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Research Article

Econometric Modeling for Integrating Weather Forecasting into Abaca Supply Chain Planning and Distribution

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Abstract
This study investigates the impact of weather variability on abaca production, a vital agricultural commodity in the Philippines. Balanced datasets of quarterly abaca production, aggregated rainfall, maximum temperature, minimum temperature, and relative humidity from selected top-producing provinces from the first quarter of 2010 to the third quarter of 2023 for the provinces of Catanduanes, Northern Samar, Bukidnon, and Surigao del Sur for a total of 212 datapoints were used. The final model employs a fixed effects regression model with bootstrapping using a 3-week moving average (MA) to filter short-term shocks and better assess the impact of each regressors. Bootstrapping was done to produce statistically appreciable estimates given the that the distributions of the regressors are not all normal and to reduce the standard errors of the estimates. The results, with varying significance values, show that the lag of MA of abaca production, the third lag of the MA of maximum temperature, the MA of minimum temperature, and the third lag of MA of minimum temperature have significant effects on the MA of abaca production. The final model shows an R^2 value of 97.47% as well, indicating a very high level of explainability of the variability of the abaca production in terms of the regressors. The results highlight the criticality of (a) including lags, (b) separating maximum temperature and minimum temperature as spatiotemporal regressors for crops, and (c) accounting for potential long-term effects of rising temperature at nighttime. Among other things, supply chain management people, local government units, and policymakers can use the findings of this paper for anticipatory action amidst the changing climate.

Keywords: abaca, bootstrapping, climate change, panel regression, supply chain, weather forecasting

1. INTRODUCTION

The global abaca sector, which sustains more than 200,000 farming households, is currently at a crucial juncture. In light of significant market opportunities and evident ecological advantages, its prospects are threatened by climate change, persistent social and economic weaknesses, and geopolitical uncertainties. The supply chain is notably concentrated, with more than 98% originating from the Philippines and Ecuador, leading to significant exposure risks. Severe weather events, particularly typhoons, along with disease outbreaks, are diminishing yields, threatening both worldwide supply and the livelihoods of smallholder farmers. The concentration of supply in just two producers namely the Philippines and Ecuador leads to significant systemic vulnerability to disruptions in both states. Any disruption in the supplies can create a shock to the global chain. In 2023, the Philippines achieved an impressive output of 66.54 thousand metric tons [1].

Historically, the Philippines accounted for approximately 87.5% of the world's abaca during the 2015–2016 period. As the crop is endemic to the Philippines, it established a more comprehensive grading system featuring nine fiber grades, in contrast to Ecuador's five. The demand is rapidly increasing due to the transition towards sustainable and eco-friendly materials as well. The abaca pulp market held a valuation of USD 444.8 million in 2023 and is anticipated to grow to USD 1.0 billion by 2030, reflecting a compound annual growth rate of 13.9%. [2]. The fiber market is projected to reach USD 822.9 million in 2025, with an anticipated growth to USD 2.24 billion by 2032, reflecting a compound annual growth rate of 15.4%. [3]. Attributes of the fiber which includes tensile strength, durability, biodegradability of abaca facilitate the replacement of wood pulp and fossil-derived materials in various applications. Food preparation papers, such as tea bags and coffee filters, lead the market with a significant revenue share of 72.8%, followed by currency paper, medical filters, and premium textiles [2]. However, the demand exceeds the available supply, as

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Table 1. Sources of data used in this study.

Variable	Source of Data
Abaca Production	PSA OpenSTAT
Rainfall	PAGASA
Maximum Temperature	
Minimum Temperature	
Relative Humidity	

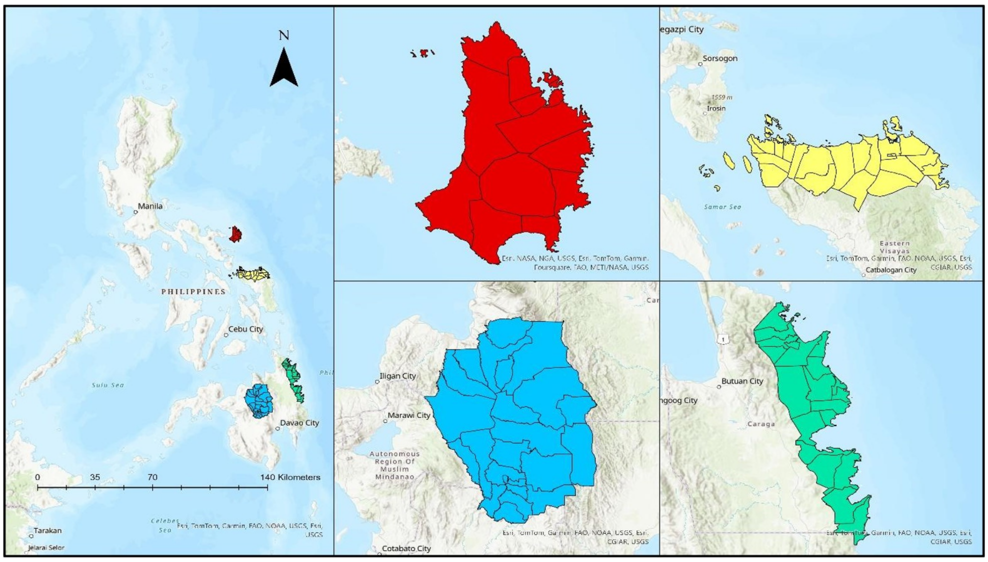

Figure 1. Map of the provinces selected as study areas: Catanduanes in red, Northern Samar in yellow, Bukidnon in blue, and Surigao del Sur in green.

evidenced by a reported shortfall of 25,000 metric tons in 2019, representing a missed chance for producers [4].

Industrial applications of the fiber extend to automotive components, where the Food and Agriculture Organization notes abaca as a superior alternative to glass fibers, reducing component weight and improving sustainability and recyclability [5]. Once limited to interior fillers, abaca now appears in semi-structural exterior parts due to its mechanical strength. Broader market trends, particularly in environmentally conscious countries, are phasing out plastics and polyvinyl chloride in favor of natural fibers, reflecting concerns that synthetic composites are often non-biodegradable and hard to recycle. This has renewed interest in natural fibers as climate-friendly substitutes [5][6]. Ecologically, abaca suits reforestation systems, enhances biodiversity when intercropped (e.g., with coconut), reduces erosion and sedimentation in coastal zones, improves soil water retention, and contributes less to soil depletion; byproducts serve as organic fertilizers. Global shifts toward greener, biodegradable materials have further elevated abaca's appeal. Recognized as the strongest natural fiber, it is favored over synthetics like plastics in sectors such as shipping (for non-slip, marine-safe cordage) and pulp and paper (for durable, highly recyclable papers). Abaca can substitute coniferous pulp at an estimated 4:1 ratio due to superior tensile and mechanical properties, implying up to 50 million metric tons of potential abaca pulp demand if benchmarked against a 200 million metric ton wood pulp market—thereby offering deforestation mitigation benefits. Abaca matures for fiber harvest in about two years, enabling reliable supply while supporting tree conservation [5].

The abaca plant (*Musa textilis*) also known as Manila hemp is a cornerstone of the Philippine economy and a globally significant, environmentally aligned fiber. The Philippines supplies most of the world's demand at around 90% for uses spanning cordage, specialty papers (e.g., currency notes, teabags, filters), textiles, furniture, handicrafts, meat casing, and composite materials for automotive, construction, and other industries. Prior to 2015, exports averaged P4.7 billion annually, with production supported by over 122,000 farmers across 176,549 hectares. Beyond its economic value, abaca contributes to environmental sustainability and forest conservation through its cultivation practices and fiber properties [5]. The Philippines' dominance is well documented. The country supplied over 86% of global abaca fiber in 2019, with Ecuador and Costa Rica providing the remainder. Production is concentrated in Bicol, the Visayas, and Mindanao, especially the eastern seaboard while Luzon has the smallest planted area, underscoring regional comparative advantages [7].

The abaca sector faces mounting climate risks. Agriculture and fisheries, making up about 10% of GDP and major sources of employment in the Philippines, are jeopardized by climate change, which intensifies pests and diseases, depresses yields, delays fruiting and harvests, degrades quality, raises labor costs, and reduces farm incomes. These threats, compounded by prolonged droughts and severe typhoons, destabilize abaca production and distribution, and are further complicated by security issues in parts of Mindanao, Bicol, and Eastern Visayas [7][8]. Integrating weather forecasting into the abaca supply chain planning can materially enhance resilience. Forecasts can optimize planting and harvesting schedules to avoid adverse conditions, as evidenced by studies showing revenue gains when precipitation forecasts inform harvest planning (e.g., a 16.7% increase in sugar beet) [9]. Anticipatory adjustments based on rainfall and temperature projections can improve yields, reduce waste, and protect fiber quality [9][10]. On the logistics side, resilience-oriented distribution planning and data-driven preparedness can help sustain timely deliveries amid extreme weather, bolstering supply chain robustness [11][12].

The impacts of climate change present significant challenges to the agricultural sector in the Philippines, hindering its potential for sustainable growth and increased productivity. The agricultural sector experiences considerable impacts from climate-related disturbances that damage crops, among others, as well as interrupting the logistics of agricultural products and supplies. Rising temperatures impact agricultural output which could lead to higher pest occurrences and diminish workforce efficiency. These can cause significant disruptions in societal and financial stability [13]. Relative to this, abaca is sensitive to drought, and even brief periods of dryness can diminish fiber quality [14]. The ideal environment ranges from 22 to 28 °C, accompanied by an annual rainfall of 1,800 to 2,500 mm [15]. Extended periods of drought and increased temperatures resulting from climate change pose a significant threat to both production and quality. With the complications stemming from the already pervasive environmental stressors, this study aims to contribute to econometrically measuring the impacts of the fluctuations in the typical weather parameters to the production of abaca. This can also serve as a contribution to one of the targets of the Philippine Fiber Industry Development Authority which is to mitigate the impacts of climate change to the abaca industry [3]. This study can also contribute by providing responses to the targets under several United Nations Sustainable

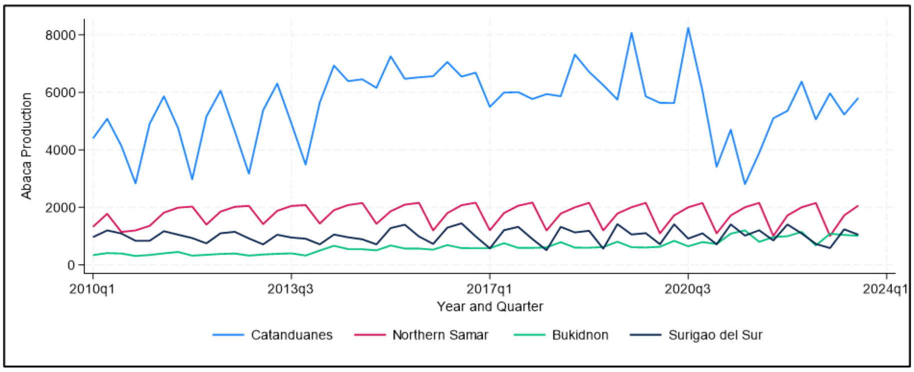

Figure 2. Abaca production by quarter of each province.

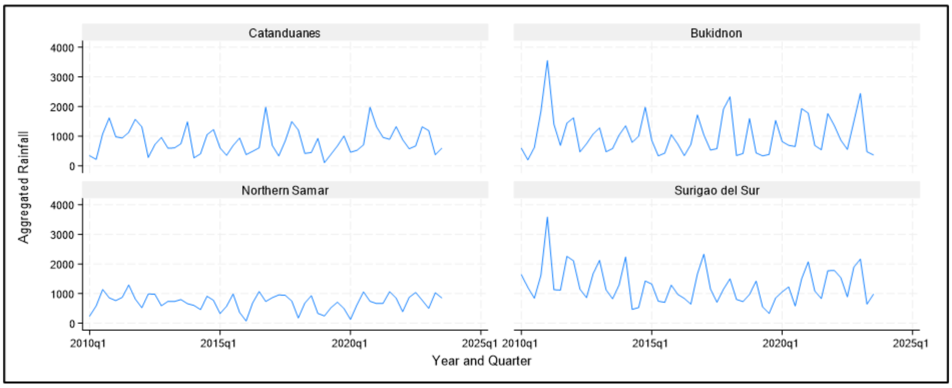

Figure 3. Aggregated rainfall by quarter of each province.

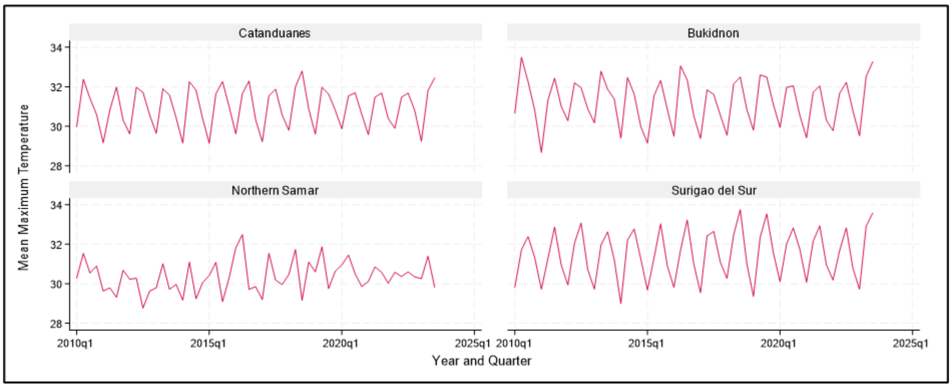

Figure 4. Mean maximum temperature by quarter of each province.

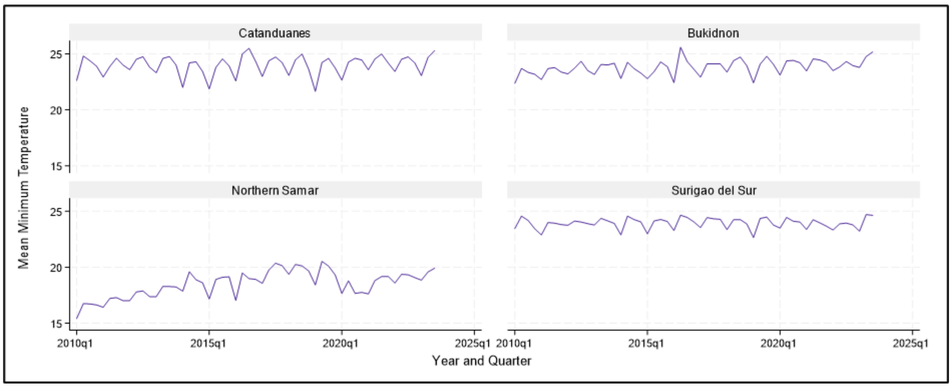

Figure 5. Mean minimum temperature by quarter of each province.

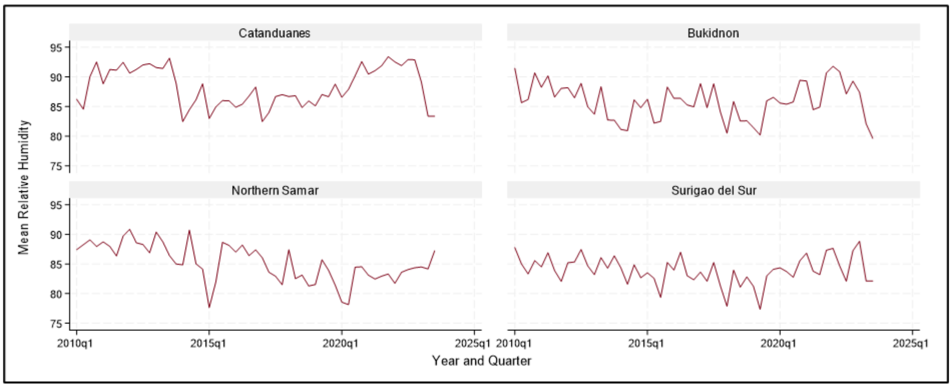

Figure 6. Mean relative humidity by quarter of each province.

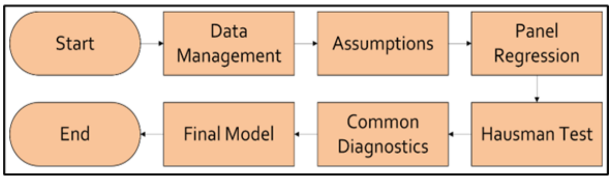

Figure 7. Flowchart of the processes applied in the study.

Development Goals [16], particularity, in Goal 1: No Poverty, Goal 13: Climate Action, and Goal 17: Partnership for the Goals.

2. MATERIALS AND METHODS

2.1. Study Areas

The response variable is the quarterly production of abaca in metric tons (MT) of Catanduanes, Northern Samar, Bukidnon, and Surigao del Sur. These provinces are the consistent top producers of abaca in the Philippines, with Catanduanes identified as the perennial largest producer. The selection of these provinces ensures that the study captures the most significant contributors to the abaca industry across Luzon (Catanduanes), Visayas (Northern Samar), and Mindanao (Bukdinon and Surigao del Sur), which are the three major island groups in the Philippines, while accounting for localized differences in weather conditions and production patterns. The data were downloaded from the Philippine Statistics Authority's (PSA) OpenSTAT website [17]. While Davao Oriental is also a huge contributor to the abaca production of the country, the absence of a weather station in the province deemed it non-included. On the other hand, the weather parameters used as regressors were requested from the Philippine Atmospheric, Geophysical and Astronomical Services Administration (PAGASA). The weather parameters include (a) rainfall measured in mm, (b) minimum temperature, (c) maximum temperature, both measured in °C, and (d) relative humidity expressed as a percentage. Table 1 provides a summary of the sources of data. On the other hand, the Geographical Information System in Figure 1, which shows the location of the selected provinces, was done in ArcGIS Pro 3.5 with the shapefile downloaded from the United Nations Office for the Coordination of Humanitarian Affairs— Humanitarian Data Exchange [18].

Table 2. Summary statistics of the variables from each province using three-quarter MA.

Province	Stats	MA of Total Production	MA of Total Rainfall	MA of Maximum Temperature	MA of Minimum Temperature	MA of Relative Humidity
Catanduanes	Mean	5,602.943	849.847	30.935	23.982	88.464
	SD	944.926	250.132	0.381	0.395	2.820
	T	53	53	53	53	53
Bukidnon	Mean	620.345	712.417	30.364	18.525	85.190
	SD	210.623	154.499	0.444	0.980	2.659
	T	53	53	53	53	53
Northern Samar	Mean	1,764.490	1,054.925	31.179	23.805	85.934
	SD	171.971	370.900	0.489	0.357	2.269
	T	53	53	53	53	53
Surigao del Sur	Mean	1,012.831	1,274.948	31.471	23.923	83.947
	SD	106.976	345.963	0.442	0.210	1.540
	T	53	53	53	53	53

2.2. Study Design and Rationale

This study employs a quantitative approach to analyze the effects of weather parameters on abaca production in the top-producing provinces of the Philippines. A panel data regression model was utilized to quantitatively evaluate the magnitude of impact of the weather variables on abaca production from the latest accessible quarterly data. The availability of the PSA abaca production data starts in the first quarter of 2010. On the other hand, the obtainable data acquired from both the PSA and PAGASA matches at the third quarter of 2023. The panel data is *balanced*, having 53 data points for each province. Moreover, the xtscc package in Stata 18.0, introduced by Hoechle in 2007 [19], has a *maximum* lag of 3. This statistical package could provide evidence of the robustness and versatility of the model as well. Figure 2 shows the time series plot of the abaca production, while Figures 3 – 6 show the separate time series plots of aggregated rainfall, mean maximum temperature, mean minimum temperature, and mean relative humidity for each province, respectively.

2.3. Procedures

The balanced data was achieved by converting the weather parameters into quarterly frequency. The daily datasets of rainfall were aggregated, while the means of maximum temperature, minimum temperature, and relative humidity were used. Missing data was not observed in the weather parameters, although traces of rainfall having values less than 0.01 were converted to 0.00. The managed data first underwent *maximum* (instead of *optimal*) lag selection. The maximum lag selection will be used for the moving average (MA) applied to all the variables. Extracting the MA in every variable is critical in this study since the quarterly data for the abaca follows the calendar quarter, i.e., January-February-March, April-May-June, July-August-September, and October-November-December. On the other hand, recent publications show the advantages of using the climatic seasonal quarter of the Philippines, which follows December -January-February (December of the previous year), March-April-May, June-July-August, and September-October-November specifically for statistical models [20][21]. Next, a unit root test for the panel data was applied to determine the applicability of a panel regression model. Should a panel regression model be deemed applicable, an appropriate test to determine which of the fixed effects or random effects models should be used. Figure 7 shows the flow of the procedures. Each analysis and line plot was done using Stata 18.0 Basic Edition.

2.4. Assumptions

The assumptions to be tested are (a) stationarity, (b) normality, and (c) and the maximum (instead of *optimal*) lags will be included, too. These are the most typical assumptions and contribute to the intended remedies if necessitated, especially in the potential anomalies in panel data.

2.5. Panel Regression Model

To spatiotemporally determine the impacts of the weather parameters on each province, the panel

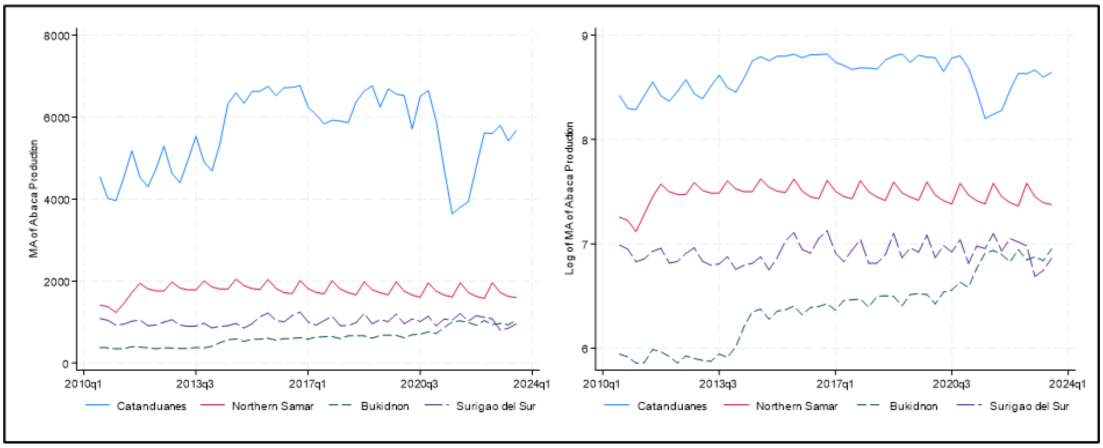

Figure 8. Three-quarter MA of abaca production by province; left panel shows the actual data; right panel shows the logarithmic transformation of the data.

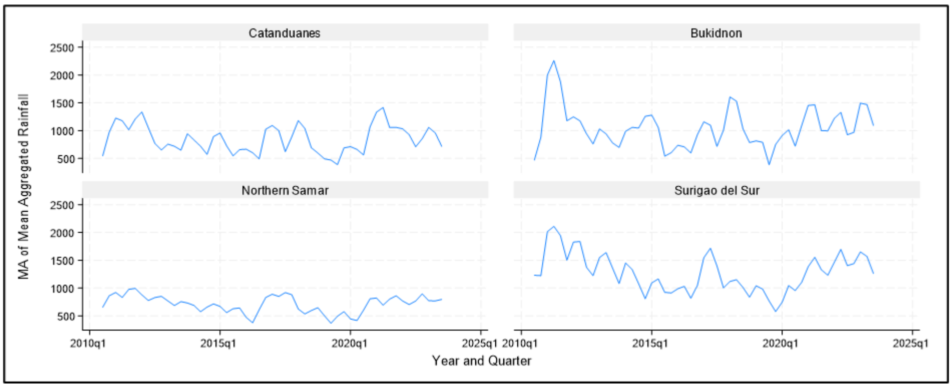

Figure 9. Three-quarter MA of the aggregated rainfall by quarter of each province.

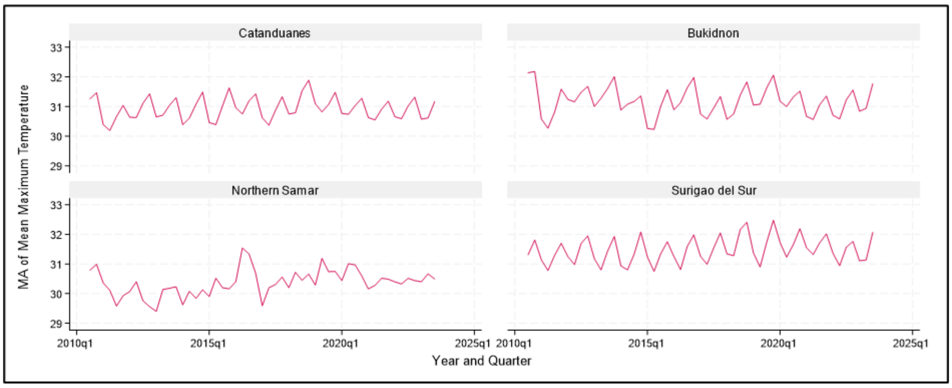

Figure 10. Three-quarter MA of mean maximum temperature by quarter of each province.

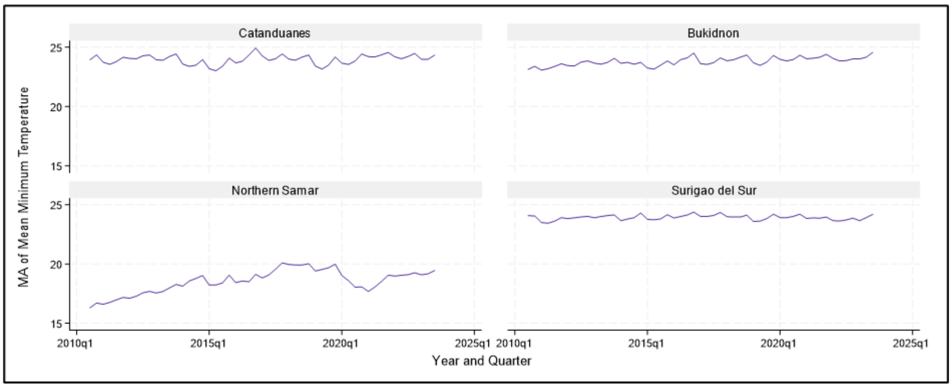

Figure 11. Three-quarter MA of mean minimum temperature by quarter of each province.

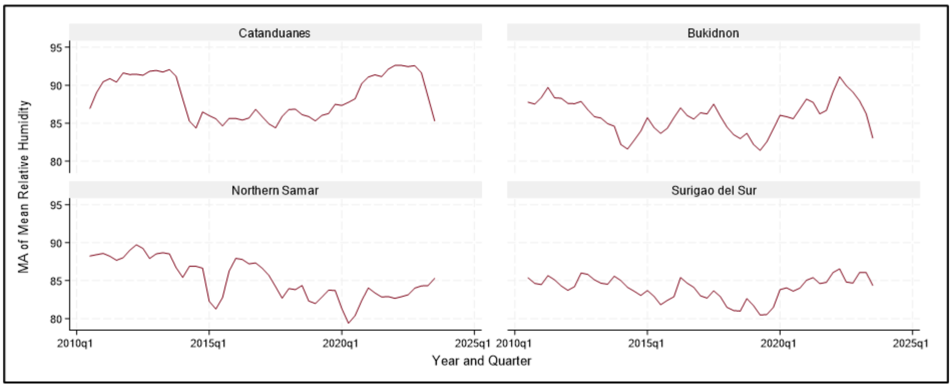

Figure 12. Three-quarter MA of mean relative humidity by quarter of each province.

Table 3. Stationarity of the panel variables.

Panel Variable	p-value	Stationarity at the Level
Log of MA of Abaca Production	0.0128	Stationary
MA of Total Rainfall	<0.0001	Stationary
MA of Maximum Temperature	<0.0001	Stationary
MA of Minimum Temperature	<0.0001	Stationary
MA of Relative Humidity	0.0120	Stationary

Table 4. Normality of the panel variables.

Panel Variable	p-value	Distribution
Log of MA of Abaca Production	<0.001*	Non-normal
Log of MA of Total Rainfall	0.833	Normal
MA of Maximum Temperature	0.776	Normal
MA of Minimum Temperature	<0.001*	Non-normal
MA of Relative Humidity	0.001*	Non-normal

Note: * - *Significant at the 0.01 level*

regression was applied. Consider the fitting models in the form of Equation 1;

$$y_{it} = \alpha + \underline{x}_{it}\underline{\beta} + \gamma_i + e_{it} \quad \textbf{(1)}$$

where y_{it} is the response variable of the panel datasets and $\underline{x}_{it}$ is a vector of observations for the unit i and time t, $\gamma_i + e_{it}$ is the error term. In Equation 1, the more interesting component, though, $\underline{\beta}$ is which denotes the panel vector of parameters to be estimated. The unit-specific residuals is γ_i which varies between units but is invariant for any other particular unit. Additionally, the e_{it} is the customary residual which can be further decomposed in the form of $e_{it} = \kappa_{it} + \lambda_{it}$ with the assumption that λ_{it} is the typical residual, and describe γ_i better [22]. If Equation 1 holds, then

$$\bar{y}_i = \alpha + \underline{\bar{x}}_{it}\underline{\beta} + \gamma_i + \bar{e}_{it} \quad \textbf{(2)}$$

where $\bar{y}_i = \frac{1}{T_i}\sum_t y_{it}$, $\underline{\bar{x}}_i = \frac{1}{T_i}\sum_t \underline{x}_{it}$, and $\bar{e}_i = \frac{1}{T_i}\sum_t e_{it}$. By subtracting Equation 2 from Equation 1, it should be equally true that

$$(y_{it} - \bar{y}_i) = (\underline{x}_{it} - \underline{x}_i)\underline{\beta} + (e_{it} - \bar{e}_i) \quad \textbf{(3)}$$

The bases to estimate $\underline{\beta}$ are Equations 1, 2, and 3. Specifically, the fixed-effects panel regression model. This amounts to using the OLS to estimate Equation 3. On the other hand, the random-effects panel regression model is a weighted average of the estimates generated by the between and within estimators. The random-effects panel regression model is given by

$$(y_{it} - \phi_i\bar{y}_i) = (1-\phi_i)\alpha + (\underline{x}_{it} - \phi_i\underline{\bar{x}}_i)\underline{\beta} + [(1-\phi_i)\gamma_i + (e_{it} - \phi_i\bar{e}_i)] \quad \textbf{(4)}$$

In Equation 4, ϕ_i is a function of σ_γ^2, σ_e^2, and T. When $\sigma_\gamma^2 = 0$ indicating that ϕ_i should be 0 throughout, ϕ_i for each i and Equation 1 can be reduced as a direct OLS estimator. On the other hand, having $\sigma_e^2 = 0$ tantamount to e_{it}, $\phi_i = 0$ for each i and the within estimator reverts all the available information [22].

Now consider an extended version of Equation 4 given by

$$(y_{it} - \phi_i\bar{y}_i) = (1-\phi_i)\alpha + (\underline{x}_{it} - \phi_i\underline{\bar{x}}_i)\underline{\beta} + [(1-\phi_i)\gamma_i + (e_{it} - \phi_i\bar{e}_i)] + (1-\phi_i)\underline{\bar{x}}_i\underline{\omega} \quad \textbf{(5)}$$

in which the panel means of the covariates as regressors are plugged in. This extended version is the known Mundlak regression, otherwise known recently as the correlated random-effects model. Whenever a panel data that is *balanced* is to be used, the estimation process using Equation 5 by the OLS method would generate identical time-invariant parameter estimates for fixed effects models [23][24]. Furthermore, an extension of this random-effects model for *unbalanced* panels is available in the literature [23][25]. For this study, though, a balanced panel model was available for modeling.

2.6. Diagnostics

The diagnostics for the adequacy of the final model will include (a) the normality of residuals, (b) the heteroskedasticity of the model variances, and (c) the first-order autocorrelation. Other diagnostics are applicable in specific econometric modeling. However, for the intended outputs, these diagnostics are the most common ones, and the authors adhered to them.

2.7. Modeling Procedures Simplified

After confirming the applicability of the model to the datasets, a suitable analysis will be implemented. The final model will utilize the significant weather parameters retained along with their lags to enhance interpretability. This step is to determine how abaca production responds to the changes in weather variables, namely rainfall, maximum temperature, minimum temperature, humidity, and applicable lags (previous quarters) specific to the selected provinces. The findings may reveal the extent of impacts as determined by the regression coefficients. The final model will be subject to some customary adequacy tests. The results could facilitate well-informed decisions for policymakers and potentially the agricultural community regarding the significance of monitoring weather parameters, particularly those that are empirically shown to have negative impacts.

3. RESULTS AND DISCUSSIONS

3.1. Descriptive Statistics

Since the *maximum* lag was predetermined to be 3, a 3-quarter MA was applied to all the original datasets, therefore. In addition, the data on the MA of abaca production and MA of aggregated rainfall still appear to have larger variances compared to the other variables. The log transformation was applied

Table 5. List of variables used in modeling.

Abbreviation	Variable
l1_ln_ma_abaca	First Lag of the MA of Abaca Production
l2_ln_ma_abaca	Second Lag of the MA of Abaca Production
l3_ln_ma_abaca	Third Lag of the MA of Abaca Production
ln_ma_rain	Natural Logarithm of the MA of Aggregated Rainfall
l1_ln_ma_rain	First Lag of the Natural Logarithm of the MA of Aggregated Rainfall
l2_ln_ma_rain	Second Lag of the Natural Logarithm of the MA of Aggregated Rainfall
l3_ln_ma_rain	Third Lag of the Natural Logarithm of the MA of Aggregated Rainfall
ma_maxtemp	MA of Maximum Temperature
l1_ma_maxtemp	First Lag of the MA of Maximum Temperature
l2_ma_maxtemp	Second Lag of the MA of Maximum Temperature
l3_ma_maxtemp	Third Lag of the MA of Maximum Temperature
ma_mintemp	MA of Minimum Temperature
l1_ma_mintemp	First Lag of the MA of Minimum Temperature
l2_ma_mintemp	Second Lag of the MA of Minimum Temperature
l3_ma_mintemp	Third Lag of the MA of Minimum Temperature
ma_humid	MA of Relative Humidity
l1_ma_humid	First Lag of the MA of Relative Humidity
l2_ma_humid	Second Lag of the MA of Relative Humidity
l3_ma_humid	Third Lag of the MA of Relative Humidity

Table 6. Results of the fixed effects panel regression model.

Variable	Coefficient	SE	t-value	p-value	Confidence Interval	
					Lower Limit	Upper Limit
l1_ln_ma_abaca	0.783	0.076	10.290	<0.001*	0.633	0.933
l2_ln_ma_abaca	0.043	0.095	0.450	0.650	-0.145	0.231
l3_ln_ma_abaca	-0.058	0.075	-0.770	0.442	-0.205	0.090
ln_ma_rain	0.042	0.040	1.060	0.289	-0.036	0.121
l1_ln_ma_rain	-0.025	0.050	-0.500	0.614	-0.124	0.073
l2_ln_ma_rain	-0.024	0.050	-0.470	0.638	-0.123	0.076
l3_ln_ma_rain	0.056	0.040	1.400	0.162	-0.023	0.135
ma_maxtemp	0.057	0.027	2.100	0.037**	0.004	0.111
l1_ma_maxtemp	0.002	0.035	0.070	0.946	-0.067	0.072
l2_ma_maxtemp	-0.046	0.034	-1.330	0.186	-0.113	0.022
l3_ma_maxtemp	0.071	0.028	2.530	0.012**	0.016	0.126
ma_mintemp	0.096	0.032	2.990	0.003**	0.033	0.159
l1_ma_mintemp	-0.154	0.048	-3.170	0.002**	-0.249	-0.058
l2_ma_mintemp	0.102	0.050	2.060	0.041**	0.004	0.200
l3_ma_mintemp	-0.031	0.031	-1.000	0.316	-0.093	0.030
ma_humid	-0.009	0.006	-1.390	0.167	-0.022	0.004
l1_ma_humid	0.012	0.011	1.130	0.260	-0.009	0.033
l2_ma_humid	-0.013	0.011	-1.220	0.223	-0.035	0.008
l3_ma_humid	-0.002	0.007	-0.220	0.827	-0.015	0.012
Constant	-0.550	1.265	-0.440	0.664	-3.046	1.946

Note: ** - Significant at the 0.01 level; ** - Significant at the 0.05 level;* R^2 *=97.47%*

for both the response variable and the specific regressor to address the above issue and minimize the heteroskedasticity. Table 2 shows the descriptive statistics of the variables used in the study. All-time points (denoted by T) per province are balanced at 53, and thus, 212 data points were used in the econometric modeling. The largest MA of abaca production output is from Catanduanes at 5,602.943 MT with a standard deviation (SD) of 944.926 MT. The logarithmic transformation of this data is 8.631 with an SD of 6.851. On the other hand, Surigao del Sur has the highest MA of aggregated rainfall at 1,274.976 mm with an SD of 106.976 mm. Surigao del Sur also has the highest MA of maximum temperature, 31.471 °C, with an SD of 0.442 °C, while the lowest MA of minimum temperature belongs to Bukidnon, 18.525 °C, with an SD of 0.980 °C. Lastly, the highest MA of mean relative humidity is from Catanduanes at 88.464% with an SD of 2.820%.

Figure 8 compares the MA of abaca production and its logarithm. Figures 9, 10, 11, and 12 show the time series plots of the MAs of total rain, mean maximum temperature, mean minimum temperature, and mean relative humidity, in succession.

3.2. Assumptions

Using the xtunitroot command, the stationarity of the variables was statistically identified [22][25]. The null hypothesis is that the panels contain unit roots, i.e., are non-stationary. Table 3 shows that all variables have p-values less than 0.05. Hence, the null hypothesis is rejected, and thus, the panel datasets are all stationary at the level. These support (a) the applicability of a panel regression model and (b) applying MAs when using spatiotemporal weather parameters [20][26]. The stationarity of these variables validates their suitability for panel regression modeling, ensuring that their statistical properties, such as mean and variance, remain constant over time. This is critical for establishing reliable relationships between weather parameters and abaca production, which can then inform supply chain planning and distribution strategies [27][28]. Furthermore, since all the variables are stationary, the lags of these variables are guaranteed to be stationary as well.

Table 4 shows that statistically, the log of MA of aggregated rainfall, as well as the MA of maximum temperature, are the only normally distributed panel data. Hence, bootstrapping shall be applied in the chosen panel regression. A literature review supports that the application of bootstrapping could improve statistical analysis considerably, specifically in addressing the limitations of customary parametric analysis, including minimizing the standard error (SE) of each parameter estimate [29].

Using the determined number of maximum lags, this study also attempts to include lags in the econometric modeling. Three lags of each variable were plugged into the model. The list of variables is presented in Table 5. On the other hand, separate panel regression models of fixed effects and random effects are shown in Tables 6 and 7 in succession.

Table 6 shows that the (a) first lag of the MA of abaca production, (b) MA of maximum temperature, (c) third lag of the MA of maximum

Table 7. Results of the random effects panel regression model.

Variable	Coefficient	SE	t-value	p-value	Confidence Interval	
					Lower Limit	Upper Limit
l1_ln_ma_abaca	0.893	0.075	11.910	<0.001*	0.746	1.040
l2_ln_ma_abaca	0.046	0.100	0.460	0.645	-0.149	0.241
l3_ln_ma_abaca	0.048	0.074	0.650	0.513	-0.096	0.193
ln_ma_rain	0.003	0.040	0.070	0.947	-0.077	0.082
l1_ln_ma_rain	-0.039	0.052	-0.760	0.448	-0.141	0.062
l2_ln_ma_rain	-0.022	0.053	-0.410	0.682	-0.125	0.082
l3_ln_ma_rain	0.026	0.040	0.650	0.519	-0.053	0.105
ma_maxtemp	0.037	0.028	1.350	0.178	-0.017	0.092
l1_ma_maxtemp	-0.013	0.036	-0.350	0.727	-0.084	0.059
l2_ma_maxtemp	-0.055	0.036	-1.540	0.123	-0.125	0.015
l3_ma_maxtemp	0.048	0.028	1.690	0.090***	-0.008	0.103
ma_mintemp	0.089	0.033	2.720	0.007**	0.025	0.152
l1_ma_mintemp	-0.166	0.051	-3.280	0.001**	-0.265	-0.067
l2_ma_mintemp	0.108	0.052	2.080	0.038**	0.006	0.209
l3_ma_mintemp	-0.032	0.033	-0.970	0.331	-0.096	0.032
ma_humid	-0.004	0.007	-0.650	0.515	-0.017	0.009
l1_ma_humid	0.016	0.011	1.380	0.167	-0.006	0.038
l2_ma_humid	-0.016	0.011	-1.380	0.169	-0.038	0.007
l3_ma_humid	0.008	0.007	1.150	0.248	-0.006	0.022
Constant	-0.482	1.108	-0.440	0.663	-2.654	1.689

Note: * - *Significant at the 0.01 level; ** - Significant at the 0.05 level; *** - Significant at the 0.10 level;* R^2 *=99.03%*

Table 8. Results of the Hausman Test.

Chi-square Value	p-value	Panel Regression Model to be used
$\chi_3^2 = 17.94$	<0.001	Fixed Effects

Table 9. Results of the fixed effects panel regression model with bootstrapping.

Variable	Observed Coefficient	Bootstrap SE	z-value	p-value	Normal-based Confidence Interval	
					Lower Limit	Upper Limit
l1_ln_ma_abaca	0.783	0.167	4.690	<0.001*	0.456	1.110
l2_ln_ma_abaca	0.043	0.172	0.250	0.801	-0.293	0.380
l3_ln_ma_abaca	-0.058	0.101	-0.570	0.568	-0.255	0.140
ln_ma_rain	0.042	0.067	0.630	0.529	-0.090	0.175
l1_ln_ma_rain	-0.025	0.088	-0.290	0.774	-0.197	0.147
l2_ln_ma_rain	-0.024	0.101	-0.240	0.813	-0.221	0.173
l3_ln_ma_rain	0.056	0.046	1.220	0.223	-0.034	0.146
ma_maxtemp	0.057	0.041	1.400	0.161	-0.023	0.137
l1_ma_maxtemp	0.002	0.020	0.120	0.906	-0.037	0.042
l2_ma_maxtemp	-0.046	0.048	-0.950	0.341	-0.140	0.048
l3_ma_maxtemp	0.071	0.037	1.900	0.057**	-0.002	0.144
ma_mintemp	0.096	0.058	1.660	0.097***	-0.017	0.209
l1_ma_mintemp	-0.154	0.054	-2.870	0.004**	-0.259	-0.049
l2_ma_mintemp	0.102	0.069	1.490	0.137	-0.032	0.237
l3_ma_mintemp	-0.031	0.043	-0.730	0.464	-0.116	0.053
ma_humid	-0.009	0.007	-1.260	0.206	-0.023	0.005
l1_ma_humid	0.012	0.011	1.080	0.282	-0.010	0.034
l2_ma_humid	-0.013	0.011	-1.210	0.226	-0.035	0.008
l3_ma_humid	-0.002	0.005	-0.300	0.765	-0.012	0.008
Constant	-0.550	2.923	-0.190	0.851	-6.279	5.178

Note: ** - Significant at the 0.01 level; ** - Significant at the 0.05 level; *** - Significant at the 0.10 level;* R^2 *= 97.47%*

Table 10. Exponential form of the significant regressors.

Significant Regressor	Log-transformed Observed Coefficient	Exponential Form of the Log-transformed Coefficient
l1_ln_ma_abaca	0.783	2.188*
l3_ma_maxtemp	0.071	1.074*
ma_mintemp	0.096	1.101*
l1_ma_mintemp	-0.154	0.857**

Note: * - *Positive effect;* ** - *Negative Effect*

temperature, (d) MA of minimum temperature, (e) first lag of the MA of minimum temperature, and (f) second lag of the MA of minimum temperature are all significant for the fixed effects panel regression model. On the other hand, the random effects panel regression model in Table 7 shows that the (a) first lag of the MA of abaca production, (b) third lag of the MA of maximum temperature, (c) MA of minimum temperature, (d) first lag of the MA of minimum temperature, and (e) second lag of the MA of minimum temperature are significant. The direction and coefficients of every variable are not interpreted yet since both models will be tested to see which is the statistically appropriate econometric approach. It is noteworthy, moreover, that the R^2 values for both panel regression models have improved when compared to using direct variables only. Table S1 shows that using direct variables produces a fixed effects panel regression model with a 22.97% R^2 value compared to the 97.47% presented in Table 6. Additionally, the random effects model in Table S2 with direct variables produced estimates with an R^2 value of 74.90% in contrast to 99.03% shown in Table 7. The Hausman Test has a null hypothesis stating that the unobserved individual effects are not correlated with the regressors and thus supports the use of the random effects model to be consistent and efficient. The alternative hypothesis, on the other hand, states that the individual effects are correlated with the regressors, which leads to concluding that the random effects model is inconsistent and alternatively supports the use of the fixed effects model. As seen in Table 8, the p-value is less than 0.05. Therefore, the null hypothesis is rejected and favors the use of the fixed effects regression model.

Given that Table 4 indicates the non-normal distribution of certain variables, and Table 8 confirms the appropriateness of the fixed effects panel regression model, a fixed effects panel regression analysis incorporating 10,000 bootstrap resampling simulations was conducted, and the results are presented in Table 9. The number of simulations was set based on the anticipated computational cost considering the total number of variables and data points. The bootstrapping SE for each variable has notably diminished. Furthermore, the bounds of the normal-based confidence intervals for each variable have also shrunk. Consequently, the bootstrapping method has enhanced the reliability of the estimated coefficients, notwithstanding the violations in the assumptions of normality for all variables. In addition, the inclusion of lags from each variable presents an encouraging outcome, as the R^2 value has increased remarkably.

Table 10 presents the consolidated estimations, in exponential form, of the significant panel regressors from Table 9. Each increment in the MA of abaca production from the preceding season can elevate the current production total by approximately 2.188 MT, assuming other factors remain unchanged. The MA of the maximum temperature from three quarters prior could enhance current production by an average of 1.074 MT for each unit increase, assuming other constraints remain constant. The direct impact of elevated minimum nighttime temperatures can enhance abaca production by approximately 1.074 MT per unit increase, holding other variables fixed. On the other hand, the MA of the lowest temperature from the preceding quarterly season may adversely affect abaca production, potentially reducing the response variable by approximately 0.857 MT on average, *ceteris paribus*. Lastly, the R^2 value of 97.47% in Table 10, which is identical to the same statistics in Table 6, denotes that 97.47% of the variability in the MA of abaca production can already be explained by the regressors.

3.3. Brief Discussions

The particular interest in Table 10 are (a) the criticality of including lags of the production of abaca itself for econometric modeling purposes, (b) contributory effects of the third lag of the MA of maximum temperature as well as the direct effects of MA of maximum temperature, and (c) the adverse impacts of the lag of MA of minimum temperature, which is also the MA of the lowest temperature at nighttime. The concept of lag effects highlights the possible impact of past *direct or indirect* climatic conditions from the past quarterly MA of the production season on present agricultural output. Such effects can be a critical consideration for economic modeling and forecasting crop production, which can be similar to the literature for predicting human diseases in the context of using weather parameters as regressors [20][26]. This also construes that crop productivity, and the resulting market supply are not solely determined by the weather experienced during the current growing season. Moreover, soil moisture may have been affected by past rainfall and temperature, which are crucial variables for agricultural production. The lagged impact of precipitation and temperature on current soil moisture levels may have exhibited lag effects on crop yields [23]. Weather conditions exert varying impacts on crop yields depending on the specific growth phase, too. Germination might be sensitive to early rainfall, while flowering could be affected by temperature during that critical period, and grain filling by late-season moisture [24].

For the varying effects of temperature, empirical evidence suggests that the observed average warming trend is primarily due to rising nighttime temperatures. This implies that models relying on the assumption of simultaneous increases in both daily temperature extremes might overestimate or underestimate the realistic economic impacts of climate change, potentially misestimating specific effects that are differentially sensitive to daytime versus nighttime temperature changes. Literature shows that mean warming arises largely from increasing nighttime temperatures [32][33]. Rising temperatures exert economic pressure on crop production through several facades. Accelerated crop maturity due to hotter days shortens the crucial grain-filling period, leading to lower yields and thus reduced potential income. Warmer nights increase the energy expenditure of plants, further diminishing harvested output. Warmer nights, on the other hand, could increase the energy spent by the plant, further reducing the harvestable output [34]. Nighttime warming and increased dryness during the night can be detrimental to global agriculture. This event can reduce crop yields worldwide [35]. The findings of this study are also consistent with the literature supporting that for other crops, too, where plugging in lags as well as separating the maximum temperature and minimum temperature can be crucial for econometric modeling [36].

3.4. Diagnostics

Three of the most commonly used diagnostics are presented herein. Firstly, Figure 13 shows a less

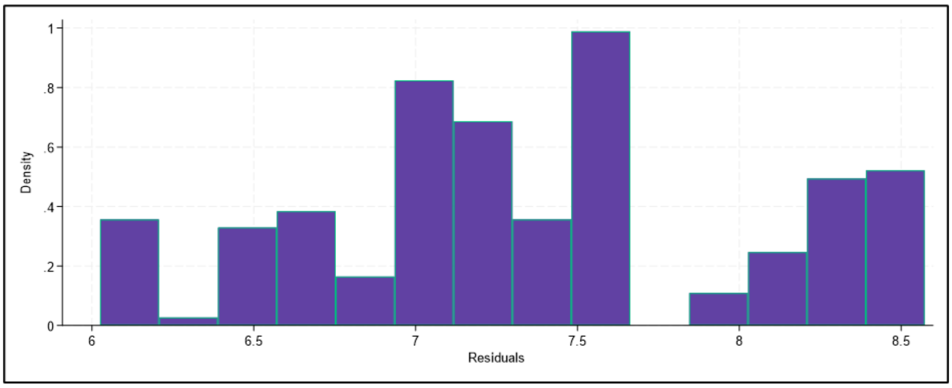

Figure 13. Visualization of the normality of the residuals of the fixed effects panel regression model with bootstrapping.

Table 11. Diagnostics for the fixed effects panel regression.

Assumption	Test	Value	p-value	Decision
Heteroskedasticity	Chi-square	$\chi_4^2 = 5.95$	<0.203	Rejected
First-Order Autocorrelation	*F*	$F_{(1,3)} = 0.016$	0.908	Rejected

formal assessment of the normality of residuals. As seen in the histogram, the residuals do not show the customary visualization of normal distribution. This condition is a common occurrence in panel data with time series, as the characteristics of the variables, including trends, seasonality, autocorrelation, outliers, and heterogeneity of some of the data, may cause non-normality, among others. On the other hand, Table 11 shows that the heteroskedasticity of the variances is not a cause for concern, with the p-value of the Modified Wald Test for groupwise heteroscedasticity using the xttest3 command exceeding the 0.05 level of significance [37]. The result indicates that the groupwise variance of the residuals is homoscedastic across every cross-sectional unit (province) in the panel data. Table 11 additionally shows that there is no first-order autocorrelation through the xtserial command, supporting the statistical validity of the inferences drawn from the modeling procedure [38].

3.5. Recommendations

The recommendations from this study aim to address the diverse needs of its primary beneficiaries: abaca farmers, supply chain managers overseeing its market progression, local government units (LGUs) responsible for regional development, and national policymakers shaping the broader agricultural framework. It is also split into short-term, medium-term, and long-term. In the short-term and for the farmers who are the cornerstone of the abaca sector, practicing aggressive adaptation *may* or *should* through the aid of experts be done. Implementing agricultural management measures contingent on weather conditions is crucial. Such practice involves training in the use of weather forecasting to synchronize planting, harvesting, and maintenance cycles with optimal circumstances. Planting and harvesting could be precisely timed to avoid a season where the minimum temperature is expected to be elevated on average. The findings of the study indicate that due mostly to increasing temperatures at night, farmers are strongly advised to use appropriate mitigating techniques, especially during warmer seasons. Scientists may develop new abaca cultivars that would be resilient against rising temperatures at nighttime as well.

LGUs are crucial for the growth of the abaca sector. For medium-term, investing in early meteorological warning systems is a crucial action. Investing in localized meteorological forecasting (and forecasting) systems by the LGUs can provide farmers and supply chain managers with timely and accurate weather information. Providing training on climate-smart agriculture is also critical. LGUs together with non-government organizations and private sectors could organize workshops and training programs to educate farmers on the best methods for responding to climatic variability and the use of robust abaca cultivars, among others. Furthermore, LGUs could emphasize the enhancement of infrastructure concerning the storage of collected fibers, particularly before or during extended periods of expected warm seasons. The study's results indicated that rainfall is not a significant predictor; yet, powerful typhoons, considering the established climatic conditions and the Philippines' susceptibility, might still adversely affect abaca plants overall.

For the long-term, national policymakers are crucial for guaranteeing long-term sustainability. Developing and implementing the national strategies that are already in place, such as the Philippine Abaca Industry Roadmap 2021–2025, should be adhered to and include financial help for farming technologies that can withstand climate changes, like irrigation systems and disease-resistant abaca plants, as well as funding for research into farming methods that can adapt to different weather conditions. It is also crucial to invest in the acquisition and distribution of meteorological data. Policymakers should augment PAGASA's capacities to collect, evaluate, and disseminate weather data relevant to agriculture, thereby enhancing access to localized weather forecasting for farmers and supply chain stakeholders. Promoting public-private partnerships can foster innovation and collaboration, leading to the development of effective methods for managing weather-related risks. Extension professionals may put turning these research results into useful tools and policies for farmers and supply chain management at the top of their list as well. This could be as simple as using the weather to help with making informed decisions or as advanced as using a mobile app to get real-time weather information. Researchers and extension workers can enable stakeholders to make empirically backed decisions and bolster the resilience of the abaca industry. Future research ought to integrate factors such as soil quality, agricultural methodologies, and insect infestations, in addition to determining appropriate variables. Research that examines the integration of supplementary factors and using sophisticated modeling methodologies, including machine learning, to enhance the precision of production forecasts may also prove advantageous. Additionally, investigating the impact of weather variability on the abaca supply chain would provide valuable insights for business and policy development.

4. CONCLUSIONS

This study focused on determining the impacts of meteorological factors – rainfall, maximum temperature, minimum temperature, and relative humidity – on abaca cultivation in the Philippines, especially in leading producing provinces. The quarterly data of abaca production from Catanduanes, Northern Samar, Bukidnon, and Surigao del Sur served as the response variable. The first until the third lags of the MA of abaca production as well as those of the spatiotemporal meteorological variables from each province were employed as regressors. With statistical substantiations, the analysis utilizing a Fixed Effects Panel Regression Model with Bootstrapping indicated that the lag of the MA of abaca production, the third lag of the MA of maximum temperature, and the direct effect of the MA of minimum temperature are beneficial in boosting the production of abaca. On the other hand, the lag of the MA of minimum temperature can be detrimental to the production of abaca. The results highlight the importance of the inclusion of lags. Further, supplemental empirical evidence was found supporting the separation of the minimum and maximum temperature as variables in crop modeling in the econometric sense. Such actions may improve inferences drawn from modeling crop results such as increased R^2. The bootstrap resampling procedure aided in addressing some concerns about the model adequacy as well.

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Conflicts of Interest

The authors declare no conflict of interest.

SUPPORTING INFORMATION

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DECLARATION OF GENERATIVE AI

During the preparation of this work, the author(s) used authentic QuillBot with a premium subscription to correct grammar and paraphrase some statements in the properly cited references. After using this tool/service, the author(s) reviewed and edited the content as needed and will take full responsibility for the content of the publication.

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