SPATIAL ANALYSIS OF CLIMATE EFFECTS ON BANANA PRODUCTIVITY IN THE DOMINICAN REPUBLIC

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Abstract - This study evaluates the spatial effects of climatic variables, precipitation and temperature, on banana productivity in the Dominican Republic. Climatic and agricultural data from historical records covering the period 1990–2023 were used. As analytical techniques, spatial econometric regressions were estimated based on the Spatial Durbin Model (SDM). The SDM results indicate that, in terms of spatial impacts, rainfall exerts a negative effect on banana agricultural productivity, both directly and indirectly (direct effect: -0.191; indirect effect: -0.260; total effect: -0.451). Thermal amplitude also shows a negative impact in both dimensions (direct effect: -0.083; indirect effect: -0.079; total effect: -0.162). In contrast, harvested area has a positive effect (direct effect: 0.144; indirect effect: 0.089; total effect: 0.233), with a greater contribution from indirect impacts.
These findings are consistent with previous studies, which establish that climate impacts on agriculture may exhibit spatial patterns, generating indirect effects on agricultural production in neighboring regions.

Keywords - Banana productivity, Precipitation, Thermal amplitude, Spatial regression, Durbin Model

I. INTRODUCTION

Climate change affects food systems differently at the regional level, with tropical and subtropical regions being particularly vulnerable to adverse impacts [1, 2]. In this regard, it can be observed that the world's major producers, as well as those of regional relevance where rising temperatures in banana-producing areas remain within optimal ranges, have recorded increases in productivity. However, in countries where temperatures have exceeded the regional optimum, declines have been observed [3].

Changes in climatic conditions can generate significant impacts on agricultural yields at the global scale [4]. These effects are particularly notable for tropical crops such as banana, whose productivity depends on relatively stable climatic conditions and adequate water availability [5]. Consequently, climate change may interfere with agricultural yields through multiple mechanisms, including changes in water availability, alterations in crop growth cycles, and increased frequency of extreme climatic events [6, 7, 8].

Bananas are one of the most important crops worldwide and play a fundamental role in food security and in the agricultural economies of numerous tropical countries [9]. In the case of the Dominican Republic, banana production represents a key economic activity, both for its contribution to agricultural exports and for its impact on rural employment [10,11, 12]. Nevertheless, the level of exposure and vulnerability to extreme climatic events has been above the regional average between 1998 and 2017, with severe consequences for local production determined by climatic hazards, including heavy rainfall, tropical storms and hurricanes, floods, and droughts [13, 14].

In this context, the objective of this study is to evaluate the spatial effects of climatic variables, precipitation and temperature, on banana productivity in the Dominican Republic. Accordingly, the paper is structured into five sections: the present introduction, a description of the methods and analytical techniques employed, the presentation of results, followed by discussion and conclusions.

II. MATERIALS AND METHODS

This study was conducted in the Dominican Republic, as shown in Figure 1. Meteorological data on precipitation and minimum, average, and maximum temperatures analyzed in this research were obtained from the Dominican Institute of Meteorology (INDOMET), based on provincial meteorological stations located nationwide and disaggregated into monthly time series for the period 1990-2023. Likewise, agricultural data used for generating indices and spatial regression models, such as harvested area and production volume, were acquired from the monthly regional agricultural reports of the Ministry of Agriculture (MARD). Using the latter, productivity data employed in the analysis were calculated.



Figure 1: Map of the Dominican Republic by Province and Agricultural Regions.
Source: Ministry of Agriculture, DR, 2016.

Correlation indices and spatial regression models were estimated using 32 spatial observations (32 provinces) over a period of 34 years. The original dataset consisted of monthly observations organized in a spreadsheet with 13 columns, structured by variables, years, months, and spatial units, comprising a total of 13,873 records.

As part of the methodological approach, exploratory spatial data analysis was conducted through spatial correlation indices, the global spatial autocorrelation index Moran's I, and the local spatial autocorrelation index (Local Indicators of Spatial Association, LISA). In addition, a descriptive spatial analysis of the variables was conducted. Subsequently, a panel-type spatial regression was specified based on the Spatial Durbin Model (SDM), which resulted in the estimation of several spatial regression models. For the estimation of these models, the variables were aggregated to an annual level to ensure consistency in spatial econometric analysis with a balanced panel of 32 provinces observed over 34 years, yielding a total of 1,088 observations.

For the development of the study, various computational tools were employed. Microsoft Excel spreadsheets were used for data storage, while QGIS was utilized for constructing spatial correlation indices, and R was used for descriptive statistics, model estimation, and spatial econometric analysis.
The geolocation of climatic and productivity variables was carried out by assigning geographic coordinates based on agrometeorological stations, following the approach of [15]. Banana productivity data were integrated with geographic information at the provincial level using Geographic Information Systems (GIS), employing polygon-type vector layers corresponding to the provinces that make up the northwestern region of the country. All spatial layers were projected using the WGS84 geographic coordinate system (EPSG:4326).

Prior to the estimation of spatial econometric models, an exploratory spatial autocorrelation analysis was conducted to identify potential geographic clustering patterns in banana productivity and climatic variables. For this purpose, Moran's I [16] was calculated. This index is defined as follows [17]:

(1)

$$I = \frac{N}{W} \cdot \frac{\sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} (x_i - \bar{x})(x_j - \bar{x})}{\sum_{i=1}^{N} (x_i - \bar{x})^2}$$

Where N represents the number of spatial units (provinces); W is the sum of all spatial weights w_{ij} $\left(W = \sum_{i=1}^{N} \sum_{j=1}^{N} w_{ij} \right)$; w_{ij} corresponds to the elements of the spatial weights matrix for locations i and j; x_i and x_j are the values of the variable under analysis at locations i and j, respectively; and $\bar{x}$ is the mean of the variable.

Positive values of the index indicate spatial clustering of similar values, while values close to zero suggest a random distribution. Negative values reflect spatial dispersion patterns. The p-value determines whether the observed autocorrelation is statistically significant, and a Z-score above ±1.96 indicates a significant spatial relationship [18]. In addition to Moran's I, the LISA index was estimated to identify specific spatial clusters and potential patterns of

regional concentration [19, 20], using the following equation [21]:

(2)

$$I_i = \frac{(x_i - \bar{x})}{m_2} \sum_{j=1}^{N} w_{ij}(x_j - \bar{x})$$

Where I_i is the Local Moran's index for the spatial unit, x_i is the value of the variable in that unit, $\bar{x}$ is the mean of the variable, and $m_2 = \frac{1}{n}\sum_{i=1}^{n}(x_i - \bar{x})^2$ corresponds to the sample variance, N denotes the total number of provinces. The term w_{ij} refers to the spatial weight between units i and j, and n is the total number of observations. This index allows for the identification of local clusters (high-high, low-low) and spatial outliers (high-low, low-high).

Spatial weight matrices were constructed using Queen contiguity criteria, which consider two spatial units as neighbors if they share at least one boundary point [22, 23]. All matrices were row-standardized to ensure comparability across regions.

To analyze the relationship between climate variability and banana productivity, a Spatial Durbin Model (SDM) was estimated using panel data. This model allows for the simultaneous incorporation of spatial dependence in the dependent variable and spatially lagged effects of the explanatory variables [24, 25]. The general specification of the Spatial Durbin Model can be expressed as follows:

(3)

$$y_{it} = \rho W * y_{it} + \beta * X_{it} + \gamma * WX_{it} + \mu_i + \lambda_t + \varepsilon_{it}$$

In this study, the model is specified as follows:

$$\begin{aligned} \text{Productivity}_{it} = {} & \rho W\text{Productivity}_{it} + \beta_1 \text{Rainfall}_{it} \\ & + \beta_2 \text{AverageTemperature}_{it} \\ & + \beta_3 \text{ThermalAmplitude}_{it} \\ & + \gamma_1 W\text{Rainfall}_{it} \\ & + \gamma_2 W\text{AverageTemperature}_{it} \\ & + \gamma_3 W\text{ThermalAmplitude}_{it} + \varepsilon_i \end{aligned}$$

Where y_{it} represents banana productivity in province i at time t; W is the spatial weights matrix that captures neighborhood relationships among provinces; ρ is the spatial autocorrelation coefficient associated with the dependent variable; X_{it} is the matrix of explanatory variables; γ captures the indirect (spatial spillover) effects; and WX_{it} represents the spatially lagged explanatory variables. The terms μ_i and λ_t correspond to spatial and temporal fixed effects, respectively, while ε_{it} represents the error term.

The explanatory variables included in the model correspond to climatic factors, specifically precipitation, average temperature, and thermal amplitude. Furthermore, according to [26], the interpretation of the model allows for the distinction of three types of effects. Direct effects represent the impact of explanatory variables on productivity within the same province. Indirect effects, or spillovers, reflect the influence of climatic conditions in neighboring provinces. Finally, total effects correspond to the sum of direct and indirect effects.

The spatial model was estimated using the Maximum Likelihood method, incorporating robust standard errors to ensure model robustness in the presence of potential heteroskedasticity [27]. Additionally, Wald restriction tests and Likelihood Ratio (LR) tests were applied to assess whether the SDM could be simplified to alternative specifications such as the Spatial Autoregressive Model (SAR) or the Spatial Error Model (SEM). To evaluate the presence of spatial dependence in the residuals, Lagrange Multiplier tests (LM-Lag and LM-Error), along with their robust versions, were employed. Finally, complementary tests for heteroskedasticity (Breusch–Pagan) and normality (Jarque-Bera) were conducted, following the methodology proposed by [28].

When the initial model did not satisfy the required statistical assumptions, alternative specifications were evaluated. In these, temperature variables were replaced by thermal amplitude, and harvested area was incorporated as an additional variable. Based on these adjustments, the revised model is presented below.

(4)

$$\begin{aligned} \text{Productivity}_{it} = {} & \rho W\text{Productivity}_{it} + \beta_1 \text{Rainfall}_{it} \\ & + \beta_2 \text{ThermalAmplitude}_{it} \\ & + \beta_3 \text{HarvestedArea}_{it} \\ & + \gamma_1 W\text{Rainfall}_{it} \\ & + \gamma_2 W\text{ThermalAmplitude}_{it} \\ & + \gamma_3 W\text{HarvestedArea}_{it} \\ & + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned}$$

However, if equation (4) does not satisfy the econometric diagnostic tests, adjustments to the model specification are carried out. These adjustments involve the logarithmic transformation of the variables and allow for the estimation of the following adjusted equation.

(5)

$$\begin{aligned} \ln(\text{Productivity}_{it}) = {} & \rho W * \ln(\text{Productivity}_{it}) \\ & + \beta * X_{it} + \gamma * WX_{it} + \mu_i + \lambda_t + \varepsilon_{it} \end{aligned}$$

Where,

$$X_{it} = \ln \text{Rainfall}_{it}, \text{ThermalAmplitude}_{it}, \text{HarvestedArea}_{it}$$

If the SDM with logarithmic transformation (5) exhibits persistent non-normality or spatial dependence in the error terms, the robust Wald test is applied. This test allows for consistent inference in

the presence of potential heteroskedasticity and dependence in the residuals using a robust variance-covariance matrix (sandwich estimator), denoted as $\mathrm{Var}(\beta)_{\mathrm{robust}}$ [29]:

$$\mathrm{WR} = (\mathrm{R}\theta\hat{} - \mathrm{r})'[\mathrm{RVarR}(\theta\hat{})\mathrm{R}'] - 1(\mathrm{R}\theta\hat{} - \mathrm{r} \quad (6)$$

In which θ includes ρ(the spatial lag coefficient), β, andγ(the spatial coefficients associated with X).

III. RESULTS

The descriptive analysis of the variables indicates that agricultural productivity (Prod) exhibits the highest variability, with extreme values and a concentration of high productivity levels in a few provinces, as reflected by a standard deviation of 8.65, positive skewness (2.90), and kurtosis of 11.31. In contrast, precipitation (Rainfall, mm) shows a more symmetric distribution closer to normality (kurtosis ≈ 3), indicating a relatively homogeneous distribution across territories.

Temperature variables (Tem. min,Tem. max and Tem. average) display low dispersion but negative skewness, suggesting a greater concentration of values within higher ranges. Additionally, their kurtosis levels above 3 indicate the presence of some extreme values. The results of the analysis are presented in Table 1.

Parameter	Prod	Rainfall (mm)	Tem. min	Tem. max	Tem. average
Mean	7.71	83.23	21.53	29.44	25.48
Median	7.36	87.54	21.78	29.48	25.58
Mode	7.36	86.35	20.91	29.70	25.30
Standard Deviation	8.65	19.96	1.55	1.86	1.49
Variance	74.84	398.38	2.39	3.45	2.23
Minimum	0.00	41.30	16.84	24.37	20.61
Maximum	40.15	128.26	23.71	32.74	27.55
Range	40.15	86.96	6.86	8.37	6.94
First Quartile (Q1)	6.03	70.53	20.79	28.73	25.24
Third Quartile (Q3)	7.36	94.76	22.51	29.92	26.21
Interquartile Range (IQR)	1.33	24.23	1.72	1.20	0.98
Skewness	2.90	-0.09	-1.41	-0.56	-1.63
Kurtosis	11.31	2.68	5.02	3.96	6.37

Table 1

Regarding the spatial autocorrelation analysis using Moran's I, productivity yielded a value of 0.2411, indicating a positive correlation among spatial units. This suggests that areas with high banana production tend to be surrounded by regions with similar productivity levels, and vice versa. The Z-score value of 2.3695 and a p-value of 0.01 indicate statistically significant spatial autocorrelation. The results obtained from the correlation indices are presented in **Table 2.**

Parameter	Prod	Rainfall(mm)	Tem. average
Moran's I	0.2411	0.8728	0.7555
Expected value	-0.0322	-0.0303	-0.0220
Z-score	2.3695	27.4452	7.6457
p-value	0.01	0.0001	0.0001

Table

The results of Moran's I for climatic data related to precipitation indicate the existence of geographic clustering that may reflect provincial climate patterns. In this regard, the Moran's I parameters0.8728, a Z-score of 27.4452 and a p-value of 0.0001reveal that precipitation exhibits a consistent and significant spatial pattern, with clear clustering of wet and dry areas, suggesting the influence of regional climatic factors.

Similarly, Moran's I applied to average temperature also shows positive spatial autocorrelation, with an index value of 0.7555, a Z-score of 7.6457, and a p-value of 0.000, indicating statistically significant spatial autocorrelation. This suggests that the thermal distribution is not random but instead follows a well-defined and consistent spatial structure.

Regarding the local spatial autocorrelation analysis (LISA) of banana productivity in the study area, as shown in Figure 2, the index confirms the existence of significant productivity clusters in the Northwest region, particularly in the provinces of Valverde (with high productivity levels), Dajabon and Santiago Rodríguez (with both high and low productivity depending on proximity effects). In the Northern region, clusters are observed in Puerto Plata, with both high and low productivity levels influenced by productive zones of influence. In the Eastern region, the province of San Pedro de Macorís shows low productivity levels, reflecting spatial heterogeneity across these regions. The rest of the country shows no significant clustering.

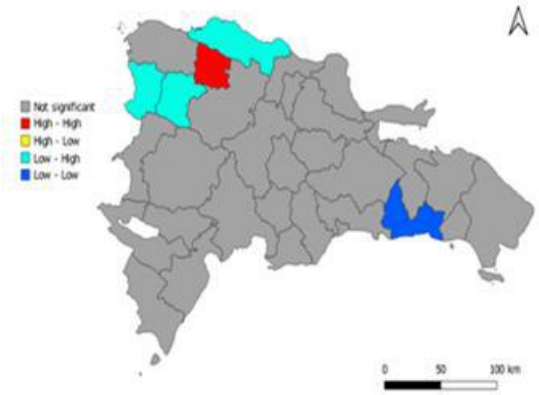


Figure 2: Spatial distribution of productivity according to LISA

In the case of rainfall, as shown in Figure 3, the LISA index indicates that precipitation follows well-defined spatial patterns. It reveals a spatial distribution characterized by low rainfall levels in some provinces of the Northwest, North, South, and Southwest regions, while, conversely, high rainfall levels are observed in the Northeast, North-Central, and Central regions. These results support the existence of a significant territorial organization in the distribution of precipitation.

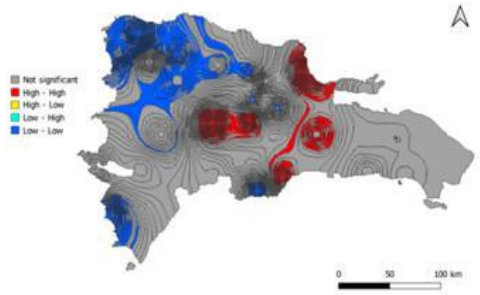


Figure 3: Spatial distribution of rainfall according to LISA

The LISA index, shown in Figure 4, applied to temperature, indicates the presence of a consistent spatial organization, with clusters of high values in the Northwest and South Regions and lower temperatures in the North Central Region, confirming significant positive spatial autocorrelation in some regions of the country.

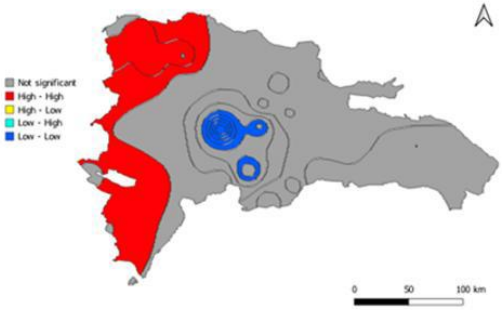


Figure 4: Spatial distribution of average temperature according to LISA

Table 3 presents the results of the spatial econometric specifications (3, 4) corresponding to the estimated regression models. In this regard, the SDM results show positive spatial dependence in agricultural productivity, captured by the coefficient ρ, which is statistically significant in the initial model ($p < 0.05$) and marginally significant in the adjusted model (4).With respect to direct effects, local climatic variables (rainfall, average temperature, and thermal amplitude) do not exhibit statistically significant effects on productivity, although thermal amplitude shows a negative effect close to significance levels in the initial model. Similarly, harvested area is not statistically significant in the adjusted model.

On the other hand, regarding indirect spatial effects, rainfall in neighboring provinces (W_Rainfall) exhibits a negative and highly significant impact on local productivity in both models ($p < 0.01$), indicating the presence of relevant spatial spillovers. The remaining spatial variables are not statistically significant

Variable dependent: banana productivity
N = 1088 (32 provinces × 34 years)

Parameter	SDM (3) Coeff.	p-value	SDM (4) Coeff.	p-value
ρ (spatial autoregressive coefficient)	0.0879	0.035	0.0804	0.0544
Rainfall	-0.0155	0.235	-0.0114	0.3721
Average Temperature	0.3998	0.459		
Thermal Amplitude	-0.9510	0.082	-0.6203	0.1385
Harvested Area			0.000071	0.8587
W_Rainfall	-0.0703	0.002	-0.0722	0.0017
W_Average Temperature	-0.9144	0.378		
W_Thermal Amplitude	-0.4535	0.669	-0.8742	0.2853
W_Harvested Area			0.001545	0.0869
Model Residuals	SDM (3)		SDM (4)	
Minimum	-29.45489		-29.27553	
First Quartile	-0.90516		-0.92558	

(Q1)		
Median	-0.24938	-0.22510
Third Quartile (Q3)	1.05333	1.06127
Maximum	66.15397	65.80888

Table 3Variable dependent: banana productivity
N = 1088 (32 provinces × 34 years)

The results of the spatial impacts for both the initial (3) and adjusted (4) models, presented in Table 4, show that precipitation has a negative total effect on agricultural productivity, with a predominance of indirect effects (-0.0781 compared to -0.0127). This indicates that rainfall conditions in neighboring provinces have a significant impact on local conditions. In model (3), averagetemperature shows a positive direct effect, a high negative indirect effect, and a negative total effect. In the case of thermal amplitude, model (3) and 4), negative effects are observed in both direct and indirect dimensions, suggesting that thermal variability in nearby regions influences agricultural productivity, thereby reinforcing the spatial dimension of climate effects.
For its part, harvested area exhibits a positive effect, although of small magnitude, with a greater contribution from indirect effects (0.00166). This suggests that agricultural expansion in neighboring provinces may generate positive externalities, possibly associated with processes of productive integration or technological diffusion.

Variable	Direct(3)	Indirect(3)	Total (3)	Direct (4)	Indirect(4)	Total (4)
Rainfall	-0.0169	-0.0771	-0.0940	-0.0127	-0.0781	-0.0908
Average Temperature	0.3818	-0.9460	-0.5642			
Thermal Amp.	-9620	-0.5779	-1.5399	-0.6375	-0.9877	-1.6252
Harvested Area				0.00010	0.00166	0.00176

Table 4

According to the diagnostic tests performed on these models, as shown in Table 5, the LM tests and their robust versions are statistically significant ($p < 0.01$) in the initial model, indicating the presence of spatial dependence among provinces. Likewise, the Wald and Likelihood Ratio (LR) tests confirm the appropriateness of using a Spatial Durbin Model (SDM). After model adjustment, the LM tests are no longer significant, suggesting that the new specification adequately captures spatial dependence. However, the Breusch-Pagan and Jarque-Bera tests indicate the presence of heteroskedasticity and non-normality in the residuals.

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Test	Statistics (3)	p-value	Statistics (4)	p-value
LM-lag	9.3376	0.0022	1.4781	0.2241
LM-error	8.4536	0.0036	1.3415	0.2468
Robust LM-lag	6.8269	0.0090	0.1377	0.7105
Robust LM-error	5.9430	0.0148	0.0011	0.9730
Wald (Chi-squared)	11.47	0.0094	15.164	0.001682
Likelihood Ratio (LR)	11.333	0.010	14.8187	0.001978
Breusch–Pagan (BP)	69.158	6.46e-15	60.237	5.231e-13
Jarque–Bera (JB)	106618	<0.001	97292	<2.2e-16
Log-Likelihood SAR (restricted)	-3246.478		-3247.408	
Log-Likelihood SDM (full)	-3240.812		-3239.999	

Table 5

The results of the SDM (5), as presented in Table 6, show that the estimated coefficients indicate positive spatial autocorrelation ($\rho = 0.294$, $p < 0.001$).Regarding the explanatory variables, rainfall exhibits negative and statistically significant effects (-0.1760; 0.0167), as does thermal amplitude (-0.079; 0.0059). In contrast, harvested area shows a positive and statistically significant effect (0.1391; 0.001).

Variable dependiente: ln(Productividad + 1) N = 1088 (32 provincias × 34 años)				
Parameter	Coefficient	Std. Error	t-value	p-value
ρ (spatial autoregressive coefficient)	0.2943	0.0373	7.89	0.001
log_Rainfall	-0.1760	0.0735	-2.39	0.0167
Thermal Amplitude	-0.0787	0.0286	-2.75	0.0059
log_Harvested Area	0.1391	0.0118	11.77	<0.001
W_log_Rainfall	-0.1420	0.1301	-1.09	0.2750
W_Thermal Amplitude	-0.0356	0.0556	-0.64	0.5223
W_log_Harvested Area	0.0252	0.0304	0.83	0.4072
Model Residuals				
Minimum	-1.587083			
First Quartile (Q1)	-0.090524			
Median	-0.013222			
Third Quartile (Q3)	0.121474			
Maximum	1.762670			

Tabla 6Variable dependiente: ln(Productividad + 1)
N = 1088 (32 provincias × 34 años)

Regarding spatial impacts (Table 7), a 1% increase in rainfall reduces total agricultural productivity by 0.45%, with more than half of this effect explained by spatial spillovers. Thermal amplitude generates both local and regional impacts, with the spatial effect being of similar magnitude to the direct effect. In contrast, a 1% increase in harvested area raises total

productivity by 0.23%, accompanied by positive spillovers.

Variable	Direct	Indirect	Total
log_Rainfall	-0.191	-0.260	-0.451
Thermal Amplitude	-0.083	-0.079	-0.162
log_Harvested Area	0.144	0.089	0.233

Table 7

The spatial dependence and model specification tests (log (5), LM, LR, BP, and JB), presented in Table 8, confirm the presence of spatial dependence, as indicated by the LM-lag and LM-error statistics. The Robust LM-lag test points to lag-type spatial dependence, while the LR test confirms that the SAR model is sufficient to capture this structure.Meanwhile, the BP and JB tests simultaneously reveal the presence of heteroskedasticity and non-normality in the error distribution.

Tests	Statistic	p-value
LM-lag	64.797	< 0.001
LM-error	57.411	< 0.00
Robust LM-lag	8.727	0.003
Robust LM-error	1.341	0.247
Likelihood Ratio (LR: SDM vs SAR)	2.301	0.512
Wald (Chi-squared)	2.3439	0.5042
Breusch–Pagan	31.119	< 0.001
Jarque–Bera	2606.9	< 0.001
Robust Wald (Chi-squared)	2.34	0.50

Table 8

Although the LR and Wald tests indicate that the SAR model is sufficient, the SDM was selected as the final model due to its ability to capture spatial complexity, particularly in terms of impact effects. Regarding heteroskedasticity and non-normality in the residuals, the robust test (6) ($\chi^2 = 2.34$; $df = 3$; $p = 0.50$) indicates that the spatial lags of the explanatory variables are not jointly significant, even after correcting for these irregularities. This confirms that spatial dependence is primarily concentrated in the dependent variable (Productivity) rather than in the indirect effects of rainfall, thermal amplitude, or harvested area.

IV. DISCUSSION

The Spatial Durbin Model (SDM) (5) confirms that agricultural productivity is influenced by spatial interactions. Precipitation exerts a negative total effect on the production system, consistent with the spatial autocorrelation analyses that revealed clustering of areas with high and low levels of productivity. This finding suggests that increases in rainfall may generate adverse effects on productivity, associated with processes such as soil saturation, flooding, erosion, or the proliferation of pests and diseases favored by moisture. Similarly, other studies [30] have documented that excessive precipitation reduces agricultural yields, particularly in systems vulnerable to climate variability.

A relevant finding is that a considerable portion of the effect of precipitation is transmitted through spatial spillovers, indicating that climatic variations in one region can indirectly affect agricultural productivity in neighboring territories. This result is consistent with other studies that have demonstrated the spatial correlation of climatic phenomena and their capacity to spread across regions, associated with the interconnection of agroecological systems, supply chains, and regional markets. Likewise, climate impacts on agriculture tend to exhibit spatial patterns, generating indirect effects on production in nearby areas [31, 32].

In the case of thermal amplitude, the results indicate negative effects on agricultural productivity in both direct and indirect dimensions, suggesting that greater temperature variability generates thermal stress in crops, affecting essential physiological processes such as photosynthesis, respiration, and reproductive development. This occurs because extreme temperature fluctuations significantly reduce yields, particularly in temperature-sensitive crops [33, 34].

Harvested area, the results show a positive effect on agricultural productivity, both locally and through spatial spillovers. These spillovers may be associated with the development of shared infrastructure, the integration of regional markets, technological diffusion, and agglomeration economies inherent to agricultural activity. As highlighted by other authors [35, 36], the concentration of productive activities can generate positive externalities related to collective learning, innovation, and efficiency improvements. Similarly, there is evidence of positive spillovers derived from productive expansion [37].

V. CONCLUSION

The results of the Spatial Durbin Model (SDM) confirm that agricultural productivity in the Dominican Republic is influenced by spatial interactions, indicating that climate effects are not confined to the local (provincial) level but rather propagate across territories. In particular, precipitation exhibits a negative total impact, dominated by indirect effects, suggesting that increases in rainfall may adversely affect agricultural productivity, especially in contexts vulnerable to

phenomena such as soil saturation, flooding, and pest proliferation.
Additionally, significant spatial spillovers associated with precipitation are identified, indicating that climatic variations in one region affect the productivity of neighboring areas, reflecting the interconnection of agroecological systems and regional markets.

Regarding thermal amplitude, the results reveal negative effects in both direct and indirect dimensions, indicating that greater temperature variability generates stress in crops and reduces their yields. In contrast, harvested area shows a positive effect at both the local and spatial levels, suggesting the presence of positive externalities associated with productive expansion, such as technological diffusion and market integration.

Overall, the findings indicate that the dynamics of agricultural productivity in the study region are shaped by spatial effects and by the interaction between climatic and productive variables, highlighting the role of precipitation and its indirect effects. In this context, it becomes necessary to guide the design of agricultural policies toward a territorial approach that considers interregional interdependence and the spatial nature of climate impacts.

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