

Article

Observed (1979–2024) and Projected (2030) Climate Trends in Relation to Farmers' Perceptions in Coffee Cooperatives of Northern Peru

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Abstract

Climate change is increasingly threatening the sustainability of coffee farming in northern Peru, particularly in the Amazonas region, where coffee cooperatives serve as vital socioeconomic hubs for thousands of families. This study analyzed historical climate data from 1979 to 2024 to project trends up to 2030, integrating local perceptions from coffee producers to identify trends, anomalies, and future scenarios within four coffee cooperatives in northern Peru. We examined variables such as precipitation, temperature, evapotranspiration, and wind speed using nonparametric statistical analyses and SARIMA time-series models. The findings indicate a steady increase in maximum and average temperatures, alongside greater irregularity in precipitation. Specifically, the Bagua Grande and COOPARM cooperatives are experiencing precipitation deficits, while the Alta Montaña and Ocumal cooperatives are facing excess rainfall. Additionally, we project an increase in evapotranspiration by 2030. Surveys conducted with coffee growers reveal a consensus regarding irregular rainfall patterns; however, there is less recognition of the rising temperature trends. This discrepancy emphasizes the importance of combining scientific data with local knowledge to develop more effective adaptation strategies at the cooperative level. We conclude that enhancing climate training and cooperative management is essential for improving the resilience of regional coffee farming.

Keywords: agribusiness; agricultural adaptation; *Coffea arabica*; climate change; climate model



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1. Introduction

Agriculture is a key component of global food security and plays a crucial role in the economic development of developing countries [1]. However, its sustainability is

increasingly threatened by the diverse effects of climate change. These include rising temperatures, more frequent extreme weather events, altered precipitation patterns, and the increased prevalence of pests and diseases [2,3]. These changes directly impact productivity, the stability of rural incomes, and the resilience of agricultural ecosystems, leading to vulnerabilities that are particularly pronounced in sensitive crops, such as coffee [4–8].

Coffee (*Coffea arabica*) is the primary species cultivated in tropical mountain systems, such as the Peruvian Amazon [9]. It ranks among the world's leading agricultural products, supporting the livelihoods of around 25 million farmers, as well as more than 100 million people who are part of its value chain [10]. The global coffee market is expanding due to increased consumption in emerging economies and a rise in specialty coffee in industrialized nations [11,12]. Recent studies indicate that climate change could significantly reduce the areas suitable for growing *Coffea arabica* in the coming decades. This is especially concerning for tropical regions in Latin America and Africa [6,13–16].

Peru plays a significant role in this dynamic, being the world's second-largest exporter of organic coffee and a major producer of specialty coffees [17]. It currently manages 425,416 hectares of coffee plantations, benefiting 223,482 families, mainly distributed across seven regions, including Amazonas, Cajamarca, Junín, and San Martín [9]. In the Amazonas region, the districts of Omia and Lonya Grande are notable for their cultivated areas of 5668.46 ha and 5457.22 ha, respectively, which together represent 2.6% of the national coffee area [18]. Coffee production in this region, organized through cooperatives and associations, not only generates economic benefits but also acts as a sociocultural and environmental hub for thousands of rural families [19].

However, coffee production in Amazonas is becoming increasingly vulnerable due to climate change. The rise in average temperatures, irregular rainfall patterns, and the spread of pests, such as coffee rust (*Hemileia vastatrix*), are significant concerns [20]. Both the coffee berry borer (*Hypothenemus hampei*) and other factors threaten the stability of production and the quality of the beans [21]. Confronted with these challenges, climate science utilizes global and regional atmospheric circulation models, along with statistical downscaling methods, to provide valuable future scenarios that aid in informed decision-making and the development of effective adaptation strategies [14]. In rural areas, farmers' perceptions are a crucial element that should not be overlooked [22,23]. The experience of coffee growers regarding climate changes, pests, and yields informs the viability and acceptance of adaptation practices proposed by science [4,24,25].

Studies in Latin America indicate some alignment between scientific projections and local perceptions, but notable differences also arise [26]. The differences observed often arise from cultural and economic factors, as well as varying access to information [27]. These elements hinder the implementation of collaborative adaptation strategies and create a disconnect between technical evidence and local knowledge [24,28].

The development of data-driven prediction tools has become essential for agricultural planning [29] and adapting to climate change [30]. Various statistical and machine learning models, such as regression analysis, decision trees, neural networks, and time series models like Seasonal Auto Regressive Integrated Moving Average (SARIMA), have been highly effective in estimating crop yields [31] and projecting trends based on environmental factors, including temperature [32], humidity [33], evapotranspiration [34], precipitation [35], and soil nutrients [36]. Among these factors, temperature is a critical element in plant physiology. While moderate temperature changes can often be tolerated or adjusted for through phenological adaptations, extreme events—such as heatwaves, droughts, or frosts—can cause irreversible damage to crops [37].

Thus, combining climate models with local perceptions is essential for designing effective public policies, agricultural extension programs, and sustainability strategies in

sensitive value chains, such as coffee [38,39]. This study addresses the challenges faced by coffee cooperatives in northern Peru. It utilizes historical climate records from 1979 to 2024. It employs statistical models to achieve the following objectives: (a) Construct current climate trends for key variables, including evapotranspiration, precipitation, maximum, average, and minimum temperatures, and wind speed; (b) Identify anomalies in these variables through time series analysis; (c) Model projections of climate conditions up to 2030; and (d) Compare observed and projected trends with the perceptions of coffee growers within associations and cooperatives in the Amazonas region. By doing so, we identified points of convergence and divergence between scientific knowledge and local insights. This provides valuable input to enhance the sustainability of regional coffee farming in the context of climate change, aligning with Sustainable Development Goals 13 and 15 of the 2030 Agenda.

2. Materials and Methods

2.1. Study Area

The research was conducted in the Amazonas region of Peru, focusing on several cooperatives: Cooperativa Agraria Cafetalera Bagua Grande, which includes 308 farms; Cooperativa Agraria Rodríguez de Mendoza (COOPARM), with 255 farms; Cooperativa Agraria Cafetalera Alta Montaña, comprising 222 farms; and Cooperativa Agraria Cafetalera Ocumal, totaling 375 farms. As illustrated in Figure 1, the Amazonas region is in northeastern Peru. This area is renowned for its coffee cultivation and is situated between 1200 and 1800 m.a.s.l. It features a humid tropical climate with average annual temperatures ranging from 18 to 24 °C. The selected cooperatives represent organized regional coffee production, encompassing a total of 1160 farms. Georeferenced coordinates for each cooperative are listed in Supplementary Table S1.

2.2. Obtaining Climate Data

We utilize the Climate Engine platform (<https://www.climateengine.org/>, accessed 10 January 2025), which is a freely accessible application for remote sensing and climate cloud computing [40]. Climate Engine is powered by Google Earth Engine, allowing us to process and download climate variable data from 1979 to 2024 [18]. The values were calculated within Climate Engine using collections of Landsat surface reflectance products provided by the United States Geological Survey (USGS) and hosted on Google Earth Engine [41,42].

Climate Engine automatically applies cloud masks from the Landsat surface reflectance collections to ensure data accuracy [18]. We calculated spatially and temporally averaged climate values within Climate Engine and downloaded these as median values. Next, we analyzed historical trends using RStudio software version 4.2.3 and the ggplot2 package.

2.3. Trends, Anomalies, and Climate Modeling

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was employed to forecast a time series [43,44]. This time series forecasting method relies solely on historical data to model and predict future values. SARIMA effectively captures seasonal patterns and recurring data fluctuations [45]. A significant benefit of this univariate method is that it relies entirely on previous observations, allowing for precise predictions based on the historical patterns of the series [46]. The SARIMA model is developed using the Box-Jenkins methodology [47,48]. The process consists of several essential steps: (i) assessing the stationarity of the time series to ensure that statistical properties, such as the mean and variance, remain stable over time; (ii) determining the appropriate structure for the Seasonal Autoregressive Integrated Moving Average (SARIMA), including seasonal components and

differentiation; (iii) estimating the model parameters; (iv) performing diagnostic checks to evaluate the adequacy of the model; and (v) generating forecasts based on the final model. For this analysis, R software version 4.2.3 and the forecast package were used.

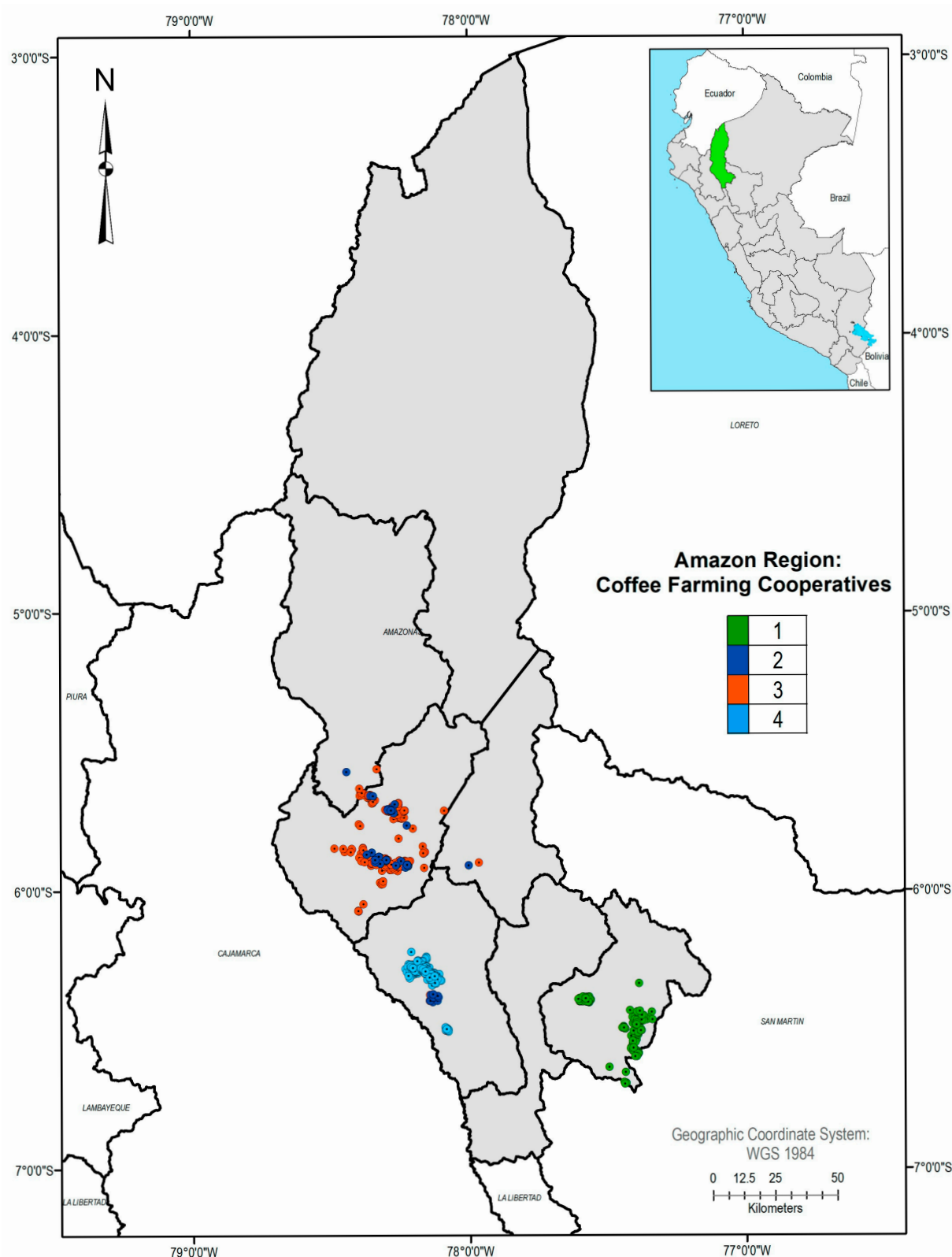


Figure 1. Location of the cooperatives that were part of this study. 1: Cooperativa Agraria Rodríguez de Mendoza (COOPARM); 2: Cooperativa Agraria Cafetalera Alta Montaña; 3: Cooperativa Agraria Cafetalera Bagua Grande; 4: Cooperativa Agraria Cafetalera Ocumal.

The Seasonal Autoregressive Integrated Moving Average (SARIMA) model was chosen because it is particularly effective for analyzing long-term climatic time series that exhibit strong seasonal patterns and temporal autocorrelation. SARIMA enables the separation of trend, seasonal, and irregular components and has been widely used in climatological studies to evaluate historical variability and generate short-term projections. However, SARIMA is a univariate approach, meaning it does not explicitly consider interactions among different climatic variables. Additionally, it requires that the series being modeled is stationary, which may limit its ability to capture complex climate dynamics. These limitations are discussed further in Section 4.4.

Application of the SARIMA Model

The SARIMA model was applied to monthly time series data for six climatic variables: precipitation, maximum temperature (Tmax), mean temperature (Tmean), minimum temperature (Tmin), evapotranspiration (ET), and wind speed [49]. This analysis was conducted for each of the four coffee cooperatives evaluated. The modeling period spanned from 1979 to 2024, with data from 1979 to 2019 used for model calibration and the years 2020 to 2024 reserved for validation [50].

Before fitting the models, we assessed the stationarity of each time series through visual inspection, autocorrelation (ACF) and partial autocorrelation (PACF) plots, as well as unit root tests. When non-stationarity was detected, we applied first-order and/or seasonal differencing as necessary. Logarithmic transformation was not utilized because the variables were expressed in consistent physical units and did not show exponential growth patterns.

Given the monthly resolution of the data, we set the seasonal period to $s = 12$ to account for annual climatic cycles. We evaluated a set of standard SARIMA candidate models commonly used in climatological studies, including SARIMA $(1,1,1)(1,1,1)_{12}$, $(2,1,1)(1,1,1)_{12}$, $(1,0,1)(1,1,0)_{12}$, and $(2,0,2)(1,1,1)_{12}$. Model selection was based on the lowest values of the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) to ensure both parsimony and a good fit.

We evaluated model performance using various metrics, including mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE), the Pearson correlation coefficient (R), and Nash–Sutcliffe efficiency (NSE) [49]:

Additionally, we conducted residual diagnostics using the Ljung–Box test to check for the absence of autocorrelation [51,52]. Models with non-significant Ljung–Box p -values ($p > 0.05$) were considered to have adequately captured the temporal structure of the data [53]. The final selected SARIMA models were then used to generate monthly projections of climatic variables up to 2030, along with 95% confidence intervals. All analyses were performed using R software (version 4.2.3) and the forecast package [54].

A conventional out-of-sample validation strategy was applied during model development. Monthly data from 1979 to 2019 were used for model calibration (training), while the period 2020–2024 was reserved as an independent validation subset. This approach allowed model performance to be evaluated under recent climatic conditions without compromising the representation of long-term trends and seasonality.

After confirming satisfactory predictive performance through error metrics (MAE, RMSE, MAPE, R, and NSE) and residual diagnostics (Ljung–Box test), the final SARIMA models were refitted using the complete historical dataset (1979–2024). This step was undertaken to maximize the information available for forecasting climatic trends up to 2030. While fitting the model to the full dataset may reduce strict independence between calibration and projection, this approach is appropriate for short-term climate trend analysis

and is commonly adopted when the objective is to characterize expected trajectories rather than to perform real-time forecasting.

2.4. Farmer Perception Surveys

To incorporate the social dimension, a semi-structured survey was administered to all coffee growers who are members of four coffee cooperatives in the Amazonas region. Before launching the study, a focus group was conducted to explain the meaning of the variables, intentionally avoiding specific examples of crop impacts to minimize any potential influence on the participants' responses [55]. Following this, the surveys were distributed to 152 coffee growers (selected through convenience sampling [56] who were members of the four cooperatives, from which georeferences of their coffee plots were obtained. The growers were asked about their perceptions of changes in climate variable patterns, their current experiences with these phenomena, and their expectations for how these patterns might evolve in the future. The validity of the survey instrument was ensured through expert review and a pilot test conducted with 15 producers. The pilot test demonstrated strong reliability with a Cronbach's α coefficient of 0.82 [57–60].

2.5. Data Analysis

To evaluate the statistical behavior of the climatic variables, data distribution was first assessed using the Kolmogorov–Smirnov test for normality. Because all variables deviated from normality, nonparametric methods were adopted to compare differences among cooperatives. To evaluate the distribution of climatic variables (evapotranspiration, precipitation, temperature, and wind speed), the Kolmogorov–Smirnov (KS) test was applied [61]. The results showed that all variables had p -values less than 0.05, indicating that they did not follow a normal distribution (see Table S1). Consequently, the nonparametric Kruskal–Wallis test [62,63] was used to identify differences between the cooperatives evaluated. The χ^2 values obtained were significant for all variables ($p < 0.05$), demonstrating the existence of statistically significant differences between cooperatives in terms of the climate indicators analyzed during the period 1979–2024.

3. Results

This section presents the empirical results of the climatic analyses, SARIMA model performance, and farmer perception surveys. Results are organized to first describe model validation outcomes, followed by observed climate trends, anomalies, projections, and their comparison with local perceptions.

3.1. SARIMA Model Performance and Validation

In some cases, such as with variable wind speed, the AIC and BIC values were found to be negative [64]. This behavior indicates that the model achieved a very high level of plausibility due to low variance and high predictability of the time series [65]. In these situations, the term $(-2 \ln(L))$ can become negative; when this value is combined with the complexity penalty, it can result in the total value of the criterion being below zero [46]. Therefore, negative AIC and BIC values should only be interpreted as evidence of an exceptional fit of the model to that variable [66]. The comparison remains valid in relative terms between alternative models, with the one with the lowest AIC or BIC value being preferable [67].

We use the same four standard SARIMA candidate models for all variables (1,1,1) (1,1,1) [12], (2,1,1) (1,1,1) [12], (1,0,1) (1,1,0) [12], (2,0,2) (1,1,1) [12] (see Table 1). We used the range 1979–2019 as training and 2020–2024 as validation.

Table 1. Performance metrics of selected SARIMA models for climatic variables across coffee cooperatives (training: 1979–2019; validation: 2020–2024).

Cooperative Variable	Model	AIC	BIC	MAE	RMSE	MAPE	R	NSE	Pred_SD	Ljung Box_Q	p_Value	H0 Random_Residuals
Bagua Grande												
Evapotranspiration	SARIMA (1,0,0) (1,0,0) [12]	6011.94	6029.68	25.91	29.72	30.09	0.08	0.01	29.75	10.592	0.564	Not rejected
Precipitation	SARIMA (0,0,0) (0,0,0) [12]	7353.08	7361.96	76.25	87.33	206.12	−0.03	0	87.4	8.278	0.763	Not rejected
Tmax	SARIMA (0,0,0) (0,0,0) [12]	3613.2	3622.07	3.78	4.36	14.32	0	0	4.37	8.366	0.756	Not rejected
Tmean	SARIMA (0,0,0) (0,0,0) [12]	3072.82	3081.69	2.42	2.83	12.53	0	0	2.83	14.224	0.287	Not rejected
Tmin	SARIMA (0,0,0) (0,0,0) [12]	3447.75	3456.63	3.33	3.82	35.26	0	0	3.82	8.086	0.778	Not rejected
Wind_speed	SARIMA (1,0,0) (1,0,0) [12]	3086.43	3104.17	2.48	2.85	342.62	0.07	0	2.85	9.292	0.678	Not rejected
COOPARM												
Evapotranspiration	SARIMA (0,0,0) (0,0,0) [12]	5955.77	5964.64	24.5	28.51	32.45	0	0	28.53	9.582	0.653	Not rejected
Precipitation	SARIMA (1,1,2) (0,0,0) [12]	7560.16	7577.9	89.25	103.39	955.53	0.08	0	103.47	11.108	0.52	Not rejected
Tmax	SARIMA (0,0,0) (0,0,0) [12]	3555.77	3564.64	3.69	4.17	13.08	0	0	4.17	11.712	0.469	Not rejected
Tmean	SARIMA (0,0,0) (0,0,0) [12]	3216.57	3225.44	2.75	3.17	13.34	0	0	3.18	15.783	0.201	Not rejected
Tmin	SARIMA (1,0,1) (2,0,0) [12]	3524.18	3550.79	3.49	4.04	31.98	0.15	0.02	4.04	7.858	0.796	Not rejected
Wind_speed	SARIMA (0,0,0) (1,0,0) [12]	2929.41	2942.72	2.15	2.52	528.2	0.04	0	2.52	9.995	0.616	Not rejected
Ata Montaña												
Evapotranspiration	SARIMA (0,1,1) (1,0,0) [12]	5937.35	5950.65	24.24	28.15	29.49	0.09	0	28.15	7.186	0.845	Not rejected
Precipitation	SARIMA (2,1,2) (1,0,0) [12]	7350.8	7377.41	74.56	87.13	223.44	0.11	0.01	87.12	2.919	0.996	Not rejected
Tmax	SARIMA (0,0,1) (2,0,0) [12]	3519.55	3541.73	3.46	4.03	11.93	0.12	0.01	4.03	9.993	0.617	Not rejected
Tmean	SARIMA (0,0,0) (0,0,1) [12]	3220.35	3233.66	2.74	3.18	12.55	0.06	0	3.18	11.459	0.49	Not rejected
Tmin	SARIMA (0,0,0) (1,0,1) [12]	3492.46	3510.21	3.39	3.95	30.61	0.05	0	3.95	3.984	0.984	Not rejected
Wind_speed	SARIMA (0,0,0) (0,0,0) [12]	2983.98	2992.85	2.26	2.63	365.65	0.09	0	2.64	13.235	0.352	Not rejected
Ocumal												
Evapotranspiration	SARIMA (0,0,0) (1,0,0) [12]	5865.3	5878.61	23.27	26.47	30	0.03	0	26.49	8.546	0.741	Not rejected
Precipitation	SARIMA (1,0,1) (0,0,0) [12]	7441.56	7459.31	80.89	93.45	4837.48	0.06	0	93.53	9.339	0.674	Not rejected
Tmax	SARIMA (0,0,0) (1,0,0) [12]	3344.6	3357.9	2.99	3.51	11.12	0.03	0	3.51	14.088	0.295	Not rejected
Tmean	SARIMA (0,0,1) (0,0,0) [12]	3216.23	3229.54	2.74	3.17	13.85	0.08	0.01	3.17	17.263	0.14	Not rejected
Tmin	SARIMA (0,0,0) (2,0,0) [12]	3548.44	3566.19	3.62	4.13	37.07	0.1	0.01	4.13	9.936	0.622	Not rejected
Wind_speed	SARIMA (0,0,0) (1,0,0) [12]	2816.1	2829.4	2	2.3	218.64	0.07	0	2.3	22.148	0.0359	rejected

3.2. Current Climate Trends

Table 2 presents the descriptive results of the time series for six key climate variables—evapotranspiration, precipitation, maximum temperature (Tmax), average temperature (Tmean), minimum temperature (Tmin), and wind speed—analyzed from 1979 to 2024 across four evaluated coffee cooperatives: Bagua Grande, COOPARM, Alta Montaña, and Ocumal.

Overall, the time series demonstrates significant climatic variability among the cooperatives, which can be attributed to the rugged topography of the Amazonas region and the spatial variability of the rainfall patterns. The differences observed in the mean, maximum, and minimum values for each variable indicate the presence of contrasting microclimates that directly influence the physiology and productivity of coffee.

Table 2. Time Series Current Climatic.

Variable		Bagua Grande	COOPARM	Alta Montaña	Ocumal
Evapotranspiration (ET, mm) *	Min	43.9654	43.9654	34.39	43.9654
	Date min	2024-09	2024-09	2024-09	2024-09
	Max	122.0476	122.0476	116.13	122.0476
	Date Max	2017-06	2017-06	2006-04	2017-06
	Mean	92.10389671 a	92.10389671 b	78.39671 a	1.07×10^{26} c
Precipitation (mm) *	SD	13.5740936	13.5740936	16.38526	13.55175
	Min	0	0	43.708	0
	Date min	2024-09	1986-06	2017-07	1986-06
	Max	122.0476	420.1671	429.67	420.1671
	Date Max	2017-06	2023-03	2015-03	2023-03
T° max (°C) *	Mean	70.9293 ab	59.01239456 a	177.9084 a	59.01239 b
	SD	41.57909368	57.57166868	83.61301	57.51764
	Min	12.53387097	12.53387097	15.66	12.53387
	Date min	1980-07	1980-07	1990-06	1980-07
	Max	23.96	23.96	24.44	23.96
T° mean (°C) *	Date Max	2010-11	2010-11	2010-11	2010-11
	Mean	19.59974461 a	19.59974461 ab	19.92645 a	19.59974 b
	SD	1.709521487	1.709521487	1.537736	1.707989
	Min	7.544651613	7.544651613	11.04	7.544652
	Date min	1979-07	1979-07	1985-07	1979-07
T° min (°C) *	Max	15.56077667	15.56077667	16.11	15.56078
	Date Max	2010-11	2010-11	2024-11	2010-11
	Mean	12.87500059 a	12.87500059 b	13.87986 a	12.875 1212 c
	SD	1.369507871	1.369507871	0.993355	1.36828
	Min	10.11958065	2.546774194	7.5	2.546774
Wind Speed *	Date min	1988-07	1979-07	2012-07	1979-07
	Max	14.87701935	11.75344828	12.81	11.75345
	Date Max	2010-10	2016-02	2024-03	2016-02
	Mean	12.8586236 a	2016-02 b	10.21498 a	8.478155 c
	SD	0.881654541	1.709866204	1.035252	1.708333
Wind Speed *	Min	0.426906667	0.426906667	0.47	0.426907
	Date min	1983-04	1983-04	1983-04	1983-04
	Max	1.163567742	5.95×10^{28}	1.24	5.95×10^{28}
	Date Max	2019-08	2009-07	2019-08	2009-07
	Mean	0.733631499 a	1.068×10^{26} a	0.782072 a	1.07×10^{26} b
Wind Speed *	SD	0.132985497	2.52×10^{27}	0.137161	2.52×10^{27}

* = statistical significance for the mean. The different letters mean different groups.

In terms of the evapotranspiration (ET) variable, the highest average values were found in Bagua Grande and COOPARM, both at 92.1 mm, while Alta Montaña had a lower average of 78.4 mm. This discrepancy may be linked to the higher altitudes and greater vegetation cover in Alta Montaña, which reduces evaporative demand. Conversely, Ocumal exhibited an unusually high average, likely due to an extreme data point, suggesting either a numerical error or significant local variability. The dates of the maximum and minimum values (June 2017 and September 2024, respectively) align with seasonal transition phases, confirming the strong influence of annual cycles on ET dynamics.

In terms of precipitation, the most significant inter-cooperative disparity was observed. Alta Montaña recorded the highest average (177.9 mm), characteristic of its location in humid mountainous areas with orographic influence; in contrast, COOPARM and Ocumal recorded averages close to 59 mm, while Bagua Grande reached 70.9 mm. This difference coincides with the rainfall patterns described for the region, where the eastern slopes

have higher humidity. Extreme years exhibit high interannual variability, characterized by maximums in 2015–2023 and minimums associated with dry periods, such as 1986 or 2017.

Maximum temperatures showed a more uniform distribution among cooperatives, with averages ranging from 19.6 to 19.9 °C. The highest values were recorded in November 2010, coinciding with a warm event associated with El Niño. The average temperature reflected a similar pattern, with averages of 12.8–13.8 °C and low standard deviations (<1.5 °C), suggesting regional thermal stability. However, the minimum values (7.5 °C in Bagua Grande and COOPARM; 11.0 °C in Alta Montaña) indicate the possibility of cooling episodes that may affect coffee flowering.

Notable differences were identified in relation to the minimum temperature: Bagua Grande had an average of 12.8 °C. In comparison, Ocumal dropped to 8.4 °C, which could be associated with higher altitude and exposure to radiative frost. These temperature variations directly affect phenological risk and cherry quality, as temperatures below 10 °C can inhibit growth and affect bean maturation.

Finally, wind speed showed moderate average values (0.7–0.8 m·s^{−1}); however, extreme peaks were recorded in COOPARM and Ocumal during isolated years (2009 and 2019), indicating the influence of episodic strong wind events rather than a sustained long-term pattern. The stability of the minimum values, shared among cooperatives (0.43 m·s^{−1}), confirms a general regime of light winds, consistent with the topographical conditions of protected inter-Andean valleys.

The differences observed highlight the necessity for tailored adaptation strategies for each cooperative. For instance, while Bagua Grande and COOPARM need to enhance water management and vegetation cover to address water shortages, Alta Montaña and Ocumal require measures to manage excess moisture and reduce the risk of low temperatures.

A joint analysis of the time series data reveals a trend of rising maximum and average temperatures, accompanied by increasingly unpredictable rainfall patterns. This aligns with the findings presented in Figures 1–4 of the manuscript. Such trends suggest a shift toward warmer conditions and greater interannual variability, reflecting global reports on the effects of climate change in tropical coffee-growing regions.

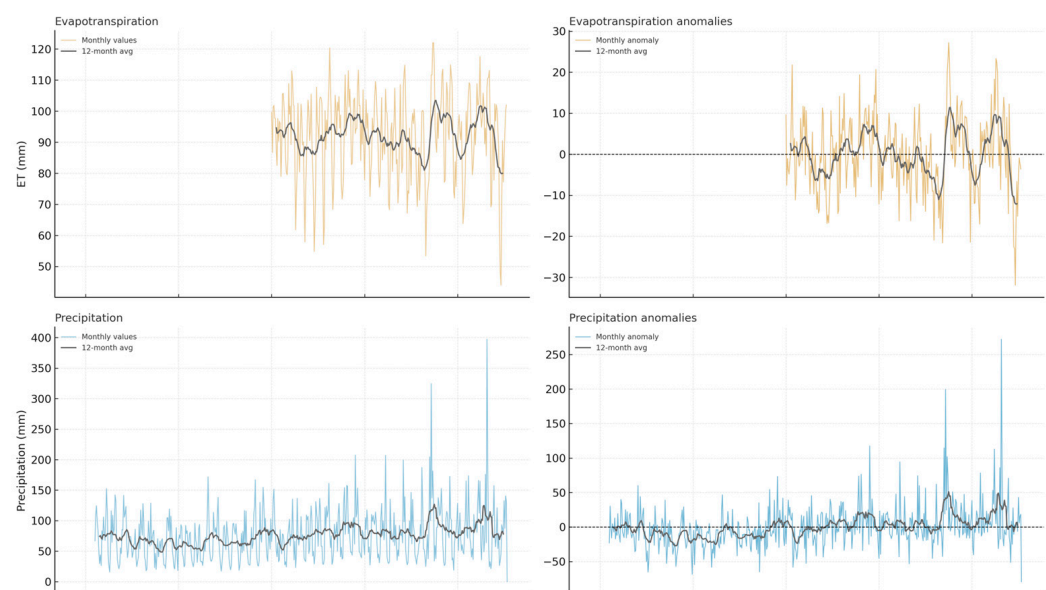


Figure 2. Cont.

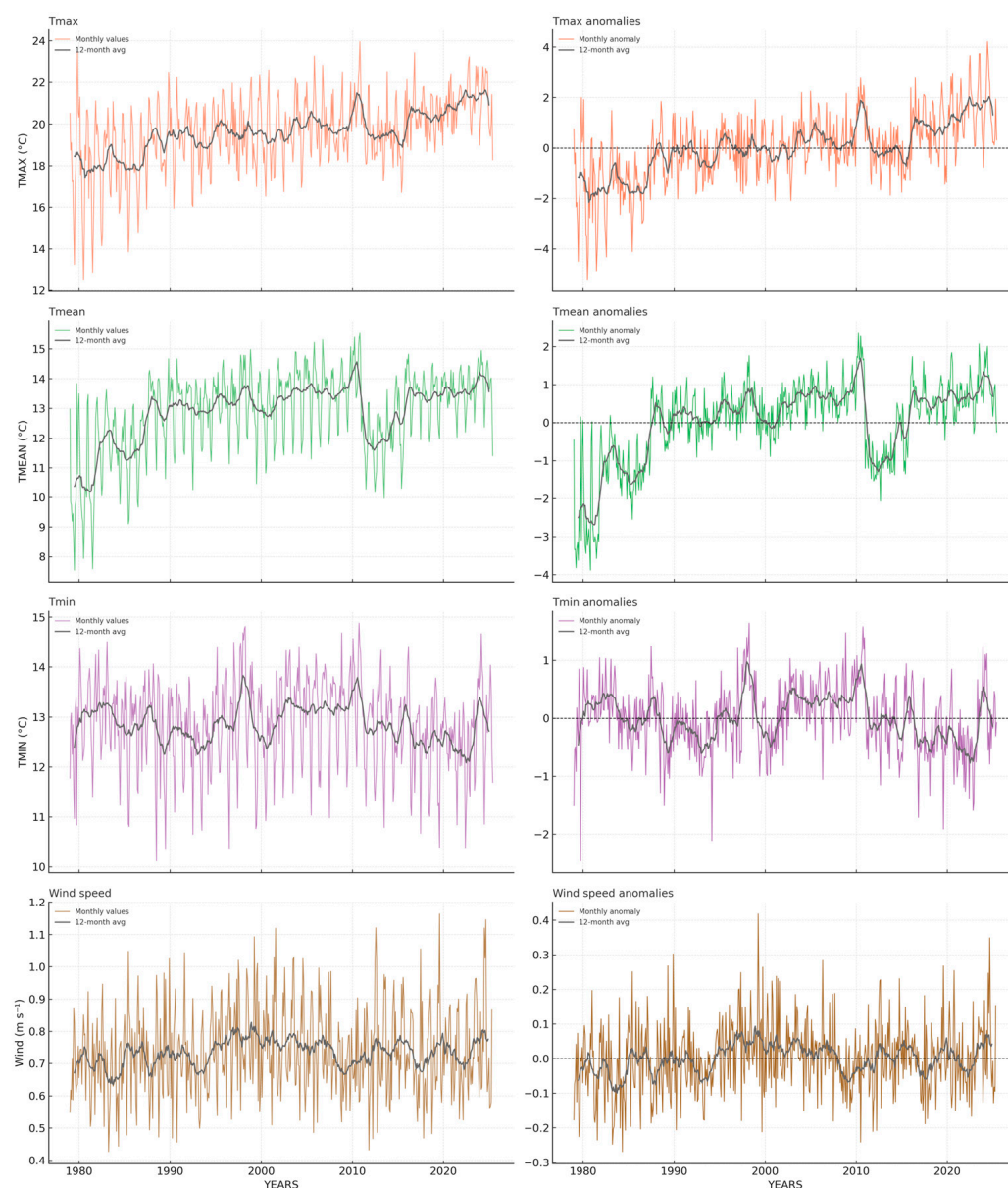


Figure 2. Time series in the left column and climate anomalies in the right column (evapotranspiration, precipitation, maximum, average, and minimum temperatures, and wind speed) recorded at the Bagua Grande Cooperative (1980–2023).

In summary, Table 2 provides crucial statistical evidence that supports further inferences regarding anomalies (Table 3) and projections (Table 4). The analysis confirms that coffee cooperatives in northern Peru are facing diverse climatic conditions, with trends that could alter the agroecological suitability of their areas by 2030. These findings underscore the importance of integrating local climate management with predictive models and farmers' perspectives, thereby guiding the development of specific, sustainable adaptation policies for Amazonian coffee farming.

3.3. Climatic Anomalies

Table 3 summarizes the climatic anomalies observed in each cooperative. It highlights years with significant rainfall deficits, such as 1995 in Bagua Grande and 2014 in COOPARM, as well as years with excessive rainfall, like 2002 in Alta Montaña and 2007 in Ocumal. These anomalies contribute to coffee growers' perceptions of irregular rainfall patterns.

Notable positive temperature anomalies were recorded in maximum temperatures (Tmax), particularly in 1997 in Bagua Grande (Table 3, Figure 2) and 1998 in COOPARM,

which were associated with the El Niño phenomenon (Table 3, Figure 3). Wind speed exhibited considerable variability across all cooperatives, with unusually high maximum values observed in 2023–2024.

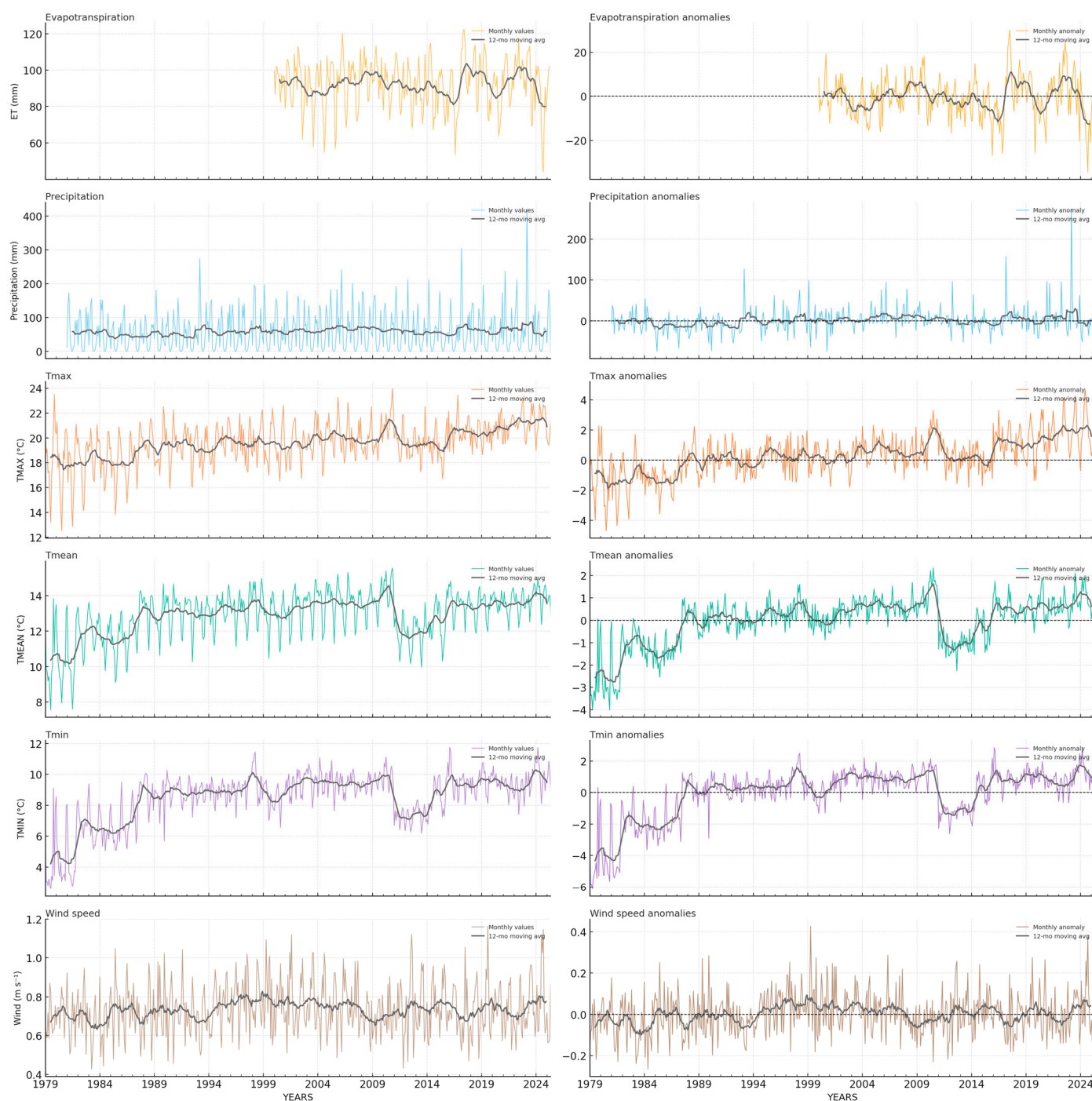


Figure 3. Time series data is presented in the left column, while climatic anomalies (including evapotranspiration, precipitation, maximum, average, and minimum temperature, and wind speed) are recorded in the right column for the Rodríguez de Mendoza Agricultural Cooperative (COOPARM) from 1980 to 2023.

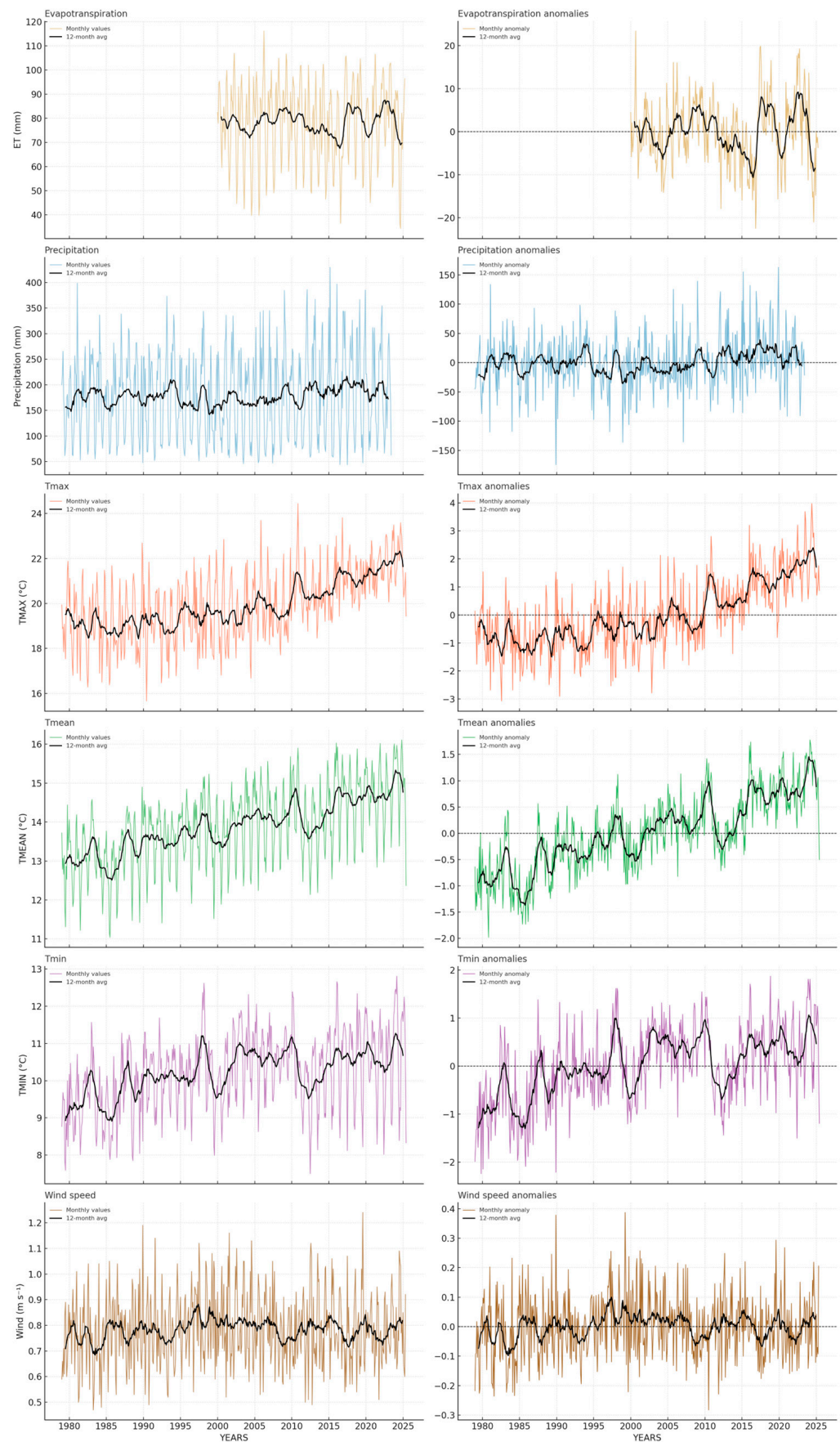


Figure 4. Time series in the left column and climate anomalies in the right column (evapotranspiration, precipitation, maximum, average, and minimum temperature, and wind speed) recorded at the Alta Montaña Cooperative (1980–2023).

Table 3. Anomalies in climate variables of coffee cooperatives.

Cooperative	Variable	Evapotranspiration	Precipitation	Tmax	Tmean	Tmin	Wind_Speed
AltaMontaña	Min	48.05302302	0.434494616	23.00300833	17.00752882	6.003542538	0.006285436
	DateMin	1 November 2020	1 December 2020	1 November 1991	1 June 1981	1 July 1992	1 June 1985
	Max	144.9125203	309.9439812	36.98111677	27.99537532	19.93776844	8.976369713
	DateMax	1 May 1983	1 June 2002	1 November 1983	1 February 1999	1 June 2023	1 December 2003
	Average	95.60439162	158.6142674	29.67638869	22.41329524	13.13051586	4.627356808
	S.D.	28.01530758	87.75208122	4.085799118	3.183295271	3.936008962	2.632323437
BaguaGrande	Min	50.50615838	1.389606901	20.07409971	15.01565105	5.000151252	0.006533908
	DateMin	1 May 1996	1 June 1995	1 November 1993	1 December 2016	1 November 2012	1 March 2021
	Max	149.9717673	299.3802332	34.99120589	24.98347511	17.97167112	9.995577033
	DateMax	1 April 2023	1 November 2014	1 January 1997	1 November 1985	1 October 1981	1 February 2023
	Average	100.8092423	149.1380067	27.3928313	19.93580712	11.54962908	4.933455643
	S.D.	29.9323363	86.65371127	4.351245815	2.838619491	3.816491961	2.841762276
Cooparm	Min	40.00818876	0.042035521	22.00190319	16.02629234	6.000949736	0.005012306
	DateMin	1 March 2020	1 August 2014	1 February 2022	1 June 2015	1 April 1986	1 October 1994
	Max	139.8918406	349.4606941	35.99501951	26.99298851	19.92620896	8.938456338
	DateMax	1 July 2018	1 October 2012	1 February 1998	1 April 2004	1 August 1983	1 November 2007
	Average	89.57483702	169.1326661	29.09500604	21.28285054	13.07134825	4.524747239
	S.D.	28.48368369	102.367741	4.169046811	3.188797801	4.051798079	2.522142603
Ocumal	Min	45.28445586	0.006421716	21.04692852	15.00308548	5.005828772	0.05124546
	DateMin	1 October 2018	1 January 2017	1 May 1997	1 January 2015	1 September 2016	1 January 2022
	Max	134.841837	319.4859225	33.99616336	25.99530812	18.99542233	7.998884022
	DateMax	1 March 1992	1 April 2007	1 September 1985	1 March 1996	1 June 1988	1 April 2024
	Average	89.00558561	167.9297747	27.60149546	20.45890102	11.85195309	4.122180525
	S.D.	26.27339577	93.24425957	3.505969928	3.214173241	4.17345555	2.317038392

Table 4. Descriptive statistics for the projected data set (2024–2030) in coffee-growing agriculture.

Cooperative		Evapotranspiration	Precipitation	Tmax	Tmean	Tmin	Wind Speed
Bagua Grande	Mean forecast	91.1	86.52	21.4	12.78	12.85	0.77
	Lower 95% CI	71.4	24.77	19.14	9.52	11.37	0.56
	Upper 95% CI	110.81	148.27	23.65	16.03	14.33	0.99
COOPARM	Mean forecast	91.1	61.66	21.4	12.78	9.14	0.77
	Lower 95% CI	71.4	6.53	19.14	9.52	4.96	0.55
	Upper 95% CI	110.81	116.78	23.65	16.03	13.33	0.98
Alta Montaña	Mean forecast	69.98	193.59	22.18	14.35	10.49	0.77
	Lower 95% CI	71.4	6.53	19.14	9.52	4.96	0.55
	Upper 95% CI	110.81	116.78	23.65	16.03	13.33	0.98
Ocumal	Mean forecast	56.86	210.28	21.65	13.65	9.97	0.57
	Lower 95% CI	23.28	124.16	19.37	10.33	5.68	0.45
	Upper 95% CI	90.44	296.4	23.92	16.96	14.27	0.68

Figures 1–4 illustrate the time series and corresponding anomalies for each cooperative. These graphical representations support the statistical findings: there is an upward trend in temperatures, significant interannual variability in precipitation, and relative stability in the evapotranspiration series. For example, Bagua Grande displays significant cycles of precipitation with recurring deficit periods; COOPARM and Alta Montaña frequently experience peaks of excess water, whereas Ocumal shows marked extreme anomalies in both directions. These local differences underscore the necessity for adaptation strategies tailored to specific regional contexts.

The results indicate considerable spatial and temporal variability among cooperatives. For instance, the Alta Montaña cooperative recorded the highest average precipitation at 177.9 mm, confirming its location in a region with higher rainfall (Table 3, Figure 4). In contrast, Bagua Grande and Ocumal recorded lower averages of 70.9 mm and 59.0 mm, respectively (Table 3, Figure 5). Maximum and average temperatures showed less variability, ranging from 19 to 20 °C, indicating relatively uniform thermal stability in the coffee-growing region. However, Ocumal faced extreme minimum temperatures as low as 2.5 °C, which may suggest local frost events that could negatively impact coffee flowering and yields.

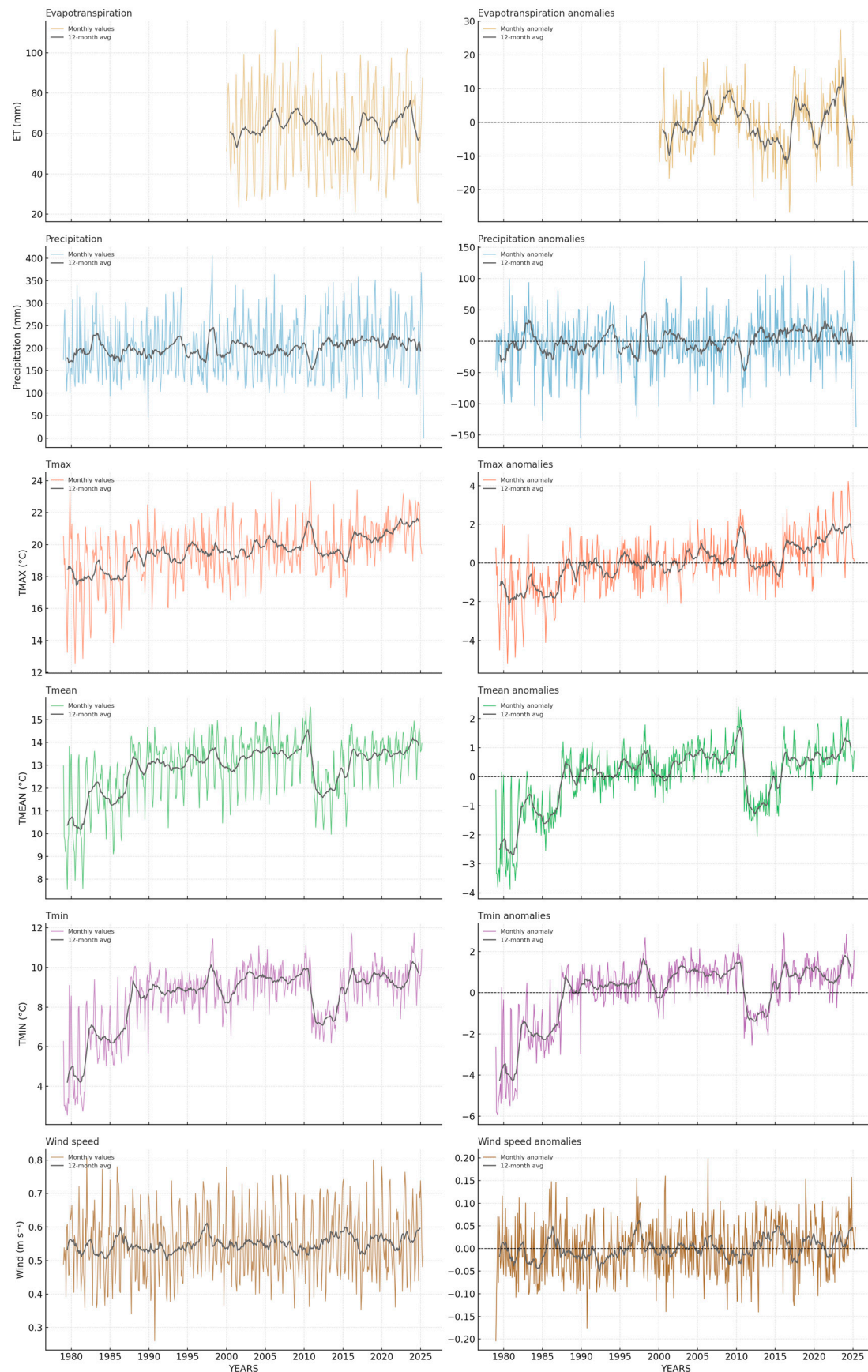


Figure 5. Time series in the left column and climate anomalies in the right column (evapotranspiration, precipitation, maximum, average, and minimum temperature, and wind speed) recorded at the Ocumal Cooperative (1980–2023).

In coffee cultivation, the ideal average air temperature is around 20 °C; deviations above or below this threshold create suboptimal conditions that can harm crop development. In agroforestry systems, the presence of shade trees can reduce air temperature by 1 to 5 °C, depending on coverage [5,68]. Recent studies have shown that shade trees can mitigate thermal variability and enhance the system's resilience to climate change, as highlighted in research exploring the cooling effects of shading (2023).

The inter-cooperative comparison of climate variables (Table 3) shows that the Alta Montaña and Ocumal cooperatives experience higher levels of precipitation and greater interannual variability. In contrast, Bagua Grande and COOPARM have more stable climates, though they do encounter occasional extreme weather events. This highlights the importance of adopting local strategies for adaptive climate management.

3.4. Projections (2024–2030) of Climate Variables

Table 4 presents the projections for climate variables from 2024 to 2030. The results indicate a consistent increase in evapotranspiration in Bagua Grande and COOPARM, averaging 91.1 mm, while Ocumal shows lower values at 56.9 mm. Projected precipitation is decreasing in Bagua Grande (86.5 mm) and COOPARM (61.7 mm), while remaining high in Alta Montaña (193.6 mm) and Ocumal (210.3 mm). The projected maximum and average temperatures range from 21 to 22 °C and 12 to 14 °C, respectively, confirming a gradual increase compared to historical averages.

These projections, based on historical data from 1979 to 2024, help us identify expected future trends in each area, along with potential agroclimatic risk scenarios that could impact the sustainability of coffee production in the Amazonas region (Table 4, Figure 5).

Evapotranspiration is projected to show an increasing trend across all cooperatives, although the magnitudes differ. Bagua Grande and COOPARM exhibit similar average values (91.1 mm), indicating a slight increase compared to the historical period. Alta Montaña has a lower average of 69.98 mm, while Ocumal records the lowest value at 56.86 mm, consistent with its higher altitude and lower temperatures. This increase in evapotranspiration implies greater water demand for crops, potentially intensifying water stress risks, particularly in Bagua Grande and COOPARM, where projected rainfall is decreasing.

The 95% confidence interval (CI) for Bagua Grande ranges from 71.4 to 110.8 mm, reflecting moderate uncertainty. In contrast, the CI for Ocumal ranges from 23.3 to 90.4 mm, indicating high interannual variability. This pattern suggests that colder areas may experience years with exceptionally low evapotranspiration values, alternating with periods of water recovery, which would affect irrigation scheduling and the phenology of coffee trees (Table 4, Figure 5).

The precipitation variable exhibits a contrasting distribution among the cooperatives, highlighting distinct microclimates. Bagua Grande and COOPARM show significant decreases in average precipitation (86.5 mm and 61.7 mm, respectively), while Alta Montaña and Ocumal maintain high levels (193.6 mm and 210.3 mm). These results reinforce the existence of an orographic humidity gradient, with increasing water deficits in the lower areas of the Utcubamba Valley and surpluses in the higher eastern slopes.

The wide range of the confidence interval (± 60 mm on average) indicates that precipitation scenarios will be characterized by significant climate uncertainty, with years potentially being drier or rainier than anticipated. The downward trend in western areas suggests the possibility of prolonged dry periods, which could negatively impact coffee flowering and ripening. Conversely, the predicted excess rainfall in Alta Montaña and Ocumal may lead to issues such as soil saturation, the spread of fungal diseases, and increased erosion (Table 4, Figure 5).

Projected maximum temperatures are expected to rise across the four cooperatives, with average values ranging from 21.4 to 22.2 °C. Bagua Grande and COOPARM exhibit similar temperature levels, while Alta Montaña reaches the highest maximum at 22.18 °C, and Ocumal records 21.65 °C. This variation of approximately +1.5 °C from historical values confirms a regional warming trend, consistent with thermal increase scenarios noted in recent climate literature for the tropical Andes.

The increase in maximum temperatures could have detrimental physiological effects on *Coffea arabica*, which thrives within an optimal growth range of 18 to 22 °C. An increase in the number of days with temperatures above this threshold may lead to thermal stress, reduced photosynthesis, and lower-quality beans. The broad confidence intervals (± 2.5 °C) indicate the potential for extreme events, such as heat waves or temporary thermal anomalies.

Additionally, the projected average temperature ranges from 12.78 °C (in Bagua Grande and COOPARM) to 14.35 °C (in Alta Montaña), showing a slight increase compared to the historical average (approximately 12.8 °C). This gradual rise reflects a sustained thermal transition, although it remains within the crop's tolerance limits. The higher average temperature in Alta Montaña is noteworthy, as it historically has had cooler conditions; this change could signify an upward shift in the optimal range for coffee production, moving the production frontier to higher elevations.

The projections also indicate an increase in temperature variability, as inferred from the confidence intervals (± 3 °C). This heightened variability could lead to more frequent diurnal fluctuations, impacting the synchrony of flowering and the uniformity of ripening, both of which are critical factors for the quality of specialty coffee.

The projected minimum temperatures (T_{min}) exhibit significant differences among the cooperatives. Bagua Grande has a relatively high T_{min} of 12.85 °C, while COOPARM and Ocumal have lower values of 9.14 °C and 9.97 °C, respectively. Alta Montaña shows an intermediate T_{min} of 10.49 °C. These findings indicate that areas at higher altitudes will generally remain colder, though there is a slight trend toward increasing minimum temperatures, which may reduce the frequency of frosts. However, the lower bound of the 95% confidence interval for COOPARM, at 4.96 °C, suggests that critical cooling events could still occur.

Regarding variable wind speed, values remain stable across most cooperatives at approximately $0.77 \text{ m}\cdot\text{s}^{-1}$, except Ocumal, where a slight decrease to $0.57 \text{ m}\cdot\text{s}^{-1}$ is observed. Although these differences are moderate, the confidence intervals indicate some variability, ranging from 0.45 to $0.99 \text{ m}\cdot\text{s}^{-1}$. This stability suggests that wind patterns are unlikely to undergo significant changes by 2030, although there may be seasonal peaks of greater intensity. Moderate winds are essential for ventilating foliage and dispersing pests; however, excessive wind speeds could lead to increased evapotranspiration and mechanical damage to leaves and flowers.

As a comparative summary, the inter-cooperative analysis of projections highlights contrasting climate patterns. Bagua Grande and COOPARM have emerged as the areas most vulnerable to water deficits and increased thermal stress. In contrast, Alta Montaña and Ocumal are likely to maintain a more humid environment, which poses a risk of soil saturation and diseases associated with excessive humidity. Overall, the projected scenario suggests that the coffee-growing region of Amazonas will encounter more variable and uncertain climatic conditions, which may have implications for yield, quality, and the sustainability of production systems.

Figure 6 displays these projections with confidence intervals, emphasizing the positive trend in temperatures and the growing uncertainty in precipitation.

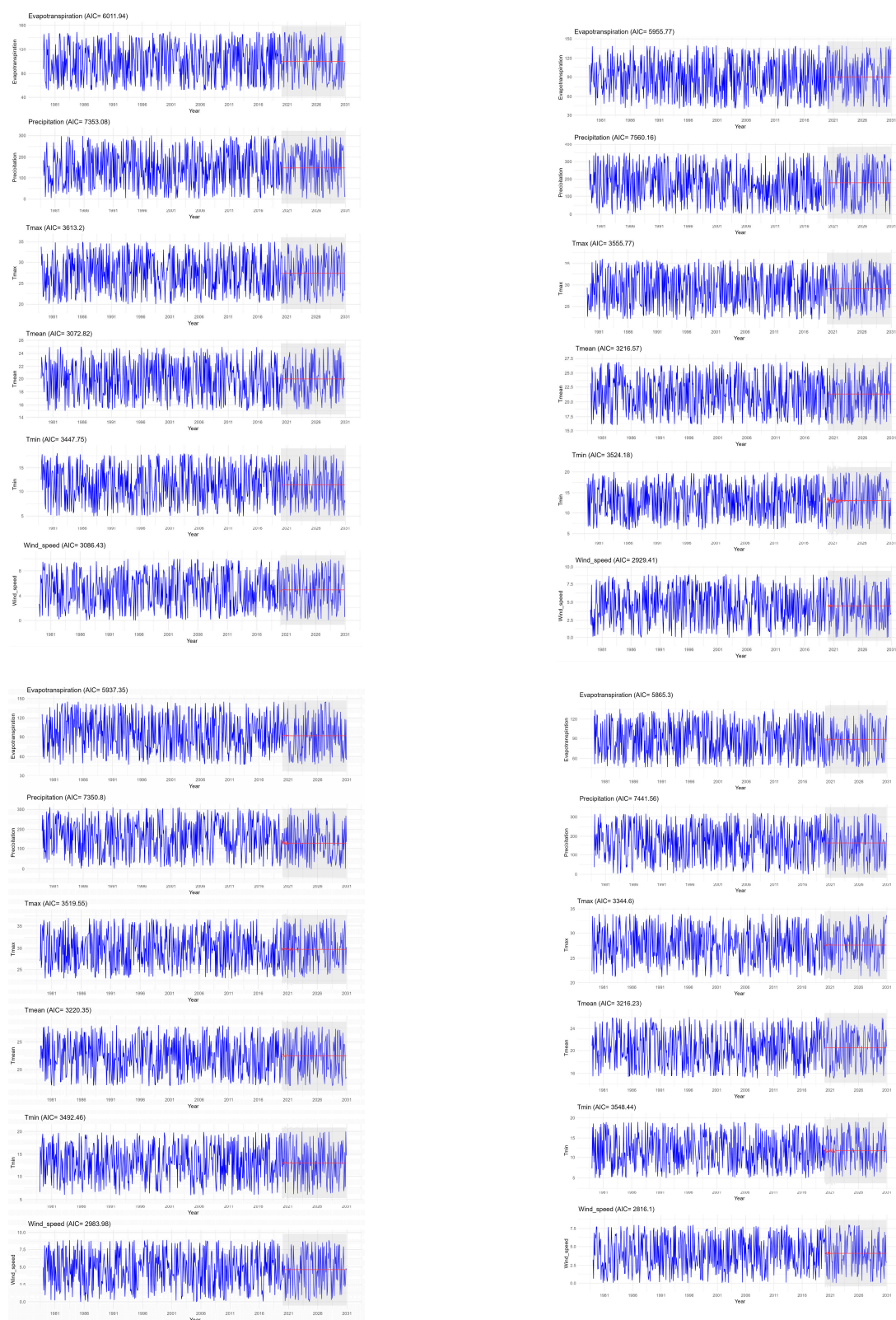


Figure 6. Projections of climate variables using ARIMA (SARIMA) models until 2030. Historical monthly observations (blue) and forecasts obtained with SARIMA (red) are shown, together with 95% confidence intervals (shaded gray), for evapotranspiration (ET, mm), precipitation (mm), maximum temperature (Tmax, °C), mean temperature (Tmean, °C), minimum temperature (Tmin, °C), and wind speed (m s^{-1}). (**top left**): Bagua Grande; (**top right**): COOPARM; (**bottom left**): Alta Montaña; (**bottom right**): Ocumal.

3.5. Trends Versus Perception (Current Climate)

Finally, Figure 7 compares climate trends with producers' perceptions. The analysis reveals high levels of agreement regarding the irregularity of rainfall and the increased frequency of extreme events. However, significant differences are identified among cooperatives in their perceptions of temperature change and environmental humidity.

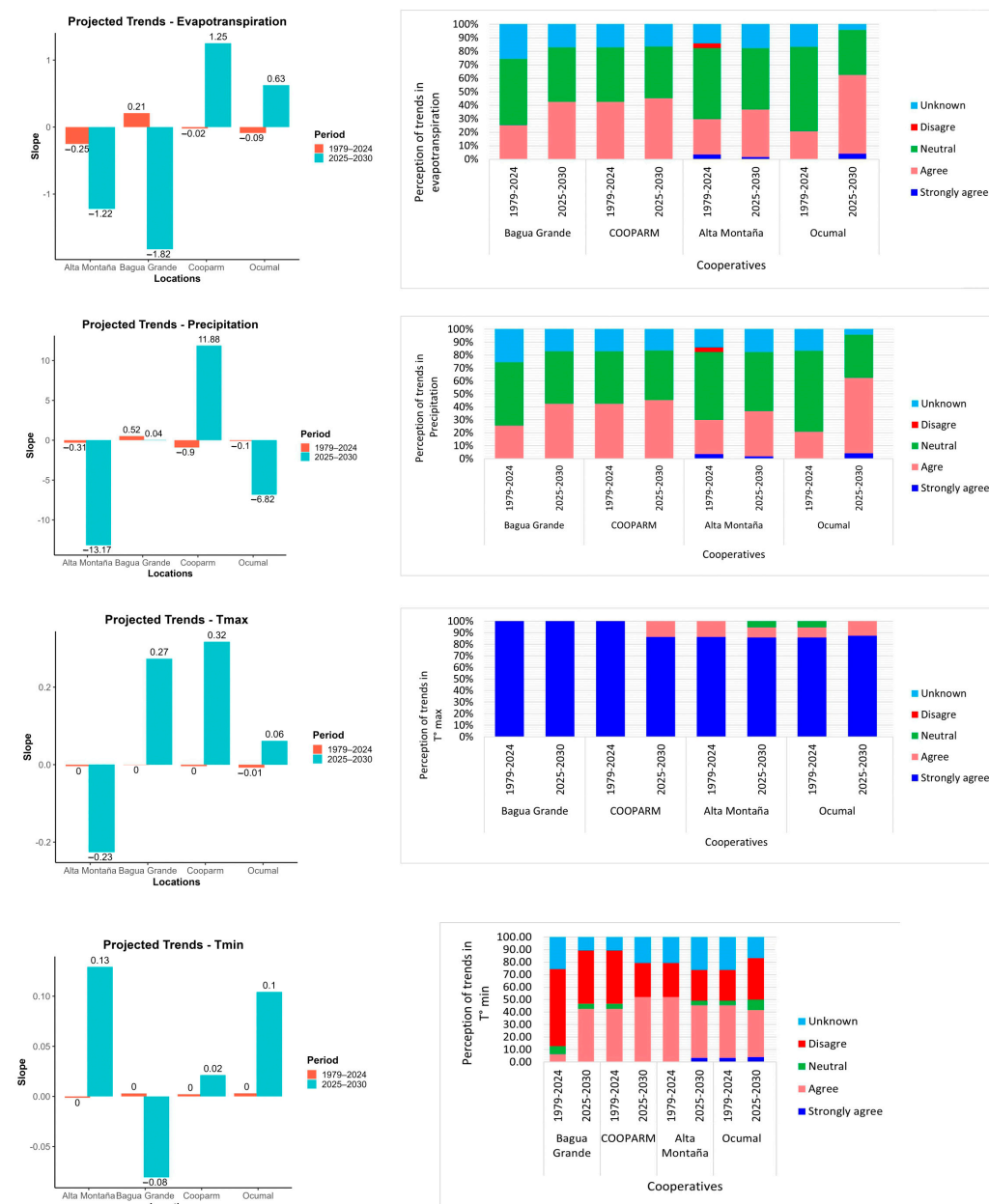


Figure 7. Cont.

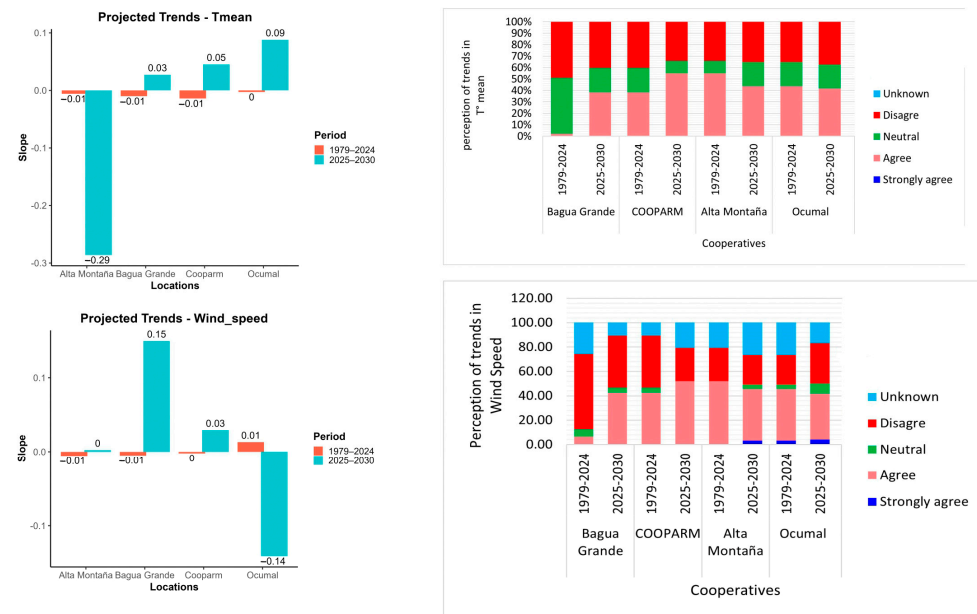


Figure 7. Trends versus perception (current climate).

About precipitation, there is a consensus on irregularity. On average, 78% of the coffee growers surveyed said that rainfall has become more irregular in the last ten years. This perception coincides with the negative or fluctuating trends observed in historical precipitation series. The Bagua Grande cooperative has the most pronounced perception: 86% of producers say that it rains less than before or that rainfall is more concentrated, which coincides with the downward trend observed ($-0.9 \text{ mm year}^{-1}$). At COOPARM, 82% report a reduction or alteration in the seasonal pattern, reflecting the irregular rainfall peaks recorded since 2015. In Alta Montaña, where the historical rainfall trend is slightly positive, only 63% perceive noticeable changes, indicating that producers interpret rainfall as “shorter but more intense.” In the Ocumal Cooperative, the perception of change is lower (58%), probably due to its naturally high rainfall regime ($>190 \text{ mm}$ monthly average), which softens the feeling of deficit. Despite these differences, more than 70% of respondents overall consider that extreme events (intense rainfall or prolonged droughts) are now more frequent. This coincidence with the anomalies recorded between 2010 and 2023 reinforces the reliability of local empirical knowledge as an early indicator of climate variability.

In the temperature variable, there were divergences between data and perception. The most obvious contrast is observed in air temperature. Although historical series show an average increase of $+1.4^\circ\text{C}$ in maximum temperature and $+0.9^\circ\text{C}$ in minimum temperature, only 46% of producers perceive that “it is hotter than before,” while 37% maintain that “the temperature has not changed significantly.” In the Bagua Grande cooperative, 62% notice greater heat during the day, especially in the summer months; however, 25% do not perceive any variation and 13% even consider that “mornings are colder.” At COOPARM, only 48% perceive a temperature rise, while 40% believe that the climate remains the same. Furthermore, at the Alta Montaña cooperative, 58% perceive that “temperatures are more pleasant” or “more temperate,” indicating possible confusion between gradual warming and thermal mitigation caused by tree shade. In Ocumal, only 34% perceive a temperature rise, while 50% consider that conditions have remained stable.

In terms of humidity and dryness in the environment, 65% of farmers report experiencing lower humidity levels, with variations that are altitude dependent. In Bagua Grande and COOPARM, 74% and 69% of farmers, respectively, describe their environment as “drier,” which aligns with the observed increase in evapotranspiration of approximately

0.7 mm per year. In Alta Montaña, 52% perceive greater dryness, while 30% believe the climate remains humid. In Ocumal, only 41% feel a sense of dryness, likely due to ongoing humid conditions with a monthly average precipitation exceeding 200 mm. These statistics indicate a clear spatial correlation between the projected water deficit and the perception of moisture loss. In the lowland areas (Bagua Grande, COOPARM), there is a more substantial alignment between data and local perceptions. In contrast, the highland areas (Alta Montaña, Ocumal) tend to underestimate the actual dryness caused by the indirect effects of warming, even if they recognize its physical causes.

Regarding wind, the perception of change is less consistent. Only 39% of producers noted an increase in wind intensity or frequency, while 51% reported no noticeable variations. In Bagua Grande, 42% of farmers perceive “stronger winds in summer.” In COOPARM, 48% of observations showed an increase in wind associated with storms. Conversely, in Alta Montaña and Ocumal, 35% and 31%, respectively, mentioned that they believe “the wind blows the same as before.” This moderate perception corresponds with recorded stability in wind speed, averaging between 0.7 and 0.8 m/s, with occasional seasonal peaks (Figure 7).

Overall, coffee growers demonstrated a strong awareness of rainfall variability and extreme events. However, their understanding of gradual increases in minimum and maximum temperatures was more limited, despite these factors significantly impacting coffee production.

4. Discussion

4.1. Current Climate Trends

Recent findings indicate a consistent trend of rising maximum and average temperatures across all coffee cooperatives, which aligns with global and regional reports on warming in tropical coffee-growing areas [15,69]. This warming is associated with adverse climatic conditions, including continuous temperature increases, irregular annual rainfall, hailstorms, strong winds, floods, and hurricanes. These factors negatively impact coffee yields in the central producing regions of the Americas, Asia, and Africa [70]. Notably, this trend is also evident in coffee cooperatives in northern Peru. The observed increase of approximately +1.4 °C in maximum temperatures (Tmax) and +0.9 °C in minimum temperatures (Tmin) from 1979 to 2024 reflects a sustained thermal transition that could affect the metabolism and yields of Arabica coffee, a species that thrives at temperatures between 18 and 22 °C [70,71].

The identified altitude-related temperature gradient, with higher values in Bagua Grande and COOPARM, and lower values in Alta Montaña and Ocumal, demonstrates the significant influence of altitude and tree cover on the microclimate [72]. These findings are consistent with studies in Brazil [73] and Ethiopia [74], which show that agroforestry systems act as natural thermal moderating factors, reducing air temperatures by 2–4 °C. However, the overall increase in temperatures may gradually alter the local climate and its impact on coffee cultivation.

4.2. Anomalies and Time Series

The anomalies detected in the time series confirm the occurrence of recurring extreme weather events associated with El Niño and La Niña phenomena [75,76]. Positive temperature anomalies were recorded in 1997, 1998, 2010, and 2016, coinciding with warm phases in the Pacific Ocean. Notable rainfall deficits were observed in 1995, 2014, and 2017, which were years linked to regional droughts [77]. These episodes highlight the high interannual sensitivity of coffee systems to variations in oceanic and atmospheric conditions [78,79].

A graphical analysis of Figures 1–4 reveals that while temperatures tend to increase steadily, rainfall patterns exhibit irregularity, alternating between wet and dry periods with significant variability [80,81]. This temporal variability is crucial for agricultural planning, as it impacts both phenology (the timing of flowering) and grain quality [78,82]. Cooperatives located in low-lying areas, such as Bagua Grande (COOPARM), are particularly vulnerable to water stress. In contrast, those situated at higher altitudes, like Alta Montaña and Ocumal, face risks of saturation and fungal diseases.

The observed pattern aligns with the global literature, which warns of a simultaneous increase in the frequency of both droughts and torrential rains. This situation reduces the optimal intermediate periods for cultivation [83,84]. These findings underscore the necessity for local water and soil management strategies, along with community climate monitoring, to maintain productivity in an environment of greater uncertainty [85].

4.3. Perceptions of Coffee Growers in Associations and Cooperatives in the Amazon Region

The results indicate that coffee growers possess a remarkable ability to recognize changes in rainfall and humidity [86,87], but they tend to underestimate the effects of thermal warming [88]. On average, 78% of these growers perceive irregular rainfall, while only 46% recognize an increase in temperature. This observation is consistent with prior studies conducted in Ethiopia [89], where farmers primarily connect climate change to alterations in rainfall rather than cumulative heat [90].

Different patterns emerge among the cooperatives: Bagua Grande and COOPARM demonstrate a high degree of alignment between growers' perceptions and objective data. In contrast, Alta Montaña and Ocumal, situated in humid areas with dense shade, exhibit a lower perception of warming. The role of agroforestry systems is essential in this context, as tree shade not only reduces thermal exposure but also creates a stable microclimate [9].

Additionally, 65% of producers report experiencing greater environmental dryness, with Bagua Grande (74% of coffee growers) and COOPARM (69% of coffee growers) being particularly affected. This aligns with observed increases in evapotranspiration. Understanding these perceptions will facilitate the development of strategies to optimize water use in coffee cultivation, considering the climatic and soil conditions typical of the intertropical Andean region, particularly on hillsides [91].

In contrast, only 41% of coffee growers in Ocumal perceive dryness, which reflects the ongoing high rainfall regime of over 200 mm per month. Perceptions regarding wind are mixed, with 39% of growers noting an increase; this aligns with the stable historical data reported by Capstick in 2015 [92]. This set of perceptions suggests that coffee growers primarily interpret climate change through its impacts on crop performance and phenology, particularly in relation to flowering, pests, and soil moisture. Notably, 82% of growers associate the rising incidence of coffee rust and broca beetles with climate change, demonstrating a validated understanding of global warming. These findings highlight the importance of local knowledge as a valuable monitoring tool and as a foundation for developing participatory adaptation strategies [51].

4.4. Future Limitations

While the SARIMA model provides robust short-term projections for 2024–2030, its univariate nature does not account for the physiological and socioeconomic variables that affect the resilience of the coffee system. Future research should consider integrating multivariate or machine learning models that incorporate climatic, edaphic, and management factors to improve our understanding of the interactions between these elements.

Another limitation is the spatial scale: Climate Engine satellite data provides regional coverage but fails to capture the microvariability present on individual farms, which is

particularly important in mountainous areas like Amazonas. Establishing cooperative weather stations would enable the collection of local data and enhance climate literacy among producers.

Additionally, farmers' perceptions of climate change encompass not only environmental conditions but also their cognitive and cultural contexts. Therefore, adaptation programs must blend scientific information with participatory educational processes, fostering the co-creation of knowledge. In this regard, strengthening cooperative governance, diversifying tree shade, and connecting climate science with traditional agricultural knowledge are vital strategies for creating a resilient and sustainable coffee industry in the northern Peruvian Andes.

This study did not include quantitative data on coffee yields due to the lack of availability and inconsistent long-term production records at the cooperative level. Coffee yields are significantly influenced by management practices, renovation cycles, pest outbreaks, and market decisions, which can obscure the direct impacts of climate. Future research should incorporate standardized yield datasets alongside climatic variables to enhance causal inference. Nonetheless, the inclusion of farmers' perceptions in this study offers a valuable perspective, highlighting how climate variability affects production conditions and decision-making processes within coffee cooperatives.

5. Conclusions

Historical trend analyses from 1979 to 2024 indicate a sustained increase in both maximum and average temperatures within the coffee cooperatives of Amazonas. This rise in temperatures is accompanied by significant variability in precipitation and wind speed. Climate anomalies point to recurring extreme events, such as water shortages in Bagua Grande and COOPARM, as well as excessive rainfall in Alta Montaña and Ocumal. These events directly affect producers' perceptions of irregular rainfall patterns.

Climate projections for 2030 suggest a gradual temperature increase of approximately 1.5 °C and a reduction in rainfall in certain areas, which could negatively impact productivity and heighten the risk of pests and diseases. A comparison between scientific findings and producers' perceptions reveals some alignments, such as the recognition of irregular rainfall and a higher incidence of pests. However, there is a divergence regarding the positive temperature trend, which coffee growers do not seem to perceive. This discrepancy underscores existing information gaps that hinder the implementation of effective adaptation measures.

To address these challenges, it is essential to strengthen climate training programs, utilize agroclimatic information systems, and promote adaptation practices within cooperatives. This approach should encourage the integration of scientific models with local knowledge to enhance the resilience of regional coffee farming.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/agriculture16010057/s1>, Table S1. Georeferenced for each cooperative.

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