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TITLE OF THE PAPER

USING SATELLITE DATA TO IMPROVE LAND VALUE ESTIMATIONS IN BOLIVIA

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Abstract

Precise land valuation is necessary for an efficient allocation of resources at the private level, and territorial planning and provision of public good at the government level. This information can be obtained from real data transactions in limited areas where they occurred, leaving the rest of the land valuation depending on precise estimation models. These estimation models may use sold land characteristics to forecast the value of land with similar characteristics, by using existing data (i.e. returns on land, productivity, surface, soil maps, precipitation data, land use constraints by law, etc.). In many low and middle-income countries this data is scarce, limiting the possibility of developing these models. This information gap may be filled using satellite data. This study uses average biomass production estimations based on satellite data as a proxy for fertility. By using biomass production estimates for Bolivia over a period of 6 years, together with administrative land transaction data and geographical maps including precipitation, average temperature, slope, distance to closest road, to closed local and national markets, we are able to significantly improve previous land price models. This improvement allowed us to develop a land price index to inform farmers about current price trends and expected sale price for their own land.

Key words: Hedonic Price Model, Earth Observation, Bolivia

Introduction

Precise land valuation is necessary at both private and governmental level as it allows efficient allocation of resources, optimal land use, territorial planning, and efficient provision of public goods. Information on land production, productivity, investment, and other key factors is crucial for price estimation models. However, in countries like Bolivia where land markets are not completely developed, this information is limited which makes land valuation a challenge. To cope with this lack of information, remote sensing data might be useful as a proxy for production, productivity and, therefore, returns.

Satellite images have been widely used in the estimation of hedonic or implicit land price models. These models provide empirical evidence on the value that farmland buyers assign to different characteristics in their decision process, by modelling the prices of a good as a function of attributes revealed from observed prices of differentiated goods (Palmquist 2006) . In particular, satellite data has been useful to improve the explanatory power of these land price models in high income countries and to solve lack of administrative information in medium and low-income countries. In United States, Nivens *et al.* (2000) applied a hedonic price model to identify the implicit price of topsoil depth and costs attributed to greater potential erosivity. Similarly, Bastian *et al.* (2000) estimated agricultural land prices in Wyoming using also a hedonic price model and GIS data, including parcel wildlife, fish habitat, landscape attributes and distance to federal lands. In the case of medium and low-income Latin-American countries, Troncoso *et al.* (2010) used GIS and satellite data to measure distance to roads and soil quality to estimate a price model for farmland in Chile. Moreover, Choumert & Phelinas (2015) identified the effect of land tenure systems and agricultural practices on soybean production land in Argentina, including agronomic soil maps to capture soil quality. In Brazil, Merry *et al.* (2008) identified the determinants of land value in the forest frontier, aiming to understand economic incentives for land use change in the Amazon, using survey data rather than satellite data. For the case of Bolivia, there are some studies that have used satellite data, mainly to explain and predict deforestation (see Paneque-Galvez *et al.* 2013 for a comprehensive literature review). However, such relevant data has not been used to explain rural land values. This is highly important, as according to the 2012 Bolivian Population Census by the National Institute of Statistics, 33% of the population lived in rural areas, and their main economic activity was related to land. Additionally, in a period of ten years urban population increased by five percentage points. Which implies that information on the determinants of rural land prices may be of great use when it comes to the design of public policies, and the optimal migration decision for people leaving rural areas and selling their land. Due to the lack of frequent administrative information on production, and productivity (last agropecuary Survey was made in 2015, and last agropecuary Census in 2013) which is needed to explain rural land prices, the usage of satellite images provides a pertinent solution in order to have timely and relevant information to improve the decision process of the different economic agents.

The aim of this paper is to estimate for the first time to our knowledge a hedonic rural land price model for Bolivia using satellite data to account for limited data. Providing policymakers at the Banks and government agencies, as well as farmers with rural land prices information can help design more sustainable policies and raise productivity and income in land tenure.

Data

A unique database of 2642 recorded land transactions over ~598 km^2 in 44 municipalities of Santa Cruz Department between 2010 and 2015 was used in this paper. Outliers with zero USD/hectare on record and observations further than 1.98 standard deviations from the mean were removed from the database. The following variables were considered in this study:

Table 1. Variables used in the hedonic price model

Variable	Description	Abbreviation in tables
Declared sale price	Price USD/hectare	Price
Land Surface	Hectares	Area
Smallholding classification	Legal classification: if farms <50 hectares, and ranches <500 hectares	Small
Classification	Farm, Ranch, Mixed production, other	Farm – reference category
Biogeographic province	Biogeographic provinces classified in 10 categories.	Provbiogeo
Municipality gross production value	GPV in USD/hectare	GPV/hectare
Municipality coca production value per hectare	GPV Coca in USD/hectare	Coca/hectare
Forest cover per plot	Percentage of the property cover by forest	Forest Land (%)

Table 2 provides overall statistics. the total transactions of rural land in 2010-2015 represent half a million hectares (almost 1.5 million acres) with most of the transactions being farms (58%), followed by ranches (41,29%). Additionally, most properties sold were classified as smallholdings (90,31%). The average price per hectare is US$1858,74, the mean area of the properties sold is 227 hectares, and on average sold properties have 26,9% of its surface covered by forest.

Table 3 and 4 respectively show that average farm and ranch sizes are 56.37 and 460 hectares. On average farm land is more expensive than ranch land (US$2,175 vs. US$1,506), and large farms have higher price per hectare than small farms (US$2,905.46 vs. US$1,084.610; Table 5)); with the same happening to ranches (US$1,679.13 vs. US$977.43; Table 6).

To estimate the forest area per plot per year, from 2010 to 2015, we used data from different Landsat missions as it was required a long-term Earth Observation archive with medium to high spatial and temporal resolutions. Landsat serie of satellites, co-managed by United States Geological Survey (USGS)

& NASA, offers the longest continuous record of multispectral data of the Earth's surface on a global basis and its imagery is freely available. In this study we used looked at two Landsat scenes (3296, 3297) and the following images: 339 Landsat 5 and 13 Landsat 7 images for 1987 to 1999; and 339 Landsat 5, 671 Landsat 7 and 193 Landsat 8 images for 2000-2018. All images were downloaded from USGS at https://landsat.usgs.gov/landsat-data-access.

Additionally, this study we used a map of vegetation in Bolivia (Navarro & Ferreira, 2007), a map of deforestation from 2013 (ACTO, 2013), and Google and Bing background imagery as reference for land cover classes.

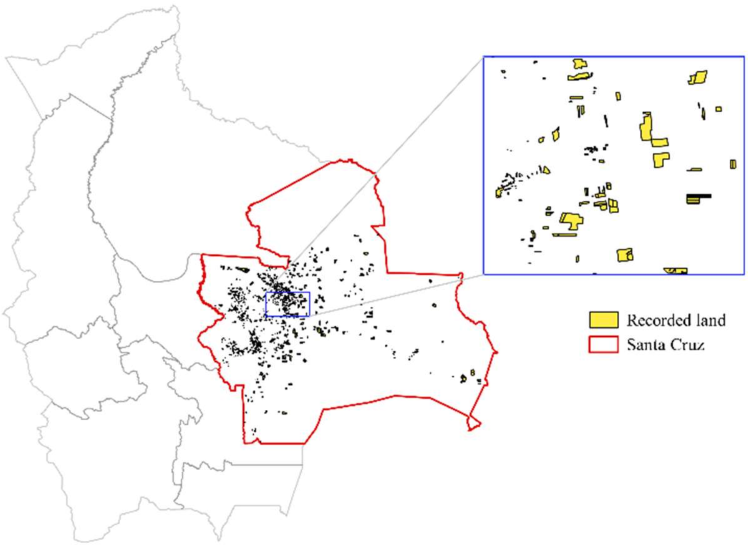

Figure 1. Santa Cruz municipality with recorded land plots with administrative information to be used on the hedonic model for price estimation

Methodology

Econometric framework

The model specification is the following: $P = f(Z)$, where P is the price of rural land per hectare, and Z is a vector of rural land characteristics. The partial derivative of the price with respect to each characteristic gives the marginal implicit price of that characteristic. Economic theory does not dictate any specific functional form; hence we use a linear form. In practice, data and the goodness of fit indicate the choice of the functional form (Oxford, 2014).

We estimate different specifications of Ordinary Least Squares (OLS) and Weighted Least Squares (WLS) models of land transaction prices (USD/hectare) using a data set containing 2 332 rural land sales in Santa Cruz Department for the period 2010-2015, while controlling for farm/ranch area in hectares, forest land per plot (%), land type (agriculture farm or ranch), average Gross Production Value (GPV in USD) per hectare and GPV of Coca (in USD) per hectare at the municipality level, which allows us to control for Coca production which is a high return crop, yearly fixed effects, and municipality fixed effects (44 different municipalities). The municipality fixed effects allow us to control for time-invariant unobservable characteristics of each municipality, capturing spatial variation in soil quality, road access, and distance to markets.

Equation 1 presents the general functional form of the estimated models:

$$= \quad + \quad +_{1} \quad +_{2} \quad +_{3} \quad +_{4} \quad +_{5} \quad * \quad +_{6} \quad +_{7} \quad +_{8} \quad + \qquad (1)$$

Where is the declared purchase price of the property in municipality at time , depicts area of land in hectares, represents the percentage of the property covered by forest before the land transaction according to satellite data, the dummy variable represents the type of land (farm or ranch), and represent average Gross Production Value (GPV in USD) per hectare and GPV of Coca per hectare at the municipality level according to the 2013 Agricultural Census (INE, 2013), and are municipality and year - fixed effects. We include an interaction term, * to account for the potential differential effect of being a small holding by land type. The effects could be different by land type since they have different restriction thresholds from which they are defined “smallholdings” (50 hectares for farms and 500 hectares for ranches), different characteristics of their production processes, capital requirements, and possible different risk preferences between ranchers and farmers. The measurement and specification error component, , represents individual municipality heterogeneity, time and stochastic elements. We assume that is normally distributed with mean zero and constant variance. Additionally, we run separate regressions for farms and ranches.

Land cover classification

All Landsat images (1 555) were pre-processed: cloud detection and removal; haze, surface reflectance and geometric correction (co-registration and reprojection). A deforestation map was created based on imagery from 1987 to 2018 using a bareness threshold over the Shortwave Infrared band (SWIR1) under the assumption that if a pixel appeared bare within the 10 years previous to the observation period, then it is no longer considered as forest.

Also, a supervised classification using the Random Forest classifier was performed using two Landsat 7 images from August 18th 2000, one per scene, to create a land cover with two classes: forest and non-forest. For training and validating the model, sample points were taken based on additional maps, together with Google and Bing background imagery. The accuracy of the classifier in predicting land cover classes from a single date image yielded 88% from the *out-of-the-bag* samples.

A preliminary land cover baseline was produced using the deforestation map of 2000, together with the land cover classification from August 18th 2000 in order to detect deforestation from 2001 and on. To generate the forest cover maps per plot for 2010 to 2015, the deforestation maps were subtracted from the land cover classification baseline map and overlaid with the polygons containing administrative and trade information per plot. An extra field was obtained with information about the percentage of forest cover per plot.

In this study, forest is defined as an extension greater than 0.5 ha of land that is characterized by being widely covered by trees, they can be constituted by different species of trees or by a predominant species, in addition to undergrowth. Forests consist of living agents (animals, insects, microorganisms, living beings, etc.) and non-living agents (water, air, soil, etc.).

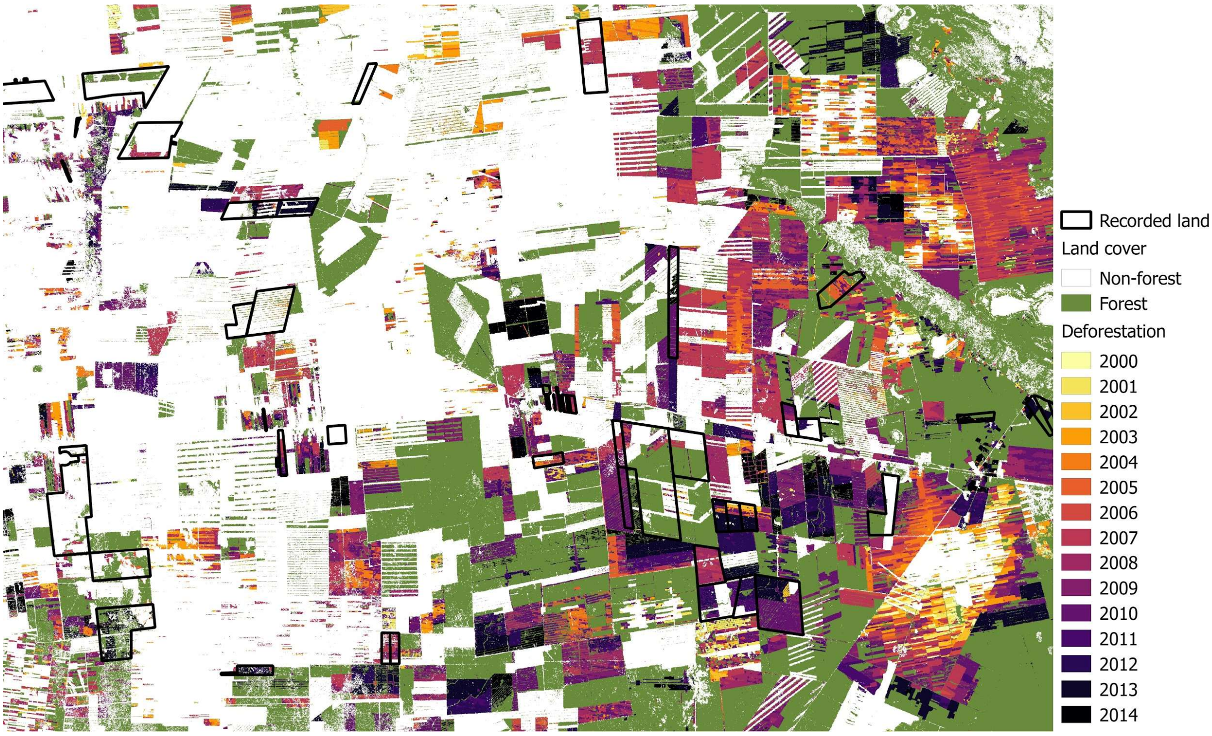

Figure 2: Forest cover and deforestation from 2000 to 2014 in Santa Cruz overlaid with recorded land with administrative and trade information

Results and discussion

Regression results with all property types (Table 7) show significant results for the Ordinary Least Square (OLS) and WLS specifications, each model contains variables that are jointly significant to explain land prices. With explanatory power ranging from 25%, explaining up to 50% of the variation in prices. Given that a sale price represents the average price of each hectare at the rural property sold, and that price varies depending on the size of the property, a WLS model with property area as weight is more appropriate to explain land values. The different WLS specifications show negative effects of farms on prices.

Additionally by including property area and its quadratic term we find that an increase in the value per hectare the larger the property (USD 1 100 per extra hectare in models 5 and 6) at an extremely small but significant decreasing rate.

We also found that the percentage of forest land has a negative effect on the prices in all the model specifications. In model (6) weighted least squares with all the controls, we find that by every extra percentage point of forest covered land, the value of the property decreases by US$1083 per hectare. The average property size is 227 hectares, hence an increase of 2,27 forest covered hectares, reduces the value by US$1083. This implies that every additional forest covered hectare that a property has reduces its value by US$477.09 per hectare, this is the average price differential of a hectare with and without forest cover. Therefore, a hectare of forest covered land costs US$1544,57 on average, and a hectare of deforested land costs 1974,57$, this differential may also reflect the deforestation cost per hectare. If there is arbitrage, the US$430 are the deforestation cost and the opportunity cost of deforestation would be higher, in which case it would lead to deforestation. If this is the case it is likely that the buyer deforests more than the seller. These negative effect would imply that buyers prefer deforested land probably due to their interest to convert forest into grass or cropland. This is a key result that we can identify only thanks to satellite data, as the marginal cost of forested area reflects the opportunity cost of a forested hectare perceived by land buyers. Biogeographic provinces are also significant in most models, despite controlling for municipality fixed effects. Both results show the importance of including satellite data to improve rural land hedonic price models, with improvements in explanatory power as presented in Table 7.

Table 8 presents the results for farm land prices, in both OLS and WLS specifications forest covered land reduces the price. Similarly, Table 9 presents the results for ranch land prices the negative relationship between forest covered area and prices still holds. A one percent increase in forest cover reduces the price per hectare in fam land more than a one percent increase forest cover in ranches, - US$764.92 for ranches and - US$2323.78 for farms.

This study became part of the Earth Observation for Sustainable Development (EO4SD), an ESA initiative. By using higher resolution sensors, like the ones from the Sentinel satellites, other important variables such as crop type could be included in the model to improve the estimation of land value in Bolivia.

Conclusion

Understanding and being able to explain and predict rural land prices is key for the decision making process of public and private economic agents. Due to the limited access and existence of administrative data in developing countries, explaining and forecasting rural land prices is extremely challenging. Recent technology allows the generation of more detailed and timely satellite data, that represent rich and useful information for rural price explanation. Including satellite data improves the explanatory power of the models, additionally it allows us to identify the cost of deforestation which would not have been possible without satellite images. The finding in this paper supports the fact that using satellite data in hedonic price models for rural land valuation in Bolivia in a context of reduced administrative information may be beneficial. Land cover can determine land valuation and its conversion may depend on price of commodities. Further improvements to the model can be made by incorporating information about crops, biodiversity, habitat quality and land conversion which can be derived from satellite data.

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Table 2. Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Simple statistics					
$/hectare	2,642	1858.473	3009.341	59.95044	21987.78
Area (hectares)	2,642	227.0673	642.1878	0.1168	5592.041
Forest Land (%)	2,642	0.26915	0.330018	0	1
GPV / hectare	2,574	2686.67	1750.719	110.0988	6518.301
GPV Coca/hectare	2,574	0.0002224	0.0011242	0	0.009872
Surface weighted statistics					
$/hectare	598,626	1586.202	3193.092	59.95044	21987.78
Forest Land (%)	598,626	0.31718	0.346066	0	1
Area (hectares)	598,626	2046.538	1654.356	1.0003	5592.041
GPV Coca/hectare	564,711	0.000065	0.0006797	0	0.009872

GPV= Gross Production Value

	Type	Frequency	Percentage
Economic Activity	Farms	1533	58,02%
	Ranches	1091	41,29%
	Mixed	2	0,08%
	Other	8	0.3%
	None	1	0,04%
Classification	Small	2,386	90.31%

Table 3. Farm Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Simple statistics					
$/hectare	1,533	2079.502	3223.845	70.44894	21987.78
Area (hectares)	1,533	56.37213	237.8214	0.2823	4144.401
Small	1,533	0.869537	0.3363222	0	1
GPV / hectare	1,510	3103.146	1862.92	110.0988	6518.301
GPV Coca/hectare	1,510	0.0002555	0.0011879	0	0.0098725
Surface weighted statistics					
$/hectare	85,673	2175.308	4253.309	70.44894	21987.78
Area (hectares)	85,673	1067.728	1320.698	1.0003	4144.401
Small	85,673	0.4008848	0.4900806	0	1
GPV / hectare	84,361	3898.345	2163.171	110.0988	6518.301
GPV Coca/hectare	84,361	0.000103	0.0004952	0	0.0098725

Table 4. Ranch Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Simple statistics					
$/hectare	1,091	1534.253	2603.415	59.95044	21699.99
Area (hectares)	1,091	460.4165	901.2126	0.4234	5592.041
Small	1,091	0.8240147	0.3809823	0	1
GPV / hectare	1,046	2101.827	1380.087	620.84	6518.301
GPV Coca/hectare	1,046	0.0001775	0.001034	0	0.0098725
Surface weighted statistics					
$/hectare	501,785	1506.646	2994.823	59.95044	21699.99
Area (hectares)	501,785	2224.727	1662.797	1.4025	5592.041
Small	501,785	0.2458144	0.4305695	0	1
GPV / hectare	469,182	1762.891	1422.069	620.84	6518.301
GPV Coca/hectare	469,182	0.0000597	0.0007153	0	0.0098725

Table 5. Farms Summary Statistics by legal type

Variable	Obs	Mean	Std. Dev.	Min	Max
Large					
$/hectare	56	2905	5210.321	92.4434	21828.78
Area (hectares)	56	1756.748	1314.156	50.0065	4144.401
GPV / hectare	56	4339.358	2167.883	110.0988	6518.301
GPV Coca/hectare	56	0.0000208	0.0001436	0	0.0010142
Small					
$/hectare	1477	2067.09	3185.7839	92.44348	21828.34
Area (hectares)	1477	28.9490	20.16326	10.2823	50
GPV / hectare	1477	3037.748	1836.5	110.0988	6518.301
GPV Coca/hectare		0.0002652	0.0012091	0	0.0098725

Table 6. Ranches Summary Statistics by legal type

Variable	Obs	Mean	Std. Dev.	Min	Max
Large					
$/hectare	192	1845.38	3640.63	59.99971	21699.99
Area (hectares)	192	1971.515	1317.507	502.5724	5592.041
GPV / hectare	192	1913.375	1550.143	623.0479	6518.301
GPV Coca/hectare	192	0	0	0	0
Small					
$/hectare	899	1467.806	1612	59.95044	19607.84
Area (hectares)	899	137.6901	168.2437	0.4234	500
GPV / hectare	899	2140.997	1376.96	620.84	6518.301
GPV Coca/hectare	899	0.0002140	0.0014046	0	0.0098725

Table 7. Regressions with all registered transactions

	(1)	(2)	(3)	(4)	(5)	(6)

	OLS	OLS	OLS	WLS	WLS	WLS
Small	-585.0*	-217.4	-234.2	-693.6***	104.2***	113.6***
Area (hectares)	0.190	0.724	0.735	0.314***	1.100***	1.110***
Areasq (sq hect)		-0.000089	-0.000091		-0.000153***	-0.000153***
Farm		599.1***	617.5***		-607.8***	-629.4***
Forest Land (%)		-1111.9***	-1134.3***		-1065.7***	-1083.0***
Road distance		0.00587	0.00612		0.0356***	0.0356***
ProvBiogeo=2		-247.9	-242.8		-925.2***	-914.0***
ProvBiogeo=3		-449.0*	-452.8*		147.5***	154.9***
ProvBiogeo=4		2709.4*	2707.7*		5109.5***	5162.3***
ProvBiogeo=5		2107.7**	2103.1**		2245.5***	2264.3***
ProvBiogeo=6		1601.6**	1592.8**		1246.8***	1243.6***
ProvBiogeo=8		312.7*	310.8*		43.61**	47.96**
ProvBiogeo=9		-476.7	-482.4		-1751.6***	-1757.2***
ProvBiogeo=10		-190.9	-188.4		-697.8***	-705.6***
GPV / hectare			0			0
GPV			0			0
Coca/hectare						
Constant	-2568.4	1519.2**	1555.1**	344.4**	1088.8***	1055.3***
R^2	0.250	0.271	0.269	0.464	0.501	0.498
BIC	50522.3	47460.0	46378.0	10685202.6	9995917.4	9612850.7
Observations	2695	2531	2471	576429	540177	518363

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. WLS=Weighted Least Squares. *Similar results are obtained with Clustered Standard Errors at the Municipality level.*

Table 8. Farms regression

	(1)	(2)	(3)	(4)

	OLS	OLS	WLS	WLS
Small	-20.86	114.013	-678.04***	1664.32***
Area (hectares)	1.4570	1.703	1.807***	3.9831***
Areasq (sq hect)		-0.0000423		-0.0010336***
Forest Land (%)		-1081.85***		-2323.78***
Road distance		-0.0242667		0.0325***
ProvBiogeo=2		-524.255		-236.457**
ProvBiogeo=3		-724.8***		-70.144***
ProvBiogeo=4		-370.358		436.07
ProvBiogeo=5		899.52		1767.663*
ProvBiogeo=6		1595.991*		2681.63***
ProvBiogeo=8		361.97***		727.8315***
ProvBiogeo=9		0		0
ProvBiogeo=10		-941.13**		-99.04
GPV / hectare		25.5017**		6.1209**
GPV Coca/hectare		4.12e+07**		8893158*
Constant	750.334	-5749.8**	668.7597***	-15096.42**
R^2	0.3416	0.3529	0.4998	0.5624

BIC	28750	28053.06	1665587	1605335
Observations	1527	1501	86213	83553

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. WLS=Weighted Least Squares. Similar results are obtained with Clustered Standard Errors at the Municipality level

Table 9. Ranches regression

	(1) OLS	(2) OLS	(3) WLS	(4) WLS
Small	-402.52	-680.553**	-517.475***	155.62***
Area (hectares)	0.1348	-0.513	0.2669***	0.8680***
Areasq (sq hect)		0.000852		-0.001039***
Forest Land (%)		-613.06***		-764.923***
Road distance		0.020822		0.0161***
ProvBiogeo=2		-323.64		-1297.602**
ProvBiogeo=3		-192.49		255.2881***
ProvBiogeo=4		3264.38**		4840.012***
ProvBiogeo=5		1832.89**		615.96***
ProvBiogeo=6		1417.78*		-6.8511
ProvBiogeo=8		311.14		292.58***

ProvBiogeo=9		-588.91		-2262.44***
ProvBiogeo=10		-230.254		-1187.82***
GPV / hectare		5.9730		0
GPV Coca/hectare		927889		0
Constant	645.28**	-5749.8**	1898.28***	11150.26***
R^2	0.3249	0.3420	0.5127	0.5337
BIC	20055.62	19283.47	8505827	8038496
Observations	1084	1039	467541	442454

$^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. WLS=Weighted Least Squares. Similar results are obtained with Clustered Standard Errors at the Municipality level