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Survey-based modeling of land-use intensity in agricultural frontiers of the Argentine dry Chaco

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A B S T R A C T

The rise of large-scale farms in modern-day agricultural frontiers has frequently displaced and fragmented smallholder farming due to an unbalanced competition for land and water resources. A better understanding of land-use decision making of heterogeneous farming systems and farmer behavior is needed for tailoring policy instruments that help shaping these frontiers towards more efficient, equitable, and sustainable outcomes. Here we analyze a survey of 235 land users, ranging from large-scale agribusiness enterprises to small-scale subsistence-oriented farmers, across the Northern Argentine Dry Chaco. We use the survey data and auxiliary geospatial data in a Bayesian network to quantify the key determinants of gross farm revenues for the surveyed farms and simulate how the farm revenues respond to alternative policy scenarios. If farms are crop or cattle farms as well as the level of intensity of farming explained a large proportion of the variation in revenues for commercial and semi-subsistence farms. Revenues in commercial farms are mainly formed by the size of the farm and the level of capital input. In contrast, access to credit and land tenure are substantially more important in shaping gross revenues in the semi-subsistence farms. The simulation of a scenario with a hypothetical land titling program combined with better access to credits suggests that unlocking these barriers could generate higher revenues for semi-subsistence farmers without compromising the revenues that can be attained by the large fully commercialized farms. Our finding hence underpins claims that secure land titles can crucially benefit particularly the economically marginalized and smaller land users and, in that way, may also contribute to more inclusive rural development.

1. Introduction

The penetration and expansion of large-scale agriculture into tropical and subtropical regions of developing countries have caused profound environmental problems and increased social inequality. Extensive land-use change and deforestation to produce agricultural commodities for export (e.g., soybeans, palm oil, beef) has created agricultural frontiers characterized by a dynamic mosaic of heterogeneous land-use systems. This results from the superimposition of successive waves of land occupation by land users that utilize distinct types of natural resources with different levels of management intensity (Morello et al., 2005).

The distribution of benefits and impacts in modern-day agricultural frontiers is highly unequal as the rise of large-scale farms has frequently displaced and fragmented smallholder farming due to an unbalanced competition over access to land and water resources (Cáceres, 2015). Unequal patterns of land tenure and land use are distinctive of agricultural frontier regions in the developing tropics in general (Rudel, 2007), and of South American "neoliberal" agricultural frontiers in particular (Brannstrom, 2009), such as those in the Brazilian Cerrado (Jepson, 2006), Bolivian lowlands (Mller et al., 2012), and Paraguayan Chaco (Correia, 2017). The Argentinean Dry Chaco represents an

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archetypal modern agricultural frontier due to the large variations in farm types and land-use intensity seen across the region.

The South American Gran Chaco contains multiple agricultural frontiers that have expanded rapidly at the expense of dry forests and savannas in the last two decades, making this region the major global deforestation hotspot of the 21st century (Hansen et al., 2013). The agricultural frontiers in the Chaco differ in their natural endowments and environmental history but they all share the recent penetration of large-scale, capital-intensive farming operations on lands that were occupied by extensive land-use systems, such as low intensity silvopastoral systems and indigenous groups relying on hunting and gathering for their livelihoods. In the Northern Argentine Dry Chaco, the conversion of large tracts of forests into crops and pastures accelerated in the late 1990s with the arrival of genetically-modified soybeans and after the 2001 economic crisis, when many agricultural companies and entrepreneurs invested their surplus capital from soybean cultivation in the temperate humid Pampas to expand their farming operations in the dry subtropics (Gasparri and Grau, 2009). Between 2002 and 2010, the Northern Argentine Dry Chaco lost between 150,000 and 200,000 ha of forest per year due to the expansion of soybean and pastures (Gasparri et al., 2013). Such rates of deforestation were twice and five times larger than the continental and global averages, respectively (Vallejos et al., 2015).

In such highly unequal agricultural frontier regions, tackling coupled environmental and social problems require targeted policies that bridge the divide between conservation and development policy arenas. Increasing public concerns about the impacts of deforestation in the Argentine Dry Chaco compelled the enactment of the National Forest Law in 2007, which mandated the zoning of forested lands to prevent agricultural expansion into areas of medium and high conservation value (Aguiar et al., 2018; Piquer-Rodríguez et al., 2018). Although deforestation without this land-use policy may have been higher (Nolte et al., 2017), its effectiveness has been limited by opposed development objectives between agricultural and environment sectors and between national and provincial levels (Seghezzo et al., 2011) and by rebound effects due to the increase in agricultural productivity, which spurred further land expansion (Ceddia and Zepharovich, 2017). In addition, there is a lack of comprehensive region-level information on the biophysical and socio-economic dimensions of agricultural frontier dynamics to inform policy design (García Collazo et al., 2013). This is unfortunate because, while the pace of deforestation has decreased in synchrony with decreases in soybean prices, the crop and pasture expansion into high-value forests has not been stopped (Volante and Seghezzo, 2018; Aguiar et al., 2018).

A better understanding of the factors driving the large variations in land-use intensity that characterize the modern-day agricultural frontiers is needed for the design of policy instruments tailored to the dynamics of heterogeneous farm systems and farmer behavior (Mastrangelo, 2018). There is a need for data and methods that allow integrating the biophysical, social, and economic factors that influence conservation and development outcomes in these frontier regions. Most studies to date in the Argentine Dry Chaco have focused either on the spatial determinants of deforestation or the expansion of cultivated areas using remote-sensing data at the pixel level (Gasparri et al., 2015; Volante et al., 2016), or on their socio-economic drivers using statistical data at the district level (Paolasso et al., 2012, Sacchi and Gasparri, 2016). Farm-level surveys can supplement such analyses with georeferenced actor-specific data about variables relevant to understand the biophysical and socio-economic drivers of land-use outcomes at the farm scale where land-use decisions are made.

Land-use decisions and outcomes of the heterogenous types of farms of the agricultural frontiers in the Chaco are determined by a multiplicity of interacting factors. Land concentration and land tenure insecurity strongly contribute to the configuration of regional farm structure, and are important, although understudied, drivers of environmental degradation and social vulnerability (Cáceres, 2015). The regional increase in mean farm size over the last 25 years has not resulted from the transition of local small farmers to medium and large size farms, but mostly from the arrival of extra-regional medium and large farmers with production strategies based on forest clearing and farm expansion. Such replacement (rather than transition) of farm types and production strategies has been facilitated by the fact that large proportions of local small famers have been using lands without definitive titles, which made them prone to displacement by larger farmers. There exists very little information on the extent of land tenure insecurity in the region, with available figures indicating between 25% to 40% of the farms being merely possessed and used without formal land titles (Reboratti, 2010). The way that farmers differentially access, accumulate, and use the multiple forms of capital or livelihood assets often configure divergent production strategies in a region (Bebbington, 1999), and are thus very useful to understand the factors underlying regional variations in land-use decisions and outcomes.

We conducted a survey of 235 land users, ranging from large-scale agribusiness enterprises to small-scale subsistence-oriented farmers across the four main provinces of the Argentine Chaco. The dataset captures land-use extent and intensity, as well as hypothesized influencing factors for these, for this diverse cross-section of land users in one of the most active global frontier regions. We linked our farm survey with fine-scale spatial attributes that we anticipate to affect land-use decisions and thus to shape regional land-use patterns. We use non-parametric Bayesian networks to analyze the survey and geospatial data with gross farm revenues and revenue per area as our outcome variables and assess how revenues will change under different situations and policy settings. We aim to answer the following two research questions: (i) What are the key determinants of farm revenue in semi-subsistence and commercial farms in the Chaco agricultural frontier? and (ii) How will farm revenues of commercial and small semi-subsistence farms change in response to alternative policy scenarios?

2. Material and methods

2.1. Study area

Our study region stretches over three ecological sub-regions of the Dry Chaco, i.e., Western Subhumid, Central Semiarid, and Central Subhumid (Adámoli et al., 2008), and intersects four provinces in the Northern Argentine Dry Chaco (Salta, Santiago del Estero, Chaco, and Formosa) (Fig. 1). Mean annual temperature ranges from 19 to 24 °C and rainfall is between 1000 mm in the eastern and western subhumid fringes of the surveyed area to 500 mm in the semiarid core (Adámoli et al., 2008). Rainfall concentrates in summer, with a long dry season from April to November. Vegetation was dominated by semi-deciduous and deciduous seasonal forests, of which almost a quarter of its original extent was lost by 2012 due to agricultural expansion (Vallejos et al., 2015).

The Northern Argentine Dry Chaco contains five agricultural frontiers that expand from the subhumid fringes of the region into the semiarid core, and negatively impact the capacity of ecosystems to regulate biophysical processes important for human well-being (Paruelo et al., 2016). This sub-region shares a history of human occupation with a large diversity of indigenous groups that declined in their numbers. Moreover, many indigenous people reduced the mobility of their traditional semi-nomadic lifestyles due to increasing contract work, competition for land with criollos (i.e., local people of European and indigenous descent), and land acquisition by extra-regional companies (Morello et al., 2005). Criollos families herded livestock extensively for more than a century, mostly under insecure land tenure and either in large landholdings with absentee owners or on government-owned land. In the last decades, indigenous and criollos were pushed and cornered into diminishing portions of marginal lands due to the arrival and expansion of capital-intensive farming operations from neighboring regions and of transnational agribusiness companies

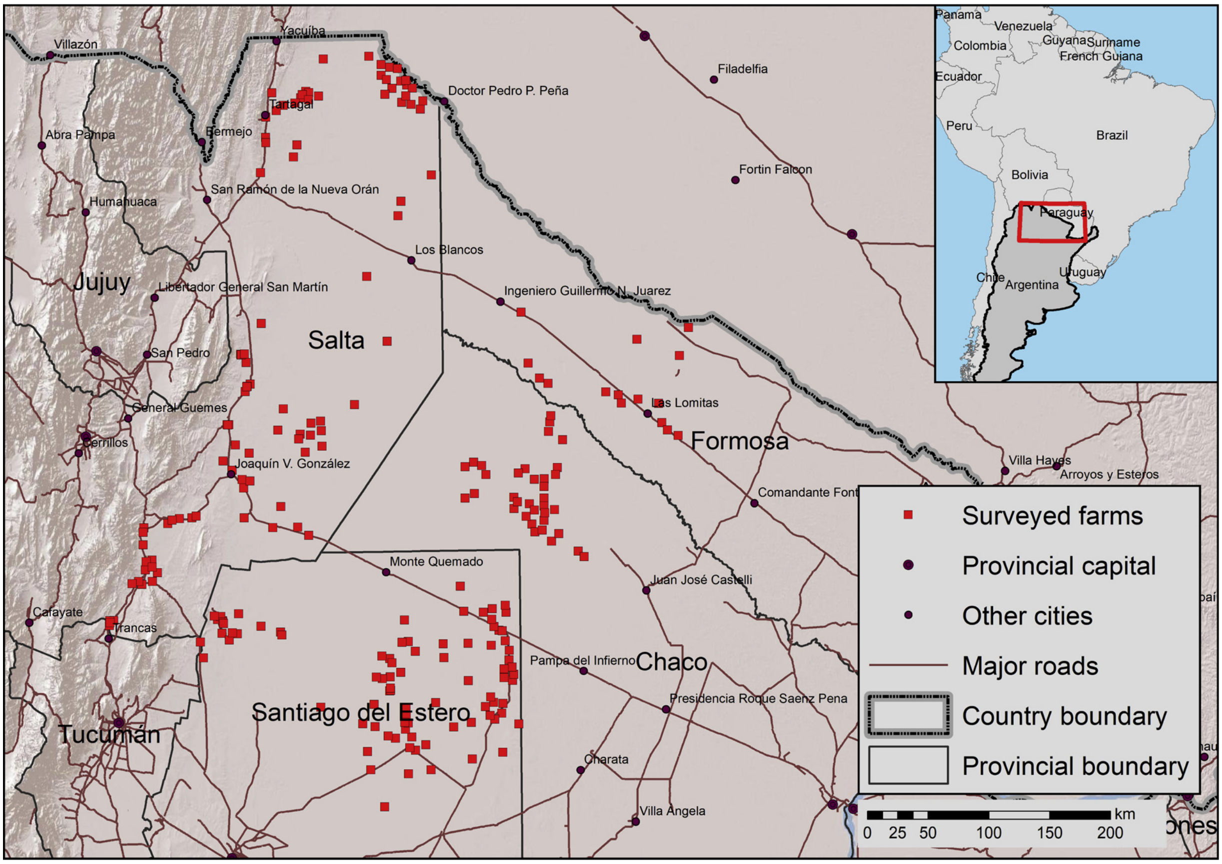

Fig. 1. Map of the Northern Argentine Dry Chaco showing the spatial distribution of surveyed farms.

(Cáceres, 2015).

2.2. Collection of survey data

We selected farms to be surveyed with the aim to obtain a sample that well represents the diversity of farms present in the study area regarding climate and soil conditions, farm size, and main production activity (i.e., crop, livestock, or mixed). We defined farms as portions of the territory where land is used with some level of intensity for production purposes, which means that native ecosystems are to some extent transformed in their structure to introduce crops and/or livestock. Indigenous people mostly base their subsistence in the harvest of products from native ecosystems (i.e. bushmeat, honey, fruits) without substantially transforming them, so their territories do not fit the definition of farms. Drawing on an initial pre-selection of farms following the above selection criteria, we compiled a list of small and large farms that are active in the study area as a sampling frame (a complete list of land users that we could have used as a sampling frame is lacking for the region). Moreover, we were unable to cover the entire area in a statistically representative way due to budget constraints (the entire study region covers 176,000 km^2). We therefore selected farms with a mixture of random selection and a purposive sampling strategy.

Once farms were selected, we contacted each selected farmer to obtain his or her agreement for the interview. We ended up interviewing 235 farms distributed all over the study area with a paper-based questionnaire (Fig. 1). Most of these farms are in areas where the agricultural frontier is consolidating (i.e., the agricultural matrix expands into remnant patches of natural cover), while some farms are located where the frontier continues to expand (i.e., patches of agricultural uses perforate the matrix of natural cover). The selected farms were visited by a trained interviewer who conducted an in-person interview in Spanish to the person responsible for making or implementing land-use decisions on the farm (hereon "farmer"). In the large farms that are typically run by big companies, which manage several farm operations, the person who decides on the major land-use strategies (e.g., crop choice) was usually absent from the farm, so we interviewed the farm manager or agronomist who implement those decisions and decide about on-farm agronomic management. On smaller farms run by small companies or by families, we interviewed the person who made overall land-use decisions.

The survey questionnaire administered to the farmers comprised 54 questions distributed over the following sections: i) characteristics of the farmer, ii) structure and composition of the farm, iii) access to different forms of capital, iv) values and attitudes of farmers towards land-use options. Most questions were close-ended and inquired about the status and trends in attributes of farm structure and functioning, while some items asked farmers to describe their perceptions and valuations using the Likert scale.

2.3. Bayesian network approach

Bayesian networks are graphical probabilistic models that encode joint probability distributions of a set of variables with a directed acyclic graph (DAG) (Nielsen and Jensen, 2009). The DAG is also known as the structure of the network, and it is composed of nodes and directed links where the nodes are the variables and the links represent the interdependencies between the variables. These interdependencies can signal a cause-effect relationship but can also capture mere statistical correlations. Nodes with links pointing to a particular node are called parent nodes of that node; nodes with links pointing from a node are called child nodes of that node. A node does not necessarily have a parent node or a child node. Each node or variable in the network denotes an attribute, feature, or hypothesis about an uncertain event with a set of state values, which are typically discrete, mutually exclusive, and collectively exhaustive. For example, a variable describing a farmer's production strategy, as in our model, can take on three possible states, namely "cattle", "crops", and "other". Originally continuous variables, such as the farm revenue in our model, were discretized into a small number of categories in the model based on break points. We determined the break points using the statistical distributions of the variables, augmented by domain expertise.

The graphical structure of a Bayesian network consists of nodes, which represent the variables, and links among the nodes, which represents the probabilistic interdependences among nodes. Each variable with a parent node, i.e., a variables that it depends on, has a conditional probability table (CPT) that quantifies the probability by which a value is influenced by the parent nodes. Mathematically, the influences among the variables are defined by conditional dependencies that are derived using probabilistic inference, which relies on Bayes' theorem (Heckerman et al., 1995; Pearl, 2000).

Compared with other statistical models such as econometric approaches, Bayesian networks have many advantages (Uusitalo, 2007; Sun and Müller, 2013): 1) Bayesian network can easily handle the missing values in the data. For example, if one question or more questions were not answered in the survey for whatever reason, that observation with missing values can still be used in Bayesian network analysis. 2) With a graphical structure, Bayesian networks are more intuitive to communicate with stakeholders, who are usually non-scientists. 3) Bayesian network can easily incorporate qualitative information including expert knowledge and opinions in constructing and parametrizing the model. 4) Bayesian network support scenario analysis by varying a particular variable or a combination of several variables, as the interactions among variables are explicitly built in.

2.4. Construction of the Bayesian network

As a Bayesian network consists of a qualitative and a quantitative component, namely, the structure (i.e., the DAG) and a set of parameters (i.e., the CPTs), its construction involves two steps. First, the elaboration and construction of the network structure (DAG) with all variable nodes and their linkages and, second, the population of the CPTs with the probabilistic estimates. We constructed the network by selecting candidate variables from our survey and spatial data, which we linked based on a combination of common sense, expert knowledge, and the statistical correlations among the variables in the data. Specifically, we developed an initial structure together with experts of agricultural land use in the Chaco region. At the same time, we used the structural learning process implemented in the Hugin software package (www.hugin.com) to explore and develop a structure based on the statistical correlations among the variables. During the learning process, we incorporated the expert knowledge by enforcing or prohibiting some links. Once we had a network, we went back to experts for further inputs and comments. Data may confirm or contradict with experts' initial judgements; data may also reveal formerly unconsidered linkages, which would need to be confirmed by experts. In addition, we followed the principle of parsimony in the construction of BN with the aim to create a network with the least possible categories of variable states and the fewest possible parent nodes to avoid excessively large CPT tables (Chen and Pollino, 2012; Marcot et al., 2006).

One useful strategy towards a parsimonious network is to use latent variables as intermediate nodes. The latent variables have no observation data but are the combination of related input variables. In our network, we constructed, for example, a node "capital input" as a latent variable that results from the combination of "chemical inputs", "irrigation", and "machinery". Once we settled on a plausible structure that reflects the interdependence embedded in the data and was approved by the experts, we populated the CPTs with the 235 observations from the farm survey data. We then learned the network with the expectation-maximization algorithm that is implemented in the Netica software (www.norsys.com).

2.5. Description of target variable

We focused on farm-gate gross farm revenues as our target variable and used it to compare heterogeneous farms with various products and strategies. Farm revenues comprise the total returns from marketed farm products, that is, the sold quantity of each product times the price per unit of this product. Farm revenues capture monetary returns from farm production irrespective of production costs and thus fall short of capturing profits (i.e., gross revenues minus variable and fixed costs). We used farm-gate revenues to control for the different destinies of farm produce in the region, and thus subtracted transportation cost to port for the farm produce destined to export. Obtaining data about farm profits (or profits per hectare or per labor unit) would have been preferable because profit maximization is one important goal in farming operations that are oriented towards marketing surplus production. However, collecting all cost components of farm operations that would be needed to quantify farm profits, was not feasible in our face-to-face surveys because cost data are often not systematically collected by farmers or because farmers are reluctant to reveal these. Moreover, estimating the amount of fixed costs, such as of investments into machinery or buildings, and the discounting of the fixed costs to their net present value is marred with uncertainties.

We believe the use of farm revenue, while being an imperfect measure of farm success and farm-decision making, is nevertheless useful to analyze determinants of land-use intensity and to assess how these differ among distinct groups of farmers. It goes beyond mere analysis of the determinants of area-based land-use extent, crop allocation, or application of intermediate inputs, such as fertilizers of machinery. Moreover, farm revenues can be compared across diverse farms and allow an estimate of the economic performance of the farms.

2.6. Description of influencing variables

The final network structure included 18 variables that we hypothesize to influence farm revenues. Among the categorical variables is chemical input, which was codified into "yes" or "no", with "yes" indicating the application of at least one of the main chemical inputs, i.e., nitrogen fertilizer, phosphorus fertilizer, herbicides, or insecticides. The continuous measure, which captures the monetary value of machinery, was discretized and categorized into "none", "low", or "high", with the cut-off value between "low" and "high" being 300,000 USD. Associativity was categorized in a 6-point scale that combined the number of associations in which the farmer participated and the frequency of participation in those associations, ranging from one for "infrequent participation in one association" to six for "frequent participation in more than two associations". Farmer education was categorized into "high" (farmer attained university or tertiary degree), "medium" (farmer finished secondary school), and low (farmer finished primary school). Finally, labor input was maintained as a continuous variable and indicated with the monetary value of salaries paid to farm workers annually. We calculated this value as the product between number of workers times mean annual salary for all three types of farm labor, i.e., temporary, permanent, and professional.

In addition to variables collected in the survey, we summarized several spatial determinants that are important for farm-level decision making and attach these to the farm-level survey data based on the geographic location of the farms. Specifically, we use soil indicators, market access, and average precipitation because these variables contribute to shaping economic land rents, following the theories of Ricardo and von Thünen. The variable measuring soil productivity is an index derived from the soil inventory database of the National Agricultural Technology Institute (INTA) of Argentina. This index combines multiple soil and environmental attributes and ranges from 0 to 100, with values closer to 100 indicating a soil with higher potential productivity for the corresponding climatic zone. We used the total annual rainfall in 2016 from the widely used global rainfall dataset of the Climate Hazards group Infrared Precipitation with Stations (CHIRPS) (Funk et al., 2015).

2.7. Validation, accuracy assessment, and robustness check

To verify and validate the Bayesian network, we firstly conducted a qualitative validation with local experts and researchers to discuss the structure of the network. The experts positively acknowledged the plausibility of the model structure (the DAG) and of the variable discretization. Of course, there is no single correct model structure and variable discretization due to the degree subjectivity involved in the setup of the DAG. We therefore conducted sensitivity analysis of the final model by exploring how variables change in response to the changes of other variables. For example, we observed the probability that a farm would fall into the category of low revenues would increase from 43% to 63% after we set the farm size to be within the smallest category, the production strategy to be "cattle", and access to credit to "None". This result confirms our prior knowledge that small farms that breed cattle without external credits tend to have lower revenues, which suggests that the model is working as expected. As such, the sensitivity analysis helped us to better understand the model and to verify that it performs the tasks for which it was designed (Pannell, 1997).

To quantitatively validate the model, we used cross-validation. We randomly split the 235 observations into 80% (188 farms) for training the model and use the remaining 20% (47 farms) for testing the model performance. To do so, we populated the CPTs of the Bayesian network with the training data, and then predicted the key output variable, gross farm revenue, with the testing data. We then compared the predicted and actual values with a confusion matrix and calculated the overall error rate. We repeated this process of randomly splitting the data into 80-20 shares ten times.

The calibrated and validated BN model can then be used for scenario analyses by changing the value distribution of influencing variables and observing the simulated changes in the target variable. Here we implemented three scenarios "land de-concentration", "land titling", and "access to credit" by varying the influencing variables, farm size, land tenure, and access to credit, respectively. For each scenario, we then examined the impact of changes in the influencing variable on gross and per hectare farm revenue.

3. Results

3.1. Characteristics of surveyed farms

The surveyed farms differed significantly in total revenue, revenue per hectare, and farm size (Table 1). Production strategy (i.e., crop, cattle, or mixed) varied in relation to characteristics of the farm (e.g., land tenure situation) and the farmer (e.g., where (s)he originally comes from). There was an inverse size-productivity relationship in the small- to medium-size part of the farm size gradient, associated to a change from intensive horticultural systems to extensive cattle systems. Farms run by local farmers had annual gross revenues almost seven times lower than those run by farmers coming from other provinces in the Chaco region, and more than 60 times lower than the mean revenues from farmers coming from the Pampas region. Farmers from the Pampas and other Chaco provinces also had more than twice the land-use intensity (proxied by revenues per hectare) compared to local farmers, and cultivated between three and 20 times more area, respectively. Farms with secure tenure right for their land ("titled", hereafter), had annual gross revenues 16 times larger than those with unsecure land tenure rights ("possessed", hereafter). Titled farms were on average eight times larger and managed land twice more intensively than farms with possessed land, on average.

We categorized farms with annual gross revenue above 20,000 USD as "commercial farms" (n = 130) (Fig. 2). These farms are typically oriented towards complete commercialization of their agricultural products. The remainder of the surveyed farms with annual gross revenue below 20,000 USD partly produce for family consumption and often only market a share of their produce. We label these farms as "semi-subsistence farms" (n = 105) (Fig. 2). While both the threshold and the labels contain subjectivity, we believe that they describe well the key distinctions and support interpretation of the results. The two farm types differed profoundly in most surveyed characteristics. Semi-subsistence farms were mostly managed for cattle ranching (85%), by local farmers (80%), predominantly operate under insecure "possessed" land tenure (60%), with low levels of educational attainment (only 32% of the farm managers completed secondary education). In contrast, most commercial farms had land titles (71%), combined crop and cattle production (68%), and were predominantly managed by farmers with a university degree (56%). On average, commercial farms were ten times larger than semi-subsistence farms (8640 ha vs. 850 ha), used between five to ten times more agrochemical inputs and machinery, were located on soils whose quality was 33% higher, and more than twice closer to roads (21 km vs. 48 km).

3.2. The Bayesian network

The final Bayesian network contained gross revenue as the key target variable and 26 influencing variables (Fig. 3). Of these, 18 variables originate from the survey data, two variables were derived using spatial data, and six were latent variables that captured the combined effect of multiple measured variables. Gross revenue was directly influenced by attributes of the farm structure (i.e., revenue per ha, farm size, production strategy, and land tenure) and by farm access to five different livelihood assets or forms of capital, represented by specific combinations of measured and latent variables (indicated by the color of the boxes in Fig. 3). Capital input represents the influence of technological inputs that require capital resources to purchase, namely agrochemicals, irrigation, and machinery. Accessibility captures access to markets and service centers via physical capital and infrastructure by combining the effect of distance to the nearest paved road and town. Natural endowments represent the influence of natural capital assets, such as soil productivity, rainfall, and the quality of underground water for animal and human consumption. The influence of financial capital is assessed with access to credit. Social-human capital capture the combined effects of labor input, associativity, and farmer competitiveness. Here, social-human capital influences gross revenues indirectly by affecting attributes of farm structure, as land tenure and farm size are influenced by farmer origin and influence production strategy and revenue per area.

The horizontal bars and associated probability values of states of each variable node in the network show the initial probability distribution of the influencing and target variables (Fig. 3). Approximately 40% of the farms were classified as semi-subsistence farms, while a similar proportion had less than 500 ha, did not have land titles, and were limited in their production activities by poor natural endowments. Around three quarters of the farms did not apply agrochemicals or irrigation and one half did not have heavy machinery. Only 22% of the farms had medium or high levels of access to credit in the last five years and only 25% actively participated in farmer associations. Almost 40% of the farmers were classified as highly competitive, owing mainly to their high level of education, which was closely associated with farmers less than 40 years old and from an extra-regional origin (Fig. 3).

3.3. Model validation and sensitivity analysis

The average error rate for target variable gross revenue was consistently around 39% in all cross-validation cycles (standard deviation = 4.4%; see Figure S1). The accuracy is not very high, but we deem it acceptable for this parsimonious model structure that serves to predict gross farm revenue, which is potentially influenced by many more

Table 1
Variables included in the Bayesian network.

Variables	Description and units	Categories or range	Median
Revenues			
Gross revenue	Gross revenue attained in 2016 (1000 USD)	0 – 112,323	25
Revenue per area	Gross revenue divided by farm size (USD per hectare)	0 – 135,616	54
Farm structure			
Farm type	Main destiny of agricultural produce	Commercial; semi-subsistence	
Production strategy	Main type of agricultural activity	Crop; cattle; mixed; timber	
Farm size	Area occupied by the farm (hectares)	1 – 180,000	900
Land tenure	Legal condition under which land is used	Titled; possessed; rented; titled and rented	
Natural capital			
Soil productivity	Soil productivity index	0 – 100	37
Rainfall	Annual rainfall in 2016 (mm)	518 – 1164	731
Water for humans	If groundwater is suitable for human consumption	Yes; no	
Water for animals	If groundwater is suitable for animal consumption	Yes; no	
Technology			
Chemical input	If the farm applies chemical inputs (N or P fertilizer, herbicide, insecticide)	Yes; no	
Irrigation	If the farm irrigates crops	Yes; no	
Machinery	Economic value of machinery owned in 2016 (1000 USD)	0 – 3,070	0
Financial capital			
Access to credit	Amount of credit received between 2011 and 2016 (USD)	0 – 5000; 5000 – 50,000; over 50,000	
Social and human capital			
Farmer education	Maximum level of formal education attained	Primary (low); secondary (medium); university or tertiary (high)	
Farmer origin	Place where the farmer family or the agricultural company are from	Local (same province); this region (other province in Chaco region); other regions (provinces outside the Chaco region or other countries)	
Associativity	Number of organizations in which the farmer participates weighted by the frequency of participation	0 - 6	1
Farmer age	Age of the farmer in 2016 (years)	23 – 83	45
Labor input	Amount of money paid as salaries to workers in 2016 (1000 USD)	0 – 88	3,350
Accessibility			
Distance to nearest town	Distance from the farm to nearest town (kilometers)	1 – 180	20
Distance to paved road	Distance from the farm to nearest paved road (kilometers)	0 – 180	10

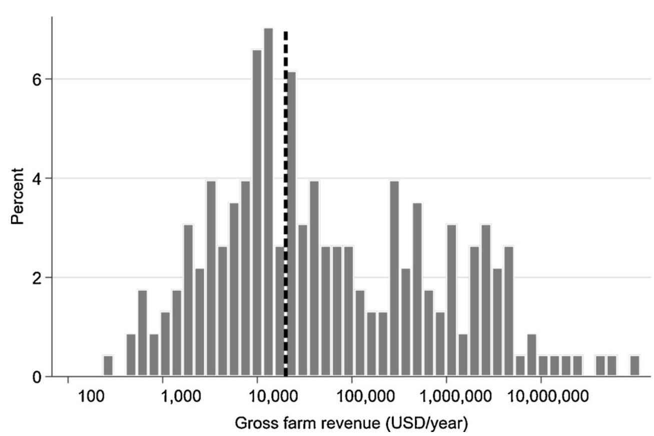

Fig. 2. Percentage of farms in each level of gross farm revenues showing the large variations in farm economic performance among all 235 surveyed farms in the Northern Argentine Dry Chaco. Dashed vertical line indicates the purposive threshold of 20,000 USD that we used to distinguishes semi-subsistence from commercial farm types in our categorization.

ingredients than the few variables used here. Error rates that are very low (for example, when most observations are predicted correctly) may indicate overfitting of the model and are therefore not necessarily preferable. Our error rate is also acceptable considering the heterogeneity of the farms in the study area.

3.4. Factors influencing revenues across farm types

Revenue per hectare is the most important variable influencing gross revenue in both farm types but is more important for semi-subsistence farms compared to commercial farms, indicated by the higher variance reduction (Fig. 4). This is consistent with the fact that an inverse farm size-productivity (i.e., revenue per area) relationship was observed for semi-subsistence farms, while a direct farm size-gross revenue relationship was observed for commercial farms. The latter pattern suggests that increases in revenue per area do not dis-incentivize farm expansion as the land-sparing hypothesis suggests (Mastrangelo and Aguiar, 2019). Production strategy, i.e., cattle or crop or mixed farms, is the next most important variable influencing gross revenues in all farms. The production strategy had more influence on gross revenues in commercial than in semi-subsistence farms. Gross revenues in commercial farms are also crucially impacted by the size of the farm and the level of capital input. The influence of farm size and capital input on gross revenues is four and three times higher for commercial than for semi-subsistence farms, respectively. Machinery, as one contributing variable to capital input, has the highest contribution to gross revenues in commercial farms. The level of social-human capital is also an important variable in commercial farms, with labor input and associativity being the components of this type of capital with higher impact on gross revenues. In contrast, access to credit and land tenure have substantial influence on gross revenues in semi-subsistence farms. The influence of access to credit and land tenure on gross revenue is 37% and 50% higher for semi-subsistence than commercial farms, respectively.

3.5. Simulation of farm revenues under alternative scenarios

We simulated several hypothetical yet plausible scenarios with the calibrated and trained model to better understand the behavior of the model and to make more informed inferences. First, we implemented the scenario of "land de-concentration" by altering the variable "farm size" in the network. The results suggest that if all commercial farms would fall into the medium-sized category between 500 and 2500 ha, their revenue per area would be 63% larger while their gross revenue would only be 21% smaller (Table S1 has the detailed results of all

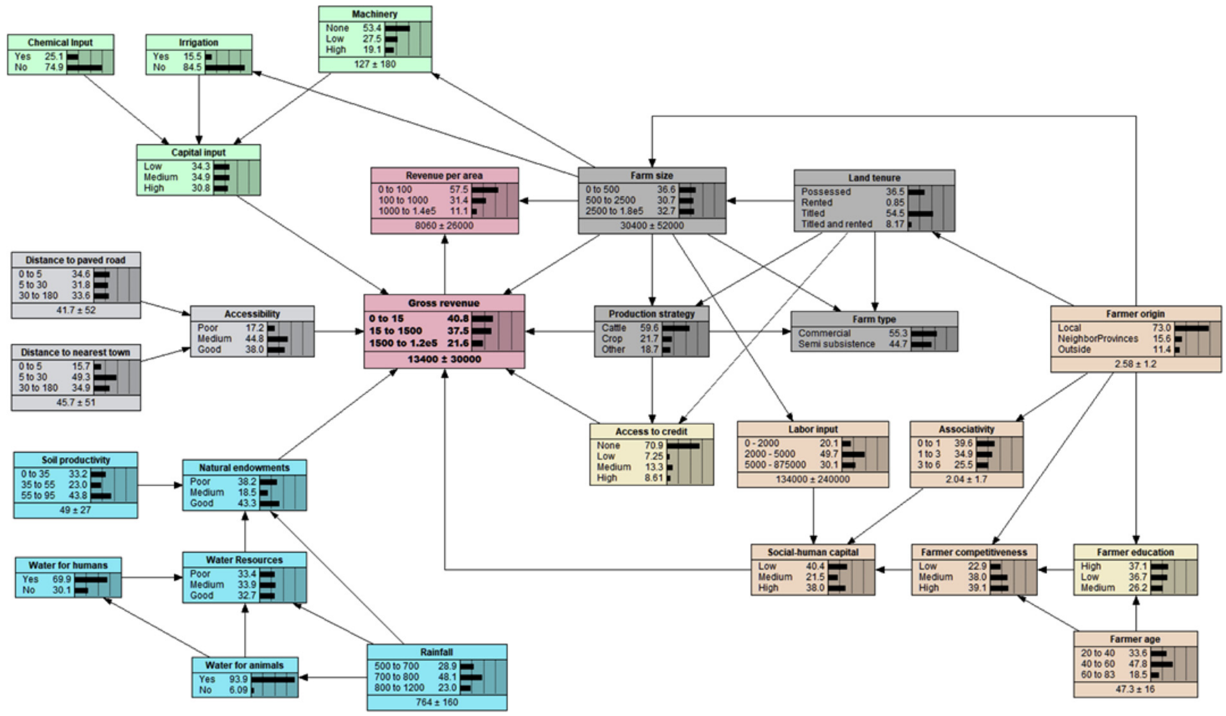

Fig. 3. Final Bayesian network with hypothesized relationships among influencing variables, and between these and the main target variables "gross farm revenue" and "Revenue per area". Target variables (pink boxes) are influenced by natural capital variables (cyan boxes), infrastructure variables (light grey boxes), capital input variables (green boxes), social-human capital variables (orange boxes), a financial capital variable (yellow box) and farm structure variables (dark grey boxes). Horizontal bars in each node show the initial probability distribution of the variable (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article).

scenarios). The lower gross revenue would derive from a 6% decrease (from 27% to 21%) in the proportion of farms in the highest gross revenue category (1,500,000 to 125,000,000 USD) and a 6% increase in the lowest revenue category (0 to 15,000 USD). Therefore, a modest regulation of land concentration can potentially lead to a large gain in revenue per area for all commercial farms at the costs of comparatively small losses in gross farm revenue, which would mainly affect the largest farms.

In the second simulation, we hypothesized that all farms in the sample were granted with land titles. The "land titling" scenario showed that the gross revenue of all farms would increase by 16%. In turn, if all semi-subsistence farms were granted land titles, their gross revenue would be 15% larger. The land titling has less influence on the commercial farms, which would only enjoy a 5% increase in their gross

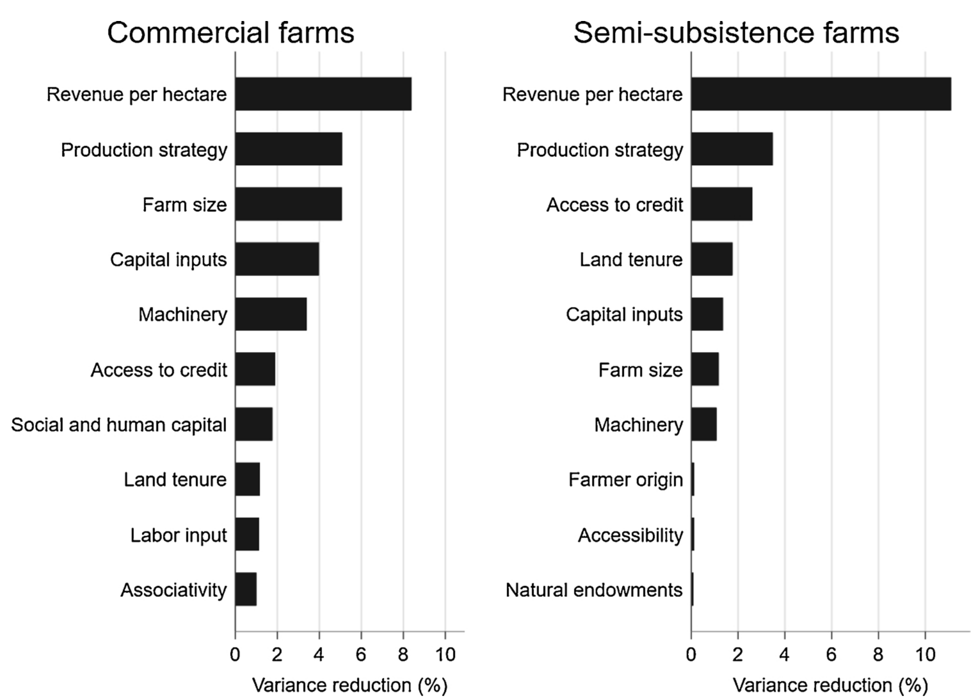

Fig. 4. Variance reduction of the ten most influential variables for gross farm revenue in commercial (left; N = 130) and semi-subsistence farms (right; N = 105).

revenue, according to our Bayesian network.

Securing the legal tenure of land may further permit additional increases in the gross revenues, particularly for the semi-subsistence farms because land titles can serve as collateral to access financial credits. We therefore add a third group of hypothetical scenarios for “access to credit” that simulate different degrees of credit penetration. As expected, the results suggest that access to credit has far larger effects on the semi-subsistence farms than on the commercial farms. If all semi-subsistence farms only received an annual credit of a maximum of 1250 USD, i.e., the “low” category in our Bayesian network, their gross revenue may be 59% larger, mainly because their revenue per area would increase by 37%. The positive effects of access to credit on gross revenue as well as on revenue per hectare become more pronounced for the semi-subsistence farms when credit access is increased to medium and high levels. Therefore, both land tenure regularization and better access to credits can unlock some of the barriers that impede higher revenues for the semi-subsistence farmers. Moreover, secure land titles may be a necessary precursor for many farmers to facilitate access to external financial capital and may hence contribute to substantial increases in production value.

4. Discussion

Our unique survey data allowed us to describe the strong variations in assets and in access to different forms of capital that define the divergent farm types, which configure the highly unequal agricultural frontiers of the Northern Argentine Dry Chaco. The use of Bayesian networks enabled assessing the complex pathways through which farmer and farm characteristics interact and influence land-use decisions and farm economic performance. The integration of farm-level socio-economic and geospatial data in a flexible modeling framework represents a crucial first step towards better identifying the key determinants of conservation and development outcomes in this global deforestation hotspot.

Our results provide valuable insights for understanding the socio-ecological dynamics in modern agricultural frontier regions, and for informing the design of development policies that reduce socio-economic inequality. Unlike archetypal depictions of agricultural frontiers of homogenous farmers and land-use systems occupying previously “empty” or “unused” lands, the Northern Argentine Dry Chaco shows a highly heterogeneous mosaic of farms with diverging trajectories and contrasting livelihood strategies (Mastrangelo and Laterra, 2015). These variations form multiple gradients and a multi-dimensional spectrum of farms. Small farms that are run by local farmers with much of their output destined for auto-consumption appear at one end of the spectrum. Their gross farm revenues are mostly determined by land-use intensity. Large commercial farms managed by extra-regional companies that attain their gross revenues mostly by cultivating large tracts of land appear in the other extreme. In the middle of this spectrum, farms of varying size with low levels of technological and labor input are often only slightly above subsistence levels in a context of increasing land grabbing and land concentration that threatens the permanence in their land possessions.

Assessing the network of influences on revenues separately for commercial and semi-subsistence farms allowed us to start unraveling the factors and mechanisms that produce the observed heterogeneous pattern of livelihood outcomes described. The main type of agricultural activity and its level of intensity consistently explained a large proportion of the variation in gross revenues in both farm types. Semi-subsistence farms base their livelihood strategy on the multiple resources provided by forests and grasslands, mainly forage for free-ranging cattle, and thus depend on the continued availability and access to semi-natural ecosystems. Within this general pattern, semi-subsistence farms that incorporated some level of capital input, such as fences for rotational grazing of cattle, showed disproportionate larger revenues than those that did not. Commercial farms base their strategy on the conversion of semi-natural ecosystems into extensive croplands and pastures, and thus depend on the continued incorporation of capital inputs (machinery, agrochemicals) to simplify the ecosystems to their needs. Accordingly, farm size, capital-based intermediate inputs, and machinery were the most important influencing variables in the commercial farms.

In the absence of significant surplus capital to reinvest in agricultural activities, obtaining financial capital through access to credits to purchase limiting production factors (e.g., farm infrastructure, variable inputs, and machinery) was a key limitation more important in the semi-subsistence farms. Similarly, insecure land tenure, along with the associated higher risks for capital investment in agricultural activities and the more difficult access to credits, also negatively affected the revenue levels of the semi-subsistence farms, of which only one third had land titles. The natural suitability of the land being used under *de jure* tenure or *de facto* possession did not have a significant influence on gross revenues, suggesting that social and institutional factors had a relatively higher influence than natural factors in controlling farm productivity. This is consistent to studies of spatial determinants of deforestation or the expansion of cultivated areas that found weak effect of natural assets, mainly rainfall and soil quality, on the amount of production output (Gasparri et al., 2015; Volante et al., 2016). This is because the spatial determinants predominantly shape the location of change and its spatial patterns but are less decisive for the levels of land-use intensity in particular locations (Meyfroidt, 2016). Better access to physical capital and economic infrastructure that reduce communication and transportation costs has been associated to higher regional-level deforestation and cultivation in this and other agricultural frontiers (Godar et al., 2012). Our analysis, however, did not detect a strong influence of accessibility to roads and towns on farm-level gross revenues. The weak influence of market and infrastructure accessibility on farm-level land-use intensity was expected for the semi-subsistence farms, which auto-consume a substantial share of their production; it was, however, surprising for the commercial farms where others have found that transportation costs are important in shaping farm profits (Piquer-Rodríguez et al., 2018).

Finally, describing regional land-use composition with the farm survey data allowed us to capture human and social characteristics of the farms that are not available in official census and cannot be captured through remote sensing. Among these, associativity is a component of human and social capital that showed an influence on gross revenues of commercial farms. This is in line with several studies which proposed that commercial farmers have a strong tendency to form groups or associations with the purpose of sharing experiences and information relevant for increasing the profit from agricultural activities (Garrett et al., 2013; Mastrangelo et al., 2014).

4.1. Advantages and limitations of Bayesian networks

Bayesian networks allowed to effectively integrate survey and geospatial data to explain large diversities of land-use outcomes, such as tree planting in China (Frayer et al., 2014), land-use decisions in Switzerland (Celio et al., 2014), and wheat yields in Russia (Prishchepov et al., 2019). Here we show that Bayesian networks enable to make efficient use of survey data for modeling a complex network of factors that are hypothesized to influencing farm economic performance across heterogeneous farm types.

Compared to frequentist regression analysis, Bayesian networks explicitly embrace the interdependence among explanatory variables to illustrate the comprehensive picture of the problem for highly heterogeneous farms in the region. In addition, their capability in dealing with missing data has been a useful asset to us because it enables using almost all of our survey data despite missing values for particular variables and incomplete questionnaires that were due to, for example, unanswered questions or lack of knowledge. Another valuable advantage of Bayesian networks is the option to incorporate both qualitative knowledge and quantitative data. Our model was not only built using the questionnaire data but also crucially benefited from expert knowledges that we had gained during workshops, qualitative interviews, and from previous studies. The intuitive graphical structure of the network with the linked nodes also allowed us to discuss and get feedbacks from our local stakeholders, such as farmers and rural extension agents.

The structure of a Bayesian network reflects our knowledge on the land-use systems of the region. This knowledge is to a certain degree subjective, which opens the network up for criticism from experts with different views. We nevertheless believe that our model serves as a starting point to further improve our understandings of agricultural systems and farm-level decision making in the Chaco. Another limitation of Bayesian networks is their limited capacity in handling continuous variables (Cobb et al., 2007). In our models, most continuous variables, including the target variable gross farm revenue, were discretized into categories. As a result, the model is only an approximation and we cannot conduct elasticity analysis, as can be done in frequentist regression analysis. Nevertheless, the sensitivity analysis with our scenarios and the two-way inference still yields valuable insights on how the different variables interact with each other and influence the target variables.

As usual, more data would have improved the model fit and the ability for inference. While Bayesian networks can achieve high accuracies with small samples, the performance of our model would have benefited from more observations, particularly given the heterogenous and large study region. Moreover, the collected data are a cross-sectional sample and thus only provide a one-time snapshot into the determinants of farm revenues. We therefore concede that the interpretation of our results requires caution in generalizing and in drawing the conclusions.

4.2. Implications for land-use policy

Modeling the network of influences on gross farm revenue allowed us to understand the relationships among its key determinants. We used such understanding to project how revenues would change under alternative policy scenarios. The definition of the scenarios was underpinned by the idea that some of the key determinants of farm revenues could be effective policy leverage points for improving farm-level outcomes and for reducing regional inequality in access to land resources. We found that the hypothetical policy for “land de-concentration”, which imposed an upper ceiling for farm sizes, has the potential to increase revenue per area without substantially reducing overall production revenue. Maintaining overall production revenues is important to reduce opposition from large companies against policies that potentially affect their interests.

Farm operators in the study area tend to intensify crop production on more suitable lands with higher Ricardian rents and expand cattle production on areas with lower Ricardian rents. Regulating farm expansion would hence represent a disincentive for the expansion of cattle production because its revenues per hectare are substantially lower than for crop production. If marginal revenue decreases as commercial farmers enlarge their farms, what is their incentive for farm expansion? Purchase and rental prices for land in areas that are suitable for agricultural intensification in the form of cropping have experienced a 20-fold increase from 2001 to 2014 (Costantino, 2016). In this context, financially well-equipped agribusiness companies have enlarged their farm operations by grabbing contiguous lands and at the same time have cleared the forest to deploy low-cost activities, such as extensive cattle ranching, with the intention of benefiting from the strong rise in land prices when sold to crop farmers. Such land speculation is a strong driver of land-tenure and land-use changes in this and other agricultural frontiers that has rarely been evaluated (Goldfarb and Van der Haar, 2016).

On the other end of the spectrum, we found that a policy of “land titling” consisting of granting secure land tenure over the land used by the semi-subsistence farms has the potential to increase the economic performance of this most vulnerable type of farmers in the region. Land tenure insecurity is a historical legacy for criollos colonists and peasant farmers. It has long been a key contributor to their vulnerability since demand and competition for agricultural land increased exponentially with the arrival in the late 1990´s and early 2000´s of Pampean farmers (le Polain de Waroux et al., 2018). Keeping semi-subsistence farmers dispossessed of the title of the land they use has provided a fertile ground for political clientelism by provincial governments and land grabbing by extra-regional companies (Goldfarb and Van der Haar, 2016). The expansion of deforestation for large-scale crop cultivation reduced the foraging grounds of cattle of semi-subsistence farmers and forced them to reduce stocks. It contributed to increasing rates of overgrazing and made many local farmers eventually leave the land and migrate to urban areas. Titling the land that is merely possessed by semi-subsistence farmers will protect them from being displaced or increasingly cornered, promotes reinvestment of surplus capital in the management of limiting production factors, and entitles the farmers to improved access credit. Indeed, we found that in the scenario in which semi-subsistence farmers are granted access to low levels of credit their gross revenue increases by almost 60%, which reinforces the observation that land tenure insecurity is a major impediment for the livelihoods of semi-subsistence farmers in the region and thus prohibits inclusive rural development.

5. Conclusion

We analyzed a survey of 235 diverse land users across of the Northern Argentine Dry Chaco. Our farm sample ranges from large-scale agribusiness enterprises to small-scale and partly subsistence-oriented farmers. We combined the farm survey data with geospatial data and calibrated in a Bayesian network to quantify the main determinants of gross farm revenues. We then use the network to simulate the effect of alternative policy scenarios on the farm revenues. We could demonstrate sings of an inverse farm size-productivity relationship for the semi-subsistence farms in our survey data while such a relationship seems not to exist for the large commercial farms. We could also show that a land titling program, which may also facilitate better access to financial credits, has much potential to substantially increase the revenues for semi-subsistence farmers without negatively affecting revenues of commercial farms, which is fundamental for its social acceptability. We therefore call for policies that facilitate securing land titles for small producers. Such policies have ample potential to contribute to inclusive rural development in the frontier region of the Argentine Chaco, and possibly also in rapidly changing deforestation frontiers in other parts of the world.

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Declaration of Competing Interest

No conflicts of interest.

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Appendix A. Supplementary data

Supplementary material related to this article can be found, in the online version, at doi:https://doi.org/10.1016/j.landusepol.2019.104183.

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