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Relationship Between Rural Poverty and Agricultural Diversification at a Local Scale in Colombia: An Approach through Spatial Effects

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Abstract

This paper examines the relationship between local agricultural diversification and rural poverty in Colombia. The evidence presented suggests that municipal-scale agricultural diversification is associated with higher levels of rural poverty. The primary mechanism driving this relationship is the loss of external economies of scale in agricultural production. However, when analyzing the spatial effects (autocorrelation and spatial heterogeneity), it was found that this relationship varies across the country. Neighboring municipalities have opposite spillover effects that offset the positive effect. In addition, the presence of small rural producers, greater provision of public goods, the existence of industrial crops, and lower persistence of acts of violence were all found to be associated with lower levels of rural poverty. This study joins the literature on the economic and social effects of agricultural diversification, particularly in the context of its promotion as a means of adapting to and mitigating the effects of climate change

Keywords

Agricultural diversification, poverty, spatial econometrics, spillover effects, regional economics.

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Introduction

In Latin America, the public policy debate of whether to promote diversified agriculture with many products or specialize in one is influenced by the recurring competition for resources between large-scale and family farming. For instance, in countries like Brazil, Uruguay, and Argentina, large-scale agriculture encourages specialization through sustained growth in the cultivation of extensive, high-volume, and low-value crops such as soybeans or sugarcane. In contrast, family farming units typically engage in multi-product cultivation, including grains, cocoa, fruits, and vegetables (Giller et al., 2021).

While some economic literature suggests that diversification may deteriorate social indicators due to the loss of economies of scale, reduced labor productivity, and underutilization of comparative advantages (Lobao and Sharp, 2013), other argue that it can enhance social performance through economies of scope, reduced income volatility for producers, and increased land productivity through better soil conservation (Klasen et al., 2016; Wardhana et al., 2017).

The debate between large-scale agriculture, generally specialized, and family agriculture, traditionally diversified, is reflected in Colombia by the competition for the use of resources, especially land, and for the food safety debates. According to data from the 2014 National Agricultural Census, 70.4% of the Agricultural Production Units (UPAs, for its acronym in Spanish) have less than 5 hectares and occupy 2.0% of the rural area; while 0.2% of the UPAs have 1,000 hectares or more and occupy 73.8% of the rural area censed. Small agricultural units are usually dedicated to the harvest of high-value products, such as legumes and fruits, or for commercialization, such as coffee and cocoa (Berry, 2023). In turn, it is estimated that the proportion of food production that comes from smallholder agriculture ranges between 50 and 68% in Colombia (Perfetti and Leibovich, 2013).

For this study, agricultural diversification is described as 'a process that transforms a simplified cropping system by introducing additional crops over time and space' (Hufnagel et al., 2020). Therefore, diversification is commonly linked to various agricultural practices, including crop rotation, adoption of cover crops, relay cropping, alley cropping, and mixed cropping.

The objective of this paper is to analyze the relationship between agricultural diversification and poverty at the local scale in Colombia, which takes the form of local administrative entities. The scale is chosen because in literature the analysis is usually developed from the perspective of agricultural units (Klasen et al., 2016; Thapa et al., 2018; Sekyi et al., 2021) but this approach ignores that the economic benefits and environmental detriments of specialization transcend the agricultural unit and have local spillover effects and economic externalities.

The paper presents that municipal-scale agricultural diversification is associated with higher levels of rural poverty. The primary mechanism driving this relationship is the loss of external economies of scale in agricultural production. However, when analyzing the spatial effects (autocorrelation and spatial heterogeneity), it was found that this relationship is not uniform across the entire national territory and has opposite spillover effects when analyzing the neighboring municipalities that offset the positive effect.

This paper presents in the Material and Methods section the methodology used to calculate the diversification index, and the econometric models used (autocorrelation and spatial heterogeneity). The Results and Discussion section presents the results of the diversification indicator, and the models calculated, as well as the interpretations of the main findings. The article closes with conclusions and their research and public policy impact.

Materials and methods

This section presents how the agricultural diversification indicator is calculated. Moreover, the model to measure the relationship between rural poverty and agricultural diversification is described.

The diversification index

The species evenness index proposed by Pielou (1966) is applied to measure agricultural diversification. This indicator is used in ecology to measure the uniformity of species within an ecosystem, i.e., to analyze how evenly they are distributed. In a literature review, Waha et al. (2022) find that this is one of the most widely used standardized indices in the agricultural economics literature for the study of agricultural diversification within rural productive units.

In the present work, agricultural diversification measured from Pielou's index calculates how uniform agricultural species are cultivated within a territory. If a local administrative entity has a low score on the index, it means greater agricultural uniformity or, in other words, that the same species tend to be cultivated within that territory. While a high score represents less uniformity and greater species diversity. The calculation uses data from the "Evaluaciones Agrícolas Municipales" (EVA), which are annual statistical records at the municipal level in Colombia with agricultural topics such as sown area, harvested area, production and crop yields, among others.

In this order, the Pielou index, H_i, is calculated for Colombia's 1,105 local administrative entities. For each entity i, p_j represents the proportion of the area planted with a crop j within each local territory. In other words, the numerator, a_j, is the area planted with a particular crop for the local territory and the denominator, A_i, is the total area planted in the respective entity (the sum of all the a_j):

$$p_j = \frac{a_j}{\sum_{j=1}^{s} a_j} \qquad (1)$$

Subsequently, the proportion of each crop in each entity is multiplied with its natural logarithm. The products are summed up for the S crops that exist in the territorial area. The result of the addition is multiplied by minus 1 and divided by the natural logarithm of the total S number of crops existing in the territorial area to normalize it in a range between 0 and 1.

$$H_i = \frac{-\sum_{j=1}^{S} p_j \ln(p_j)}{\ln(S)} \qquad (2)$$

The EVA databases from 2007 to 2021 were used to calculate the diversification indicator for the local administrative entities of the country in each year. Subsequently, an average per locality of agricultural diversification is calculated for the 15 years of the study. The indicator has shown a stable behavior during the period analyzed, which means the absence of a trend or patterns of behavior (more details in the Appendix).

The model

To quantify the impact of agricultural diversification on rural poverty in the country's municipalities, the following regression model is constructed:

$$MPI = \beta_0 + Pielou\ Index + \sum_{2}^{k} \beta_k X_k + \varepsilon \qquad (3)$$

In this model the dependent variable is the rural component of the Multidimensional Poverty Index (MPI) at the municipal (local) level, the main independent variable of interest is the agricultural diversification indicator constructed above. The controls are: 1. the management component of the municipal performance measurement indicator constructed by the Colombian National Planning Department (DNP, for its acronym in Spanish) which is composed of an assessment of the territorial entity in mobilization and execution of resources, own resources, citizen attention and accountability, and management of land use planning instruments (this is our approximation to local authorities policy performance), 2. the percentage of Agricultural Production Units within the municipality that have an extension between 0 and 1 hectares, 3. the percentage of the population living in rural areas, 4. the percentage of UPA within the municipality with access to irrigation systems, 5. number of occurrence of violence threat events in 2021 according the 'Registro Único de Victimas', as a violence indicator proxy, 6. a dummy variable for the presence of industrial and/or exportable crops (coffee, sugar cane, sugar cane, cocoa, flowers, oil palm, cotton, timber and bananas) in the municipality, 7. the percentage of land use that are in conflict due to underutilization, and 8. the altitude of the municipality measured in meters above sea level (more details in the Appendix).

Conceptualization of geographic space

The decision to include spatial effects in the modeling is justified by the findings of Galvis and Meisel (2010) that poverty at the municipal level in Colombia has a high and significant spatial correlation. In other words, there is a relationship between the poverty indicator of a municipality and that of its neighbors, even at a timeless level. Therefore, there are "neighborhoods" in which poverty is concentrated in the country and persist over time.

In an econometric model, the presence of spatial relationships between the variables of interest in the model affects the statistical tests or generates biased estimators (Lesage et. al., 2009). In this order, it is necessary to resort to spatial econometrics, a subfield of econometrics that aims to study spatial interaction effects between different geographical units (Elhorst, 2014). In this paper, the geographical units analyzed are the country's local administrative entities, also known as municipalities, while the economic phenomenon of interest is the relationship between rural poverty and agricultural diversification within and between municipalities. The study relationship is analyzed from two spatial effects: i. spatial autocorrelation and ii. spatial heterogeneity.

Spatial dependence

Spatial dependence or autocorrelation refers to the phenomenon whereby the values of a region i depend on the values of its neighboring observations. That is, the presence of a simultaneous data generation process where the values of y_i depend on the values of y_j and vice versa (Anselin, 1988; LeSage and Pace, 2009).

This phenomenon refers to a cross-sectional relationship where the correlation or covariance structure between random variables depends on their relative position in geographic space (Arbia, 2006; Anselin, 2010). In this paper, a spatial Durbin model to represent the spatial dependence model will be run, which has the following representation:

$$Y = \rho WY + \alpha t_N + X\beta + \theta WX + \varepsilon \qquad (4)$$

The terms that are common with traditional linear regression model are: Y, which is an n x 1 vector representing the dependent variable for each sample unit; t_N, which is an n x 1 vector of ones, used to represent the value of the constant or intercept α of the model; X denotes an n x k matrix of exogenous explanatory variables and β is associated with the k x 1 vector of parameters to be estimated.

In contrast to traditional ordinary least squares models, two types of spatial interactions can be evidenced: i. endogenous interaction effects on the dependent variable (Y) and ii. exogenous interaction effects on the independent variables (X) (Anselin, 1988; Elhorst, 2014). Each type of interaction has a coefficient to be estimated that captures the influence of neighboring observations: ρ, on the dependent variable Y and θ, on the independent variables X. In this paper, the independent variable of interest is the diversification index.

In econometric modeling, the spatial lags are represented by the multiplication between the spatial weighting matrices (W) with the spatial coefficients. Specifically, WY represents the endogenous spatial interaction between the dependent variables, and WX between the independent variables of the different units of analysis (Elhorst, 2014).

As used in the literature studying the relationship between agriculture and poverty, or in rural poverty studies, this paper modelling used as a binary contiguity weighting matrix. (Palmer-Jones and Sen, 2006; Wardhana, et al., 2017; da Silva, et al., 2022; Rahmawati, et al., 2023). In this type of matrix, each element indicates whether two units share a common boundary, with a value of 1 representing adjacency and 0 representing non-adjacency.

Spatial heterogeneity

The hypothesis of spatial uniformity of the effects of explanatory variables is unrealistic (Brunsdon et al. 1996) because global estimators hide spatial variations of the parameters (de Bellefon and Floch, 2018). The spatial heterogeneity is the phenomenon of structural instability that manifests itself in space. In other words, the coefficients of explanatory variables of a model can be the same at different points in the geography, but not have the same grade of effects in each of them. Therefore, spatial heterogeneity characterizes the phenomenon in which the parameters of the model are variable at different points (Anselin, 1988; Lesage et. al., 2009).

The Geographically Weighted Regression model (GWR) allows to analyze the variation in space in a continuous way and is represented as follows (Anselin, 2010):

$$y_i = \beta_o(u_i, v_i) + \sum \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \qquad (5)$$

Where y_i is the dependent variable of observation i, β_k (u_i, v_i) are the coefficients of the regression that vary according to the coordinates (u_i, v_i) and ε_i is the error term. In this framework, the coefficients are estimated separately for each location (u_i, v_i). This modeling implicitly assumes that observations near location i have greater influence on the estimate of β_k (u_i, v_i) than observations that are farther away from i; thus, nearby values will have relatively similar magnitudes and signs. Therefore, to estimate the parameter at location i, a traditional linear regression with the subset of data near i is employed. For the next observation, a different set of nearby points is used to estimate the parameter (Fotheringham et. al., 2003). The main output of this modeling is a map showing the spatial variability of the behavior of an economic relationship.

There are 3 elements of the kernel function that define the spatial relationships within a GWR model. First, the kernel shape refers to the function that defines the weight given to each observation within the neighborhood surrounding the given observation. Functions can be uniform, Gaussian, or exponential; however, the choice of function only slightly changes the results (Brunsdon et al. 1996). Second, there is a choice between a fixed or adaptive kernel, where the former refers to the extent of the kernel being defined by the distance to the point of interest, whereas, in the latter the extent of the kernel is determined by the number of neighbors of the point of interest. That is, in the adaptive kernel, the lower the density of observations, the smaller the kernel. Finally, the last element is the definition and choice of the bandwidth, which represents the distance from which the relationship between observations will have a value of zero. Thus, the value of the bandwidth h is the parameter of choice that has the most influence on the results, since the greater the bandwidth, the greater the number of observations that will have a weight different from 0 (de Bellefon & Floch, 2018, p. 235).

For the application of the current model, a continuous or Gaussian kernel function was chosen because the dependent variable of the model (rural component MPI) does not take binary or discrete values. Additionally, an adaptive kernel was chosen because this extension is recommended for spatial data that do not have a homogeneous distribution (de Bellefon & Floch, 2018), such as the country's municipalities. Finally, for the calculation of the bandwidth, the Akaike criterion was chosen, i.e., to determine the bandwidth, a set of local regression models is calculated and the Akaike criterion defines the number of optimal neighborhoods from the set of regressions.

Results and discussion

This section presents the results of the calculation of the agricultural diversification indicator and the two models estimated: spatial dependence and spatial heterogeneity.

Diversification index

Table 1 presents the local administrative entities of the country with the lowest and highest agricultural diversification for the average of the 15 years of study.

In terms of production, the three products that most promote local agricultural specialization in Colombia are sugarcane, potatoes, and coffee. Sugarcane occupies 93% of the planted areas of Palmira, Valle, and 94.3% of Candelaria, Valle. Potato occupies 90.5% of Tutazá, Boyacá and 91.23% of Sesquilé, Boyacá. Coffee occupies 93.8% of Piendamó, Cauca, and 91.5% of Betania, Antioquia.

Figure 1 shows municipal diversification in Colombia. There is a high agricultural specialization in regions such as 'Altillanura de la Orinoquía' (Rice), middle and upper Cauca River basins (Sugar cane), Colombian Massif (Coffee), Eastern Cundinamarca and western Boyacá (Potato), the Mojana region (Cereals), and Santander, south of Bolivar and Cesar (Oil palm). Therefore, the most agriculturally specialized regions in the country are located mainly in regions with ample access to water resources and in Andean, sub-Andean, or tropical forest ecosystems (ecosystems marked by high rainfall and a tropical climate dependent on altitude).

The most diversified areas are the northern Colombian Pacific, the Amazonian foothills, the Magdalena Medio, and the department of Guaviare. These areas are characterized by their ombrophilous or sub-hygrophilous-hygrophilous equatorial forest ecosystems (ecosystems marked by high humidity and species diversity).

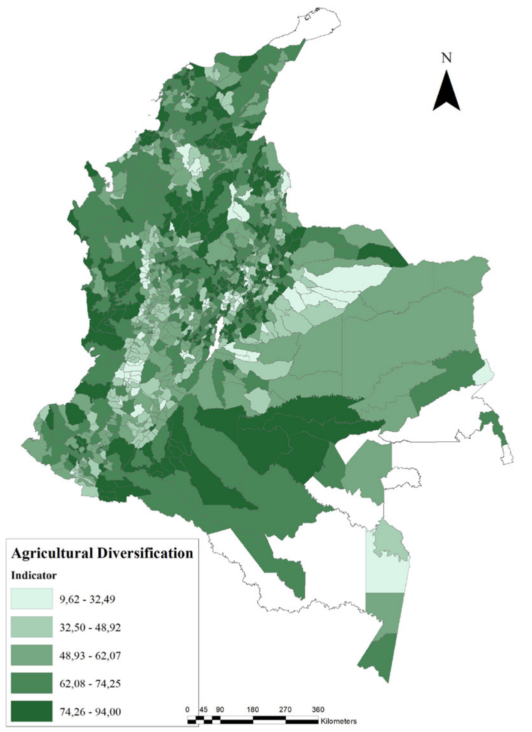

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Figure 1: Municipal diversification in Colombia.

An analysis of the distribution of municipalities according to their agricultural diversification reveals the existence of marked natural boundaries between highly specialized and diversified regions. The main examples of this characteristic are the Eastern Cordillera, which separates the specialized municipalities of the Cauca basin from the diversified municipalities of the Colombian Pacific; the Central Cordillera

Municipalities with the lowest agricultural diversification in Colombia		Municipalities with the highest agricultural diversification in Colombia	
Municipalities	Diversification index	Municipalities	Diversification index
Sesquilé, Cundinamarca	0.0961846	Fómeque, Cundinamarca	0.8673471
Palmira, Valle del Cauca	0.0976485	Peñón, Antioquia	0.8675603
Puerto Tejada, Casanare	0.1063187	Sáchica, Boyacá	0.8687919
Candelaria, Valle	0.1090595	Rionegro, Antioquia	0.8703443
Villapinzón, Cundinamarca	0.1139393	Tibaná, Boyacá	0.8750623
Betania, Antioquia	0.1209051	Puerto Asís, Putumayo	0.8763599
Tausa, Cundinamarca	0.1259753	Certegui, Chocó	0.8781608
Tutazá, Boyacá	0.1300443	Medio San Juan, Chocó	0.8847447
Piendamó, Cauca	0.1309135	Guapi, Cauca	0.8871211
Padilla, Cauca	0.1357833	Remedios, Antioquia	0.8905849

Source: Author's own calculations

Table 1: Local administrative entities with the lowest and highest agricultural diversification in Colombia from 2007 to 2021.

between the specialized municipalities of the Colombian massif and the diversified municipalities of the Amazonian foothills; and the Western Cordillera between the specialized municipalities of the Altillanura and the diversified municipalities of the department of Cundinamarca. Therefore, a key conclusion of this paper is that geography and natural resource endowment influence diversification-specialization decisions.

Models

The results of the estimations of the models proposed to analyze the relationship between rural poverty and agricultural diversification are presented below, taking into account separately the spatial phenomena of: 1. autocorrelation and 2. spatial heterogeneity. Models with both spatial effects are estimated because first the relationship of interest is quantified and later it will be analyzed if it is uniform for the whole territory of the country.

Spatial dependence

Table 2 presents the modeling results with Durbin's spatial autocorrelation. The calculation was performed using the Maximum Likelihood estimation method as recommended by Anselin (1988). The model is evidenced to possess an explanatory power indicated by a Pseudo R^2 value close to 0.5. Additionally, the p-values of the Wald test indicate that the spatial terms such as the spatial lags of the dependent ($\hat{\rho}$) and independent ($\hat{\theta}$) variable have a statistically significant effect, therefore, the Durbin is preferable over the traditional linear regression model (Elhorst, 2014).

The coefficients are not directly interpretable. In a non-spatial model, the total effect on the dependent variable is the coefficient estimate holding all other variables constant and regardless of their location. Whereas, in a spatial model such as the Durbin Model, the total effect depends on both the neighboring units and the coefficients of the spatial variables (Goméz and Hernan, 2015). Therefore, within a spatial model it is relevant to isolate the effect that spatially lagged variables have on a variable of interest.

VARIABLES	(1) Spatial Durbin Model
Agricultural diversification	0.1883***
	(0.0222)
Municipal Performance	-0.3215***
	(0.0303)
% of agricultural units with an area of less than 1 hectare	-0.1421 ***
	(0.0183)
% of the population living in rural areas	0.1503***
	(0.0163)
% of agricultural units with access to irrigation systems	-0.0546***
	(0.0139)
Altitude	-0.0042***
	(0.0005)
Acts of threats (Violence indicator)	0.0150***
	(0.0036)
% of the municipal productive land underutilized	-0.0832***
	(0.02242)
Intercept	60.8806***
	(2.6560)
$\hat{\rho}$	-0.5668***
	(0.0061)
$\hat{\theta}$	0.0644***
	(0.0083)
Observations	1.084
Pseudo R^2	0.491
p-value	0.00
Wald Spatial Test	0.00

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own calculations

Table 2: Spatial Durbin Model estimation.

In this context, Table 3 presents the marginal effects of the Durbin model. Direct effects correspond to the direct impact of an explanatory variable on the dependent variable in each geographic unit, without taking into account spatial neighborhood effects. Therefore, these effects are interpreted similarly to how an OLS model would be interpreted. On the other hand, indirect effects refer to the impact of spatially lagged variables, i.e., spatial neighborhood influencing all units in the model. Finally, the total effect refers to the aggregate impact of the model coefficients, including both direct and indirect effects (Le Saout and Floch, 2018).

There is evidence that an increase of one percentage point in the diversification index of the municipalities is related to an increase of 0.1816 percentage points (p.p.) in the rural

Variables	(1) Direct effect	(2) Indirect effect	(3) Total effect
Agricultural diversification	0.1816***	-0.1195***	0.0620**
	(0.0220)	(0.0175)	(0.0277)
Municipal Performance	-0.3246***	-0,0553***	-0.3800***
	(0.3049)	(0,0102)	(0.0351)
% of agricultural units with an area of less than 1 hectare	-0.1435**	-0.0244***	-0.1679
	(0.0184)	(0.0052)	(0.0218)
% of the population living in rural areas	0.1518***	0.0258***	0.1777***
	(0.0164)	(0.0052)	(0.0195)
% of agricultural units with access to irrigation systems	-0.0551***	-0.0094***	-0.0645***
	(0.0140)	(0.0028)	(0.0164)
Altitude|	-0.0043***	-0.0007***	-0.0050***
	(0.0005)	(0.0001)	(0.0006)
Acts of threats (Violence indicator)	0.0152***	0.0025***	0.0178***
	(0.0036)	(0.0008)	(0.0043)
% of the municipal productive land underutilized	-0.0840***	-0.0143***	-0.0983***
	(0.0226)	(0.0043)	(0.0262)

Note: Standard errors in brackets; *** p<0.01, ** p<0.05, * p<0.1
Source: Author's own calculations

Table 3: Marginal effects of the Durbin model.

component of the Multidimensional Poverty Index; while the spillover effect of neighboring municipalities is close to -0.1195 p.p. of increase in rural poverty. In other words, a higher level of diversification in a municipality is associated with an increase in rural poverty; however, if its neighbors diversify, rural poverty tends to decrease. In fact, the indirect effect almost manages to offset the increase in poverty by the direct effect.

It can be postulated that agricultural diversification can lead to a dispersion of resources and efforts, with the consequent inability of farmers to achieve the economies of scale necessary for competitiveness. This may result in lower efficiency and, consequently, high levels of poverty (Baumgärtner and Quaas, 2010). However, the positive relationship between diversification in the municipality as a whole and rural poverty can be explained, to a large extent, by the loss of economies of scale external to the agricultural unit, and not so by internal economies of scale. If internal economies of scale were significant, the increase in the number of small agricultural units (e.g., 0 to 1 hectares) would have a poverty-increasing effect, because internal economies of scale are present mainly in large farm units (Chavas, 2001).

On the other hand, indirect local effects can be explained through the impact of the specialization of neighboring municipalities in the consolidation and improvement of markets and short marketing circuits. Two possible mechanisms can be observed. First, when neighboring municipalities diversify, they generate a greater variety of products in the local market, thus boosting trade and income with the central municipality. This improves the ability of farmers in the central area to sell their products and access more diverse and potentially lucrative markets. Second, diversification into surrounding municipalities can strengthen resilience to economic and climatic risks, stabilizing markets and providing a more secure economic environment for the central municipality. This economic stability and risk reduction can translate into reduced poverty levels (Klasen et al., 2016; Sotelo, 2020).

This paper shows that the effects of agricultural diversification are dynamic since they affect not only the unitary farm or the local territory itself but also neighboring local units and territories. Therefore, the socioeconomic effects of this type of decision should be analyzed with a regional approach, and not in isolation.

For the remaining variables, a positive relationship was found between rural poverty with the proportion of the population living in rural areas and the occurrence of events involving threats of violence against the population. While, a negative relationship was found with access to irrigation systems (external to the agricultural units), quality of policy management by local authorities, the presence of small production units and percentage of underutilization.

Spatial heterogeneity

Figure 2 shows the results of the agricultural diversification coefficient of the geographically weighted regression. An increase of between one percentage point in the diversification index of the country's municipalities is related to an increase of between almost 0 and 17 percentage points (p. p.) in the rural component of the Multidimensional Poverty Index. In other words, a higher level of diversification in a municipality is related to an increase in its rural poverty.

The relationship between diversification and poverty is positive and significant for the country, but its intensity varies in different regions. Specifically, in the southwestern regions of the country, such as the Pacific, and some municipalities of the Eje Cafetero. In fact, the further west a municipality is located in the country, the stronger this relationship will be.

This relationship can be interpreted from two levels. First, Valle del Cauca and Cauca are among the departments that allocate the most planted area to agro-industrial products (more than 7.5% of the planted area of the UPAs), such as coffee, African palm, sugarcane, sugarcane, rubber, cotton, etc. (DANE, 2015). Secondly, the departments of Antioquia, Nariño, Tolima, Valle del Cauca, Meta and Cauca represent about 45% of the total harvested area of the country (DANE, 2015). In other words, there is, broadly speaking, a concentration of agroindustrial crops and agricultural production in the western part of the country.

In this sense, the western intensification of the relationship between rural poverty and diversification is explained by the relevance of the external economies obtained by concentrating production in a certain geographic area. External economies of scale are exemplified by shared infrastructure (roads, irrigation, storage, and transportation), dissemination of technical knowledge and technology, and the development of markets and product linkages encouraged by specialization in one or a few agricultural products.

In particular, it is worth highlighting the role of Valle del Cauca in the intensification of the relationship due to the loss of potential benefits from productive linkages when adopting diversification strategies.

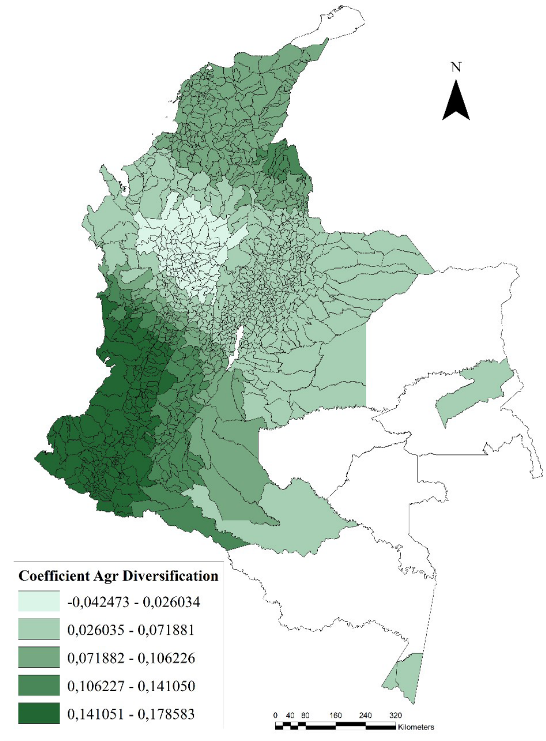

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Figure 2: Results of the diversification coefficient.

In other words, if a local administrative entity decides to diversify in an environment of constant specialization benefits, it will be more disadvantaged in its social indicators than a municipality that does so in an environment with low external economies of scale due to specialization.

In Table 4, it is presented the diagnosis of the GWR model. In the model presented, the bandwidth is determined by the number of nearest neighbors, ensuring that each local estimation is based on the same quantity of features. Rather than specifying a particular distance, the analysis is conducted using a set number of neighbors. Additionally, it can be noted that a higher R^2 and a R^2 adjusted is preferable.

Variable	Value
Neighbors	585
Residual Squares	118997.7
Effective Number	51.47
Sigma	10.7
AICc	8259.34
R^2	0.5979
R^2 adjusted	0.5783

Source: Author's own calculations

Table 4: Diagnosis of the GWR model.

On the other hand, Figure 3 presents the local R^2 that measures the fit of the model at regression point i and its capacity to replicate the data in the vicinity of point i (de Bellefon and Floch, 2018, p. 216).

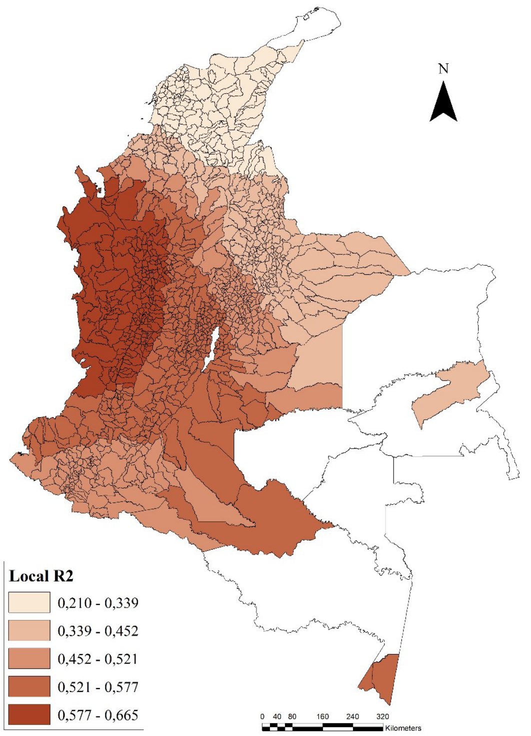

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Figure 3: Local R^2.

In this map it is evident that the proposed model has a higher explanatory capacity in the northwest of the country with a Local R^2 close to 0.6; while, in the other regions it is close to 0.5.

Conclusion

Economic studies that analyze the relationship between poverty and agricultural diversification usually focus on the analysis of production within an agricultural unit and its same social outcomes (Seo, 2010; Ullah and Shivakoti, 2014; Thapa et al., 2018; Sekyi et al., 2021). This paper, from an innovative approach, analyzes the relationship from the local scale, because it recognizes the importance of spatial effects and externalities that transcend agricultural units.

The evidence presented suggests that municipal-scale agricultural diversification is associated with higher levels of rural poverty. However, when analyzing the spatial effects (autocorrelation and spatial heterogeneity), it was found that this relationship is not uniform across the entire national territory and has opposite spillover effects when analyzing the neighboring municipalities that offset the positive effect.

The positive relationship between rural poverty and agricultural diversification is not uniform throughout the country. Specifically, the relationship is intensified in the western part of the country, including the Pacific region, and some municipalities of the Eje Cafetero. This situation is due, broadly speaking, to a concentration of agroindustrial crops and agricultural production in the western part of the country. In this sense, the western intensification of the relationship between rural poverty and diversification is explained by the relevance of external economies that are obtained by concentrating production in a certain geographic area and are lost by adopting diversification strategies.

The results obtained demonstrate the importance of considering the differences and particularities of each territory in the formulation of sectoral public policies. To this extent, it is essential to approach territorial convergence from the grouping of regions with similar characteristics, opportunities and challenges in "convergence clubs", as discussed in the literature on regional economic convergence (Royuela and García, 2015; Vásquez and Bara, 2009). Although this literature focuses on regional convergence in terms of economic growth, its focus on the formulation and approach of heterogeneous solutions according to "convergence clubs" should be equally addressed in sectoral policies, as in this case agriculture.

The paper's findings are framed by global discussions favoring agricultural diversification as a measure for adaptation and mitigation of climate change effects in agricultural areas (FAO et. al., 2022; IFPRI, 2022). However, it also raises concerns about the economic sustainability and social impacts of this strategy on rural communities, which are already highly vulnerable. Thus, in these discussions around the impact of climate change in rural areas, adaptation and mitigation strategies must be reconciled with their potential social benefits or detriments. A certain degree of specialization in a municipality generates benefits for the farmer and his municipality, provided that there is greater agricultural diversity at the higher scale of analysis (province, subregion, department) to mitigate environmental damage and ensure the sustainability of his activity. Policy recommendations should be oriented toward promoting more tailored and targeted local and regional agricultural policies that coordinate clusters and different levels of specialization; in addition, some social protection measures should be coordinated with agricultural diversification initiatives to mitigate the potential adverse effects of diversification strategies.

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Appendix

In this appendix, the description of the variables used can be found (Table 5).

Additionally, to ensure that the agricultural diversification index is not a function of time, unit root tests for panel data were calculated using the Fisher Dickey-Fuller Augmented Fisher test (Maddla and Wu, 1999) and the Fisher Phillips-Perron test (Choi, 2001). Table 5 shows that with both tests and all statistics the null hyptothesis of the existence of unit roots is rejected. In other words, municipal agricultural diversification in Colombia has a constant mean and variance over time and does not show a trend in the last 15 years (Banerjee, 1999).

Variable	Description	Year	Source
Rural component of the Multidimensional Poverty Index (MPI) at the municipal (local) level.	The MPI is composed of 15 variables in 5 dimensions (educational conditions, children and youth, health, work, access to public utilities and housing conditions). In 2020, based on information from the National Population and Housing Census, multidimensional poverty was calculated at the municipal level (DANE, 2020).	2020	Departamento Administrativo Nacional de Estadística - DANE
Management component of the municipal performance measurement indicator.	Municipal Performance Measurement is an indicator calculated by the DNP that has two components: management and results: 1. mobilization, 2. execution of own resources, 3. attention to citizens and accountability, and 4. management of land use planning instruments.	2021	Departamento Nacional de Planeación
Agricultural Production Units within the municipality that have an extension between 0 and 1 hectares.	The percentage of agricultural production units in the municipality that have between 0 and 1 hectare of land area.	2014	National Agricultural Census, DANE
Percentage of UPA within the municipality with access to irrigation systems.	Percentage of agricultural production units within the municipality that have access to an irrigation system.	2014	National Agricultural Census, DANE
Percentage of land use that is in conflict due to underutilization.	The percentage of the municipality's land use that is in conflict due to underutilization with respect to the land use vocation.	2012	Departamento Nacional de Planeación based on information from the Instituto Geográfico Agustín Codazzi.
Presence of industrial and/or exportable crops.	Dummy variable that takes the value of 1 if at least 10% of the municipality's cultivated land is destined to the cultivation of industrial and exportable products (subject to industrial transformation and/or export), such as coffee, sugar cane, sugar cane, cocoa, flowers, oil palm, cotton, timber and banana.	2007-2021	Own calculations based on EVAs
Percentage of the population living in rural areas.	Percentage of the municipality's population living in rural areas	2022	Departamento Administrativo Nacional de Estadísticas - DANE
Altitude of the municipality measured in meters above sea level.	Dummy variable that takes the value of 1 if at least 10% of the municipality's cultivated land is destined to the cultivation of industrial and exportable products (subject to industrial transformation and/or export), such as coffee, sugar cane, sugar cane, cocoa, flowers, oil palm, cotton, timber and banana.	2007-2021	Own calculations based on EVAs

Source: Author’s own elaboration

Table 5: Description of the variables employed.

FISHER CHI-SQUARE - ADF			FISHER CHI-SQUARE - PP		
Test	**Value**	**P-value**	**Test**	**Value**	**P-value**
Inverse chi-squared	4295.6982	0.0000	Inverse chi-squared	4485.0296	0.0000
Inverse normal	-20.8552	0.0000	Inverse normal	-19.7097	0.0000
Inverse logit t	-23.8588	0.0000	Inverse logit t	-23.9772	0.0000
Modified inv. chi-squared	31.7276	0.0000	Modified inv. chi-squared	34.5858	0.0000

Source: Author’s own elaboration

Table 6: Tests of stationarity of the municipal agricultural diversification index.