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Adoption of sustainable silvopastoral practices in Argentina's Gran Chaco: A multilevel approach

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A R T I C L E I N F O

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A B S T R A C T

The Gran Chaco is currently a global hotspot of deforestation and environmental degradation. Halting global warming and curbing biodiversity losses are urgent priorities and recent research suggests that sustainable smallholder production systems could contribute to maintain and restore key ecosystem services. This article examines the adoption of two silvopastoral practices in Argentina's Gran Chaco. We conducted a survey of 552 smallholders in three municipalities in the province of Salta. With the resulting data, we used multilevel models to assess adoption of the two practices. Our multilevel models indicate several factors that are associated with adoption, including: gender of the household head, year of establishment, literacy of the household head, membership in a producer organization, and socio-economic status. Our results suggest that paraje – groups of neighbouring households or joint settlements – are a good predictor of adoption, whereas nearby villages are only marginally associated with adoption. We conclude by highlighting the importance of accounting for local structures and groups of households in rural studies.

1. Introduction

In recent decades, the Gran Chaco ecoregion, home to South America's second-largest forest, has become a deforestation hotspot (Baumann et al., 2017). Recent trends point to dramatic changes related to deforestation and forest fragmentation, including significant loss of biodiversity, unique landscapes, and land cover types (Torres et al., 2014; Semper-Pascual et al., 2018). As seen elsewhere, the expansion of agriculture is the main cause of deforestation in the Gran Chaco. In particular, the export of agricultural commodities is a key proximate driver of deforestation. Other causes relate to socio-economic factors, including a weak legislative framework to control deforestation as well as various forms of inequality (Ceddia, 2019; Vallejos et al., 2021). Whereas expansion of commercial soybean cultivation drove deforestation in the 1980s and 1990s (Fehlenberg et al., 2017), more recently it is the expansion of large-scale cattle ranching in dryer areas of the Gran Chaco that is driving loss of natural habitat (Piquer-Rodríguez et al., 2018).

At the same time, the expansion of the agricultural frontier in the Gran Chaco is leading to the eviction and/or relocation of both indigenous peoples and peasant communities. Such eviction or relocation occurs either by means of forced expulsion or people's gradual surrender to the economic competition of capital-intense commercial agriculture (de Waroux et al., 2017; Mioni et al., 2013). This, in turn, has dramatic social consequences in terms of further marginalization and impoverishment of vulnerable populations (Córdoba and Camardelli 2017). Meanwhile, these processes of marginalization could further accelerate environmental degradation in the region. Recent studies in Latin America show that areas belonging to or managed by indigenous peoples (IP) and local communities exhibit less environmental degradation (Marinaro et al., 2017). By contrast, areas where local communities and IP are excluded display greater deforestation (Naughton-Treves and Kelly, 2014; Stevens 2014). The challenging situation facing IP and peasant communities is made more difficult by the increasing frequency of extreme weather events, which could further accelerate environmental degradation and loss of key ecosystem services in the region (Hoyos et al., 2013). Against this background, it is especially important to identify possible interventions capable of enhancing the ability of these actors to withstand the social and economic pressures caused by expansion of agricultural frontiers, as well as the environmental pressures associated with a changing climate.

Here, we analyse the experience of *criollo* smallholding farmers in

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Argentina's Gran Chaco by presenting results from a survey conducted in three municipalities in the province of Salta (Fig. 1). We chose to focus on Salta because it is a part of the Chaco ecoregion that has undergone a dramatic expansion of the agricultural frontier over the past 30 years, yet it still possesses the largest area of native forests. *Criollo* smallholders have been raising cattle under silvopastoral production systems in the Chaco forests for many decades. Production takes place in a system known as *campo abierto* ("open field"), meaning that most farms do not have defined limits and cattle freely feed on trees, bushes, shrubs, and natural pasture while roaming with only limited farmer supervision (Camardelli 2005).

The environmental impacts of small-scale cattle farming are still debated. On the one hand, some experts claim that pressures from free-ranging livestock cause environmental degradation and changes in the composition of landscapes and land cover of forest ecosystems in the Chaco. Indeed, evidence points to a change in forest composition, with bushes and shrubs gradually encroaching on natural pastures (Grau et al., 2015). On the other hand, *criollo* small-scale cattle production operates according to a multifunctional/land-sharing system, in which cattle are reared without forest clearing (Camardelli 2005). This type of production system can be beneficial for several ecosystem functions. Researchers have highlighted that different land uses practised by *criollo* smallholders and indigenous communities support a diversity of habitats and are favourable in terms of biodiversity conservation (Marinaro and Grau, 2015). Further, the silvopastoral systems of smallholders feature higher soil carbon accumulation than other agricultural land uses (Marinaro et al., 2017).

In Latin America, different policies have been implemented to address deforestation and its underlying drivers (Nolte et al., 2017). In Argentina, the National forest law (National Law Nº 26,331, hereafter "forest law") was passed in 2007 in response to the high deforestation rate occurring in the Gran Chaco native forests (Fernández Milmanda and Garay 2019). The forest law requires each province to enact a Territorial Classification of Native Forests (OTBN), which consists of land use regulations and a zoning map (Fernández Milmanda and Garay 2019). Salta was the first province in the country to enact its OTBN. It includes three types of land use categories of native forest: red areas for highest-priority conservation zones; green areas for productive use; and yellow areas for medium-level conservation value.

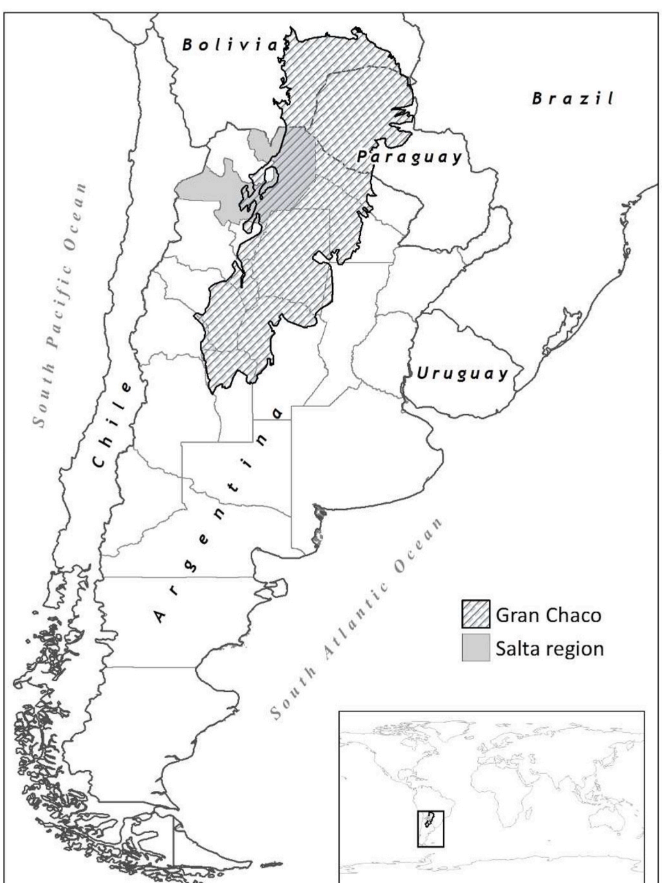

Fig. 1. Map of the study area.

One prominent criticism of the OTBN and forest law has concerned the lack of clarity and consensus regarding what land use types and economic activities can be pursued in yellow/medium conservation areas. The Argentinian state recently promoted a set of public policies – referred to as *Manejo de Bosque con Ganaderia Integrada* (forest management with integrated cattle ranching, hereafter "MBGI") – with the aim of addressing this ambiguity (Peri 2018). MBGI aims to reconcile conservation of native forests with smallholder production, in particular by allowing certain economic activities – such as silvopastoral cattle production – in an important area of the remaining native forest. Seven technical guidelines were formulated within the MBGI, including the introduction of artificial pastures (in mixed-production systems) and the adoption of land use planning that defines strict conservation areas (Alaggia et al., 2019). In this way, the MBGI aims to build on local knowledge and practices of *criollo* smallholders.

Some of the MBGI-compatible practices (e.g. the introduction of artificial pastures) have already been adopted to some extent in an effort to better adapt to the changing climate. Other practices, such as selective breeding of drought-resistant cattle breeds, are not explicitly mentioned in the MBGI plans, but are increasingly adopted by smallholders in the region. However, the patterns of adoption of these practices remains unclear and more information is needed about the motivations and characteristics of early adopters in order to enable broader implementation of the MBGI and similar policies. Understanding adoption patterns is also crucial to improve smallholders' livelihoods and productivity, thereby providing alternatives to the agro-industrial cattle production system that is currently the main driver of deforestation in the region. Improving the resilience and adaptation capabilities of smallholders in dry areas is essential to meet global challenges, especially regarding multifunctional agricultural production systems that are often overlooked in international debates on biodiversity conservation (Gassner et al., 2020).

In contrast to local aboriginal peoples, *criollo* smallholders are not considered indigenous communities. Indeed, the majority of them are of Spanish descent. As a result, *criollos* do not enjoy the same rights as IP in many Argentinian provinces – including Salta. In particular, *criollo* communities do not have access to community land titles. Despite this, it is very common for *criollo* smallholders to organize their activities in collaboration with a number of other households, dispersed over a certain area, forming what is locally known as a *paraje* or *puesto*. Each *paraje* is effectively a joint settlement or group of neighbours, often comprising members of an extended family. *Paraje* vary in size, typically ranging from two to a dozen households (exceptional cases are even larger and function as small towns), and provide settings in which resources such as labour, information, and agricultural practices are shared or exchanged. Cattle production is usually individual, with each animal assigned to a specific household. As a result, agricultural practices like the introduction of artificial pastures and/or new animal breeds to the herd generally stem from household-level decisions. However, in some exceptional cases, such practices stem from joint decisions made at the *paraje* level, or may be influenced by the decisions of neighbours. Finally, other resources, like water resources for cattle and some grazing areas, may be shared by members of the same *paraje*. Fig. 2 provides a basic illustration of the *paraje* resource system:

In the following, we analyse the adoption of two silvopastoral practices that both improve economic performance and help to cope with increased weather variability in the region. We propose to use a

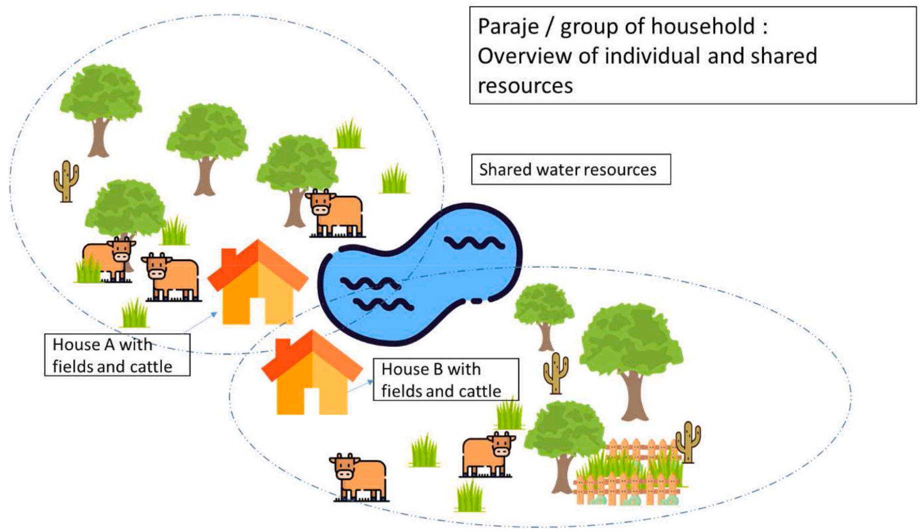

Fig. 2. *Paraje* structure in the Gran Chaco.

multilevel model that captures variations linked to local structures. The remainder of the article is structured as follows: Section two presents a brief literature review on the adoption of agricultural innovations and various methods to approach the analysis of such adoption. Section three illustrates our methodological approach. Section four then presents the main results, which are subsequently discussed in section five. Lastly, the final section summarizes our main conclusions.

2. Adoption of agricultural innovations: A methodological digression

2.1. Literature review on adoption of innovations

Diffusion of innovations and adoption of new agricultural practices has been an important focus of rural sociology, agricultural economics, and geography for several decades. Early work on adoption focused on the key role of technology and innovations for agricultural development (Feder 1982). Other researchers have focused on the role played by extension services, as well as that of the political, economic, and institutional context vis-à-vis development of new agricultural technologies and their adoption by farmers (Biggs 1990).

In recent years, many case studies on technology adoption have emerged and shed important light on how farmers can adapt their farm management to new constraints by incorporating new technologies and/or more sustainable agricultural practices. Research has also highlighted the role of social capital – particularly membership in cooperatives or producer organizations– as well as the influence of social networks (Wossen et al., 2017). Another important area of the literature focuses on different household characteristics, including the age and gender of the household head (Ndiritu et al. 2014; Kassie et al., 2015), education levels, as well as household size and available labour force (Graaff et al., 2008).

2.2. Methodological issues in adoption studies: a case for using multilevel models

Studies on technology adoption typically face two methodological challenges. First, they have to address the adoption of multiple, often correlated practices. As noted by Kassie et al. (2015), some practices are adopted simultaneously by households, while others can act as substitutes for particular practices and are thus mutually exclusive (Kassie et al., 2015). As a result, using a single modelling framework to assess adoption of each practice separately can result in biased conclusions, since single models ignore potential correlations between outcome variables and fail to account for correlated error terms. Different solutions to this problem exist. One key approach (Cappellari and Jenkins 2003) involves assessing different practices at the same time by means of a multivariate probit model. These models have been shown to be more efficient than those estimating adoption of different practices individually. There has been an increase in the number of studies following this approach in recent years (Ndiritu et al. 2014; Teklewold et al., 2013; Theriault et al. 2017; Tschopp et al., 2020).

The second methodological challenge concerns the fact that models of technology adoption must deal with data that are nested in villages and provinces, which can violate the assumption of independence of least squares regression models. To address this issue, we rely on multilevel models (MLM also known as hierarchical models). These models were first developed in education studies to account for the nested structures of outcome variables in different classes and schools (Goldstein, 1987). Today, they are widely used in various fields including the social and behavioural sciences and epidemiology (Sommet and Morselli 2017). They address some of the issues associated with analysis of clustered data such as patients treated by different doctors in different hospitals, or farmers from different villages practising agriculture. Traditional ordinary least squares regression models are based on the assumption that predictors should not be correlated with the error terms – an assumption that is violated if cluster affiliation has an influence on the outcome of the variable (Huang 2018). Hence, the statistical prerequisite for multilevel analysis is a positive interclass correlation coefficient within observations from different clusters. Using OLS regressions in these situations might result in biased standard error estimates and increase type I error rates.

In the literature on adoption of agricultural practices, publications that account for the nested structure of data via the MLM approach remain sparse. Examples include a study by Borchers et al. (Borchers et al. 2014) that looked at adoption of farm technologies in the United States; a study by Barnes et al. (2019) that examined the adoption of precision agriculture in several EU countries; and a study by Gray et al., (2008) that investigated land use in indigenous territory of Ecuador. The present study aims to address the corresponding research gap by examining the determinants of adoption of sustainable agricultural practices among *criollos* in the Chaco Salteño.

3. Material and methods

3.1. Latent response model

Our investigation focused on two different silvopastoral practices:

improved breeding techniques (B) and *introduction of artificial pastures* (P). Both of these variables can either take the value 0 (household currently *is not* using this practice) or the value 1 (household currently *is* using this practice). In this way, the decision to adopt a certain practice can be thought of as a binary variable Y that takes the value 0 or 1.

We assume that the dichotomous variables (practices) observed in our models are the representations of an unobserved or latent variable Y*. If the latent response is greater than 0, then the observed response is 1; if it is less than 0, then the observed response takes the value 0. The nested structure of the data imply that the dichotomous variable Y_{nijk} reflects the adoption of a certain practice n=(B, P) as observed in a *household i* (first level), belonging to a *paraje j* (indicating a group of households, second level), located in a village *area k* (third level). So,

$$Y_{nijk} = \begin{cases} 1 \; if \; Y^{*}_{nijk} > 0 \\ 0 \; otherwise \end{cases} \quad n = \mathrm{B}, \mathrm{P} \tag{1}$$

3.2. Multilevel model specifications

In our analysis, we account for the specific social organizations of *criollo* peasant households in the Chaco, which are often grouped together in a *paraje*. A *paraje* (literally a "location") refers to a single house or a group of houses (joint settlement) that share a common ranch name (e.g. "La Paloma"). A *paraje* can encompass several households (up to seven in our data, although larger *paraje* have been mentioned in the region), which share common resources such as water and often labour power. To simplify matters, we begin with a two-level model (i.e. household and *paraje*). The two-level random intercept model that assesses the adoption of both of these practices (B,P) can be described using the following equation (2):

$$Y_{nij} = \alpha + \beta X_{ij} + \gamma W_j + \eta_j + \varepsilon_{ij} \tag{2}$$

Where Y_{nij} is the outcome variable, determining the adoption (or not) of an nth practice (B,P) by the household i, which is located within the *paraje* j; α is the common intercept; and X_{ij} is a vector of household characteristics with a vector of coefficients β. W is a vector of *paraje*-level predictors multiplied by a vector of coefficient γ. The random intercept η_j is assumed to be independent from each other and from predictors. The error term ε_{ij} is also assumed to be independent from the random intercepts as well as the vector of predictors X_{ij} and W_j.

To include a more comprehensive approach, we also developed and applied a three-level model. Households and *paraje* depend on the villages closest to them in their day-to-day activities. This dependence might also influence the adoption patterns of individual households. In our survey, we asked each household to identify the closest village or centre of commerce that they usually visit. We subsume this information in a single variable "closest village" and estimated models to account for this three-level structure, which can be defined using the following equation:

$$Y_{nijk} = \alpha + \beta X_{ijk} + \gamma W_{jk} + \eta_j + \theta_k + \varepsilon_{ijk} \tag{3}$$

Where Y_{nijk} is the outcome variable determining the adoption (or not) of an nth practice (B,P) by the *household i*, which is located in the *paraje* j and the geographical zone corresponding to the closest village k. The model is similar to that shown in (2), but includes an additional random intercept θ_k at the village level.

Finally, in order to determine whether the correlation among the adoption patterns of the different practices (B, P) has a significant effect, we also estimated a multivariate probit version of the two-level model.

In order to test the different models, we used data from a survey we conducted in 2018 in the province of Salta. A total of 552 households were interviewed, but several observations were excluded from our analysis because of missing variables. All of the households interviewed were small-scale cattle ranchers that produce mostly for local markets in traditional farming systems with 30 animals on their farm per average. Table 1 describes the different variables included in our model, as well as the level they correspond to. The vector of household-level predictors (X) includes the following elements: SES, a non-monetary wealth index summarizing information from eight domestic and productive asset variables into a single socio-economic status variable (see Annex A); LANDT, a binary variable expressing whether the household has a formal land property title or not; YEAR, indicating the year in which the household settled on the land; SIZE, identifying household size; OFF, a binary variable indicating whether the household has off-farm income; GENDER, indicating the gender of the household head; EDUCA, an ordered three-level variable indicating the highest level of education attained by the household; SOC, a binary variable indicating membership in a producer association. According to previous studies, household size, gender of household head, education level, socio-economic status, and membership in producer association are frequently associated with adoption of new practices and technology. Further, formal ownership of land is said to provide incentives to innovate (Ndiritu et al. 2014; Kassie et al., 2015). In addition to these, we included the year of settlement (YEAR) because length of occupation can be a crucial element in contexts where land tenure is insecure (Camardelli 2005; Liu et al. 2018). Moreover, our model also captures the existence of conflicts over land access (CONFL). A value of 1 here indicates that the farmer is involved in a conflict with a neighbour or a large-scale farm, which might discourage the household from investing in sustainable practices. We

Table 1
Descriptive statistics.

Variable		Obs	Mean	SD	Min	Median	Max
First-level variable (household-level)							
P	Hh has artificial pastures (1 = yes)	502	0.454	0.498	0.000	0.000	1.000
B	Hh is using breeding improvement techniques (1 = yes)	502	0.245	0.431	0.000	0.000	1.000
SES	Socio-economic status (see Appendix A, table A1)	502	2.926	1.463	1.000	3.000	5.000
YEAR	Year in which the family arrived in the region	502	1955.257	36.929	1850.000	1958.000	2018.000
SIZE	Size of the household (in persons)	502	4.177	2.456	1.000	4.000	12.000
OFF	Someone in the hh has off-farm employment (1 = yes)	502	0.329	0.470	0.000	0.000	1.000
GENDER	Gender of the hh head (1 if man)	502	0.785	0.411	0.000	1.000	1.000
LIT	Everyone aged >15 within the hh can read and write	502	0.918	0.274	0.000	1.000	1.000
SOC	Membership in a producer association	502	0.456	0.499	0.000	0.000	1.000
CONFL	Hh currently has a conflict over access to land (1 = yes)	502	0.231	0.422	0.000	0.000	1.000
LANDT	Hh has land tenure security	502	0.438	0.497	0.000	0.000	1.000
EDUCATTAIN	Highest level of education attained within hh	502	Primary: (reference level) 234 (46.6%) Secondary: 182 (36.25%) University/technical university 86 (17.13%)				
Second-level variable (paraje level)							
DIST	Distance from the closest village (in km).	502	29.382	16.352	1.000	29.667	80.000
COUNTPARA	How many households per PARAJE	502	2.438	1.604	1.000	2.000	7.000

further hypothesize that it is important to capture the interaction between land tenure and conflicts, as the prevalence of a conflict could reduce the positive effects of land tenure. Conversely, being a member of an association could reduce some of the uncertainty of a conflict as associations provide support to the farmers involved and contribute to solve land conflicts through collective action. Therefore, our model includes two interaction effects related to conflicts: LANDT × CONFL, and SOC × LANDT.

The second-level (*paraje*) predictors (W) include a constant (η) and the distance between the *paraje* and the closest village or market centre (DIST) and the number of households in the same *paraje* (COUNTPARA). Finally, we also estimated a number of models with a three-level structure. While the households in a *paraje* are geographically spread out, in most cases they interact with a specific village, often located on the main road and not necessarily in the same municipality in which the households are situated (although the effect of municipalities was also tested as a third model variable; see Appendix B). The third-level intercept (θ) captures the effect of these villages.

Our models include two dependent variables. The first variable is the introduction of artificial pastures (P). Throughout the Dry Chaco, introduction of artificial pasture is common in small-scale production systems in order to increase the amount of forage available, in particular during the dry season. Large-scale farms tend to focus on intensive pasture systems associated with deforestation, while most smallholder cattle producers in our study area produce in silvopastoral systems with pasture being planted under tree cover. The second dependent variable is the use of improved breeds within the farmers' herd (B). Most of the cattle herds belonging to smallholders in the Gran Chaco are composed of *criollo* cattle, which are mostly a product of natural selection and adaptation of Spanish breeds introduced in the 15th and 16th century to the area. While being adapted to the harsh local conditions, the productivity of *criollo* cows is lower than other breeds. In order to address these problems, agronomists have been introducing other breeds in the Gran Chaco, in particular breeds such as the Brangus, which include

Table 2
Univariate models for genetic improvement and breeding (B) and introduced pastures (P).

	Dependent variable B			Dependent variable P		
VARIABLES	Model B1: Two-level model with random intercept for *paraje*	Model B2: Three-level model with random intercept for *paraje* and closest village	Model B3: Three-level model with random intercept for *paraje* and closest village. With interaction effects	Model P1: Two-level model with random intercept for *paraje*	Model P2: Three-level model with random intercept for *paraje* and closest village	Model P3: Three-level model with random intercept for *paraje* and closest village. With interaction effects
SES	1.192*	1.238*	1.198	1.172*	1.254*	1.215*
	(0.718)	(0.745)	(0.738)	(0.667)	(0.696)	(0.677)
CONFL	−0.0252	−0.0327	1.061*	0.242	0.202	**1.161****
	(0.386)	(0.398)	(0.562)	(0.357)	(0.367)	(0.543)
YEAR	**−0.0107****	**−0.0122*****	**−0.0123*****	0.00123	1.32e-05	−0.000559
	(0.00437)	(0.00452)	(0.00451)	(0.00403)	(0.00406)	(0.00399)
SIZE	−0.0597	−0.0574	−0.0577	−0.0587	−0.0534	−0.0563
	(0.0705)	(0.0726)	(0.0725)	(0.0647)	(0.0661)	(0.0647)
OFF	0.0100	0.0382	0.0501	0.217	0.229	0.211
	(0.327)	(0.337)	(0.336)	(0.309)	(0.316)	(0.308)
GENDER	**0.967****	**0.950****	**0.910****	**0.665****	**0.688****	**0.651***
	(0.399)	(0.409)	(0.411)	(0.339)	(0.348)	(0.342)
EDUATTAIN_2	0.232	0.135	0.161	−0.239	−0.249	−0.177
	(0.363)	(0.375)	(0.378)	(0.344)	(0.349)	(0.341)
EDUATTAIN_3	0.539	0.462	0.462	−0.508	−0.505	−0.515
	(0.458)	(0.474)	(0.473)	(0.455)	(0.464)	(0.456)
LIT		**1.464****	**1.442****	0.112	0.0685	0.0163
		(0.725)	(0.732)	(0.523)	(0.536)	(0.526)
SOC	**0.782****	**0.849****	0.791*	**1.029*****	**1.054*****	0.700*
	(0.322)	(0.335)	(0.432)	(0.308)	(0.315)	(0.396)
LANDT	−0.177	−0.327	0.188	0.529	0.481	0.597
	(0.340)	(0.351)	(0.517)	(0.337)	(0.339)	(0.480)
LANDTCONFL			**−2.128*****			**−1.664****
			(0.806)			(0.713)
SOCLANDT			0.00479			0.653
			(0.637)			(0.593)
DIST	−0.0140	−0.0165	−0.0128	**0.0265****	**0.0259****	**0.0267****
	(0.0106)	(0.0110)	(0.0110)	(0.0110)	(0.0112)	(0.0109)
COUNTPARA	−0.111	−0.124	−0.145	0.0381	0.00390	−0.0161
	(0.126)	(0.126)	(0.125)	(0.124)	(0.121)	(0.116)
α (household constant)	18.57**	20.23**	20.33**	−4.958	−2.540	−1.332
	(8.521)	(8.725)	(8.733)	(7.922)	(7.962)	(7.825)
η (paraje average)	**1.631*****	**1.705*****	**1.658*****	**1.843*****	**1.900*****	**1.773*****
	(0.404)	(0.439)	(0.424)	(0.403)	(0.442)	(0.414)
θ (village average)		9.46e-07	2.02e-07		−5.81e-08	−4.52e-07
		(0.295)	(0.267)		(0.279)	(0.266)
Log-likelihood	−255.562	−253.74	−249.92	−330.54	−314.04	−315.26
AIC	539.12	539.48	535.83	665.08	658.08	662.51
BIC	598.19	606.98	611.77	673.51	721.36	730.01
Observations	502	502	502	502	502	502

Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

some genetic material from buffalo and are well adapted to dry climates. We measured the adoption of these two variables as absolute (either 1 or 0). Unfortunately, our model does not account for the *intensity* of adoption (how far a household commits to a specific practice), as recommended in recent literature on adoption (Pannell and Roger, 2020).

We estimated our models as multilevel univariate probit (i.e. assuming that the two practices B and P are uncorrelated, the adoption decisions are estimated separately). However, in order to address issues associated with the possible correlation in adoption patterns, we also estimated the best model via bivariate multilevel probit (i.e. the adoption of practices B and P is estimated simultaneously). These models account for a random effect and correlation between both dependent variables, similar to what is done with multivariate probit. Our bivariate model only includes a second-level variable (*paraje).*

The multilevel models were estimated with the user command GLLAMM (Generalized Linear Latent and Mixed Models) available on Stata 16 (Rabe-hesketh, Skrondal, and Pickles 2004). GLLAMM is a freely available software program that provides estimations of models containing latent variables (common factors or random effects) that can be assumed to be discrete or to have a multivariate normal distribution.

4. Results

In this section, we present the results of different multilevel models. Table 2 shows the results of a number of multilevel univariate probit models with improved breeding (B) and artificial pastures (P) defined as the outcome variables. Model B1 is a two-level model (household–*paraje* structure), while model B2 is a three-level model (household–*paraje*–village). Model B3 replicates model B2 while adding two interaction effects. The results for the models with Introduction of artificial pastures (P) defined as the outcome are presented on the right side of Table 2 and are labelled analogously. Finally, Table 3 shows the results of our bivariate model. This model includes only a second-tier level (*paraje*) variable, but accounts for potential correlations between both dependent variables.

A quick glance at Table 2 reveals the two-level models to be the best performing (as the third-level constant θ is not statistically significant). For this reason, and to determine whether the correlation between the adoption of practices B and P has an important effect on the estimated parameters, we also present the results of a bivariate two-level probit (Table 3). The results, in terms of both coefficients magnitude and significance, are quite similar to the two-level models presented in Table 2 (model B1 and P1, respectively), thus confirming their robustness.

Table 3
Bivariate two-level models for genetic improvement and breeding (B) and introduced pasture (P).

Bivariate multilevel model		
VARIABLES	P	B
SES	**1.161****	1.109*
	(0.589)	(0.634)
CONF	0.379	−0.120
	(0.312)	(0.350)
YEAR1	−0.00380	−0.00426
	(0.00288)	(0.00288)
SIZE1	−0.0646	−0.0351
	(0.0523)	(0.0586)
OFF	0.107	0.0913
	(0.267)	(0.300)
GENDER	**0.598****	**0.814****
	(0.299)	(0.370)
LIT	0.112	1.220*
	(0.465)	(0.654)
SOC	**0.890*****	**0.734*****
	(0.257)	(0.284)
LANDT	0.471*	−0.215
	(0.286)	(0.310)
DIST	**0.0244*****	−0.0134
	(0.00916)	(0.00974)
COUNTPARA	0.00124	−0.0596
	(0.101)	(0.110)
α (household constant)	5.068	5.068
	(5.624)	(5.624)
η (paraje average)	**1.406*****	**1.406*****
	(0.188)	(0.188)
Observations	1004	1004

Multilevel with simultaneous estimation.
Standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5. Discussion

This discussion is mainly based on the results of the univariate multilevel probit model (Table 2), since the reults of the bivariate model (Table 3) do not differ significantly. Our findings point to multiple factors that are consistently associated with the adoption of both agricultural practices considered in our analysis. At the same time, the results indicate important differences between the adoption patterns associated with the two practices. The year of settlement was associated with adoption of genetic improvement (B), with a negative coefficient. This indicates that older settlements were more likely to adopt this practice, which makes sense considering that these households were more experienced and likely had access to additional resources including financial resources or knowledge about such practices. Further, older settlements are more likely to have land tenure security, even in the absence of a formal land title. This relates to a legislative system that recognizes the use to which land is put, and generally values settlements established for longer than 20 years (Camardelli, 2005). The gender of the household head was also associated with adoption of genetic improvement of cattle and introduction of pasture. This result echoes other studies finding that the gender of the household head plays an important role in determining adoption of agricultural innovations and new technologies (Ndiritu et al., 2014; Nigussie et al., 2017; Theriault et al., 2017). Literacy of the household head was also positively associated with adoption of new breeding techniques (B). However, the highest level of education in the household was not significantly associated with adoption. This would suggest a negative effect of lack of literacy in the household.

For introduction of artificial pastures (P), we see that there are only a few positive coefficients associated with adoption. Belonging to a producer organization was associated both with adoption of pasture and with adoption of new breeding techniques (B). Socio-economic status was also associated with adoption of both practices, albeit with only a 10% significance threshold for new breeding techniques (B). At the second level, we find that the *paraje* constant (η) is positive and significant vis-à-vis adoption of both practices; at the same time, the distance to the closest village was positively associated with introduction of pastures only, meaning that households located further away from villages were more likely to adopt such practices. This result is surprising as we would expect households that are closer to villages or urban centres to be more familiar with, and willing to invest in, new agricultural practices. Nevertheless, while the literature often indicates a negative association between distances to villages/markets and adoption of such practices, there are multiple counter examples of positive associations, in particular regarding practices not based on the most-recent technological innovations (Arslan et al., 2014). In our case, household proximity to the closest villages could also be correlated with other exogenous variables, such as opportunities to benefit from other income-generating activities or ease of access to fodder markets. These factors could explain why households would be less likely to invest in introducing pastures. Finally, neither the land tenure variable nor the conflict variable were consistently associated with adoption of either practice when considered in isolation (with some exceptions for models P3 and B3). However, the interaction effect between these two variables was significant with a negative coefficient, suggesting that even households with relatively secure land tenure are less likely to invest in adopting the practices considered here in contexts of wider land conflict. This finding highlights the importance of addressing land conflicts to enable progress towards adoption of sustainable farming practices (Marinaro et al., 2017).

Our results highlight two consistently significant factors associated with adoption of both practices addressed, namely: (a) belonging to a specific network of households (the *paraje* effect); and (b) membership in a producer association. These findings are consistent with the existing literature pointing to the importance of social networks and social capital in the adoption of sustainable practices by smallholders (Bodin and Crona 2009; Bandiera and Rasul 2006). Belonging to a producer association has been consistently associated with diffusion or adoption of new farming practices in other recent studies (Inguaggiato et al. 2013; Wossen et al., 2017). Cooperatives and producer associations can facilitate adoption of innovative practices in several ways. First, they can provide direct resources such as credits or subsidies, market information, or farming equipment to their members (Wossen et al., 2017). Second, by providing a platform for exchange of information, they can enable sharing of new innovations and serve as a knowledge broker that introduces rural households to new technologies (Inguaggiato et al. 2013). In our research context, we observed associations corresponding to both mechanisms. While many producer organizations were originally established as a means of defending land rights, a number of them now also provide capacity-building services to familiarize their members with new production techniques.

Finally, our findings indicate that the *paraje* variable is a good predictor of adoption of new practices. This effect remains significant when including distance to the nearest village in the model. Interestingly, the proportion of variance explained by the *paraje* variable is higher for the introduction of pasture (P) than for new breeding techniques (B). This finding reflects a specificity of the local context: while breeding decisions are often taken by individual households, grazing space – including pasture space – is often shared between households (Camardelli 2005). The *paraje* structure could function as a peer-learning mechanism. This has important policy implications for the diffusion of agricultural practices and, in particular, extension services. One strategic policy implication would be to rely on small settlements for effective information sharing. Another would be to rely on diffusion of knowledge among different *parajes* and to seek to maximize the number of *parajes* reached. At the same time, the *paraje* structure shows that decisions about production are not always shared. Indeed, more research is needed to shed additional light on the complex interplay between belonging to a producer organization and a *paraje*, on the one hand, and taking decisions about productive practices, on the other.

6. Conclusion

In this article, we described use of multilevel models to assess the adoption of different agricultural practices by smallholders in Argentina's Gran Chaco. We identified several factors associated with adoption, including year of establishment, belonging to a producer organization, literacy of the household head, and gender of the household head. We also found that *parajes* were a good predictor of adoption of new practices, whereas municipal units and proximate villages were only marginally associated with adoption.

In the current era, halting global warming and curbing biodiversity losses are urgent priorities. Ambitious public policies are needed. In Latin America, promotion of multifunctional agricultural production through agroforestry and silvopastoral systems, in particular, can play an important role in transitioning to more sustainable agricultural systems (Gassner et al., 2020). Two important policy implications can be derived from our results.

First, our findings indicate that small groups and settlements play a key role in the diffusion and adoption of new agricultural practices, while other administrative units such as the municipality or nearby villages have only limited influence. Considering social networks and local structures is thus paramount when seeking to incentivize households to invest in more sustainable production patterns and practices. In addition, our results suggest that in an extensive production system, such as that found in the Gran Chaco, public policies aimed at fostering the adoption of sustainable production practices might be more effective if implemented at the landscape level, in addition to the household level.

Secondly, our findings show that certain practices, such as investment in pasture implantation, are especially sensitive to land tenure security. This result is consistent with many other studies in the literature (Liu et al., 2018). Thus, policies encouraging more sustainable modes of production should be developed in concert with efforts to formalize smallholders' access to land. Such efforts represent an important inflection point for public policies, as they can simultaneously stimulate smallholder investment in sustainable production systems and contribute to reducing deforestation (Robinson et al. 2014). However, corresponding policies should be carefully designed at different governance levels in order to avoid deforestation displacement, rebound effects, or Jevons paradox (Ceddia and Zepharovich, 2017).

CRediT authorship contribution statement

Maurice Tschopp: Conceptualization, Methodology, Formal analysis, Investigation, Writing – review & editing. **Michele Graziano Ceddia:** Writing – review & editing, Supervision, Project administration, Funding acquisition. **Carla Inguaggiato:** Writing – review & editing, Supervision, All authors have read and agreed to the published version of the manuscript.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Calculation of the socio-economic index

A socio-economic index was created via Principal Component Analysis (PCA) of several asset variables, according to the procedure of Filmer and Pritchett (Filmer L. Pritchett 1998). The PCA was conducted on a polychoric correlation matrix in order to improve the robustness of the model (Kolenikov and Angeles 2009). We included 10 variables in this model; their weights are shown in Table A1 below.

Table A.1
Variables included in socio-economic index

Name of variable	Description	Type	Weight (loading PC1s)
HOUSE2	1 if household owns another house	binary	0.56 (0.50)
FLUSH	1 if household has flush toilets	binary	0.04 (0.19)
ENERGY	1 if household has electricity (or a generator)	binary	0.34 (0.48)
ROOF	1 if main house has a roof made of solid material (clay tiles, wood, or metal)	binary	0.65 (0.48)
TV	1 if household has a television	binary	0.09 (0.28)
FRIDGE	1 if household has a refrigerator	binary	0.36 (0.48)
WM	1 if household has a washing machine	binary	0.09 (0.29)
TRUCK	1 if household has a pickup truck	binary	0.18 (0.38)
MBIKE	1 if household has a motorcycle	binary	0.82 (0.39)
BIKE	1 if household has a bicycle	binary	0.44 (0.50)

Total variance explained by the polychoric PCA: 0.22.
Total variance explained by traditional PCA (for reference): 0.21.
PCA models were estimated using the r package psych.

Appendix B. Estimation of residual intraclass correlations

The residuals estimated interclass correlation of the latent response given the Covariates X under different levels of i' can be expressed with the following equations:

$$\rho = \mathrm{Cor}\left(Y^*_{ij,}\ Y^*_{i'j,}\middle|X_{ij}\ ,X_{i'j}\right) = Cor(\varepsilon_{ij,}\ \varepsilon_{i'j,}\ ) \tag{B.1}$$

where the intraclass correlation correspond to the correlation between total residual variance and the residual variance for i'. In logistics multilevel models, can be expressed by the following equation:

$$\rho\ = \frac{\psi}{\psi + \frac{\pi^2}{3}} \tag{B.2}$$

Where is the level-specific residual variance and is equal to the total residual variance. These equations enable us to estimate the intraclass correlations, which are presented in Table B1.

Table B.1
Intraclass correlations of the different models

ICC	Paraje	Closest village
Model B1	0.337	
Model B2	0.347	2.461e-07
Model B3	0.3342	1.272e-07
Model P1	0.356	
Model P2	0.349	6.058e-07
Model P3	0.348	9.286e-07

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References

Alaggia, Francisco, Julia Cabello, María, Carranza, Carlos A., Cavallero, Laura, Daniele, Gonzalo, Erro, Melisa, Ledesma, Marcela, et al., 2019. Manual de Indicadores Para Monitoreo de Planes Prediales MBGI. INTA, Buenos Aires.

Arslan, Aslihan, McCarthy, Nancy, Lipper, Leslie, Solomon, Asfaw, Cattaneo, Andrea, 2014. Adoption and intensity of adoption of conservation farming practices in Zambia. Agric. Ecosyst. Environ. 187 (April), 72–86. https://doi.org/10.1016/j.agee.2013.08.017.

Bandiera, Oriana, Rasul, Imran, 2006. Social networks and technology adoption in Northern Mozambique. Econ. J. 116 (514), 869–902. https://doi.org/10.1111/j.1468-0297.2006.01115.x.

Barnes, A.P., Soto, I., Eory, V., Beck, B., Balafoutis, A., Sánchez, B., Vangeyte, J., Fountas, S., van der Wal, T., Gómez-Barbero, M., 2019. Exploring the adoption of precision agricultural technologies: a cross regional study of EU farmers. Land Use Pol. 80, 163–174. https://doi.org/10.1016/j.landusepol.2018.10.004. November 2017.

Baumann, Matthias, Gasparri, Ignacio, Piquer-Rodríguez, María, Gavier Pizarro, Gregorio, Griffiths, Patrick, Hostert, Patrick, Tobias, Kuemmerle, 2017. Carbon Emissions from agricultural expansion and intensification in the Chaco. Global Change Biol. 23 (5), 1902–1916. https://doi.org/10.1111/gcb.13521.

Biggs, Stephen D., 1990. A multiple source of innovation model of agricultural research and technology promotion. World Dev. 18 (11), 1481–1499. https://doi.org/10.1016/0305-750X(90)90038-Y.

Bodin, Örjan, Crona, Beatrice, 2009. The role of social networks in natural resource governance: what relational patterns make a difference? Global Environ. Change 19 (3), 366–374. https://doi.org/10.1016/j.gloenvcha.2009.05.002.

Borchers, Allison M., Xiarchos, Irene, Beckman, Jayson, 2014. Determinants of wind and solar Energy system Adoption by U.S. Farms: a multilevel modeling approach. Energy Pol. 69, 106–115. https://doi.org/10.1016/j.enpol.2014.02.014.

Camardelli, Maria Cristina, 2005. Estrategias reproductivas y sustentabilidad de Sistemas Ganaderos criollos del Chaco Salteño: El caso de Los puesteros criollos del lote fiscal

N°20 En El departamento Rivadavia. Revista Interdisciplinaria de Estudios Agrarios 22, 57–93.

Cappellari, Lorenzo, Jenkins, Stephen P., 2003. Multivariate probit regression using simulated maximum likelihood. STATA J. 3 (3), 278–294. https://doi.org/10.1177/1536867x0300300305.

Ceddia, M. Graziano, 2019. The impact of income, land, and wealth inequality on agricultural expansion in Latin America. Proc. Natl. Acad. Sci. U.S.A. 116 (7), 2527–2532. https://doi.org/10.1073/pnas.1814894116.

Ceddia, Michele Graziano, Zepharovich, Elena, 2017. Jevons paradox and the loss of natural habitat in the argentinean Chaco: the impact of the indigenous communities' land titling and the forest law in the province of Salta. Land Use Pol. 69 (December), 608–617. https://doi.org/10.1016/J.LANDUSEPOL.2017.09.044.

Córdoba, Gisela Soledad, Camardelli, María Cristina, 2017. Caracteristicas socioeconomicas del sitio piloto de Degradacion de Tierras y desertificacion (ONDTYD). Breves Contribuciones Del I.E.G 28, 61–90.

de Waroux, Polain, le, Yann, Baumann, Matthias, Gasparri, Nestor Ignacio, Gavier-Pizarro, Gregorio, Godar, Javier, Tobias, Kuemmerle, Müller, Robert, Vázquez, Fabricio, Volante, José Norberto, Meyfroidt, Patrick, 2017. Rents, actors, and the expansion of commodity frontiers in the gran Chaco. Ann. Assoc. Am. Geogr. 108 (1), 204–225. https://doi.org/10.1080/24694452.2017.1360761.

Feder, Gershon, 1982. Adoption of interrelated agricultural innovations: complementarity and the impacts of risk, scale, and credit. Am. J. Agric. Econ. 64 (1), 94–101. https://doi.org/10.2307/1241177.

Fehlenberg, Verena, Baumann, Matthias, Gasparri, Nestor Ignacio, Piquer-Rodriguez, Maria, Gavier-Pizarro, Gregorio, Tobias, Kuemmerle, 2017. The role of soybean production as an underlying driver of deforestation in the South American Chaco. Global Environ. Change 45 (May), 24–34. https://doi.org/10.1016/j.gloenvcha.2017.05.001.

Filmer, L., Pritchett, D., 1998. The effect of household wealth on educational attainment: evidence from 35 countries. Popul. Dev. Rev. 25 (1), 85–120.

Gassner, Anja, Dobie, Philip, Harrison, Rhett, Vidal, Adriana, Somarriba, Eduardo, Pythoud, Francois, Kumar, Chetan, Laumonier, Yves, Chhatre, Ashwini, 2020. Making the post-2020 global biodiversity framework a successful tool for building biodiverse, inclusive, resilient and safe food systems for all. Environ. Res. Lett. 15 (10), 101001. https://doi.org/10.1088/1748-9326/abae2b.

Goldstein, H., 1987. Multilevel Models in Education and Social Research. Charles Griffin & Co; Oxford University Press.

Graaff, J. de, Amsalu, A., Bodnár, F., Kessler, A., Posthumus, H., Tenge, A., 2008. Factors influencing adoption and continued use of long-term soil and water conservation measures in five developing countries. Appl. Geogr. 28 (4), 271–280. https://doi.org/10.1016/j.apgeog.2008.05.001.

Grau, H. Ricardo, Torres, Ricardo, Ignacio Gasparri, N., Blendinger, Pedro G., Marinaro, Sofía, Macchi, Leandro, 2015. Natural Grasslands in the Chaco. A Neglected ecosystem under threat by agriculture expansion and forest-oriented conservation policies. J. Arid Environ. 123 (December), 40–46. https://doi.org/10.1016/J.JARIDENV.2014.12.006.

Gray, Clark L., Bilsborrow, Richard E., Bremner, Jason L., Lu, Flora, 2008. Indigenous land use in the Ecuadorian amazon: a cross-cultural and multilevel analysis. Hum. Ecol. 36 (1), 97–109. https://doi.org/10.1007/s10745-007-9141-6.

Hoyos, L.E., Cingolani, A.M., Zak, M.R., Vaieretti, M.V., Gorla, D.E., Cabido, M.R., 2013. Deforestation and precipitation patterns in the arid Chaco forests of central Argentina. Appl. Veg. Sci. 16 (2), 260–271. https://doi.org/10.1111/j.1654-109X.2012.01218.x.

Huang, Francis L., 2018. Multilevel modeling and ordinary least squares regression: how comparable are they? J. Exp. Educ. 86 (2), 265–281. https://doi.org/10.1080/00220973.2016.1277339.

Inguaggiato, Carla, Navarra, Cecilia, Vailati, Alex, 2013. Innovation patterns in Grassroots producers' organisations: a Mozambican case study. J. Contemp. Afr. Stud. 31 (1), 37–61. https://doi.org/10.1080/02589001.2012.759038.

Kassie, Menale, Teklewold, Hailemariam, Jaleta, Moti, Marenya, Paswel, Erenstein, Olaf, 2015. Understanding the adoption of a portfolio of sustainable intensification practices in Eastern and southern africa. Land Use Pol. 42, 400–411. https://doi.org/10.1016/j.landusepol.2014.08.016.

Kolenikov, Stanislav, Angeles, Gustavo, 2009. Socioeconomic status measurement with discrete proxy variables: is principal component analysis a reliable answer? Rev. Income Wealth 55 (1), 128–165. https://doi.org/10.1111/j.1475-4991.2008.00309.x.

Liu, Tingting, Randall, J., Bruins, F., Heberling, Matthew T., 2018. "Factors Influencing Farmers' Adoption of Best Management Practices: A Review and Synthesis." *Sustainability (Switzerland)*. MDPI AG. https://doi.org/10.3390/su10020432.

Marinaro, Sofia, Grau, Ricardo H., 2015. Comparison of animal biodiversity in three livestock systems of open Environments of the semi-arid Chaco of Argentina. Rangel. J. 37 (5), 497. https://doi.org/10.1071/RJ15052.

Marinaro, Sofía, Grau, H. Ricardo, Gasparri, Nestor Ignacio, Tobias, Kuemmerle, Baumann, Matthias, 2017. Differences in production, carbon stocks and biodiversity outcomes of land tenure regimes in the Argentine dry Chaco. Environ. Res. Lett. 12 (4), 045003 https://doi.org/10.1088/1748-9326/aa625c.

Milmanda, Fernández, Belén, Garay, Candelaria, 2019. Subnational variation in forest protection in the Argentine Chaco. World Dev. 118, 79–90. https://doi.org/10.1016/j.worlddev.2019.02.002.

Mioni, Walter, Alcoba, Laura, Godoy Garraza, Gastón, Alcoba, Laura, 2013. Tierra Sin Mal. Aspectos Juridicos e Institucionales Del Acceso a La Tierra En Salta. IPAF/INTA.

Naughton-Treves, Lisa, Kelly, Wendland, 2014. Land tenure and tropical forest carbon management. World Dev. 55 (March), 1–6. https://doi.org/10.1016/j.worlddev.2013.01.010.

Ndiritu, S. Wagura, Kassie, Menale, Shiferaw, Bekele, 2014. Are there systematic gender differences in the adoption of sustainable agricultural intensification practices? Evidence from Kenya. Food Pol. 49 (P1), 117–127. https://doi.org/10.1016/j.foodpol.2014.06.010.

Nolte, Christoph, le Polain de Waroux, Yann, Jacob, Munger, Reis, Tiago N.P., Lambin, Eric F., 2017. Conditions influencing the adoption of effective anti-deforestation policies in South America's commodity frontiers. Global Environ. Change 43, 1–14. https://doi.org/10.1016/j.gloenvcha.2017.01.001.

Pannell, David J., Roger, Claassen, 2020. The roles of adoption and behavior change in agricultural policy. Appl. Econ. Perspect. Pol. 42 (1), 31–41. https://doi.org/10.1002/aepp.13009.

Peri, Pablo L., Fermani, Sebastián, Mónaco, Martín, Rosales, Victor, Díaz, Franco, Collado, Leonardo, Torres, Silvana Carolina, et al., 2018. Management of Forests with Integrated Livestock (MBGI) in Argentina. In: Rusch, Veronica (Ed.), IV Congreso Nacional de Sistemas Silvopastoriles. INTA Ediciones, Neuquen, 724–42.

Piquer-Rodríguez, M., Butsic, V., Gärtner, P., Macchi, L., Baumann, M., Pizarro, G. Gavier, Volante, J.N., Gasparri, I.N., Kuemmerle, T., 2018. Drivers of agricultural land-use change in the Argentine pampas and Chaco regions. Appl. Geogr. 91 (January), 111–122. https://doi.org/10.1016/j.apgeog.2018.01.004.

Rabe-hesketh, Sophia, Anders, Skrondal, Pickles, Andrew, 2004. "GLLAMM Manual." *U. C. Berkeley Division Of Biostatistics Working Paper Series Year*, vol. 160.

Robinson, Brian E., Holland, Margaret B., Naughton-Treves, Lisa, 2014. Does secure land tenure save forests? A meta-analysis of the relationship between land tenure and tropical deforestation. Global Environ. Change 29 (November), 281–293. https://doi.org/10.1016/J.GLOENVCHA.2013.05.012.

Semper-Pascual, Asunción, Macchi, Leandro, Maria Sabatini, Francesco, Decarre, Julieta, Baumann, Matthias, Blendinger, Pedro G., Gómez-Valencia, Bibiana, Mastrangelo, Matías E., Tobias, Kuemmerle, 2018. Mapping Extinction debt highlights conservation opportunities for birds and mammals in the South American Chaco. J. Appl. Ecol. https://doi.org/10.1111/1365-2664.13074. July: 1–12.

Sommet, Nicolas, Morselli, Davide, 2017. Keep calm and learn multilevel logistic modeling: a simplified three-step procedure using Stata, R, mplus, and SPSS. Int. Rev. Soc. Psychol. 30 (1), 203–218. https://doi.org/10.5334/irsp.90.

Stevens, S., 2014. Indigenous Peoples, National Parks, and Protected Areas: A New Paradigm Linking Conservation, Culture, and Rights. Arizone Press.

Teklewold, Hailemariam, Kassie, Menale, Shiferaw, Bekele, Köhlin, Gunnar, 2013. Cropping system diversification, conservation tillage and modern seed adoption in Ethiopia: impacts on household income, agrochemical use and demand for labor. Ecol. Econ. 93, 85–93. https://doi.org/10.1016/j.ecolecon.2013.05.002.

Theriault, Veronique, Smale, Melinda, Haider, Hamza, 2017. How does gender affect sustainable intensification of cereal production in the west african sahel? Evidence from Burkina Faso. World Dev. 92, 177–191. https://doi.org/10.1016/j.worlddev.2016.12.003.

Torres, Ricardo, Ignacio Gasparri, N., Blendinger, Pedro G., Ricardo Grau, H., 2014. Land-use and land-cover effects on regional biodiversity distribution in a subtropical dry forest: a hierarchical integrative multi-taxa study. Reg. Environ. Change 14 (4), 1549–1561. https://doi.org/10.1007/s10113-014-0604-1.

Tschopp, Maurice, Ceddia, M. Graziano, Inguaggiato, Carla, Bardsley, Nicholas O., Hernández, Hernán, 2020. Understanding the adoption of sustainable silvopastoral practices in Northern Argentina: what is the role of land tenure? Land Use Pol. 99 (December), 105092. https://doi.org/10.1016/j.landusepol.2020.105092.

Vallejos, M., Camba Sans, G.H., Aguiar, S., Mastrángelo, M.E., Paruelo, J.M., 2021. "The law is spider's web: an assessment of illegal deforestation in the Argentine dry Chaco ten years after the Enactment of the 'forest law.'" *environmental development*, bridging science and policy through collaborative. Interdisciplinary Global Change Research in the Americas 38 (June), 100611. https://doi.org/10.1016/j.envdev.2021.100611.

Wossen, Tesfamicheal, Abdoulaye, Tahirou, Alene, Arega, Haile, Mekbib G., Feleke, Shiferaw, Olanrewaju, Adetunji, Manyong, Victor, 2017. Impacts of extension access and cooperative membership on technology adoption and household welfare. J. Rural Stud. 54, 223–233. https://doi.org/10.1016/j.jrurstud.2017.06.022.