from FAO (FAO 2013).

If unit costs are not available in local currency units but are available in US dollars, I convert US dollar units back to the local currency units, use the GDP deflator for the local currency to convert to 2010 values in the local currency, and then convert this back to US dollars. Import prices of machines in my data set are available only in US dollar units. This exercise has been done in order to consistently apply equation (1) for all cost items.

Exclusion of outliers

After conversion of all unit costs into 2010 US dollars I exclude outlier observations. It is important to exclude outliers for two reasons. First, there are some values that differ by two orders of magnitude or more compared to values in other years. These values are likely to reflect errors in recording the data rather than actual cost differences. For example, the per unit import price of a combine harvester in Denmark in 2009 is \$8 while other years' values range from \$80,000 to \$150,000 from 2002 to 2008. Second, some countries experienced rapid changes in the value of their currency during this time period. In some cases, the timing of currency changes within a country reflected in the GDP deflator from the World Bank, or in the exchange rate from IMF, does not match precisely with that reflected in the FAOSTAT data set.

I use median absolute deviation (MAD) to set a threshold to detect outliers. MAD measures how far a value is from the median of a series of values. It is used widely for the detection of outliers because of its simplicity and robustness (Rousseeuw and Croux

1993). It is easy to calculate and more robust to outliers than using standard deviations from the mean because the presence of outliers significantly affects the value of standard deviations from the mean. An observation (p_t^i) is removed if the following condition holds:

$$\frac{\left|p_k^i - median\left(P_K^i\right)\right|}{\sigma} > 2, \tag{2}$$

$$\sigma = 1.4826 \times MAD = 1.4826 \ \times median\left(\left|p_k^i - median\left(P_K^i\right)\right|\right)$$

where p_k^i is the unit cost of fertilizer, labor, machine, or seed in country *i* in 2010 US dollars and P_K^i is a set of all available unit costs in country *i*. The value 1.4826 is the constant scale factor for the *MAD* to be a consistent estimator of the standard deviation under the assumption of a normal distribution. It is standard practice to use values of 2 or 3 for determining the threshold for outliers. I chose to use 2 as the cutoff value. I report in each cost section how many observations have been excluded. I also report how many observations would have been excluded if I had used 3 as a cutoff value. Additional exclusion of observations of extreme values is done as explained in each cost item section.

Averaging time series data for a country

I provide one average per unit cost for each country for each input instead of providing year specific numbers for each year in the data set. I also do not predict the values using either interpolation or forecast methods. This is because I want to use the same method for all cost items, and some data, such as fertilizer unit costs, are too sparse to interpolate or to predict for the purpose of providing consistent estimates for each year.

After conversion to 2010 US dollars and excluding inconsistent unit costs for each country, I use the average of the most recently available five years' data for a given country, where the number of observations in each country should be greater than or equal to two. Averaging across multiple years makes the reported data less susceptible to errors introduced in any given year. Averaging the most recent data makes the data more current and more reliable because there is less chance of currency devaluations in recent years than there was in the early 1990s.

Detailed country specific data

I collect and use detailed country specific data if such globally consistent data are available. However, some data are not available for some countries in all years. For example, crop specific labor use hours, machinery, or seed costs are available in the US but not in most other countries. When this is the case, I use detailed information from the US but adjust it for differences in various factors such as unit costs, applications differences in yields, number of growing days, and agricultural productivity.

The countries or regions with zero observation even after adjustment using US data because of missing adjustment factors are filled using a weighted regional average value described in the following section.

Weighted average by geographic region

Data for individual countries often have significant variability and may be subject to a high degree of error. Therefore, I grouped countries into regions to increase the reliability of the calculated cost numbers. Regional averages are calculated as a weighted average of cost using total agricultural production value in each country as the weight. I used 19 geographic regions defined by FAO (FAOSTAT 2011a).

Production intensity

I define three production intensity levels: actual, low intensity, and high intensity. I use different fertilizer input, machinery cost, and seed cost for each intensity level. In future research I hope to consider different input levels for labor as well.

Fertilizer input and corresponding yield data are from Mueller et al. (2012). Actual fertilizer input is defined as fertilizer quantity that is currently in use in each country. Mueller et al. (2012) divided the world into 100 climate bins using precipitation and growing degree-day characteristics. Low intensity production and high intensity production fertilizer input are defined as fertilizer quantities that are required to produce 25% and 75% of maximum yield in the climate bin, respectively.

I assume that low intensity agriculture does not use machinery, so that machinery cost for low intensity production is zero. Machinery cost for high and actual intensity agriculture is calculated by adjusting per hectare US machinery cost data. A similar procedure is applied to the calculation of seed cost for each intensity level. The details on how high, actual, and low intensity machinery and seed costs are calculated are explained in detail in the following section “Cost Calculation Methods.”

Cost Calculation Methods

Fertilizer Cost

Fertilizer unit cost ($/ton)

I use the most recently available years of data between 1991 and 2002, to construct the fertilizer unit cost data (FAOSTAT 2011b). There are no updates of the data after 2002. Fertilizer unit cost is measured as the average price per metric ton of nutrients, nitrogen (N), phosphate (P), and potassium (K), in each region. I chose the top two most frequently available fertilizer items from the FAO fertilizer price archive data set: ammonium sulfate and urea for nitrogenous fertilizer; concentrated superphosphate and single superphosphate for phosphate fertilizer; and muriate over 45% K_2O and potassium sulfate for potassium fertilizer. I used unit costs of urea and superphosphate for the nutrients N and P, respectively, because they are used more frequently and they contain higher percentage of nutrients than the other commodity. If these are not available, I then use ammonium sulfate and single superphosphate unit costs if these are available. The average unit cost of potassium sulfate and muriate over 45% is used for the nutrient K. The average per metric ton unit cost of fertilizer *n* in country *i* in 2010 US dollar, FP_n^j, is

$$FP_n^i = adj_n^{US} \times \frac{1}{Z^i}\sum_{t=k}^{2002} FP_{nt}^i \qquad (3)$$

$$where\ 1998 \geq k \geq 1993\ such\ that\ Z^i \geq 2$$

where Z^i is the number of positive observations in country *i* between *k* and *2002*; FP_{nt}^i is the price of per metric ton of fertilizer nutrient n of country i in year t expressed in 2010 US dollars by the equation (1); adj_n^{US} is an adjustment factor for fertilizer nutrient of n in the US, which is the average inflation-adjusted fertilizer price increase in the US from USDA ERS data set.

The unit costs are "per metric ton of plant nutrients for straight fertilizers" (FAOSTAT 2011b). After conversion of the unit costs to 2010 US dollars, the MAD method using 2 as a cut-off value excluded 203 observations out of 2,368 observations (using 3 as a cut-off value excludes 91 observations). Additionally, I excluded 15 outliers with extreme unit costs that are below \$10 or more than \$10,000 per metric ton of N, P, or K fertilizers. The countries with excluded outliers include Botswana, Bulgaria, Burundi, Ghana, Guinea, Guyana, Honduras, Kenya, Lao People's Democratic Republic, Madagascar, Malawi, Nigeria, Romania, Swaziland, and Ukraine. These extreme values result from either measurement error or mismatch of currency reform period between FAO and World Bank data.

I average the most recent five years of available data between 1993 and 2002 and adjust for the unit cost increase for each fertilizer type using the average inflation-adjusted fertilizer unit cost increase in the US (adj_n^{US}) from the USDA ERS data set. I use increase in the unit cost of fertilizer in the US data because the US is one of major producers of most fertilizer types and have data readily available. This adjustment is necessary because fertilizer unit costs increased significantly in the 2000s due to changes in other factors such as oil price. Therefore, just using the average of available data between 1993 and 2002 will underestimate the unit cost of fertilizer. I adjust each fertilizer price to an average price between 2008 and 2012.

Fertilizers may provide other benefits other than just providing nutrients. For example, ammonium in ammonium sulfate fertilizer lowers the pH balance of the soil. I do not account for other benefits or change application rates to account for these other benefits. I measure application in terms of the amount of N, P, or K delivered by the fertilizer. For example, farmers need to apply 2 tons of potassium sulfate in order to apply 1 ton of K_2O. Table 3-3 represents conversion rates that FAO used to calculate fertilizer unit costs per metric ton of plant nutrients from unit costs for 6 fertilizer commodities chosen for the data set.

Fertilizer quantity

Crop-specific application rates of N, P, and K fertilizers for each country are taken from the Mueller et al. (2012) fertilizer data set. This data set harmonized estimates of crop-specific application rates with country and subnational fertilizer consumption statistics between 1997 and 2003 centered on year 2000. The major data set that it uses is the 5th edition of the FAO publication "Fertilizer use by crop" (FAO 2002). It is a joint publication from the International Fertilizer Industry Association (IFA), the International Fertilizer Development Center (IFDC), the International Potash Institute (IPI), the Phosphate and Potash Institute (PPI), and FAO. It covers Latin America, Africa, West Asia, North Africa, South Asia, and Southeast Asia. Mueller et al. (2012) combined this data set and national agricultural census reports to make a globally consistent fertilizer use data set by crop.

I define actual fertilizer input as fertilizer quantity that is currently in use in each country. Low intensity production and high intensity production fertilizer input are defined as fertilizer quantity that is required to produce 25% and 75% of attainable yield in the climate bin, respectively. Mueller et al. (2012) divided the world into 100 climate bins using precipitation and growing degree-day characteristics to define attainable yields by identifying areas with high yields within a similar climate zone.

Fertilizer cost per ha

The weighted average per ha fertilizer cost of crop k in region j (FC_k^j) is calculated using each country's calculated fertilizer cost values. Per ha fertilizer cost of crop k of country i in 2010 US dollar, FC_k^i, is calculated using average fertilizer price of nutrient n in country i, FP_n^i, from equation (3) and fertilizer quantity of nutrient n for crop k in country i, FQ_{nk}^i from Mueller et al. (2012) data set:

$$FC_k^j = \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} FC_k^i = \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} \sum_{n} FP_n^i \, FQ_{nk}^i \qquad (4)$$

where *I* is the number of countries that have both unit cost and quantity data in region j; $\frac{\sum_{k=1}^{K} \mathrm{P}_k^w \mathrm{Q}_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} \mathrm{P}_k^w \mathrm{Q}_k^i}$ is the proportion of total value of agricultural production of country *i* in region j, which is used as a weight to get the weighted average of fertilizer cost in region *j*, where P_k^w is the world price of agricultural commodity *k* in constant 2004-2006 international dollars from FAOSTAT (FAOSTAT 2012); Q_k^i is average quantity produced of crop *k* in country *i* between 2006 and 2010; *K* is the number of all agricultural products produced in country *i*.

Agricultural Labor Cost

Agricultural labor unit cost - wage rate ($/hour)

Agricultural labor unit cost is defined as the average hourly wage rate for male agricultural workers. Agricultural hourly wage can be divided into two categories: hourly wage rate for hired labor and hourly wage rate for unpaid labor, e.g., family labor. The wage rate for unpaid labor is defined as the wage rate of non-farm workers paid to farm operators working off farm (AAEA 2000). I use both unpaid labor and hired labor wage rates for all countries. I assume that unpaid labor workers can work as laborers in other industries or work as a supervisor in other farms, and use the higher value as an opportunity cost of unpaid labor. Therefore, I define unpaid labor wage rate as either the average of a laborer's wage rate in other industries including textile, printing, manufacturing of chemical and industrial products, machinery, and construction, or the supervisor's wage rate, whichever is greater. The data on wage rates comes from the International Labor Organization (ILO)'s "October Inquiry". ILO sends out a questionnaire to ask for wages for different occupations within particular industries. I used wage rates for field crop and plantations workers for hired labor wage rates and wage rates for field crop and plantations supervisors and laborers for other industries including textile, printing, manufacturing of chemical and industrial products, machinery, and construction for unpaid labor wage rates. Definitions from ILO for each type are as follows (ILO 2010):

> Agricultural Worker: performs a variety of tasks relating to propagation, cultivation and harvesting of plantation products
>
> Agricultural Supervisor: supervises operations in connection with growing, harvesting and marketing of agricultural produce, and maintenance of machinery, implements and equipment, under the direction of the farm manager
>
> Industry Laborer: performs one or more manual tasks requiring a minimum of training, little or no previous experience and mainly physical effort.

Freeman and Oostendorp (2005) and Oostendorp (2005) refined the ILO data and these data were updated by Oostendorp (2012). Freeman and Oostendorp (2005) and Oostendorp (2005, 2012) removed outliers and standardized the data using country-specific data correction factors. The method used for the data set is explained in detail in Oostendorp (2005). ILO does not report wage rate data in a consistent format. For example, ILO reports male monthly wage rate for some countries and female weekly wage rate for others. Freeman and Oostendorp (2005) normalized the ILO data by changing the unit of available wage rate data to hourly wage rate for male workers. The data are downloadable at the National Bureau of Economic Research (NBER) website.

The available hourly wage rate data for each country between 1990 and 2008 are expressed in 2010 US dollars using the equation (1) and inconsistent observations have been excluded as is explained in the general method section. The MAD method using 2 as a cut-off value excluded 471 observations out of 4,700 observations (using 3 as a cut-off value excludes 274 observations). Additionally, I excluded 54 outliers with unit costs of labor higher than \$25/hour, which is higher than the wage rate in the US. The average hourly wage rate of agricultural workers and supervisors and laborers in other industries in country i, W_{type}^{i}, is

$$W_{type}^{i} = \frac{1}{Z^{i}} \sum_{t=k}^{2008} W_{type,t}^{i} , \qquad (5)$$

$$type \in \{paid, unpaid\}$$

$$where\ 2004 \geq k \geq 1990\ such\ that\ Z^i \geq 2$$

where Z^i is the number of positive observations in country *i* between year *k* and *2008*; $W^i_{type,t}$ is the wage rate of a country *i* between year *k* and *2008* for paid or unpaid workers, expressed in 2010 US dollars calculated using the equation (1).

Agricultural labor quantity

Agricultural labor quantity is measured as the average number of hours required per hectare to grow crop *k* in country *i*, LH^i_k/ha. Data on average number of hours required per hectare for crop *k* is not available for most countries. I use the following methods to estimate labor quantity per hectare by country by crop.

Data on the average number of hours required per hectare for crop *k* in the US, LH^{US}_k/ha, can be calculated using data from USDA ERS. I also have labor productivity numbers for the whole agricultural sector (but not for specific crops) for most countries and I have yield by crop for most countries. To estimate LH^i_k/ha I use the following identity:

$$\frac{LH^i_k}{ha} \times \frac{Q^i_k/LH^i_k}{Q^i_k/ha} = \frac{LH^{US}_k}{ha} \times \frac{Q^{US}_k/LH^{US}_k}{Q^{US}_k/ha} = 1 \tag{6}$$

where Q^i_k/LH^i_k is labor productivity for crop *k* in country *i*, and Q^i_k/ha is per hectare yield for crop *k* in country *i*; Q^{US}_k/LH^{US}_k is labor productivity for crop *k* in the US; Q^{US}_k/ha is per hectare yield for crop *k* in the US. I rearrange equation (6) to solve for LH^i_k/ha:

$$\frac{LH^i_k}{ha} = \frac{LH^{US}_k}{ha} \times \frac{Q^{US}_k/LH^{US}_k}{Q^i_k/LH^i_k} \times \frac{Q^i_k/ha}{Q^{US}_k/ha} \tag{7}$$

The first term on the right hand side, $\frac{LH^{US}_k}{ha}$, is calculated by dividing per hectare labor cost for production of crop *k* by agricultural wage rate in the US. USDA ERS estimates per hectare labor cost by summing up paid and unpaid labor costs. Paid labor cost is calculated by using direct cost for paid and contract workers including benefits. Unpaid labor cost is calculated by multiplying unpaid labor hours and "estimated opportunity wage rate of farm operators working off-farm" (ERS 2014). Since I have two different wage rates and labor costs for paid and unpaid workers, I divide labor cost by wage rate for each type:

$$\frac{LH_k^{US}}{ha} = \sum_{type} \frac{LH_{type,k}^{US}}{ha} = \sum_{type} \frac{c_{type,k}^{US}}{W_{type}^{US}} \tag{8}$$

$$type \in \{paid, unpaid\}$$

where $c_{type,k}^{US}$ is national average per hectare paid and unpaid labor cost for production of crop *k* in the US calculated from USDA ERS and university extension data as described in the USDA ERS data documentation (ERS 2014); $W_{type}^{US}$is hourly wage rate of paid and unpaid workers in the US from equation (5).

To estimate the second term on the right hand side of the equation (7) I make two additional assumptions. First, total output quantity in country *i*, Q^i, can be measured using the world price of each agricultural commodity as a weight. Alston et al. (2009) used the world price of agricultural commodities as the weight to measure total agricultural quantity in order to calculate labor productivity. Using the price as a weight is necessary because agricultural commodities have different size and volume. For example, a ton of potatoes and a ton of blueberries cannot sensibly be aggregated using weight or volume measures. A similar kind of weight adjustment using prices can be found in Hayami and Ruttan (1970) and their following papers (Hayami and Ruttan 1971; Kawagoe et al. 1985; Kawagoe and Hayami 1985). Second, I assume that labor productivity of crop *k* relative to overall agricultural labor productivity is the same in the US and in country *i*, i.e., $\frac{\mathrm{Q_k^{US}/LH_k^{US}}}{\mathrm{Q^{US}/LH^{US}}} \approx \frac{\mathrm{Q_k^i/LH_k^i}}{\mathrm{Q^i/LH^i}}$.

Using these two assumptions I calculate $\frac{Q_k^{US}/LH_k^{US}}{Q_k^i/LH_k^i}$ by

$$\frac{Q_k^{US}/LH_k^{US}}{Q_k^i/LH_k^i} \approx \frac{Q^{US}/LH^{US}}{Q^i/LH^i} = \frac{\frac{1}{Z^i}\sum_{t=2006}^{2010} \frac{\sum_{k=1}^{K} P_k^w Q_{kt}^{US}}{L_t^{US} TLH^{US}}}{\frac{1}{Z^i}\sum_{t=2006}^{2010} \frac{\sum_{k=1}^{K} P_k^w Q_{kt}^i}{L_t^i TLH^i}}, \tag{9}$$

$$L_t^{US} = L_{t\,male}^{US} + \gamma^{US} L_{t\,female}^{US} \; and \; L_t^i = L_{t\,male}^i + \gamma^i L_{t\,female}^i$$

$$TLH^{US} = ALH^{US} \times growingdays^{US}\ and\ TLH^{i} = ALH^{i} \times growingdays^{i}$$

where Z^i is the number of positive observations in country *i* between 2006 and 2010; P_k^w is the world price of agricultural commodity k in constant 2004-2006 international dollars from FAOSTAT (FAOSTAT 2012); Q_{kt}^{US} and Q_{kt}^{i} are quantity produced of crop k in the US and in country *i* in year *t*, respectively; $L_t^{US}$and L_t^i are the number of total effective number of agricultural production workers in the US and in country *i* in year *t*; TLH^{US} and TLH^i are yearly total number of hours actually worked by an agricultural employee in the US and in country *i* between 2006 and 2010; $L_{t\,male}^{US}$ and $L_{t\,male}^{i}$ is male agricultural production workers in the US and in country *i* in year *t*, respectively; $L_{t\,female}^{US}$ and $L_{t\,female}^{i}$ are female agricultural production workers in the US and in country *i* in year *t*, respectively; γ^{US} and $\gamma^i$are multipliers to convert the number of female workers to comparable number of male workers for the US and for country *i* calculated in Oostendorp (2012). The average value of γ^i in each region is used for countries with no γ. ALH^{US} and ALH^i are average weekly number of hours worked by agricultural, forestry, and fishery laborers in the US and in country *i* between 2001 and 2013 (ILO 2014;NASS 2014). $growingdays^{US}$ and $growingdays^i$ are the number of growing days in the US and in country *i*. The number of growing days is the area weighted average length of growing period in each country using length of growing season data from FAO (FAO 2015) and total agricultural area data from FAOSTAT.

There are a number of assumptions that I make for the calculation of labor quantity per hectare. The number of male and female economically active population in agriculture does not exclude population in fishery and forestry in the FAOSTAT (2011d). I assume that the effect of those populations on relative labor productivity between US and each region is not significant. I also assume that the number of growing days is approximately same as the number of working days in each country. For example, mean actual farm work days for male field crop farm workers between 2006 and 2010 were calculated as 210.2 days or 36.1 weeks from the National Agricultural Workers Survey (NAWS) data, which is not too much different from the area-weighted length of growing days of 225 days (NASS 2014). Using the average weekly number of hours worked by ILO I excluded observations that are not represented as annual average due to seasonality. For example, I used Mexico's annual average hours actually worked within a week for agricultural workers, which are 45 between 2009 and 2010 instead of using the average hours actually worked during the second quarter of the year, which are 35.2 between 2011 and 2013. ALH^{US} was calculated using the data from NAWS data by USDA (NASS 2014) because the data were not available in the ILO data set. Mean number of hours worked by hired labor workers was 49.07 hours between 2006 and 2010.

The per hectare yield of crop *k* in country *i* to that in the US in the third term in equation (7) is calculated by

$$\frac{Q_k^i/ha}{Q_k^{US}/ha} = \frac{\frac{1}{Z^i}\sum_{t=2006}^{2010}\frac{Q_{kt}^i}{area_{kt}^i}}{\frac{1}{Z^i}\sum_{t=2006}^{2010}\frac{Q_{kt}^{US}}{area_{kt}^{US}}} \tag{10}$$

where $area_{kt}^i$ is total production area of crop *k* in country *i* in year *t*.

Labor cost per ha

Per hectare weighted average of labor cost for production of crop *k* for region *j*, LC_k^j is calculated by using the proportion of the value of total agricultural products of country *i* in region *j* as in equation (4) as follows:

$$LC_k^j = \sum_{i=1}^{I}\frac{\sum_{k=1}^{K}P_k^wQ_k^i}{\sum_{i=i}^{I}\sum_{k=1}^{K}P_k^wQ_k^i}LC_k^i = \sum_{i=1}^{I}\frac{\sum_{k=1}^{K}P_k^wQ_k^i}{\sum_{i=i}^{I}\sum_{k=1}^{K}P_k^wQ_k^i}\sum_{type}W_{type}^i \times \frac{LH_{type,k}^i}{ha} \tag{11}$$

$$type \in \{paid, unpaid\}$$

where $LH_{type,k}^i$ is the average number of hours required per hectare for crop *k* in country i.

Machinery Cost

I calculate per hectare machinery cost in each region and provide estimates of machinery cost for three different intensity levels: low, high, and actual intensity. I adjust per hectare machinery cost in the US by using the relative list price of machines because the price of machines are used to calculate depreciation, maintenance, and operating costs of agricultural machines in the literature (AAEA 2000). I adjust the calculated high intensity production cost in each country by the ratio of average per hectare number of machines in use in the country compared to those in the US.

I use per unit import price for three types of machinery in each country as the list price of new machinery. FAOSTAT (2011c) has data on total import value and quantity of agricultural machinery since 1961. I use the most recent 5-year data of import price per machine. Machinery import value and quantity in use data are available in 198 countries between 2000 and 2009. I use import price data on agricultural tractors, plows, and combine harvesters-threshers because of their high use and the availability of data around the world: 198 countries have tractor prices; 136 have prices combine harvester prices; and 158 have plows prices. The available import price of machinery data for each country between 2000 and 2009 are expressed in 2010 US dollars using the equation (1) and inconsistent observations have been excluded as is explained in the general method section. The MAD method using 2 as a cut-off value excluded 313 observations out of 2,334 observations (using 3 as a cut-off value excludes 188 observations). Additionally, I excluded 12 outliers with unit costs of machinery lower than $100.

There are a number of additional factors that affect machinery cost that I did not include because of lack of data. For example, I did not consider the freight cost of moving machinery from port to field. I assumed that the estimated life and cumulative maintenance and other operating costs are a constant proportion of list price of machines and this does not vary across countries for the same machine.

High intensity cost per ha

High intensity per hectare machinery cost in region j, $High\_MC_k^j$, is measured as the weighted average of per hectare machinery cost for the production of crop *k* in all countries in the region in 2010 US dollars. Individual country *i*'s high intensity machinery cost, $High\_MC_k^i$, is calculated by adjusting per hectare machinery cost in the

US using average initial list price of machines as a weight. The following formula is used to estimate $High\_MC_k^j$:

$$\begin{aligned} High\_MC_k^j &= \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} High\_MC_k^i \\ &= \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} MC_k^{US} \frac{LP^i}{LP^{US}} \\ where\ \ LP^i &= \sum_{M} \frac{1}{Z^i} \sum_{t=k}^{2009} LP_{tM}^i \\ LP^{US} &= \sum_{M} \frac{1}{Z^i} \sum_{t=k}^{2009} LP_{tM}^{US} \\ where\ M \in \{tractor, plow, &combine\}\ and\ 2005 \geq k \geq 2000\ such\ that\ Z^i \geq 2 \end{aligned} \tag{12}$$

where MC_k^{US} is the per hectare average cost of machinery for the production of crop *k* in the US collected from USDA ERS and other university extension data; LP^i is the sum of average list price of machinery, M, tractor, plow, and combine in country *i* between *k* and 2009 in 2010 US dollars; LP^{US} is the sum of average list price of tractor, plow, and combine in the US between *k* and 2009 in 2010 US dollars; LP_{tM}^i is the list price of machinery *M* in year *t* for country *i* in 2010 US dollar calculated using the equation (1); LP_{tM}^{US} is the list price of machinery *M* in year *t* in the US; Z^i is the number of positive observations in country *i* between *k* and 2009 in 2010 US dollars.

Actual cost per ha

Actual intensity per hectare machinery cost in region *j*, $Actual\_MC_k^j$, is measured as the weighted average of per hectare machinery cost in all countries in the region for the production of crop *k* in 2010 US dollars. Actual per hectare machinery cost in country *i*, Actual_MC_k^i, is measured as the average per hectare machinery cost for the production of crop *k* in 2010 US dollars. I divide countries into two groups, “high use” and “low use” countries, using per hectare number of machines in use. All countries are defined as “high use” if the number of per hectare machinery use is higher than that in the US, and as “low use” otherwise. The actual production machinery cost for “high use” countries in production of crop k in country i is assume to be the same as $High\_MC_k^i$. The actual production machinery cost for the "low use" countries in production of crop k in country i, $Actual\_MC_k^i$, is calculated by adjusting high intensity cost by the ratio of per hectare number of machines in use in a country compared to that of the crop in the US.

$$Actual\_MC_k^j = \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} Actual\_MC_k^i, where$$

$$Actual\_MC_k^i = \begin{cases} High\_MC_k^i, if\ use^i/ha \geq use^{US}/ha \\ High\_MC_k^i \frac{use^i/ha}{use^{US}/ha}, otherwise \end{cases} \tag{13}$$

where $High\_MC_k^i$ is per hectare machinery cost for the production of crop k in country i from equation (12); use^i/ha is per hectare number of combine or tractor in use in country i; use^{US}/ha is per hectare number of combine or tractor in use in the US; $\frac{use^i/ha}{use^{US}/ha}$ is relative average per hectare number of machines in use in country i to that in the US.

Seed Cost

I calculate per hectare seed cost in each region for three different intensity levels: low, high, and actual intensity. I use crop producer price and yield data from FAOSTAT, and seeding rate from USDA's Agricultural Resource Management Survey (ARMS) and from reports of various university extension services in the US. There are a number of factors that affect seed cost that I did not include because of lack of data. For example, I did not consider different seeding rate of a crop in each region as a function of soil condition and climate.

I assume that low intensity agriculture does not use hybrid seed and calculate the opportunity cost of using seed from previous year's harvest. I calculate per hectare low intensity seed cost by multiplying each crop's seeding rate per hectare in the US by the producer price of each crop in country i.

For high intensity seed cost, I assume that the price of seed determines the seed cost more than the seeding rate does, and use the relative price of seed compared to that in the US to adjust the seed cost in the US. I divide all crops into two different categories: self-pollinated and cross-pollinated crops.

Self-pollinated: barley, wheat, rice, potato, soybean, sunflower

Cross-pollinated: maize, oil palm, rapeseed, rye, sugar beet, sugarcane

For self-pollinated crops, a high percentage of farmers use seeds saved from harvest for planting the next crop and do not purchase commercial seeds. According to the survey of International Seed Federation (ISF), about 68% of farmers used their own seed for cereals in 14 countries that included Canada, China, Italy, Finland, and U.K. (ISF 2005). I use the relative average producer price of crop, which is the price of self-pollinated seeds saved from the previous harvest season, to adjust the US seed cost for high intensity seed cost for self-pollinated crops.

Seeds for cross-pollinated crops are more likely to be purchased. For cross-pollinated crops I assume that the seed price is the import price for seed, and adjust the seed cost in the US using the relative ratio of average per ton import price of all seeds in the US and in each country in 2012. The available producer price of crop data for each country between 2001 and 2010 are expressed in 2010 US dollars using the equation (1) and inconsistent observations have been excluded as is explained in the general method section. The MAD method using 2 as a cut-off value excluded 862 observations out of 7,244 observations (using 3 as a cut-off value excludes 411 observations).

I set actual intensity seed cost equal to the high intensity seed cost if the average yield in a country i is greater than or equal to the yield of US. Otherwise, I adjust the calculated high intensity production seed cost by the ratio of yield of a crop in the country compared to the yield of the crop in the US.

Low intensity cost per ha

The low intensity production seed cost for the production of crop k in region j, $Low\_SC_k^j$, is calculated using the weighted average of per hectare low intensity seed cost of all countries in the region for the production of crop k in 2010 US dollars. The low intensity production seed cost for the production of crop *k* in country *i*, $Low\_SC_k^i$, is calculated by using seeding rate and producer price of the crop. I use the following formula:

$$Low\_SC_k^j = \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} SR_k^{US} PP_k^i$$
$$where \ \ PP_k^i = \frac{1}{Z^i} \sum\nolimits_{t=k}^{2010} PP_{kt}^i \qquad (14)$$
$$where \ 2006 \geq k \geq 2001 \ such \ that \ Z^i \geq 2$$

where SR_k^{US} is per hectare seeding rate of crop *k* in the US in metric ton from Table 3-4; PP_k^i is the average per metric ton of price of crop *k* of country *i* in 2010 US dollars; Z^i is the number of positive observations in country *i* between year *k* and 2010; PP_{kt}^i is per metric ton producer price of crop *k* of country *i* in year *t* expressed in 2010 US dollars.

High intensity cost per ha

The high intensity production seed cost for the production of crop *k* in region *j*, $High\_SC_k^j$, is calculated using the weighted average of per hectare high intensity seed cost of all countries in the region for the production of crop *k* in 2010 US dollars. It is calculated by adjusting per hectare seed cost in the US using average per ton import price of all seeds as a weight. The following formula is used to estimate $High\_SC_k^i$:

$$High\_SC_k^j = \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} SC_k^{US} \frac{P_k^i}{P_k^{US}} \qquad (15)$$

$where \ P_k^i = PP_k^i \ and \ P_k^{US} = PP_k^{US}$, if *k*=self-pollination crop

$P_k^i = IP^i \ and \ P_k^{US} = IP^{US}$, if *k*=cross-pollination crop

where SC_k^{US} is the average per hectare seed cost for the production of crop *k* in the US collected from USDA ERS and other university extension data; IP^i is the average per ton import price of all seeds of country *i* in 2012; IP^{US} is the average import price of all seed in the US in 2012.

Actual cost per ha

I divide countries into two categories: high-yield and low-yield countries and apply different rules. I define high-yield countries as those with yield of a crop *k* higher than that in the US. For high-yield countries, I assume that the actual seed cost is equal to the high intensity seed cost. For low-yield countries, the actual production seed cost is calculated by adjusting high intensity seed cost by the ratio of yield of a crop in the region compared to the yield of the crop in the US. I use the following formula to calculate weighted average of per hectare actual production seed cost for crop *k* in region *j*, $Actual\_SC_k^j$ as:

$$\begin{gathered} Actual\_SC_k^j = \sum_{i=1}^{I} \frac{\sum_{k=1}^{K} P_k^w Q_k^i}{\sum_{i=i}^{I} \sum_{k=1}^{K} P_k^w Q_k^i} Actual\_SC_k^i, where \\ Actual\_SC_k^i = \begin{cases} High\_SC_k^i, if\ Q_k^i/ha \geq Q_k^{US}/ha \\ High\_SC_k^i \dfrac{Q_k^i/ha}{Q_k^{US}/ha}, otherwise \end{cases} \end{gathered} \tag{16}$$

where $High\_SC_k^i$ is per hectare machinery cost for the production of crop *k* of country *i* from equation (15); $\frac{Q_k^i/ha}{Q_k^{US}/ha}$ is relative average per hectare yield for production of crop *k* in country *i* to that in the US from equation (10).

III. Validation of the Constructed Data

In this section I use existing country- and crop-specific production cost data set to test the validity of the constructed data set. I use wheat production cost both at country and regional level as an example. I compare the constructed cost values for wheat against values from CIMMYT and FADN. Overall, most of the constructed cost values are not unreasonably high or low compared to values from CIMMYT and FADN. The regional weighted averages relatively match better than individual countries' values. The comparison is done for the purpose of getting a general idea on the validity of the data set constructed using the methods described above. Methods and data used by CIMMYT and FADN differ so we would not expect an exact matching but large differences raise doubts about accuracy of the various data sets.

I compare the constructed cost of wheat production in my data set and other data sets in countries and regions that are commonly available in both data sets. Wheat is one of the most widely produced crops in the world and thus has a good data coverage across the globe. I use readily available data from the International Wheat and Maize Improvement Center (CIMMYT), and the Farm Accounting Data Network (FADN) from European Commission data sets for the comparison of wheat production cost. I mainly use these two data sets to compare with my constructed data set because they are the most comprehensive and consistent data sets available. The values from CIMMYT are collected using the literature and based on the experts' opinions, and are published in "Wheat Facts and Futures 2009 (Dixon et al. 2009)." Not all values represent actual cost estimates from survey data. The CIMMYT data set represents the cost per hectare for "bread wheat production using commercial seed" in 2009. If there are multiple values for each cost item because of different management practices in the CIMMYT data set, I calculated average of cost values from all management practices. The values from FADN are from survey data that are consistent across the European Union countries, where available. I calculated average of available values between 2006 and 2010. All the values used for validation from CIMMYT and FADN have been converted using the same price conversion method outlined in equation (1).

I took weighted average of per hectare cost of wheat production for each cost using total value of agricultural product, $\sum_{k=1}^{K} P_k^w Q_{kt}^i$ from equation (4) in country *i*. Then, I compare country-specific cost values from my data set to those from the CIMMYT and FADN data sets. I calculated how much the CIMMYT or FADN values are higher or lower compared to the values from my constructed values as a percentage of the constructed value. This value is represented as the "Diff (%)" column in Tables 3-5,6,7, and 8. I define the difference as being large if the absolute value of the difference is higher than 50%.

Table 3-5 compares per hectare fertilizer cost for wheat production between my data set and CIMMYT data set. Overall, the regional averages match better between constructed and CIMMYT values than do the country specific values. Country specific comparisons show some extreme values such as Kyrgyzstan, Bangladesh, and Nepal. These countries have significantly lower constructed values compared to the CIMMYT values because of low N, P, and K application rates when compared to other countries within the same region. South America, Eastern and Northern Europe have relatively larger difference between constructed and CIMMYT values, while the regional weighted average of constructed values for all countries in European Union matches well with that of the CIMMYT values. In South America, Argentina and Brazil have significantly lower constructed values than those of the CIMMYT because Argentina has zero K application and Brazil has relatively lower prices for all fertilizer items and low N application rate compared to other countries. Norway has significantly high constructed value because of relatively high use of K fertilizer compared to other European countries. Among countries with absolute value of difference more than 50%, the constructed values underestimate the fertilizer cost in South American and Asian countries compared to the CIMMYT values. The comparison of constructed values and values from FADN shows that my constructed values in Europe tend to be closer to the estimates from FADN than are the estimates from CIMMYT (e.g., estimates in Hungary, Poland, Italy, and Germany).

Table 3-6 compares per hectare labor costs for wheat production between my data set and the CIMMYT and FADN data sets. The weighted regional averages in Central and South America for the constructed data set match well with the CIMMYT data. Argentina has an extremely low constructed value compared to the CIMMYT value. Argentina’s low value of labor cost comes from low constructed value of labor quantity, which is lower than the other countries in South America and similar to that in the US. The reason that the labor quantity value is similar to that in the US is because wheat yield and agricultural productivity in Argentina are comparable to those in the US, i.e., adjustment factors in equation (8) are close to 1. The regional average of constructed value in Central Asia is significantly different from the value from CIMMYT because there is only one observation, Kazakhstan, in my constructed dataset.

The constructed values in European countries are closer to the values from FADN than are the CIMMYT values, except for Italy, which has significantly high labor cost compared to the other European countries. Italy’s unpaid labor cost per hectare production of wheat is about 9-10 times higher than that in France. Poland and Austria's values match better with the values from FADN. CIMMYT underestimate the labor cost compared to the values from FADN in both countries.

Table 3-7 compares per hectare machinery cost for wheat production between my data set and CIMMYT and FADN. I summed soil preparation and harvest costs from CIMMYT data set to compare to the constructed machinery cost in my data set. The values represented here are high machinery cost values for the countries that have per hectare machinery usage greater than that in the US, adjusting the US machinery cost using the relative list price of machines in country *i* compared to the list price in the US. Therefore, the constructed values reflect the differences in the price of machines compared to that in the US.

The constructed values in Eastern and Western Asia countries have values similar to those from CIMMYT, with differences less than 50%. Out of 14 countries that have values commonly available in both data sets of constructed and CIMMYT, four countries' constructed values, i.e., Bulgaria, Czech Republic, Spain, and Switzerland, are significantly different from values from CIMMYT. Among those countries, the constructed values of all countries except Switzerland are higher than the values from CIMMYT. These high values come from the fact that these countries have relatively higher prices of tractor, combine, and plow compared to the prices of those in the US in the FAO data set.

The comparison with FADN data set shows that five out of nine countries' constructed values are closer matches than are the CIMMYT values: Hungary, Poland, Lithuania, Italy, and Germany.

Table 3-8 compares per hectare high intensity seed cost for wheat production between my constructed data set and other data sets from CIMMYT and FADN. I compare the constructed high intensity seed cost to the values from CIMMYT because CIMMYT values are for production of wheat using commercial seeds. High intensity cost was calculated adjusting the seed cost in the US using relative producer prices in each country compared to those in the US. The differences in the constructed seed costs reflect the difference of producer prices in each country compared to those in the US. For example, high constructed seed cost in Rwanda reflects high price of wheat in Rwanda compared to that in the US.

Overall, the differences between the constructed values and the CIMMYT values are more prevalent for European countries compared to the rest of the countries while most of the constructed values are similar to the values from FADN. The weighted regional averages in South America and South Asia using constructed values are very similar to the weighted regional average using CIMMYT values. Comparing the constructed values to the values from FADN, I find that all constructed values in European countries except Germany and Spain are closer to the values from FADN.

IV. Comparison between Profit and Revenue

Comparison of revenue and profit maps from wheat production using Figures 3-1, 3-2, and 3-3 highlights two points. Firstly, many areas with high revenue appear to have negative profits when using the constructed wheat production cost data. Secondly, there is a shift in regions where the profit from wheat production is the highest compared to where production of wheat brings the most revenue.

Comparing changes in color schemes in Figure 3-1 and 3-2 suggests that using revenue as the economic rent measurement not only presents regions with negative profit as having high economic returns but also changes the relative value of the economic rent from wheat production among different regions of the world. The regions that appear to have high revenues while profit becomes negative include the following regions: Americas (central US, southern Canada, northeastern and southern Peru), Europe (Spain, Italy, Ukraine, Belarus, Turkey, and Russian Federation), and Asia (southern India, western China, and South Korea). The use of revenue as the measure of profit will indicate these regions as areas with high profit when it is actually not profitable to grow wheat. The regions where relative value of economic rent changes are as follows. In the Americas, some parts of the western US, Mexico, Columbia, Chile, and Argentina have high revenue from wheat production while only the western US appears to have high profit in the Americas. In Europe, most countries in eastern Europe(Belarus, Bulgaria, Czech Republic, Hungary, Poland Russian Federation), western Europe (France, Germany, Netherlands), and northern Europe (UK, Ireland, Lithuania) have high revenue, but none of these areas appears to have high profits. Many Sub-Saharan African countries, including Nigeria, Chad, Madagascar, Namibia, and Zambia also have high revenues, while only Madagascar, Namibia, Zambia, and Zimbabwe seem to have high profits. In Asia, India, China, Turkey and Pakistan have high revenue from wheat production, while Kyrgyzstan, Tajikistan, Uzbekistan, Pakistan, northern India, and eastern China have high profits from wheat production.

Miscalculation of profit due to the omission of production costs can lead to inefficient land-use decisions. For example, as seen in Figure 3-1, using revenue as profit shows that many European and Sub-Saharan African countries have comparable profit per hectare. Using this result would seem to indicate that the cost of conserving one hectare of land in these regions is the same. In contrast, Figure 3-2 using correctly calculated profit and shows that Sub-Saharan African countries have higher profit, represented by darker colors, compared to the European countries. This means that European countries would have higher priority for conservation if both European and Sub-Saharan African countries have the same value of other ecosystem services because the cost of conservation is lower in European countries.

The regions with high profits in the US, northern India, and eastern China, as seen in the profit map, reflect actual high wheat production areas. The areas with high revenue from the revenue map of Figure 3-1 highlight areas that are not major wheat producing areas. The areas with high fraction of land in wheat production, as seen in Figure 3-3, represent regions in each country which have a high percentage of wheat cultivation. It shows that the central US, southern Canada, eastern Argentina, northern Kazakhstan, northern India, and eastern China, western Australia have higher percentages of land under wheat cultivation than the rest of the world. These regions appear to be consistent with the areas with high profit (i.e., Eastern Argentina, northern India, and eastern China) from Figure 2, except for some regions (i.e., central US, southern Canada), which are discussed in the next section.

V. Discussion

There is an increasing need for the valuation of ecosystem services and for evaluating tradeoffs among them as we face challenges to use land more efficiently. Successful implementation of any land-use policies to increase net benefits is significantly affected by whether we use the correct value of benefits and costs associated with alternative land-use scenarios.

There has been an increasing availability of global data sets that can be used for valuation of ecosystem services such as global carbon sequestration, hydrology, and elevation data sets. However, I find that an important and very basic component is missing when evaluating the opportunity cost of taking land out of crop production: agricultural production cost. There has not been a development of globally consistent production cost data set in the production economics literature. This caused many studies in other fields outside of economics to use revenue as a measurement for profit to value the opportunity cost of taking land out of production. Specifically, many studies in conservation planning literature have referenced Naidoo and Iwamura (2008) which measures revenue.

In this paper, I constructed a globally consistent agricultural production cost data set to include the data for the calculation of profit. After the validation of the constructed data set by comparing the values from it to those of other data sets, I compared values between the estimated profit and revenue. The comparison showed how much difference it makes to use profit instead of revenue. The results highlighted the importance of including the production cost in measuring profit because using the cost data enables us to identify areas with negative profit. Also, relative values of the profit changed as I include the production cost. When combined with other ecosystem services such as carbon, identification of areas with negative profit will make a significant difference in calculating net benefits/costs. The difference will change the tradeoffs between agricultural production and other ecosystem services and change our land-use decisions that maximize net benefits.

The construction of globally consistent production cost data through this study was a first attempt to provide production cost data for different crops globally. The documentation of methods and data used provides a base for other studies to improve upon the current cost data. There remains much that can be done to improve estimates of production cost. There is a pressing need for concerted efforts among agricultural production economists to provide globally consistent production cost data set.

There is a need for better use and integration of national and sub-national statistics to improve production cost estimates in particular regions. Figures 3-2 and 3-3 show that there are some areas where there is a discrepancy between high profit and high fraction of wheat harvested areas. For example, most of the areas in the Russian Federation have negative profit from wheat production, which could be because Russia’s constructed production cost is higher than its actual production cost. Figure 3-4 shows that Russia has a higher production cost than central Asian countries (e.g., Kazakhstan, Uzbekistan, and Turkmenistan) that are close to areas with a high fraction of wheat production in Russia. The production cost in Russia was calculated using regional average of fertilizer and labor costs due to the lack of country-level values, as indicated by low level of data quality in Figure 3-2. The regional average cost of fertilizer and labor in Eastern Europe, where Russia is a part of, might be higher than the level of those costs in Russia, leading to the negative profit. Improvement of the current cost data with more detailed regional information combined with sub-national scale data will make the assessment of cost finer in scale, compatible with the 5 minute by 5 minute yield data used in the yield data. It will provide more accurate calculation of the opportunity cost of land for more efficient land-use decisions at a finer resolution.

This data set did not factor in agricultural policies including subsidies for farmers. Subsidies can significantly change the profitability of crop production. In the US, both the Northern Great Plains and Prairie Gateway farm resource regions, as defined by

USDA ERS (ERS 2000), have high fraction of wheat harvested area (Figure 3-3) but have negative profit from wheat production (Figure 3-2). This result may occur because subsidies make it profitable for farmers to grow wheat. The profitability of wheat in the US has been declining over the past two decades because of low price from competition with foreign countries and less investment in research compared to other crops (ERS 2013). The value of wheat production less total cost in the US had been negative between 2004 and 2010 except for the year 2008 according to the farm budget report by USDA (ERS 2015a). In the central US, some areas previously dominated by wheat have switched to more profitable crops such as corn (Beddow and Pardey 2015). Wheat farmers in the US are largely subsidized by the government through various programs such as loan deficiency payment and direct payment (ERS 2015b). Consideration of governmental subsidies will give better information on farmers' profitability, which then provides a better sense of values that drive farmers' actual cropping decisions.

The improvement of the current constructed cost data to include more comprehensive list of crops at a finer resolution will increase the accuracy of production costs. It will enable more accurate assessment of benefits and costs from various land-use scenarios. My constructed data set also attempts to calculate costs by different agricultural intensity levels, i.e., high and low. Such efforts can help answer other research questions on the benefits and costs of agricultural intensification when combined with other biophysical models such as the yield model.

Despite its limitations, this study improves upon currently existing method of using revenue as an alternative calculation of profit and contributes both to the production economics and land-use planning literature. The evidence from Figures 3-1,3-2, and 3-3 showed that areas with high profits reflect the areas with high fraction of wheat harvested area better than the areas with high revenue. The constructed production cost data set provided by this study combined with other biophysical and socioeconomic data sets will help improve assessment of benefits and costs from agricultural production and other ecosystem services for more efficient use of land.

Calculation of profit using the constructed cost data set will also help inform land-use decisions such as those under the United Nation’s program on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD). The information can be used to estimate how much we should compensate farmers for taking land out of crop production in the regions with relatively low value of agricultural production and high value of other ecosystem services.

Table 3-1. Description of available unit cost ($/unit) and quantity data (unit/ha) for cost per ha calculation

	Unit cost ($/unit)	Quantity (unit/ha)	Data source
Fertilizer	Most recent 5 years' average unit cost of N, P, and K paid by producers between 1993-2002 in constant 2010 US dollars ($/kg) adjusted for price increase from 1990s to 2010s using US unit costs.	Actual application rates per hectare along with low or high intensity application rates of N, P, and K for different crops (kg/ha) between 1997 and 2003	FAO, Mueller et al. (2012)
Labor	Most recent 5 years' average hourly wage rate of male agricultural paid and unpaid workers between 1990 and 2008 in constant 2010 US dollars ($/hour)	Hours of labor required for the production of crop per hectare (hours/ha) estimated by adjusting the labor quantity data in the US between 2006 and 2010	FAO, ILO, NBER, USDA-ERS
Machinery	For high intensity production, I used average machinery cost in the US between 2006 and 2010 in constant 2010 US dollars ($/ha) adjusted by most recent 5 years' average import price of combine, tractor, and plow between 2000 and 2009 in a country. Actual intensity is equal to high intensity if number of machines in use per hectare is greater than or equal to that in the US. Otherwise, actual intensity is estimated by adjusting high intensity machinery cost in a country by relative number of machines in use per hectare in the country to that in the US. I assume that there are zero machinery costs for low intensity production.		FAO, USDA-ERS
Seed	For high intensity production, I used average seed cost in the US ($/ha) adjusted by average of most recent 5 years' producer price of crops between 2001 and 2010 or import seed prices in a country depending on the crop type: self-pollination and cross-pollination. For actual intensity I adjust high intensity costs by relative yield of a country compared to that in the US. For low intensity I use crop price in each region ($/kg) and seeding rate (kg/ha) to calculate the opportunity cost of using seed from previous year's harvest.		FAO, USDA-ERS, ISF, University extension

Table 3-2. List of countries in each region

Continent	Region	Countries
Africa	Eastern Africa	Burundi, Comoros, Djibouti, Eritrea, Ethiopia, Kenya, Madagascar, Malawi, Mauritius, Mayotte, Mozambique, Réunion, Rwanda, Seychelles, Somalia, Uganda, United Republic of Tanzania, Zambia, Zimbabwe
	Central Africa	Angola, Cameroon, Central African Republic, Chad, Congo, Democratic Republic of the Congo, Equatorial Guinea, Gabon, Sao Tome and Principe
	Northern Africa	Algeria, Egypt, Libya, Morocco, South Sudan, Sudan, Tunisia, Western Sahara
	Southern Africa	Botswana, Lesotho, Namibia, South Africa, Swaziland
	Western Africa	Benin, Burkina Faso, Cape Verde, Cote d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauritania, Niger, Nigeria, Saint Helena, Senegal, Sierra Leone, Togo
Americas	Caribbean	Anguilla, Antigua and Barbuda, Aruba, Bahamas, Barbados, Bonaire, Saint Eustatius and Saba, British Virgin Islands, Cayman Islands, Cuba, Curaçao, Dominica, Dominican Republic, Grenada, Guadeloupe, Haiti, Jamaica, Martinique, Montserrat, Puerto Rico, Saint-Barthélemy, Saint Kitts and Nevis, Saint Lucia, Saint Martin (French part), Saint Vincent and the Grenadines, Sint Maarten (Dutch part), Trinidad and Tobago, Turks and Caicos Islands, United States Virgin Islands
	Central America	Belize, Costa Rica, El Salvador, Guatemala, Honduras, Mexico, Nicaragua, Panama
	South America	Argentina, Bolivia (Plurinational State of), Brazil, Chile, Colombia, Ecuador, Falkland Islands (Malvinas), French Guiana, Guyana, Paraguay, Peru, Suriname, Uruguay, Venezuela (Bolivarian Republic of)
	Northern America	Bermuda, Canada, Greenland, Saint Pierre and Miquelon, United States of America
Asia	Central Asia	Kazakhstan, Kyrgyzstan, Tajikistan, Turkmenistan, Uzbekistan
	Eastern Asia	China, China, Hong Kong Special Administrative Region, China, Macao Special Administrative Region, Democratic People's Republic of Korea, Japan, Mongolia, Republic of Korea
	Southern Asia	Afghanistan, Bangladesh, Bhutan, India, Iran (Islamic Republic of), Maldives, Nepal, Pakistan, Sri Lanka
	South-Eastern	Brunei Darussalam, Cambodia, Indonesia, Lao People's Democratic Republic, Malaysia, Myanmar, Philippines,

	Asia	Singapore, Thailand, Timor-Leste, Viet Nam
	Western Asia	Armenia, Azerbaijan, Bahrain, Cyprus, Georgia, Iraq, Israel, Jordan, Kuwait, Lebanon, Occupied Palestinian Territory, Oman, Qatar, Saudi Arabia, Syrian Arab Republic, Turkey, United Arab Emirates, Yemen
Europe	Eastern Europe	Belarus, Bulgaria, Czech Republic, Hungary, Poland, Republic of Moldova, Romania, Russian Federation, Slovakia, Ukraine
	Northern Europe	Åland Islands, Channel Islands, Denmark, Estonia, Faeroe Islands, Finland, Guernsey, Iceland, Ireland, Isle of Man, Jersey, Latvia, Lithuania, Norway, Sark, Svalbard and Jan Mayen Islands, Sweden, United Kingdom of Great Britain and Northern Ireland
	Southern Europe	Albania, Andorra, Bosnia and Herzegovina, Croatia, Gibraltar, Greece, Holy See, Italy, Malta, Montenegro, Portugal, San Marino, Serbia, Slovenia, Spain, The former Yugoslav Republic of Macedonia
	Western Europe	Austria, Belgium, France, Germany, Liechtenstein, Luxembourg, Monaco, Netherlands, Switzerland
Oceania	Oceania	Australia, New Zealand, Norfolk Island, Fiji, New Caledonia, Papua New Guinea, Solomon Islands, Vanuatu, Guam, Kiribati, Marshall Islands, Micronesia (Federated States of), Nauru, Northern Mariana Islands, Palau, American Samoa, Cook Islands, French Polynesia, Niue, Pitcairn, Samoa, Tokelau, Tonga, Tuvalu, Wallis and Futuna Islands

Table 3-3. Conversion rate used by FAO to calculate per metric ton of plant nutrient for N, P, and K from fertilizer commodity unit cost

Nutrient (*n*)	Commodity	Conversion Factor
N	Ammonium sulfate	21% N
	Urea	46% N
P	Single superphosphate	18% P_2O_5
	Superphosphate	46% P_2O_5
K	Potassium sulfate	50% K_2O
	Muriate over 45%	60% K_2O

Table 3-4. Seeding rate of crops in the US

Crop	Seeding rate (tons per 100 ha) (SR_k^{US})
Wheat	10.5
Rice	9.8
Corn	2.2
Soybean	8.1
Barley	5.7
Sugar beet	0.2
Sunflower	0.4
Rapeseed	0.6
Rye	16.7
Potato	308.9

Source: Wheat, rice, corn, soybean, and barely data are from USDA ARMS survey and data for the other crops are from Purdue and Missouri university extension websites.

Table 3-5. Comparison of per hectare fertilizer cost for wheat production data values between constructed data set and CIMMYT and FADN data sets

Region/Country	Constructed	CIMMYT		FADN	
	Fert Cost/ha	Fert Cost/ha	Diff (%)	Fert Cost/ha	Diff (%)
Southern Africa	146	131	-10		
South Africa	146	131	-10		
South America	127	195	54		
Argentina	66	167	151		
Brazil	128	216	69		
Peru	152	167	10		
Uruguay	156	176	13		
Central Asia	25	163	540		
Kyrgyzstan	25	85	233		
Eastern Asia	598	375	-37		
China	460	376	-18		
Southern Asia	239	209	-12		
Bangladesh	92	229	148		
Nepal	45	590	1223		
Pakistan	338	261	-23		
Western Asia	126	156	24		
Turkey	122	166	36		
Eastern Europe	163	257	58		
Hungary	183	250	37	129	-29
Czech Rep.	208	171	-18	135	-35
Poland	256	303	19	265	4
Northern Europe	192	291	52		
Norway	648	156	-76		
Southern Europe	207	189	-8		
Italy	229	325	42	105	-54
Portugal	228	130	-43		
Spain	209	78	-62	81	-61
Western Europe	197	113	-42		
France	196	166	-15	171	-13
Germany	167	50	-70	179	7
Switzerland	204	255	25		
European Union	205	178	-13		

Table 3-6. Comparison of per hectare labor cost for wheat production data values between constructed data set and CIMMYT and FADN data sets

Region/Country	Constructed	CIMMYT		FADN	
	Labor cost/ha	Labor cost/ha	Diff (%)	Labor cost/ha	Diff (%)
Eastern Africa	177	117	-34		
Madagascar	155	42	-73		
Rwanda	244	398	63		
Central America	158	111	30		
Mexico	158	111	-30		
South America	65	67	4		
Argentina	12	33	172		
Brazil	76	71	-6		
Peru	182	219	20		
Central Asia	10	75	643		
Kazakhstan	10	13	31		
Eastern Asia	354	218	-38		
China	354	219	-38		
Southern Asia	95	161	69		
Bangladesh	209	539	159		
Pakistan	37	89	142		
Eastern Europe	152	43	-72		
Poland	198	47	-76	338	-71
Southern Europe	150	208	39		
Italy	154	398	158	1120	-627
Western Europe	213	61	-71		
Austria	216	108	-50	173	20
Belgium	154	24	-84		
European Union	191	142	-26		

Table 3-7. Comparison of per hectare machinery cost for wheat production data values between constructed data set and CIMMYT and FADN data sets

Region/Country	Constructed	CIMMYT		FADN	
	Machinery cost/ha	Machinery cost/ha	Diff (%)	Machinery cost/ha	Diff (%)
Eastern Asia	439	537	22		
China	444	538	21		
Western Asia	561	438	-22		
Georgia	415	224	-46		
Turkey	664	471	-29		
Eastern Europe	547	282	-48		
Bulgaria	800	313	-61	276	66
Hungary	328	338	3	290	12
Czech Rep.	749	368	-51	422	44
Poland	335	241	-28	405	-21
Northern Europe	277	499	80		
Lithuania	386	547	41	314	19
Norway	302	360	19		
Southern Europe	238	258	8		
Italy	331	470	42	402	-21
Spain	240	79	-67	144	40
Western Europe	301	317	5		
Austria	177	210	19	287	-62
Germany	361	304	-16	342	5
Switzerland	386	877	127		
European Union	327	278	-15		

Table 3-8. Comparison of per hectare high intensity seed cost for wheat production data values between constructed data set and CIMMYT and FADN data sets (high intensity)

Region/Country	Constructed	CIMMYT		FADN	
	Seed cost/ha	Seed cost/ha	Diff (%)	Seed cost/ha	Diff (%)
Eastern Africa	217	280	29		
Rwanda	304	132	-57		
Southern Africa	118	69	-41		
South Africa	118	69	-41		
Central America	75	146	95		
Mexico	75	146	95		
South America	91	88	-4		
Argentina	77	40	-48		
Brazil	74	112	52		
Peru	147	130	-11		
Uruguay	95	78	-17		
Central Asia	105	139	33		
Kazakhstan	60	67	11		
Kyrgyzstan	136	233	72		
Tajikistan	192	227	18		
Eastern Asia	306	124	-59		
Mongolia	122	114	-7		
China	116	124	7		
Southern Asia	160	149	-7		
Bangladesh	169	190	13		
Nepal	146	190	30		
Pakistan	157	155	-1		
Western Asia	140	125	-11		
Georgia	118	214	81		
Turkey	137	129	-6		
Eastern Europe	80	131	62		
Bulgaria	102	148	46	93	-9
Hungary	69	134	94	71	3
Czech Rep.	65	110	69	85	30
Poland	77	130	69	81	6
Northern Europe	45	136	205		
Lithuania	84	135	60	79	-7
Norway	64	139	118		
Southern Europe	60	99	66		
Italy	54	123	125	85	56
Portugal	58	98	68		
Spain	56	78	40	66	18
Western Europe	40	83	108		

Austria	33	72	115	63	89
France	39	69	77	51	30
Germany	39	85	121	65	68
Switzerland	85	277	226		
Belgium	38	102	165		
European Union	55	100	81		

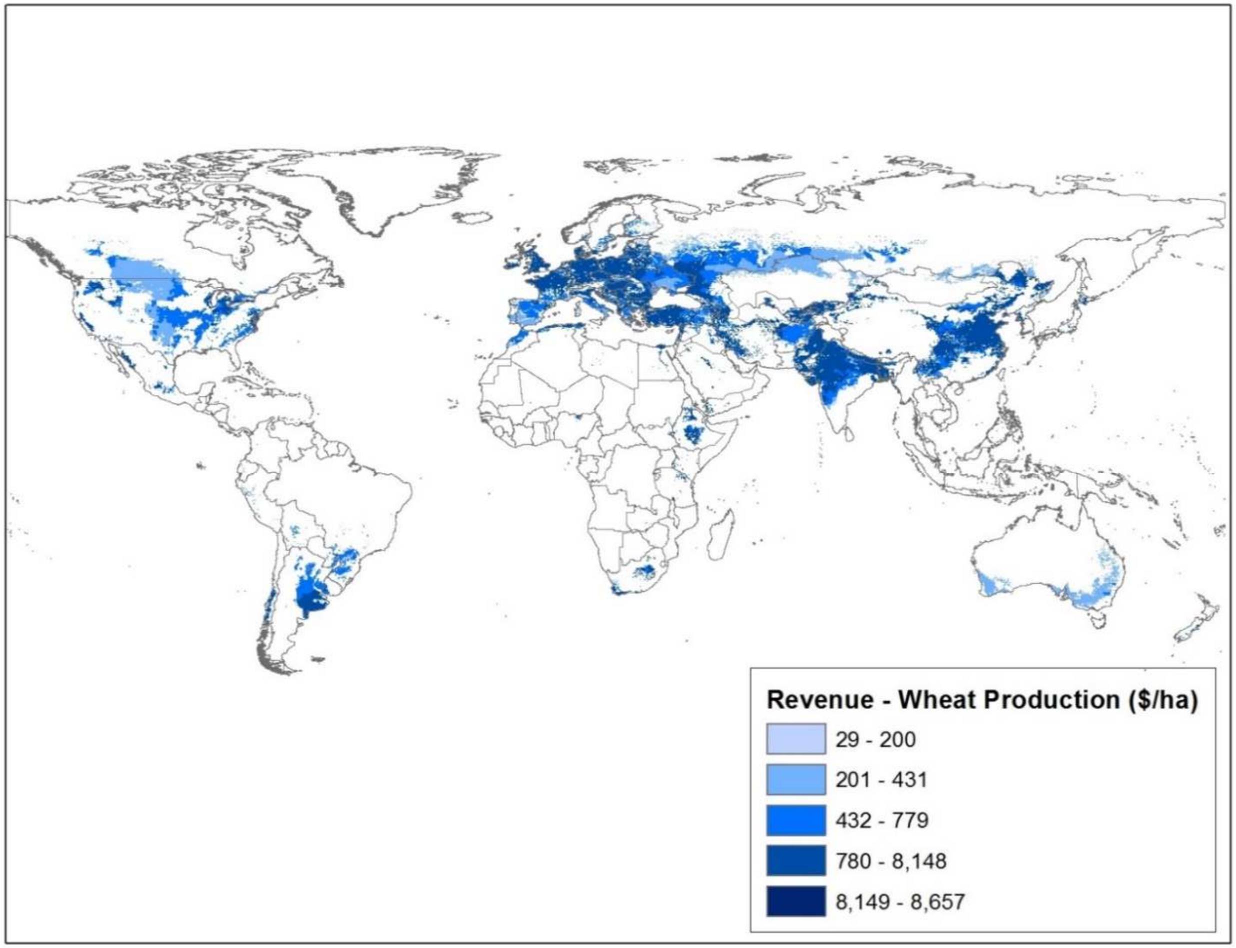


Figure 3-1. Revenue per hectare from planting wheat, calculated by average price between 2006 and 2010 times average yield between 1997 and 2003, in 2010 US dollar value

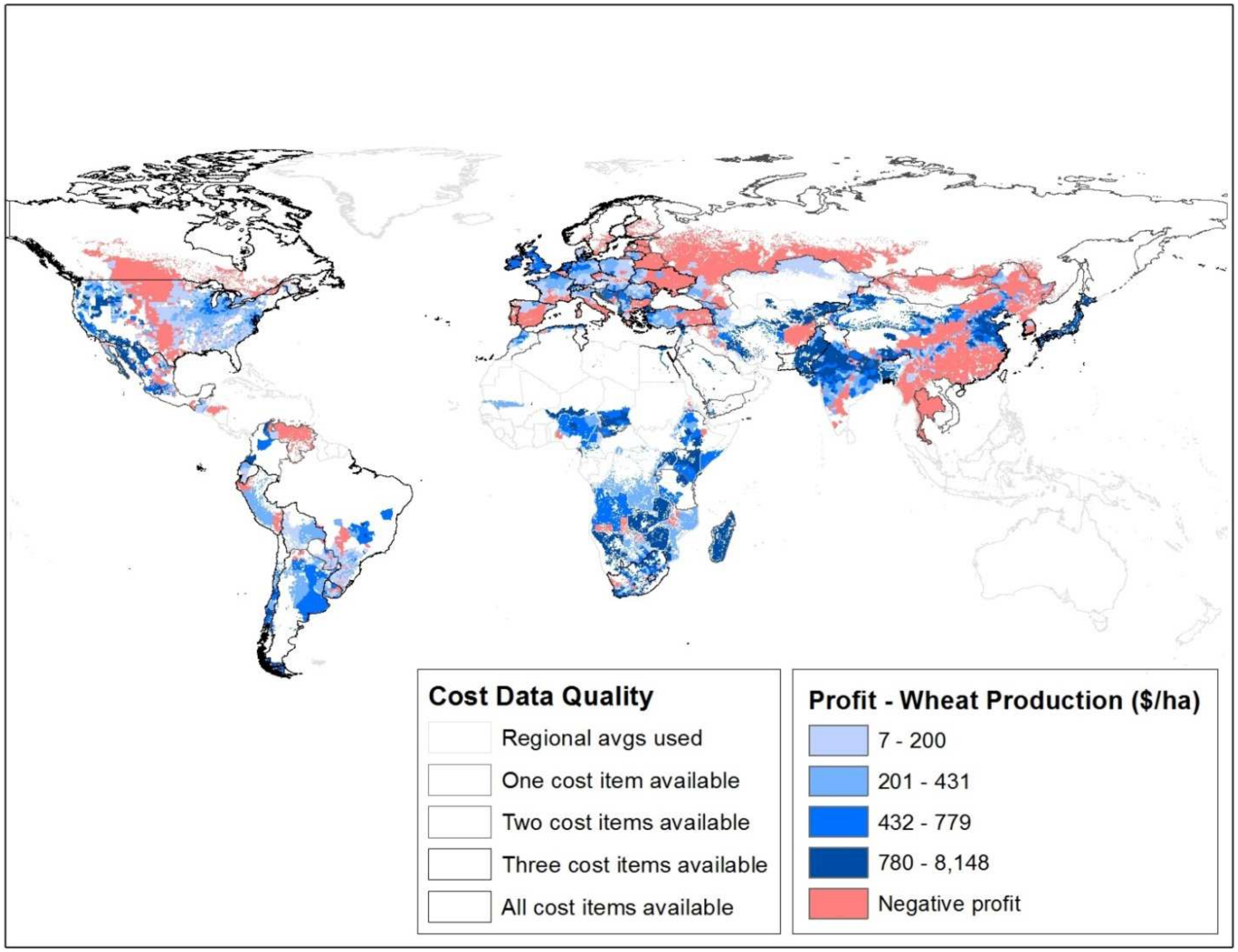


Figure 3-2. Profit per hectare from planting wheat, calculated by average price between 2006 and 2010 times average yield between 1997 and 2003 subtracting per hectare cost of wheat production, in 2010 US dollar value and cost data quality index

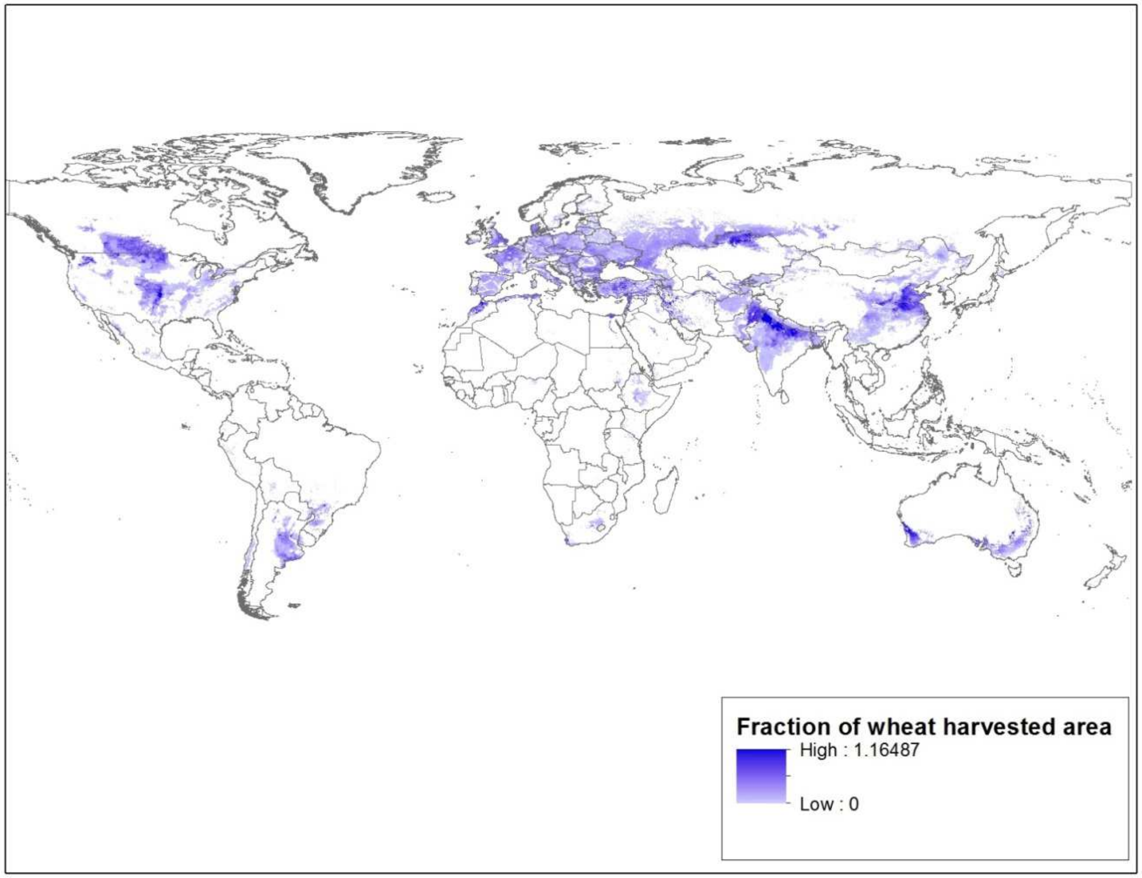


Figure 3-3. Fraction of wheat harvested area over total area in a given cell around the world (some areas have values over 1 because of double cropping)

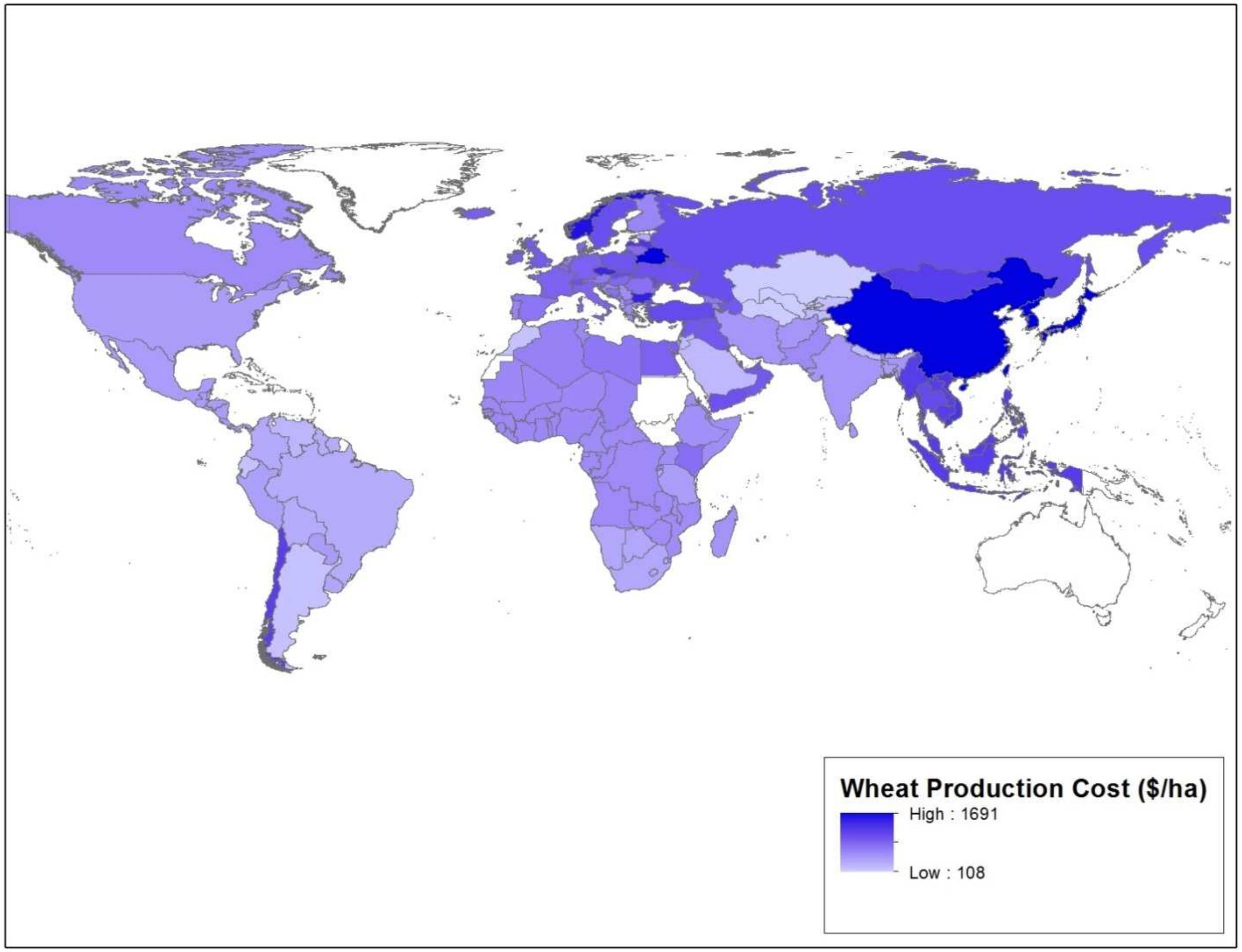


Figure 3-4. Production cost per hectare from planting wheat in 2010 US dollars

Bibliography

AAEA. 2000. Commodity Costs and Returns Estimation Handbook. AAEA Task Force on Commodity Costs and Returns. http://www.nrcs.usda.gov/wps/portal/nrcs/detail/national/technical/econ/costs/?&cid=nrcs143_009751

Abadie, A. and G. Imbens. 2006. Large Sample Properties of Matching Estimators for Average Treatment Effects. Econometrica 74(1): 235-267.

———. 2008. On the Failure of the Bootstrap for Matching Estimators. Econometrica 76(6): 1537-1557.

———. 2011. Bias-Corrected Matching Estimators for Average Treatment Effects. Journal of Business and Economic Statistics 29(1): 1-11.

Abadie, A., D. Drukker, J.L. Herr, and G. Imbens. 2004. Implementing Matching Estimators for Average Treatment Effects in Stata. The Stata Journal 4(3): 290-311.

Ajayi, O.C., F.K. Akinnifesi, G. Sileshi, W. Kanjipite. 2009. Labour inputs and financial profitability of conventional and agroforestry-based soil fertility management practices in Zambia, Agrekon: Agricultural Economics Research, Policy and Practice in Southern Africa, 48(3): 276-292.

Alston, J.M., Beddow, J.M., Pardey, P.G. 2009. Agricultural Research, Productivity, and Food Prices in the Long Run. Science 325(4): September.

Andam KS, P.J. Ferraro, A. Pfaff, G.A. Sanchez-Azofeifa, and J.A. Robalino. 2008. Measuring the Effectiveness of Protected Area Networks in Reducing Deforestation. Proceedings of the National Academy of Sciences of the United States of America 105:16089-16094.

Anthoff, D. and R.S.J. Tol. 2013. The Uncertainty about the Social Cost of Carbon: A Decomposition Analysis Using FUND. Climatic Change 117(3): 515-530.

Arriagada, R.A., P.J. Ferraro, S. Pattanayak, E.O. Sills, and S. Cordero. 2010. Do Payments for Environmental Services Reduce Deforestation? A Farm-Level Evaluation from Costa Rica. Land Economics 88(2): 382-399.

Ashenfelter, O. 1978. Estimating the Effect of Training Programs on Earnings. Review of Economics and Statistics 60(1): 47-57.

Avila, F., and R. Evenson. 2010. Total Factor Productivity Growth in Agriculture: The Role of Technology Capital, in Handbook of Agricultural Economics, Vol. III, Amsterdam: Elsevier, pp. 3769-3822.

Baccini, A., Goetz, S. J., Walker, W. S., Laporte, N. T., Sun, M., Sulla-Menashe, D., Hackler, J., Beck, P. S. A., Dubayah, R., Friedl, M. A., Samanta, S., and

Houghton, R. A. 2012. Estimated Carbon Dioxide Emissions from Tropical Deforestation Improved by Carbon-Density Maps. Nature Climate Change 2: 182-186.

Balmford, A., A. Bruner, P. Cooper, R. Costanza, S. Farber, R.E. Green, M. Jenkins, P. Jefferiss, V. Jessamy, J. Madden, K. Munro, N. Myers, S. Naeem, J. Paavola, M. Rayment, S. Rosendo, J. Roughgarden, K. Trumoer, R. Turner. 2002. Economic Reasons for Conserving Nature. Science 297:950-953.

Beddow, J.M., P.G. Pardey. 2015. Moving Matters: The Effect of Location on Crop Production. The Journal of Economic History 75(1): 219-249.

Bertrand, M., E. Duflo, and S. Mullainathan. 2004. How Much Should We Trust Differences-in-Differences Estimates? Quarterly Journal of Economics 119(1): 249-275.

Blackman, A., J. Rivera. 2011. Producer-Level Benefits of Sustainability Certification. Conservation Biology 25(6): 1176-1185.

Blackman, A. 2013. Evaluating Forest Conservation Policies in Developing Countries Using Remote Sensing Data: An Introduction and Practical Guide. Forest Policy and Economics 34: 1-16.

Busch, J., R.N. Lubowski, F. Godoy, M. Steininger, A.A.Yusuf, K. Austin, J. Hewson, D. Juhn, M. Farid, F. Boltz. 2012. Structuring Economic Incentives to Reduce Emissions from Deforestation Within Indonesia. Proceedings of the National Academy of Sciences of the United States of America 109: 1062-1067.

Büthe, Tim. 2010. Private Regulation in the Global Economy: A (P) Review. Business and Politics 12 (3): Article 2.

Cleary, D. 2004. Cargill visit report. The Nature Conservancy.

Cleary, D. 2007. Responsible Soy Production in the Amazon: the Work of the Cargill-TNC Partnership Around Santarem, 2004-2007. The Nature Conservancy.

Coelli, T.J., D.S.P.Rao. 2005. Total factor productivity growth in agriculture: A Malmquist Index analysis of 93 countries, 1980–2000. Agricultural Economics 32: 115-134.

Dixon, J., H.J. Braun, J.H. Crouch. 2009. Wheat Facts and Futures 2009. CIMMYT.

EMBRAPA. 2013. Zoneamento Ecológico-Econômico (ZEE) da Rodovia BR-163. http://zeebr163.cpatu.embrapa.br/index.php

ERS. 2000. Farm Resource Regions. Agricultural Information Bulletin Number 760. Economic Research Service.

ERS 2013. Wheat – Background. USDA ERS. http://www.ers.usda.gov/topics/crops/wheat/background.aspx

ERS. 2014. Commodity Costs and Returns Documentation.

http://www.ers.usda.gov/data-products/commodity-costs-and-returns/documentation.aspx#valuing

ERS 2015a. Commodity Costs and Returns. http://www.ers.usda.gov/data-products/commodity-costs-and-returns.aspx

ERS 2015b. Wheat Policy. http://www.ers.usda.gov/topics/crops/wheat/policy.aspx

European Commission 2012. Sustainability and Production Costs in the Global Farming Sector: Comparative Analysis and Methodologies. JRC Scientific and Policy Reports.

FAO. 2002. Fertilizer Use by Crop. 5th edition. http://www.fao.org/fileadmin/templates/ess/ess_test_folder/Publications/Agrienvironmental/FUBC5thEditioncomplete.pdf

FAO. 2013. Currency Table 2013. http://faostat.fao.org/site/564/default.aspx

FAO. 2014. Handbook on Agricultural Cost of Production Statistics. Guidelines for Data Collection and Compilation. http://www.gsars.org/wp-content/uploads/2014/09/Handbook-on-Agricultural-Cost-of-Production-Statistics-FINAL_18092014.pdf

FAO. 2015. Length of Growing Season. GeoNetwork. http://www.fao.org/geonetwork/srv/en/main.home

FAOSTAT. 2011a. Country groups and list of all countries in each group. http://faostat.fao.org/site/371/DesktopDefault.aspx?PageID=371

FAOSTAT. 2011b. Resources – Fertilizers Archive: prices paid by farmers. http://faostat.fao.org/site/422/default.aspx#ancor

FAOSTAT. 2011c. Resources – Investment: Machinery. http://faostat.fao.org/site/576/default.aspx#ancor

FAOSTAT. 2011d. Resources – Population: Annual time series. http://faostat.fao.org/site/550/default.aspx#ancor

FAOSTAT. 2012. Production – Value of Agricultural Production. http://faostat.fao.org/site/613/default.aspx#ancor

FAOSTAT. 2015. Agricultural Inputs – Land. http://faostat3.fao.org/download/R/RL/E

Fearnside P.M. 2005. Deforestation in Brazilian Amazonia: History, rates, and consequences. Conservation Biology 19:680–688.

Freeman, R.B. and R.H. Oostendorp. 2005. Occupational Wages around the World (OWW) database. http://www.nber.org/oww/

Fuchs, D., and A. Kalfagianni. 2010. The Causes and Consequences of Private Food Governance. Business and Politics 12(3): article 5.

Goldstein J, Caldarone G, Duarte T K, Ennaanay D, Hannahs N, Mendoza G, Polasky S, Wolny S, Daily G C. 2012. Integrating ecosystem services into land-use planning. Proceedings of the National Academy of Sciences 109: 7565–7570.

Hayami, Y and V. Ruttan. 1970. Agricultural productivity differences among countries. American Economic Review 60(5): 895-911.

Hayami, Y and V. Ruttan. 1971. Agricultural development and international perspective. Baltimore: Johns Hopkins.

Hayami, Y and V. Ruttan. 1985. Agricultural Development: An International Perspective. Johns Hopkins University Press, Baltimore, MD.

Heckman, J., H. Ichimura, and P. Todd. 1997. Matching as an Econometric Evaluation Estimator: Evidence from Evaluating a Job Training Program. Review of Economic Studies 64(4): 605-654.

Heckman, J., H. Ichimura, J. Smith, and P. Todd. 1998. Characterizing Selection Bias Using Experimental Data. Econometrica 66(5): 1017-1098.

Honey-Roses, J., K. Baylis, and M.I. Ramírez. 2011. A Spatially Explicit Estimate of Avoided Forest Loss. Conservation Biology 25(5):1032-1043.

Hope, C. 2013. Critical issues for the calculation of the social cost of CO2: why the estimates from PAGE09 are higher than those from PAGE2002. Climatic Change 117(3): 531-543.

Huerta, A.I. and M.A. Martin. 2002. Soybean Production Costs: An Analysis of the United States, Brazil, and Argentina. Selected Paper Presented at the 2002 AAEA Annual Meeting. Long Beach, CA.

IBGE. 2006. CIDADES@, IGBE. http://www.cidades.ibge.gov.br/xtras/home.php?lang=_EN

IBGE. 2015. Municipality agricultural production. http://www.sidra.ibge.gov.br/bda/pesquisas/pam/default.asp?o=18&i=P

ILO. 2010. ILO October Inquiry: Occupational Wages and Hours of Work. http://laborsta.ilo.org/applv8/data/to1ae.html

ILO. 2014. ILO Database: Working Time. http://www.ilo.org/ilostat/faces/home/statisticaldata/data_by_subject/subject-details?_adf.ctrl-state=w0q28kdgp_14&_afrLoop=1149069625019184

Imbens, G.W. and J.M. Wooldridge. 2009. Recent Developments in the Econometrics of Program Evaluation. Journal of Economic Literature 47:5-86.

INPE. 2015. Taxas anuais do desmatamento - 1988 até 2014 http://www.obt.inpe.br/prodes/prodes_1988_2014.htm

IPEA. 2015. IPEAData - Séries Estatísticas. Brasília, Instituto de Pesquisa Econômica Aplicada (IPEA). www.ipeadata.gov.br

ISF 2005. Meeting on Enforcement of Plant Breeders' Rights. http://www.grain.org/system/old/brl_files/ueisf.pdf

IWG. 2015. Techinical Support Document: Technical Update of the Social Cost of Carbon for Regulatory Impact Analysis – Under Executive Order 12866. Interagency Working Group on Social Cost of Carbon, United States Government. https://www.whitehouse.gov/sites/default/files/omb/inforeg/scc-tsd-final-july-2015.pdf

Jin, S., Huang, J., Rozelle, S., 2010. Agricultural productivity in China. Chapter in "The Shifting Patterns of Agricultural Production and Productivity Worldwide." The Midwest Agribusiness Trade Research and Information Center, Iowa State University, Ames, Iowa.

Johnston, J.A., C.F. Runge, B. Senauer, J. Foley, and S. Polasky. 2014. Global Agriculture and Carbon Trade-offs. Proceedings of the National Academy of Sciences 111(34): 12342-12347.

Kawagoe, T. and Y. Hayami. 1985. The Intercountry Comparison of Agricultural Production Efficiency. American Agricultural Economics Association 67(1): 87-92.

Kawagoe, T., Y. Hayami, and V. Ruttan. 1985. The Intercountry Agricultural Production Function and Productivity Differences among Countries. Journal of Development Economics 19:113–32.

Koh L.P., J. Ghazoul. 2010. Spatially Explicit Scenario Analysis for Reconciling Agricultural Expansion, Forest Protection, and Carbon Conservation in Indonesia. Proceedings of the National Academy of Sciences 107:11140-11144.

Landell-Mills, N., and B. Porras. 2002. Silver Bullet or Fools' Gold: A Global Review of Markets for Forest Environmental Services and Their Impacts to the Poor. London: IIED.

Lu, D., G. Li, E. Moran, S. Hetrick. 2013. Spatiotemporal Analysis of Land-Use and Land-Cover Change in the Brazilian Amazon. International Journal of Remote Sensing 34(16): 5953-5978.

Mayer, F. and G. Gereffi. 2010. Regulation and Economic Globalization: Prospects and Limits of Private Governance. Business and Politics 12 (Article 11):1-25.

Macedo M, DeFries R, Morton D, Stickler C, Galford G, Shimabukuro Y. 2012. Decoupling of deforestation and soy production in the southern Amazon during the late 2000s. Proceedings of the National Academy of Sciences 109: 1341–1346

McCarthy, D.P., P.F. Donald, J.P. Scharlemann, G.M. Buchanan, A. Balmford, J.M. Green, L.A. Bennun, N.D. Burgess, L.D. Fishpool, S.T. Garnett. 2012. Financial Costs of Meeting Global Biodiversity Conservation Targets: Current Spending and Unmet Needs. Science 338: 946-949.

Millennium Ecosystem Assessment (MEA). 2005. Ecosystems and Human Well-Being. Island Press, Washington, DC

Miteva, D.A., S.K. Pattanayak, and P.J. Ferraro. 2012. Evaluation of Biodiversity Policy Instruments: What Works and What Doesn't? Oxford Review of Economic Policy 28(1): 69-92.

Moraes, T.M.. 2010. Economic History of Santarém. http://www.santarem.pa.gov.br/conteudo/?item=190&fa=60

Mueller, N. D., J.S. Gerber, M. Johnston, D.K. Ray, N. Ramankutty, and J.A. Foley. 2012. Closing Yield Gaps through Nutrient and Water Management. Nature 490(7419): 254-7.

Naidoo, R. and T. Iwamura. 2007. Global-scale Mapping of Economic Benefits from Agricultural Lands: Implications for Conservation Priorities. Biological Conservation 140: 40-9.

NASS. 2014. Farm Labor. National Agricultural Statistics Service. United States Department of Agriculture. http://usda.mannlib.cornell.edu/MannUsda/viewDocumentInfo.do?documentID=1063

Nelson A, and K.M. Chomitz. 2011. Effectiveness of Strict vs. Multiple Use Protected Areas in Reducing Tropical Forest Fires: A Global Analysis Using Matching Methods. PLoS ONE 6(8):e22722.

Nordhaus, W. 2014. Estimates of the Social Cost of Carbon: Concepts and Results from the DICE-2013R Model and Alternative Approaches. Journal of the Association of Environmental and Resource Economists 1(1/2): 273-312.

O'Connell, C.S., K. Carlson, S. Cuadra, K. Feeley, J.A. Foley, S. Polasky, P. West. 2015. Tradeoffs in Amazonia between agricultural production and key environmental variables are spatially misaligned and undermine conservation cobenefits. Dissertation Chapter, University of Minnesota

O'Gorman, M. and M. Pandey. 2010. Cross-Country Disparity in Agricultural Productivity: Quantifying the Role of Modern Seed Adoption. Journal of Development Studies 46(10): 1767-1785.

Oostendorp, R.H. 2005. The Standardized ILO October Inquiry 1983-2003. http://www.nber.org/oww/

Oostendorp, R.H. 2012. The Occupational Wages around the World (OWW) Database: Update for 1983-2008. http://www.nber.org/oww/

Pardey, J. Roseboom, B. Craig. 1992. A Yardstick for International Comparisons: an application to national agricultural research expenditures. Economic Development and Cultural Change 40:333-350.

Pattanayak, S.K., S. Wunder, and P.J. Ferraro. 2010. Show Me the Money: Do Payments Supply Environmental Services in Developing Countries? Review of Environmental Economics and Policy 4(2): 254-274.

Pickett-Baker, J. and R. Ozaki. 2008. Pro-Environmental Products: Marketing Influence on Consumer Purchase Decision. Journal of Consumer Marketing 25(5): 281-293.

Ramalho Filho, A. and L.C. Pereira. 1995. Sistema de Avaliaçao da Aptidao Agricola das Terras. EMBRAPA, Rio de Janeiro. http://library.wur.nl/isric/index2.html?url=http://library.wur.nl/WebQuery/isric/11658

Robalino, J.A. and A. Pfaff. 2013. Ecopayments and Deforestation in Costa Rica: A Nationwide Analysis of PSA's Initial Years. Land Economics 89: 432-448.

Rosenbaum, P.R. and D.B. Rubin, D.B. 1985. Constructing a Control Group Using Multivariate Matched Sampling Methods that Incorporate the Propensity Score. The American Statistician 39(1): 33-38.

Rousseeuw, P.J., C. Croux. 1993. Alternatives to the Median Absolute Deviation. Journal of the American Statistical Association December: 1273-1283.

SEMA 2012. Sistema Integrado de Monitoramento e Licenciamento Ambiental. http://monitoramento.sema.pa.gov.br/simlam

Singh, A., R. Yadav, and S. Singh. 2013. Exploring Possibilities of Extending Wheat Cultivation to Newer Areas: A Study on Economic Feasibility of Wheat Production in Southern Hills Zone of India. Agricultural Economics Research Review 26(2): 281-286.

Vincent, J.R. 2015. Impact Evaluation of Forest Conservation Programs: Benefit-Cost Analysis, Without the Economics. Environmental and Resource Economics. Published online.

Wendland, K.J., M. Honzák, R. Portela, B. Vitale, S. Rubinoff, J. Randrianarisoa. 2010. Targeting and implementing payments for ecosystem services: opportunities for bundling biodiversity conservation with carbon and water services in Madagascar. Ecological Economics 69(11): 2093-2107.

World Bank. 2012a. Inflation, GDP deflator (annual %) http://data.worldbank.org/indicator/NY.GDP.DEFL.KD.ZG

World Bank 2012b. PPP conversion factor, GDP (LCU per international $) http://data.worldbank.org/indicator/PA.NUS.PPP

World Bank 2013. World Commodity Prices. http://econ.worldbank.org/WBSITE/EXTERNAL/EXTDEC/EXTDECPROSPECTS/0,,contentMDK:21574907~menuPK:7859231~pagePK:64165401~piPK:64165026~theSitePK:476883,00.html

World Bank 2015. GDP per capita (Current US dollar $), GDP Deflator, and Purchasing Power Parity. http://data.worldbank.org

Wunder, S., S. Engel, and S. Pagiola. 2008. Taking Stock: A Comparative Analysis of Payments for Environmental Services Programs in Developed and Developing Countries. Ecological Economics 65:834-852.

Wünscher, T., S. Engel, S. Wunder. 2008. Spatial Targeting of Payments for Environmental Services: A Tool for Boosting Conservation Benefits. Ecological Economics 65(4): 822-833.

Appendix

Regional Averages of Constructed Cost by Crop

Here I show regional weighted averages of constructed cost by crop using the methods presented in the II. Construction of the Global Production Cost Data in Chapter 3. In each table, I display how many observations in each region were used to calculate the averages, which demonstrates the representativeness of the value for the region. If there is no observation (Obs = 0) within the region, then the value is substituted for the weighted average of countries of a bigger region of which the region is a subset. No values (".") indicate that there is no observation in the region and in the bigger region because either there is no baseline data or there is no data for adjustment factors. I also present how much percentage each cost item occupies in total cost for the crop production.

Table 1. Weighted averages of wheat production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Wheat	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	3	110 (25)	3	113 (25)	0	74 (17)	3	601	3	148 (33)	217	91	445
Central Africa	1	65 (15)	2	157 (36)	0	74 (17)	1	410	0	143 (33)	181	76	439
Northern Africa	2	389 (62)	4	12 (2)	4	80 (13)	5	184	5	146 (23)	178	74	627
Southern Africa	1	146 (43)	0	38 (11)	1	43 (12)	1	454	1	116 (34)	118	49	344
Northern America	2	103 (24)	2	56 (13)	2	226 (53)	2	265	2	46 (11)	46	19	431
Central America	0	127 (29)	1	158 (36)	0	76 (17)	1	164	1	75 (17)	75	31	436
South America	6	127 (38)	5	65 (19)	4	76 (23)	10	508	9	67 (20)	91	38	334
Central Asia	1	25 (15)	1	10 (6)	2	66 (39)	2	549	3	67 (40)	105	44	169
Eastern Asia	2	598 (35)	1	380 (22)	4	439 (26)	4	439	2	300 (17)	306	128	1717
Southern Asia	3	239 (59)	2	33 (8)	2	3 (1)	3	114	4	131 (32)	160	67	406
South-Eastern Asia	2	518 (67)	0	61 (8)	1	68 (9)	1	68	0	131 (17)	160	67	779
Western Asia	3	126 (15)	2	25 (3)	7	561 (68)	9	539	8	108 (13)	140	58	820
Eastern Europe	4	163 (17)	3	152 (16)	8	547 (59)	8	719	8	72 (8)	80	34	934
Northern Europe	6	192 (24)	4	295 (36)	8	277 (34)	9	379	9	45 (6)	45	19	809
Southern Europe	4	207 (32)	2	150 (23)	9	238 (36)	10	267	9	60 (9)	60	25	654
Western Europe	4	197 (26)	3	213 (28)	7	301 (40)	7	301	7	40 (5)	40	17	751
Oceania	1	103 (.)	0	. (.)	0	. (.)	1	435	1	21 (.)	45	19	
European Union	15	205 (27)	13	191 (25)	25	318 (41)	26	333	26	54 (7)	55	23	768

Table 2. Weighted averages of rice production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Rice	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	3	78 (11)	3	285 (39)	0	188 (26)	3	1477	5	171 (24)	454	97	722
Central Africa	1	54 (9)	2	148 (23)	0	188 (30)	1	1008	0	239 (38)	414	89	630
Northern Africa	2	286 (34)	3	20 (2)	3	207 (25)	4	455	2	329 (39)	419	90	842
Southern Africa	1	364 (47)	0	73 (9)	1	105 (13)	1	1115	0	239 (31)	414	89	782
Western Africa	2	15 (2)	1	575 (66)	0	188 (22)	2	541	4	92 (11)	297	64	870
Northern America	1	224 (22)	1	163 (16)	1	519 (50)	1	624	1	137 (13)	137	29	1043
Central America	0	115 (7)	4	136 (8)	1	1,368 (80)	4	516	5	96 (6)	166	35	1715
Caribbean	2	252 (.)	1	455 (.)	0	. (.)	2	1425	1	440 (.)	724	155	
South America	6	115 (20)	6	164 (28)	4	186 (32)	10	1248	9	118 (20)	199	43	584
Central Asia	1	35 (7)	1	35 (7)	2	163 (33)	2	1348	3	257 (53)	596	128	489
Eastern Asia	2	427 (13)	1	835 (26)	3	1,080 (34)	3	1080	2	852 (27)	984	211	3193
Southern Asia	4	139 (43)	3	71 (22)	2	7 (2)	4	274	4	107 (33)	219	47	324
South-Eastern Asia	4	235 (15)	4	285 (18)	3	914 (59)	5	889	5	117 (8)	239	51	1550
Western Asia	1	142 (6)	0	202 (8)	1	1,632 (65)	1	1632	1	523 (21)	537	115	2499
Eastern Europe	3	138 (8)	1	109 (6)	5	1,285 (76)	5	1840	2	163 (10)	257	55	1695
Southern Europe	4	220 (16)	2	307 (23)	4	656 (49)	4	685	0	163 (12)	257	55	1346
Western Europe	2	120 (9)	0	247 (19)	1	799 (60)	1	799	0	163 (12)	257	55	1330
Oceania	1	113 (.)	0	. (.)	0	. (.)	1	1069	1	119 (.)	119	26	
European Union	7	194 (15)	3	247 (19)	8	781 (60)	8	797	7	74 (6)	95	20	1296

Table 3. Weighted averages of barley production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Barley	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	2	138 (41)	0	7 (2)	0	110 (33)	2	838	2	81 (24)	145	42	336
Northern Africa	2	298 (62)	3	7 (1)	3	125 (26)	4	209	4	49 (10)	114	33	479
Southern Africa	1	101 (44)	0	7 (3)	1	53 (23)	1	562	1	68 (30)	88	25	229
Northern America	2	76 (17)	2	65 (14)	2	280 (62)	2	328	2	35 (8)	35	10	456
Central America	0	78 (30)	1	72 (28)	0	67 (26)	1	203	1	41 (16)	60	17	258
South America	6	78 (30)	4	73 (28)	3	67 (26)	8	630	8	38 (15)	55	16	256
Central Asia	1	6 (5)	1	11 (8)	2	82 (64)	2	679	3	29 (23)	67	19	128
Eastern Asia	2	511 (34)	1	275 (18)	4	543 (36)	4	544	3	180 (12)	209	60	1509
Southern Asia	3	168 (81)	2	12 (6)	2	4 (2)	3	142	3	23 (11)	92	26	207
South-Eastern Asia	2	179 (52)	0	34 (10)	1	84 (24)	1	84	0	49 (14)	103	30	346
Western Asia	3	99 (12)	2	14 (2)	7	695 (81)	9	667	6	51 (6)	87	25	858
Eastern Europe	4	90 (10)	3	115 (13)	8	678 (74)	8	890	5	38 (4)	59	17	921
Northern Europe	6	180 (23)	4	211 (27)	8	343 (44)	9	470	1	45 (6)	45	13	779
Southern Europe	4	187 (28)	2	141 (21)	9	295 (45)	10	331	7	37 (6)	43	12	659
Western Europe	4	162 (22)	3	163 (22)	7	373 (51)	7	373	2	29 (4)	29	8	727
Oceania	1	104 (.)	0	. (.)	0	. (.)	1	539	1	15 (.)	34	10	
European Union	15	168 (23)	13	150 (20)	25	394 (53)	26	412	26	26 (4)	26	8	737

Table 4. Weighted averages of maize production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Maize	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	3	22 (10)	4	32 (14)	0	105 (46)	4	830	4	69 (30)	349	12	228
Central Africa	1	55 (14)	2	67 (17)	0	105 (27)	1	561	0	164 (42)	325	13	392
Northern Africa	2	522 (57)	3	8 (1)	3	115 (13)	4	253	2	276 (30)	388	15	922
Southern Africa	1	204 (68)	0	19 (6)	1	59 (20)	1	621	1	17 (6)	40	7	298
Western Africa	2	7 (2)	1	83 (23)	0	105 (29)	2	301	0	164 (46)	325	13	359
Northern America	2	213 (29)	2	64 (9)	2	310 (42)	2	363	2	152 (21)	153	3	739
Central America	0	136 (14)	4	31 (3)	1	762 (77)	4	287	3	58 (6)	188	9	987
Caribbean	2	211 (.)	1	26 (.)	0	. (.)	2	793	0	. (.)			
South America	6	136 (40)	6	44 (13)	4	104 (31)	10	695	5	53 (16)	164	9	337
Central Asia	1	19 (4)	1	15 (3)	2	91 (19)	2	750	1	359 (74)	750	5	484
Eastern Asia	2	875 (52)	1	172 (10)	3	601 (36)	3	601	1	24 (1)	47	18	1673
Southern Asia	4	117 (51)	3	24 (10)	2	4 (2)	4	153	0	83 (36)	165	10	228
South-Eastern Asia	4	227 (26)	4	70 (8)	3	509 (58)	5	495	3	66 (8)	151	8	872
Western Asia	3	270 (24)	1	5 (0)	6	771 (67)	8	740	5	99 (9)	139	11	1146
Eastern Europe	4	162 (15)	3	73 (7)	8	749 (69)	8	984	8	102 (9)	208	8	1086
Northern Europe	0	272 (26)	1	26 (2)	1	529 (51)	1	529	1	202 (20)	202	8	1028
Southern Europe	4	435 (45)	2	130 (14)	8	326 (34)	9	366	8	73 (8)	93	5	964
Western Europe	4	229 (26)	3	95 (11)	7	412 (47)	7	412	6	141 (16)	141	4	878
Oceania	1	94 (.)	0	. (.)	0	. (.)	1	595	1	44 (.)	79	4	
European Union	10	312 (33)	9	95 (10)	17	441 (47)	17	446	16	85 (9)	103	5	933

Table 5. Weighted averages of rye production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Rye	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Northern Africa	2	209 (.)	1	4 (.)	1	30 (.)	2	37	0	. (.)			
Southern Africa	1	85 (.)	0	4 (.)	1	10 (.)	1	111	0	. (.)			
Northern America	2	46 (24)	2	59 (31)	2	55 (29)	2	65	2	32 (17)	32	23	192
Central America	0	116 (37)	1	149 (47)	0	13 (4)	1	40	1	37 (12)	37	62	315
South America	5	116 (54)	4	65 (30)	2	13 (6)	6	132	3	21 (10)	34	25	215
Central Asia	1	41 (25)	1	16 (10)	2	16 (10)	2	134	1	92 (56)	156	32	166
Eastern Asia	1	624 (80)	0	16 (2)	2	107 (14)	2	107	0	33 (4)	43	60	781
Southern Asia	1	60 (28)	0	16 (7)	0	109 (50)	0	111	0	33 (15)	43	60	218
South-Eastern Asia	1	420 (73)	0	16 (3)	0	109 (19)	0	111	0	33 (6)	43	60	578
Western Asia	1	121 (38)	0	16 (5)	3	157 (50)	3	158	1	22 (7)	22	65	316
Eastern Europe	4	76 (18)	3	180 (42)	8	133 (31)	8	175	8	43 (10)	43	48	433
Northern Europe	6	167 (24)	4	420 (62)	8	68 (10)	9	92	7	28 (4)	28	27	683
Southern Europe	4	218 (45)	2	187 (39)	8	58 (12)	9	65	8	19 (4)	19	39	482
Western Europe	4	112 (25)	3	243 (53)	7	73 (16)	7	73	7	30 (6)	30	25	458
Oceania	1	103 (.)	0	. (.)	0	. (.)	1	106	0	. (.)			
European Union	15	149 (31)	12	237 (49)	23	78 (16)	24	81	22	22 (4)	22	35	486

Table 6. Weighted averages of potato production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Potato	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	3	92 (14)	4	85 (13)	0	121 (19)	4	993	6	348 (54)	2212	1620	645
Central Africa	1	104 (6)	2	83 (5)	0	121 (7)	1	671	0	1,426 (82)	3408	2496	1734
Northern Africa	2	907 (31)	4	25 (1)	4	131 (4)	5	301	5	1,862 (64)	4023	2946	2925
Southern Africa	1	1,237 (46)	0	38 (1)	1	70 (3)	1	743	1	1,343 (50)	1783	1305	2688
Western Africa	1	73 (3)	0	38 (1)	0	121 (5)	1	369	2	2,365 (91)	5787	4238	2597
Northern America	2	372 (23)	2	131 (8)	2	371 (23)	2	434	2	763 (47)	786	576	1637
Central America	0	485 (14)	4	112 (3)	1	911 (26)	4	344	5	1,951 (56)	3449	2526	3460
Caribbean	1	579 (.)	1	501 (.)	0	. (.)	1	987	2	2,234 (.)	4654	3408	
South America	6	485 (29)	5	89 (5)	4	124 (7)	10	831	10	988 (59)	2111	1546	1685
Central Asia	1	49 (4)	1	21 (2)	2	108 (10)	2	898	3	953 (84)	2473	1811	1131
Eastern Asia	2	629 (18)	1	546 (15)	4	718 (20)	4	718	3	1,667 (47)	2688	1969	3560
Southern Asia	4	521 (37)	3	51 (4)	2	5 (0)	4	183	5	838 (59)	2234	1636	1415
South-Eastern Asia	4	350 (15)	2	201 (8)	3	609 (25)	3	609	4	1,228 (51)	3337	2444	2388
Western Asia	3	548 (17)	2	43 (1)	7	919 (29)	9	881	8	1,649 (52)	2784	2038	3159
Eastern Europe	4	165 (7)	3	138 (6)	8	896 (40)	8	1177	8	1,069 (47)	2106	1542	2267
Northern Europe	6	433 (21)	4	274 (13)	9	451 (21)	10	620	9	944 (45)	961	704	2102
Southern Europe	4	410 (16)	2	172 (7)	9	389 (15)	10	437	9	1,652 (63)	1864	1365	2623
Western Europe	4	296 (17)	3	202 (11)	7	493 (27)	7	493	7	803 (45)	806	590	1794
Oceania	1	387 (.)	0	. (.)	0	. (.)	1	712	1	1,103 (.)	1379	1010	
European Union	15	336 (18)	13	185 (10)	25	521 (28)	26	544	25	816 (44)	1382	1012	1858

Table 7. Weighted averages of sugar beet production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Sugar beet	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	0	241 (23)	0	23 (2)	0	466 (44)	0	646	1	339 (32)	339	1	1069
Northern Africa	2	241 (23)	1	23 (2)	2	466 (45)	3	646	2	311 (30)	373	0	1041
Northern America	2	142 (8)	2	437 (26)	2	953 (57)	2	1116	1	152 (9)	152	0	1682
Central America	0	368 (.)	0	891 (.)	0	504 (.)	1	689	0	. (.)			
South America	5	368 (.)	2	891 (.)	1	504 (.)	4	1276	0	. (.)			
Central Asia	1	102 (15)	1	72 (10)	2	278 (40)	2	2308	1	250 (36)	720	0	703
Eastern Asia	1	1,540 (42)	0	132 (4)	2	1,867 (51)	2	1867	1	89 (2)	93	0	3628
Southern Asia	1	753 (74)	1	137 (14)	1	19 (2)	1	406	0	108 (11)	181	0	1018
South-Eastern Asia	1	620 (24)	0	132 (5)	0	1,713 (67)	0	1774	0	108 (4)	181	0	2573
Western Asia	1	316 (10)	0	132 (4)	3	2,713 (83)	4	2634	2	89 (3)	110	0	3249
Eastern Europe	4	248 (7)	3	783 (23)	8	2,302 (67)	8	3024	8	116 (3)	200	0	3449
Northern Europe	5	258 (10)	4	980 (38)	7	1,159 (45)	8	1604	6	156 (6)	156	0	2553
Southern Europe	4	385 (15)	2	1,052 (42)	8	1,002 (40)	9	1125	7	79 (3)	89	0	2517
Western Europe	4	284 (12)	3	744 (31)	6	1,265 (52)	6	1265	5	139 (6)	139	0	2431
European Union	15	334 (13)	12	866 (33)	22	1,339 (51)	23	1400	22	98 (4)	105	0	2638

Table 8. Weighted averages of soybean production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Soybean	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	2	10 (4)	3	31 (11)	0	105 (38)	3	624	2	133 (48)	347	84	279
Central Africa	1	51 (10)	1	87 (18)	0	105 (22)	1	426	0	244 (50)	320	78	487
Northern Africa	2	325 (41)	1	2 (0)	1	127 (16)	2	158	1	346 (43)	346	84	800
Southern Africa	1	44 (19)	0	18 (8)	1	45 (19)	1	471	1	124 (54)	206	50	230
Western Africa	1	12 (3)	0	18 (5)	0	105 (28)	0	377	0	244 (64)	320	78	380
Northern America	2	90 (19)	2	40 (8)	2	235 (49)	2	275	2	117 (24)	118	29	482
Central America	0	110 (13)	3	34 (4)	1	578 (70)	4	218	2	110 (13)	194	47	832
South America	6	110 (28)	4	54 (14)	4	79 (20)	9	538	8	146 (38)	185	45	388
Central Asia	1	6 (4)	1	12 (7)	2	69 (38)	2	570	1	92 (51)	150	37	179
Eastern Asia	2	361 (25)	1	129 (9)	3	456 (32)	3	456	2	500 (35)	849	206	1446
Southern Asia	4	275 (64)	3	15 (3)	2	3 (1)	4	116	4	140 (32)	391	95	433
South-Eastern Asia	4	88 (13)	3	60 (8)	3	386 (55)	4	415	4	171 (24)	343	83	705
Western Asia	1	62 (6)	0	39 (4)	2	683 (67)	2	683	2	234 (23)	235	57	1018
Eastern Europe	4	185 (21)	3	47 (5)	7	519 (59)	7	709	5	130 (15)	243	59	880
Northern Europe	0	177 (20)	0	55 (6)	1	532 (60)	1	532	0	124 (14)	189	46	888
Southern Europe	4	188 (28)	1	101 (15)	7	252 (38)	8	282	6	124 (19)	130	31	665
Western Europe	4	157 (25)	2	28 (4)	4	347 (55)	4	347	2	101 (16)	101	24	634
Oceania	1	57 (.)	0	. (.)	0	. (.)	1	452	1	86 (.)	113	27	
European Union	10	202 (28)	6	55 (8)	13	353 (49)	13	357	8	108 (15)	133	32	718

Table 9. Weighted averages of sunflower production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Sunflower	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	2	37 (11)	0	10 (3)	0	23 (7)	1	130	1	263 (79)	263	4	333
Northern Africa	2	327 (55)	4	10 (2)	4	25 (4)	5	58	3	232 (39)	259	4	595
Southern Africa	1	82 (37)	0	10 (5)	1	14 (6)	1	143	1	118 (53)	154	3	224
Northern America	2	35 (13)	2	68 (26)	2	71 (27)	2	84	2	91 (34)	91	1	264
Central America	0	74 (18)	1	109 (27)	0	38 (9)	1	52	1	189 (46)	189	3	409
South America	5	74 (24)	4	71 (23)	3	38 (13)	8	173	4	122 (40)	147	2	304
Central Asia	1	29 (12)	1	11 (5)	2	21 (9)	2	173	2	174 (74)	264	4	235
Eastern Asia	0	. (.)	0	27 (.)	1	140 (.)	1	140	0	238 (.)	293	5	
Southern Asia	3	331 (56)	1	29 (5)	1	1 (0)	1	30	1	228 (39)	282	5	590
South-Eastern Asia	2	401 (73)	0	27 (5)	1	21 (4)	1	21	1	101 (18)	204	3	551
Western Asia	2	219 (26)	0	27 (3)	3	201 (24)	4	194	3	402 (47)	406	7	848
Eastern Europe	4	108 (19)	3	147 (25)	8	172 (30)	8	226	7	154 (26)	184	3	582
Southern Europe	4	104 (22)	2	188 (40)	8	75 (16)	9	84	7	107 (23)	107	2	474
Western Europe	3	210 (38)	2	154 (28)	4	105 (19)	4	105	3	81 (15)	81	1	550
Oceania	1	49 (.)	0	. (.)	0	. (.)	1	137	1	91 (.)	109	2	
European Union	9	155 (30)	7	161 (31)	13	105 (20)	13	107	11	97 (19)	110	2	518

Table 10. Weighted averages of rapeseed production cost per hectare ($/ha) and percentage of each cost item over total cost by region

Rapeseed	Fertilizer ($/ha (%))		Labor ($/ha (%))		Machinery ($/ha (%))				Seed ($/ha (%))				Total Cost ($/ha)
Region	Obs	Actual	Obs	Actual	Obs	Actual	Obs	High	Obs	Actual	High	Low	Actual
Eastern Africa	1	133 (35)	0	62 (16)	0	13 (3)	1	256	1	175 (46)	254	4	384
Northern Africa	1	78 (24)	2	62 (19)	2	13 (4)	3	70	0	175 (53)	254	4	329
Southern Africa	0	106 (30)	0	62 (17)	1	12 (3)	1	131	0	175 (49)	254	4	356
Northern America	2	216 (48)	2	62 (14)	2	65 (14)	2	77	2	110 (24)	110	2	454
Central America	0	169 (41)	1	90 (22)	0	36 (9)	1	47	1	118 (29)	129	3	413
South America	5	169 (43)	3	71 (18)	2	36 (9)	5	160	0	118 (30)	129	3	394
Central Asia	1	77 (46)	1	10 (6)	2	19 (11)	2	158	0	63 (37)	66	5	170
Eastern Asia	2	632 (63)	1	217 (22)	3	127 (13)	3	127	1	22 (2)	34	6	997
Southern Asia	3	446 (83)	2	25 (5)	2	1 (0)	2	33	0	63 (12)	66	5	535
South-Eastern Asia	1	503 (70)	0	41 (6)	0	111 (15)	0	117	0	63 (9)	66	5	718
Western Asia	1	136 (31)	0	41 (9)	1	192 (43)	1	192	1	76 (17)	76	4	444
Eastern Europe	4	200 (30)	3	198 (30)	8	158 (24)	8	208	7	111 (17)	114	4	667
Northern Europe	6	236 (35)	4	240 (36)	8	80 (12)	9	109	8	114 (17)	114	2	671
Southern Europe	4	262 (46)	1	173 (30)	6	72 (13)	7	80	5	66 (12)	66	2	573
Western Europe	4	261 (40)	3	208 (31)	7	87 (13)	7	87	6	104 (16)	104	2	659
Oceania	1	62 (.)	0	. (.)	0	. (.)	1	126	0	. (.)			
European Union	15	266 (42)	11	203 (32)	22	93 (14)	23	97	21	79 (12)	80	2	641