v. 5, n. 4, 2025

International Journal of Biological and Natural Sciences

Acceptance date: 19/12/2025

TEMPERATURE BEHAVIOR IN THREE SOIL TYPES USING THE MANN-KENDALL AND SEN'S SLOPE TESTS ON THE ECUADORIAN COAST

Manuel Mesias Monar Solorzano
Facultad de Ciencias de la Educación Filosóficas y Humanisticas, Universidad Estatal de Bolívar, Guaranda Ecuador

Manuel Abarca Zaquinaula
Facultad de Ciencias Agropecuarias y Recursos Naturales de la Universidad Técnica de Cotopaxi, Latacunga. Ecuador

Darwin Llacsaguache Calle
Facultad de Ciencias departamento de estadística, Universidad nacional de Piura, Perú

Mariela Soledispa Gutiérrez
Departamento de Estadística, Universidad Nacional de Tumbes, Perú

Ángel Ramón Sabando-García
Escuela de Ciencias Sociales y Humanidades Pontificia Universidad Católica del Ecuador Sede Santo Domingo, Santo Domingo, Ecuador

Jorge Zavaleta
Departamento de Ciências ambientales. Universidad Federal Rural de Rio de Janeiro (UFRRJ). Bolsista de Pós-Doutorado Júnior (CNPq). Brasil

Abstract. Global changes in climatic factors are generating significant impacts on agricultural systems, especially in equatorial regions where agriculture is a predominant activity. In this context, the present study analyzed the influence of ambient temperature on three types of agricultural soils with different types of cover: bare soil, dry cover (mulch), and live cover (grass). A climate dataset recorded over six consecutive years, from 2015 to 2020, was used, with measurements taken at a depth of 20 cm in humid tropical agricultural soils. The research combined descriptive statistical analyses with linear regression models and Pearson correlation coefficients to establish relationships between ambient and soil temperatures. In addition, the non-parametric Mann-Kendall and Sen's slope methods were applied to detect and quantify trends in the temperature time series. The results showed statistically significant correlations between ambient and soil temperatures, with greater thermal stability observed in soils with live and dry vegetative cover. The trends identified indicate a decrease in ambient temperature (-23.22%) and a stronger negative trend in soils covered with grass (-32.63%) and mulch (-28.54%), compared to bare soils. These patterns were consistent at both annual and monthly levels. It is concluded that vegetative cover acts as a thermal regulator for soil, mitigating extreme temperature fluctuations. Continuous monitoring of these variables is essential to anticipate the effects of climate change on tropical agricultural systems and to propose adaptive strategies that support the sustainability of production.
Keywords: soil temperature, agricultural soil, climate change, vegetative cover.

INTRODUCTION

In the context of climate change, a sustained increase in thermal variability has been documented, directly affecting the dynamics of terrestrial ecosystems (Del Río et al., 2012; Bhutiyani et al., 2007). At a regional scale (mesoscale), particularly in equatorial countries such as Ecuador, these thermal changes have direct repercussions on agricultural production and food security, with soil being one of the most vulnerable and climate-sensitive components (Sabando-García et al., 2024). In this regard, soil temperature emerges as a key environmental parameter, influencing microbial activity, nutrient availability, root development, and plant productivity (Feng et al., 2019; Mall et al., 2021). At the local scale (microscale), the type of vegetation cover substantially alters soil temperature, with notable differences observed between bare soils and those protected by live or dead covers (Lingxue et al., 2022; Maiken et al., 2024).

Recent studies have shown that the relationship between air and soil temperature is not strictly linear, and may be mediated by factors such as solar radiation, soil moisture, vegetation cover, and topography (Bayatvarkeshi et al., 2021; Oluwaseyi et al., 2022). In fact, it has been observed that vegetation restoration has a mitigating effect on both air and soil temperatures, with the latter being more sensitive to changes in vegetative cover (Dorau et al., 2022; García-García et al., 2023). Understanding these thermal patterns is essential for sustainable agricultural adaptation, particularly in coastal areas of Ecuador, where agricultural soils face thermal stress conditions at certain times of the year (Gadedjisso-Tossou et al., 2021).

To evaluate these thermal dynamics, various authors have employed robust, non-parametric statistical tools such as the Mann-Kendall (MK) test and Sen's slope estimator (SS), due to their ability to detect monotonic trends in time series without requiring the assumption of a normal distribution (Wang et al., 2020; Gocic & Trajkovic, 2013). These methods have been successfully applied in multiple regions to analyse trends in maximum and minimum temperatures, precipitation, and runoff, revealing significant variations associated with climate change (Frimpong et al., 2022; Atta-ur-Rahman & Dawood, 2017; Gupta & Verma, 2023). In specific studies on soil temperature, it has been confirmed that Sen's slope effectively estimates the magnitude of thermal change, even in the presence of noisy or outlier data (Manoj et al., 2018; Roshani et al., 2023).

Likewise, the use of regression and correlation models between air temperature and soil temperature has been reported as an effective approach for assessing their degree of interaction, with important implications for the design of mitigation strategies (Li et al., 2023; Brown et al., 2000). However, there remains a need for local studies that incorporate vegetation cover variables, multi-year data series, and reliable statistical methodologies to better understand thermal trends in agricultural soils.

In this context, the present study aims to analyse soil temperature trends under different types of vegetative cover (bare soil, mulch, and grass), and their relationship with ambient temperature in the coastal region of Ecuador over the period 2015–2020. To this end, the Mann-Kendall and Sen's slope tests were applied, following the pre-whitening of the time series (Frimpong et al., 2022), which allowed the identification of both the direction and magnitude of thermal trends in a real agricultural setting. This approach seeks to contribute scientific evidence applicable to agronomic planning and climate monitoring in equatorial regions.

MATERIALS AND METHODS

STUDY AREA

This research was conducted at the meteorological station of the Escuela Superior Politécnica Agropecuaria de Manabí (ESPAM), located on the university campus at the geographical coordinates: latitude 0° 49' 10" south, longitude 80° 10' 40" west, and an altitude of 15 metres above sea level. The study covered the period from the beginning of 2015 to the end of 2020. This area presents agroclimatic conditions typical of the Ecuadorian coastal region, with an average annual temperature of 26 °C, average annual precipitation of 1027 mm, relative humidity of 82%, and an approximate sunshine duration of 1113.3 hours/year (Sabando et al., 2020).

The predominant crops in the surroundings of the agrometeorological station include fine-flavour national cocoa, plantain, pitahaya, cotton, maize, peanut, watermelon, and melon, as well as minor crops such as cassava and various vegetables. The data collected at this station provides strategic climatic information to support agronomic decision-making for thousands of farmers in the cantons of Junín, Bolívar, Tosagua, and Chone.

DATA COLLECTION

Ambient temperature measurements were obtained from ESPAM's meteorological station records during the 2015–2020 period. Data were collected in three daily time slots: morning, afternoon, and evening, recording maximum, minimum, and average temperatures in degrees Celsius (°C). Simultaneously, thermal instrumentation was installed at a depth of 20 cm to measure soil temperature under three conditions: bare soil (no cover), soil with dry vegetative cover (mulch), and soil covered with grass. This depth was chosen due to its high biological activity, ion exchange, and root concentration (Feng et al., 2019).

In total, 13,140 raw data points were collected and subsequently averaged, resulting in 2,193 consolidated observations for the mean temperature in each soil type, as well as the same number for ambient temperature.

TREND ANALYSIS

The analysis of trends in climatic variables allows for the assessment of potential climate change effects on agriculture and other human activities. In this study, the trends in ambient and soil temperature under different vegetative covers were examined using the non-parametric Mann-Kendall and Sen's Slope methods (Kumar et al., 2023). These methods have proven suitable for time series analysis without the assumption of normality, making them especially useful in variable and heterogeneous climatic contexts (Chakraborty & Joshi, 2016).

The Mann-Kendall test detects the presence of a monotonic trend (increasing or decreasing), while Sen's slope estimator quantifies the magnitude of the trend. Both procedures were complemented with statistical significance testing at the 5% level to validate the results (Roshani et al., 2023), providing a robust basis for interpreting the observed thermal changes.

MANN-KENDALL TEST (MK)

The analysis of climate trends in time series requires statistical techniques that do not rely on strict assumptions such as data normality. For this reason, the Mann-Kendall test (MK), a non-parametric method ideal for detecting monotonic trends (increasing or decreasing) in variables such as air and soil temperature without the need for data transformation, was employed in this research (Zhiqiang et al., 2021; Wang et al., 2020). This approach has been widely validated in hydrometeorological and climate studies due to its robustness against skewed distributions and its sensitivity to gradual changes (Alencar et al., 2017; Mann, 1945; Kendall, 1975).

The MK test is based on the comparison of all possible pairs of values within the time series, assigning a positive or negative sign depending on the direction of the change. The S statistic is calculated using equation (1):

$$S=\sum_{b=1}^{n-1}\sum_{c=b+1}^{n} sign(x_c - x_b) \tag{1}$$

where x_b and x_c represent values of the variable in years b and c, respectively, and n is the total number of observations. A positive S indicates an upward trend, whereas a negative S suggests a downward trend.

To evaluate the statistical significance of this trend, the variance of S is calculated using equation (2), which accounts for ties in the data.

$$var(s)=\frac{1}{18}\left[n(n-1)(2n+5)-\sum_{p-1}^{q} f_p(f_p-1)(2f_p+5)\right] \tag{2}$$

where f_p is the number of tied values in group p, and q is the total number of tie groups. Subsequently, the Z statistic is calculated to test the null hypothesis of no trend, using equation (3).

$$z=\begin{Bmatrix} (s-1)/sr, & if s>0 \\ 0, & if s=0 \\ (s-1)/sr, & if s<0 \end{Bmatrix} \tag{3}$$

SEN'S SLOPE ESTIMATOR

Sen's slope test, also known as the Theil-Sen estimator, was used in this study to calculate the magnitude of the trend in both air and soil mean temperatures across different ground covers. This non-parametric technique is based on the median of all possible slopes between data pairs, making it resistant to outliers and noise in time series (Gupta & Verma, 2023; Sen, 1968; Theil, 1992).

Each slope between two observations is calculated using equation (4).

$$T_i = \frac{x_{ab} - xac}{j - k} \quad for \quad a = 1,2,3,\ldots N \tag{4}$$

where x_j and x_k are observed values at times j and k. The full set of slopes T_i is then sorted, and Sen's slope (Q) is defined as the median of this set, as per equation (5).

$$Q = \begin{cases} T_{\left[\frac{N+1}{2}\right]}, & if \ N \ is \ odd \\ \dfrac{T_{\left[\frac{N}{2}\right]} + T_{\left[\frac{N+2}{2}\right]}}{2} & if \ N \ is \ even \end{cases} \tag{5}$$

This test has become a standard in climate change studies, as it enables the quantification of variation rates with precision and without biases from extreme values. Its use has been extended to the analysis of hydrological variables, air temperature, humidity, and, in this study, soil temperature under different vegetative covers (Agarwal et al., 2021; Malik et al., 2020).

Sen's slope has proven to be an effective tool for assessing warming or cooling rates in agricultural ecosystems, providing an objective numerical value that complements the significance analysis performed using the Mann-Kendall test (Ray et al., 2021; Worku et al., 2019). In this work, it was employed to identify not only the presence of a thermal trend but also its intensity according to soil type: bare, mulched, or grass covered.

COEFFICIENT OF VARIATION (CV)

In this study, the coefficient of variation (CV) was used as a statistical measure to assess the degree of dispersion of temperature values in relation to their mean. This metric quantifies relative variability, where a higher CV indicates greater instability in the data (Sarkar et al., 2021). Spatial and temporal patterns in temperature standard deviation were also identified, highlighting the importance of considering both daily and monthly averages in thermal variability analyses (Volodin & Yurova, 2013).

According to the classification proposed by Asfaw et al. (2018), CV magnitude can be categorised as very high (CV > 40%), high (CV > 30%), moderate (20% ≤ CV ≤ 30%), and low (CV < 20%). This classification is useful for interpreting thermal stability across different soil types and times of day. The coefficient is calculated using equation (6).

$$CV = \frac{S}{\mu} * 100 \tag{6}$$

where S represents the standard deviation and μ the mean temperature. As a proportional measure, it is expressed as a percentage. This tool is widely used in experimental studies due to its effectiveness in comparing variability between treatments.

STATISTICAL ANALYSIS

Data processing was carried out using the RStudio statistical environment, version 4.1.2, due to its open-source programming framework and applicability in climate studies (Sabando-García et al., 2024). Temperature trends for both air and soil were evaluated using the Mann-Kendall and Sen's Slope tests, through the installation of the trend package, applying the functions mk.test() and sens.slope().

These functions provide key statistical outputs such as the Gaussian Z-statistic, sample size (n), p-value, confidence intervals, variance, standard deviation, Kendall's tau (τ) correlation coefficient, and Sen's slope estimator. The modelling of the effect of air temperature on soil temperature, differentiated by type of vegetative cover, was performed through linear regression using packages such as tidyverse, colourpicker, psych, GGally, xts, and ggplot2. This enabled the extraction of relevant indicators including model estimators, Student's t statistic, p-values, correlation and determination coefficients (R^2), and Fisher's test applied to the residuals (Elsayed et al., 2023).

RESULTS

This section presents the analysis of thermal behavior in the coastal region of Ecuador, considering both air temperature and soil temperature under different coverage conditions (bare soil, mulch, and grass) during the period 2015–2020. Linear regression analyses and significance tests were employed to determine the relationships between variables, while non-parametric tests (Mann-Kendall and Sen's Slope) were used to evaluate trends.

Figure 1 illustrates the evolution of air and soil temperatures by vegetation cover. It can be observed that the lowest temperatures correspond to air, while bare soil exhibited the highest thermal values. In contrast, soils covered with mulch and grass recorded more stable temperatures, with reduced variability and thermal amplitude, evidencing their attenuating effect against environmental changes.

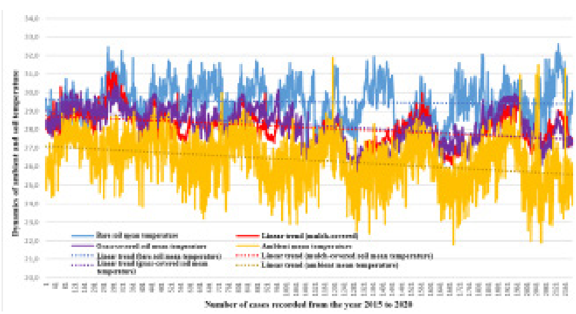

Figure 1. Dynamics of air and soil temperature.

Figure 2 analyses the impact of air temperature on bare soil. The linear model revealed a positive, albeit weak, relationship (R^2 = 3.78%), yet statistically significant. The regression coefficient was 0.159 °C for every one-degree increase in air temperature (p < 0.001), with an F value of 86.11 and a t statistic of 9.28, indicating a moderately increasing and consistent trend.

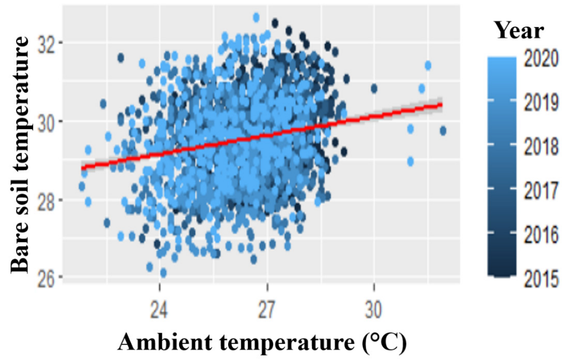

Figure 2. Impact of air temperature on bare soil temperature.

For soil covered with dry vegetative matter (mulch), Figure 3 shows a stronger relationship. The regression coefficient was 0.341 °C per degree of ambient temperature, with an explained variance of 26.57% (adjusted R^2 = 26.54%). The results were highly significant (p < 0.001), with F = 792.9 and t = 28.16. This suggests that such coverage enables a more direct soil response to environmental changes, while still providing a buffering effect.

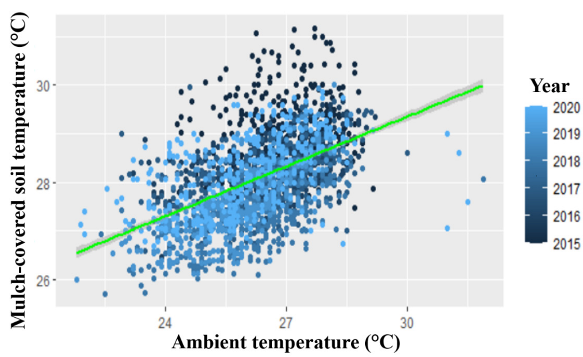

Figure 3. Influence of air temperature on soil covered with mulch.

Lastly, Figure 4 represents the effect of air temperature on grass-covered soil. A positive correlation was observed with a coefficient of 0.386 °C per degree of ambient temperature, and an explained variance of 27.64% (adjusted R^2 = 27.61%). The model was statistically significant across all tests (p < 0.001), including F = 837.1 and t = 28.93. This type of live coverage maintained more stable temperatures but demonstrated higher sensitivity to climate change than mulch.

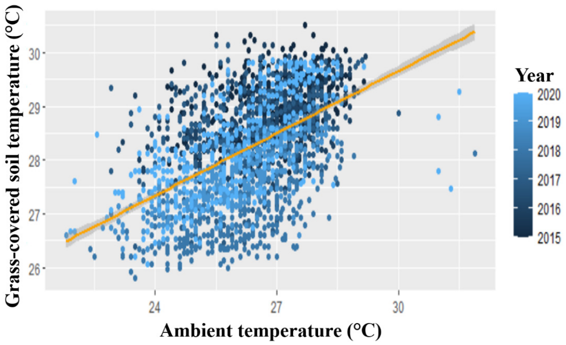

Figure 4. Incidence of air temperature on grass-covered soil.

These results highlight the moderating effect of vegetation cover on soil temperature. As interaction with the environment increases—as observed in bare soil—thermal variability tends to rise, whereas vegetative covers, particularly grass, stabilise temperature fluctuations and exhibit a more homogeneous response to ambient warming.

TRENDS IN AIR AND SOIL TEMPERATURE

The descriptive and trend analyses for the 2015–2020 period are presented in Table 1. Overall, bare soil exhibited the highest temperature values (M = 29.50 °C), exceeding those recorded under dry mulch (M = 28.11 °C) and live grass cover (M = 28.25 °C). In contrast, air temperature showed the lowest average value (M = 26.35 °C).

Regarding variability, both the standard deviation and the coefficient of variation (CV) indicate greater thermal stability in soils with vegetation cover, with CV values below 3.5%, suggesting low data dispersion. This reduced variability reflects the buffering effect of vegetative layers against external thermal fluctuations.

With respect to trend analysis, the Mann-Kendall (Zc) and Sen's Slope coefficients confirmed a statistically significant negative trend across all variables. The strongest downward trends were found in grass-covered (Tau = –32.63%) and mulch-covered soils (Tau = –28.54%), while bare soil and ambient air temperature showed less marked declines (Tau = –3.76% and –23.22%, respectively). This suggests that protected soils have responded more noticeably to regional climatic changes during the study period.

The monthly trend analysis of bare soil temperature is summarised in Table 2, assessing the significance of changes through the Mann-Kendall and Sen's slope tests. A significant negative trend was observed in six months of the year, January, June, July, October, and December with Tau coefficients ranging from –13.2% to –29.1%. These findings reflect a progressive thermal decline during those months, which may be linked to local seasonal variations.

On the other hand, the months of March, April, and November did not exhibit statistically significant trends, while February, May, August, and September showed slight but non-significant negative trends. This indicates a certain degree of thermal stability during these months, possibly influenced by microclimatic factors, interannual variability, and local edaphoclimatic characteristics.

Table 3 presents the trend analysis of soil temperature under dry vegetative cover (mulch). In contrast to bare soil, this condition exhibited a negative trend throughout all months of the year, although only the months from May to December showed statistically significant results. These months coincide with the dry season across various agricultural areas of the Ecuadorian coast, which may explain the more pronounced thermal decline observed.

Temperature type	Mean (M)	SD (Dt)	CV	Zc	P-value	Tau (%)	Sen's slope	Description
Ambient	26.35	1.31	4.97	-16.153	<0.001	-23.22	-0.0007	Significant negative trend
Bare soil	29.50	1.08	3.66	-26.243	0.009	-3.76	-0.0001	Significant negative trend
Mulch-covered soil	28.11	0.87	3.09	-19.856	<0.001	-28.54	-0.0006	Significant negative trend
Grass-covered soil	28.25	0.96	3.40	-22.780	<0.001	-32.63	-0.0008	Significant negative trend

Table 1. Trends in air and soil temperature using the Mann-Kendall and Sen's slope tests.

Notes: p-values were calculated using the Mann–Kendall test; $p < 0.01$ denotes statistical significance; Zc: Mann–Kendall standardized test statistic; Tau: Kendall's Tau correlation coefficient; Sen's slope: Median slope of the trend.

Month	Mean (M)	SD (Dt)	CV	Zc	P-value	Tau (%)	Sen's slope	Description
January	28.81	0.90	3.14	-2.655	0.007	-13.20	-0.003	Significant negative trend
February	28.49	0.66	2.32	-0.865	0.387	-4.50	-0.000	Non-significant negative trend
March	29.39	0.94	3.20	0.305	0.760	1.50	0.000	No trend
April	29.70	0.79	2.66	1.606	0.108	8.00	0.002	No trend
May	29.61	0.95	3.20	-0.379	0.704	-1.80	-0.000	Non-significant negative trend
June	29.11	1.06	3.65	-4.243	<0.001	-21.46	-0.006	Significant negative trend
July	28.68	0.85	2.98	-5.847	<0.001	-29.11	-0.006	Significant negative trend
August	29.61	0.83	2.79	-0.991	0.322	-4.94	-0.001	No trend
September	30.05	0.95	3.15	-1.202	0.229	-6.07	-0.001	No trend
October	30.39	0.78	2.56	-2.838	0.005	-14.18	-0.003	Significant negative trend
November	30.57	0.75	2.46	0.529	0.596	2.68	0.000	No trend
December	29.59	1.03	3.47	-2.754	0.006	-13.69	-0.004	Significant negative trend

Table 2. Behaviour of bare soil temperature based on Mann-Kendall and Sen's slope tests.

Month	Mean (M)	SD (Dt)	CV	Zc	P-value	Tau (%)	Sen's slope	Description
January	28.00	0.54	1.93	-2.690	<0.01	-13.45	-0.001	Significant negative trend
February	28.14	0.52	1.85	1.109	0.267	5.83	0.000	Non-significant positive trend
March	28.65	0.56	1.96	-0.607	0.544	-3.05	0.000	Non-significant negative trend
April	28.71	0.53	1.84	0.852	0.394	4.35	0.000	Non-significant positive trend
May	28.63	0.61	2.12	-2.735	<0.01	-13.67	-0.002	Significant negative trend
June	27.82	0.76	2.75	-8.251	<0.001	-41.84	-0.007	Significant negative trend
July	27.34	0.86	3.16	-10.145	<0.001	-50.75	-0.011	Significant negative trend
August	27.60	0.91	3.28	-9.412	<0.001	-46.88	-0.011	Significant negative trend
September	28.02	1.05	3.76	-8.984	<0.001	-45.46	-0.012	Significant negative trend
October	28.26	1.08	3.83	-9.140	<0.001	-45.65	-0.014	Significant negative trend
November	28.25	0.78	2.76	-4.533	<0.001	-22.99	-0.005	Significant negative trend
December	27.88	0.70	2.51	-6.043	<0.001	-30.13	-0.006	Significant negative trend

Table 3. Monthly trend of soil temperature under dry vegetative cover (mulch).

Month	Mean (M)	SD (Dt)	CV	Zc	P-value	Tau (%)	Sen's slope	Description
January	28.10	0.68	2.42	-1.745	0.081	-8.70	-0.001	Non-significant negative trend
February	28.27	0.65	2.28	-1.374	0.169	-7.22	-0.000	Non-significant negative trend
March	28.89	0.72	2.51	-1.201	0.229	-6.02	-0.001	Non-significant negative trend
April	28.99	0.61	2.09	-1.891	0.058	-9.63	-0.001	Non-significant negative trend
May	28.87	0.70	2.43	-4.700	<0.001	-23.55	-0.005	Significant negative trend
June	28.26	0.97	3.45	-7.776	<0.001	-39.40	-0.008	Significant negative trend
July	27.89	0.92	3.30	-8.279	<0.001	-41.27	-0.009	Significant negative trend
August	28.06	1.13	4.01	-7.464	<0.001	-37.16	-0.012	Significant negative trend
September	27.80	0.99	3.55	-9.087	<0.001	-45.93	-0.011	Significant negative trend
October	28.03	1.17	4.17	-8.131	<0.001	-40.51	-0.014	Significant negative trend
November	27.98	0.78	2.79	-6.731	<0.001	-34.09	-0.008	Significant negative trend
December	27.86	0.91	3.27	-4.794	<0.001	-23.87	-0.008	Significant negative trend

Table 4. Soil temperature dynamics under grass cover using the Mann-Kendall and Sen's slope tests.

Month	Mean (M)	SD (Dt)	CV	Zc	P-value	Tau (%)	Sen's slope	Description
January	26.40	0.96	3.66	-0.069	0.944	-0.53	-0.000	Non-significant negative trend
February	26.93	0.95	3.52	-0.069	0.945	-0.36	-0.000	Non-significant negative trend
March	27.42	0.85	3.10	-2.883	0.003	-14.47	-0.003	Significant negative trend
April	27.49	0.88	3.19	-0.189	0.849	-0.97	-0.000	Non-significant negative trend
May	27.09	0.91	3.38	-5.414	<0.001	-27.06	-0.006	Significant negative trend
June	26.10	1.25	4.77	-8.533	<0.001	-43.24	-0.015	Significant negative trend
July	25.43	1.23	4.83	-7.255	<0.001	-36.15	-0.012	Significant negative trend
August	25.67	1.30	5.05	-6.468	<0.001	-32.24	-0.010	Significant negative trend
September	25.85	1.32	5.10	-6.667	<0.001	-33.72	-0.012	Significant negative trend
October	25.81	1.31	5.06	-3.180	0.001	-15.88	-0.005	Significant negative trend
November	25.87	1.21	4.69	-5.308	<0.001	-26.91	-0.009	Significant negative trend
December	26.17	1.19	4.55	-5.896	<0.001	-29.40	-0.009	Significant negative trend

Table 5. Air temperature behaviour based on the Mann-Kendall and Sen's slope tests.

Additionally, during this period, there was a slight increase in both standard deviation and coefficient of variation, indicating a broader thermal fluctuation range under mulch cover in the second half of the year. This pattern may result from the interaction between dry cover and direct solar radiation during the warmer months, generating greater thermal amplitude at the soil surface.

Regarding the soil covered with live vegetation (grass), the monthly trend analysis revealed a consistent decreasing pattern throughout the year, as shown in Table 4. The most significant negative trends were concentrated between May and December, with Tau coefficients reaching −45.93% (September) and Sen's slope values of up to −0.014 °C per month (October). These results reflect a sustained decline in soil temperature under grass cover during the coastal dry season in Ecuador, typically extending from May to December.

During the same period, a progressive increase in standard deviation and coefficient of variation (CV) was observed, peaking at 4.17% in October. This suggests a greater thermal variability under live cover, indicating that although grass helps reduce soil temperature, it may also amplify temperature fluctuations under certain local climatic conditions.

Regarding air temperature, the main causal variable in this study, Table 5 shows a general negative trend throughout the year, though statistically significant only from March and from May to December. During this interval, Tau coefficients reached –43.24% (June), and Sen's slope values ranged from –0.003 to –0.015 °C per month.

Although monthly mean air temperatures remained relatively stable, ranging from 25.4 °C to 27.5 °C, the standard deviation and coefficient of variation revealed increasing thermal variability during the drier months, with CV values of up to 5.10% in September. This confirms that despite relatively stable average thermal conditions, significant fluctuations occurred during the second half of the year, potentially associated with regional climatic phenomena such as El Niño or intra-seasonal variability in the equatorial zone.

DISCUSSION

The results obtained in this study reveal a statistically significant negative trend in soil temperature under live vegetative cover (grass), particularly between May and December, according to the non-parametric Mann-Kendall test and Sen's slope estimator. This decreasing pattern is consistent with findings from various international studies that have employed similar methodologies to analyse long-term thermal changes in terrestrial ecosystems. For instance, Frimpong et al. (2022) and Manoj et al. (2018) applied these tests to detect persistent trends in soil temperature, thereby validating their usefulness in climate change research.

The progressive temperature reduction observed in grass-covered soils may be attributed to the synergistic interaction between vegetative cover and atmospheric conditions. This aligns with the findings of Genxu et al. (2012), who highlighted the buffering role of vegetation in modulating soil thermal dynamics. Lingxue et al. (2022) further demonstrated that vegetation restoration not only reduces air temperature but has an even more pronounced effect on soil temperature, confirming the relevance of vegetative structure in regulating microclimatic conditions.

Regarding air temperature, a significant downward trend was also observed in most months, especially from March onwards. These results contrast with those reported by Gupta and Verma (2023) and Atta-ur-Rahman and Dawood (2017), who documented rising trends in annual maximum temperatures across Asian regions. Such discrepancies underscore the high dependency of thermal patterns on geographic, altitudinal, and land cover characteristics.

Although air temperature is commonly considered a predictor of soil temperature (Brown et al., 2000; Dorau et al., 2022), the findings of this study suggest that the relationship is neither strictly linear nor proportional. This supports the observations of Bayatvarkeshi et al. (2021), who argued that additional factors—such as soil moisture, solar exposure, physico-chemical soil properties, and agricultural management practices—can influence soil thermal dynamics (Oluwaseyi et al., 2022; García-García et al., 2023). In this context, the relatively stable air temperature means contrasted with greater thermal fluctuations in the soil further illustrate the complexity of thermal responses in agroecosystems.

A critical aspect identified in this study is the increase in the coefficient of variation (CV) during the warmest months, indicating greater thermal volatility. This may be linked to the broader impacts of climate change. According to Sabando et al. (2024), thermal variability could become a key driver of global warming in the long term, aligning with models that project sustained temperature increases under scenarios such as SSP5-8.5 (Iyakaremye et al., 2021).

On the other hand, while regions such as northern Pakistan have recorded rising maximum temperatures alongside falling minimum values (Atta-ur-Rahman & Dawood, 2017), the present study observed a uniformly decreasing trend. This could be explained by the continuous presence of vegetative cover and more stable orographic conditions, as similarly reported by Maiken et al. (2024) in valley environments characterised by greater humidity and shade.

Finally, the findings of this research confirm the relevance of applying the Mann-Kendall test and Sen's slope estimator to environmental time series, provided their sensitivity to white noise and sample size is considered (Wang et al., 2020). This study contributes to a better understanding of soil thermal dynamics in tropical contexts and offers empirical evidence to inform agricultural adaptation strategies and soil management practices in the face of climate variability, as suggested by Gadedjisso-Tossou et al. (2021) and Hamal et al. (2021).

CONCLUSIONS

This study analysed the effect of ambient temperature on agricultural soil temperature at 20 cm depth, differentiating among bare soil, soil with live vegetative cover (grass), and soil covered with dry organic matter (mulch), over the period 2015–2020 in a coastal agricultural zone. The results show that bare soils exhibit higher and more variable temperatures, while soils with live or dry cover maintain more stable thermal conditions that are favourable for root development, microbial activity, and nutrient exchange processes. Ambient temperature acted as a thermal moderator in protected soils—particularly those with grass cover—highlighting a complex but significant relationship between these variables.

Furthermore, the Mann-Kendall and Sen's slope tests revealed significant negative trends in soil temperature under live cover, especially during the dry season months. This may indicate a soil-level response to environmental changes or specific agricultural management practices.

Among the main limitations of this study is its focus on a single agroecological zone, which restricts the generalisability of the results to other regions with different climatic, altitudinal, or land-use conditions. Additionally, other relevant environmental variables—such as soil moisture, precipitation, and solar radiation—were not included, which could have enriched the analysis of thermal dynamics.

For future studies, it is recommended to expand the research to different regions along the Ecuadorian coast and highlands, consider longer time periods, and incorporate additional variables to more accurately model soil-climate interactions. It is also suggested to explore the combined effects of temperature and humidity on specific crops, to propose sustainable management strategies that enhance agricultural resilience in the face of climate variability.

ACKNOWLEDGMENTS

This study was partially funded by the Coordination for the Improvement of Higher Education Personnel - Brazil (CAPES) - Financial Code 001 and partially sponsored by CNPq – 150731/2024-8 Junior Postdoctoral Fellow. The authors thank CNPq for their productivity grants, ALDA Research Institute (CNPq Registration 490600000002), and I3S for their invaluable support in carrying out this study, providing the essential infrastructure for its execution.

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