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Short-term Response of Soil Temperature to Atmospheric Conditions

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ABSTRACT

Soil is very important for many purposes and it is directly affected by various atmospheric factors that are linked to its temperature. Moreover, soil temperature plays a significant role in both ecological and agricultural systems. It also has influence on various biochemical processes that affect plant growth, crop production, soil microbial and geological activities. Hence, it is so essential to determine the response of soil temperature to the various atmospheric conditions. The daily meteorological data utilised in this work were obtained from the Agro-Meteorology Station, Federal University of Agriculture, Abeokuta for the period January, 2014 – March, 2019, and were analysed to determine the short-term response of soil temperature to maximum air temperature, evaporation, and relative humidity using multiple linear regression model. In addition, the 5-fold cross-validation approach was employed to ascertain the performance of the obtained model, and to mitigate overfitting as well as providing a comprehensive evaluation of its predictive capabilities. The results of analysis revealed that the model has a high predictability value of 0.8174 for the coefficient of determination (R^2). Thus, this highlights the model's potential applicability in forecasting variations in soil temperature, using maximum air temperature, evaporation, and relative humidity as its significant predictors. Likewise, significant results were obtained for the correlation of soil temperature with all the atmospheric parameters considered. Also, the Mann-Kendall trend test utilised in examining how these variables have changed within the short period of investigation revealed that all the variables, except relative humidity, have significant increasing trend. This shows that the rate at which the climate change impact is been felt at this location is alarming, even within the short period of time. Therefore, the results of this study would be of great importance for agriculture, climate change, ecological conservation and geological purposes.

Keywords: Soil temperature, Atmospheric condition, Cross-validation, Correlation, Climate change impact

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1. INTRODUCTION

Understanding the interaction between soil temperature and atmospheric conditions is essential for various ecological and agricultural applications. Soil temperature plays an important role in regulating microbial activity, plant growth, and nutrient cycling, thereby influencing overall ecosystem health. By examining how the atmospheric conditions influence soil temperature, we can appreciate better how these interactions affect not only crop production but also broader ecological processes. Therefore, this work attempts to find the relationships between daily atmospheric conditions (maximum temperature, evaporation, and relative humidity) and soil temperature. Moreover, their short-term fluctuations to soil temperature as a direct response to atmospheric influences and the dynamics involved with regards to climate change is further explored.

Soil has been reported to be directly affected by various atmospheric factors including temperature, humidity, precipitation, and solar radiation among others. However, the extent of the effect varies in different parts of the earth [1], thereby creating the scope to investigate the relation between soil and key climatic variables in a specific zone. Soil temperature plays a significant and a crucial role in both ecological and agricultural systems. It influences various biochemical processes that affect plant growth and soil microbial activity. It acts as a primary factor in determining seed germination, root development, and nutrient availability which are critical elements in determining crop yields and ecosystem stability [2]. Below the ground surface, soil temperature is considered an important factor influencing ecosystem processes [1, 3]. It also aids many processes like soil respiration, crop production, pest growth, germination, and even pavement design [4].

Variations in soil temperature, often driven by atmospheric conditions, can lead to significant shifts in these processes. For example, climate change brings about fluctuations in temperature patterns, with possible repercussions magnifying the existing challenges posed by pests and diseases in agriculture [5]. In that regard, a deeper comprehension of these relationships is essential for sustainable land management and agricultural productivity. Soil temperature also varies in response to changes in the radiant, thermal, and latent energy exchange processes that take place primarily through the soil surface. The effects of these phenomena are propagated into the soil profile via a series of transport processes, the rates of which are affected by time-variable and space-variable soil properties.

1.1 Atmospheric Factors Influencing Soil Temperature

The proper understanding of the significant atmospheric factors influencing soil temperature is crucial for predicting short-term responses to varying climatic conditions. Solar radiation, snow depth, precipitation, air temperature, and moisture levels play significant roles in regulating soil temperature. For instance, increased incident solar radiation during summer months can lead to marked increases in soil temperatures due to the direct heating of the surface layer, subsequently affecting microbial activity and nutrient cycling in the soil.

In colder regions such as those underlain by permafrost, elevated air temperatures can induce thawing, releasing previously sequestered carbon and further impacting soil dynamics [6]. Changes in air temperature and other atmospheric factors, including precipitation and snow depth, affect soil temperature in a complex way [7]. Studies suggest that climate change impacts nutrient cycling, particularly nitrogen and phosphorus, which are becoming increasingly important [8]. Understanding these multifaceted relationships is essential for developing appropriate models to predict how soil temperature responds to atmospheric fluctuations and for assessing the broader implications for ecosystem health.

1.2 Variability of Soil Temperature

Soil temperature is critical for various processes, including physical, hydrological, and biogeochemical processes, but it exhibits high spatiotemporal variability. Its variability shows both diurnal and seasonal changes. The rate of these changes depends on the soil type, such as whether it is heavy or light, and whether it contains leaf litter. The extent of change also depends on prevailing climatic conditions. For example, the amount of water present in the soil, conditions for evaporation, and plant cover all play roles in determining soil temperature [9]. Also, the types and rates of chemical reactions in the soil, as well as evaporation and aeration, are governed by temperature [10]. Biological processes such as seed germination, growth, root development, and microbial activity are strongly influenced by soil temperature [10]. For instance, the observed regional differences in soil temperature trends have been attributed to changes in seasonal air temperatures, precipitation, and snow depth [1].

1.3 Soil Temperature and Climate Change

As climate change has altered atmospheric conditions including temperature [11, 12] and precipitation [13], it has also led to a shift in soil-climatic zones. For instance, in northern Russia, soil-climatic zones have shifted northward due to increasing air and soil temperatures [14]. However, research indicates that soil temperature trends are more stable and unbiased than air temperature trends for assessing global warming effects [14]. In Canada, air temperature and soil temperature at a depth of 20 cm increased by 1.0°C and 0.6°C, respectively. In China, soil temperature increases were negligible in warmer eastern and southern regions but more pronounced in colder northern and western regions [1]. Soil temperature has been identified as a critical indicator of climate change and its impacts on ecosystems. This highlights the importance of understanding soil temperature dynamics to adapt agricultural and ecological management strategies in the face of global warming.

2. METHODOLOGY

The daily atmospheric parameter data for soil temperature at 50cm (°C), maximum daily air temperature (°C), relative humidity at 3pm and evaporation (mm) obtained from the Federal University of Agriculture, Abeokuta (FUNAB) for the period, January 1, 2014 to March 31, 2019 were analysed using statistical analyses and the multiple linear regression model to determine the short-term response of soil temperature to maximum air temperature, evaporation, and relative humidity. Moreover, the cross-validation procedure was utilised in selecting the appropriate model that best fits these set of data. Thus, the 5-fold cross-validation approach was employed to ascertain the performance of the obtained model, and to mitigate overfitting, as well as providing a comprehensive evaluation of the model's predictive capabilities.

2.1 Outlier Detection and Winsorization

The boxplots were used to detect the presence of outliers in each of the variables, particularly in the soil temperature at 50cm (°C), humidity at 3pm and evaporation (mm), which may affect the results of the Mann-Kendall test used to detect the significance of variability in each data set. With the detection of outliers, the Winsorization method was applied to transform the extreme values in the data sets. Winsorization offers a more accurate representation of central trend and reduces the influence of these outliers. Thus, the Winsorization was utilised to give the data distribution more desirable statistical properties [15]. One of the advantages of this Winsorization is that it preserves the information among the lowest (or highest) values in a distribution and protects against some of the harmful effects of outliers.

2.2 Autocorrelation and Prewhitening

Many literatures [16-19] have suggested prewhitening (PW) of atmospheric data and other types of natural time series in eliminating the adverse effect of autocorrelation on trend test. This is because PW helps to address the issues regarding the alterations of variance and the different types of errors emanating from serial autocorrelation in datasets by the removal of such autocorrelation.

2.3 The Mann–Kendall Test

The Mann-Kendall test (MK test) is a nonparametric ranked-based statistical procedure widely used in detecting monotonic upward or downward trend in the time series of variable data in hydrology, meteorology, climatology and other atmospheric scientific-related research [11, 13, 20, 21, 22]. As a nonparametric test, it does not require distributional assumptions. Therefore, this study employs the MK test to estimate and assess the presence of trends in each of the variables, as it is robust to the influence of extremes with skewed variables [11, 23]. It was also used to verify whether the values of each variable exhibit a monotonic trend by computing the indicator function $sgn\,(x_j - x_k\,)$ for a *jk* time series of length n. However, the number of positive differences minus the number of negative differences between the precipitation data values (equation 1) in MK test is given as:

$$S = \sum_{k=1}^{\mathrm{n}-1} \sum_{j=k+1}^{\mathrm{n}} sgn\left(x_j - x_k\right) \tag{1}$$

where x_j and x_k are data values, n is the number of years observed in study, and sgn is an indicator function that takes on the values 1, 0, or −1 according to the sign of $\left(x_j - x_k\right)$ [11].

That is

$$sgn\left(\mathrm{x_j} - \mathrm{x_k}\right) = \begin{cases} +1, & if\left(x_j - x_k\right) > 0 \\ 0, & if\left(x_j - x_k\right) = 0 \\ -1, & if\left(x_j - x_k\right) < 0 \end{cases} \tag{2}$$

A positive (negative) value of S (equation 2) indicates an increasing (decreasing) precipitation trend. S is normally distributed [19, 20], with variance given by:

$$\mathrm{VAR(S)} = \frac{1}{18} n(n-1)(2n+5) \tag{3}$$

Equation (3) is used to ascertain if the difference between the measurements at time j and k are positive, negative or zero.

Equation (4) is applicable in computing the MK test statistic (*Z*) by ensuring that large sample sizes are distributed approximately using the mean S and the variance *VAR(S)*.

$$Z = \begin{cases} \dfrac{S-1}{\sqrt{var(S)}}, & if\ S > 0 \\ 0, & if\ S = 0 \\ \dfrac{S+1}{\sqrt{var(S)}}, & ifs < 0 \end{cases} \tag{4}$$

The first step in the Mann-Kendall test for a time series x_1, x_2, x_3......., x_n of length *n* is to compute the indicator function $sgn(\mathrm{x_j} - \mathrm{x_k})$, followed by computation of mean *S* and variance *VAR (S),* then M-K test statistic *Z.* To determine if the observed trend is significant, the Mann-Kendall test compares the computed test statistic Z with critical values from the standard normal distribution based on a chosen significance level, 5% in this case. The 5% was used to test the null hypothesis of non-monotonic trend against the alternative hypothesis of an upward or downward monotonic trend. However, whenever the observed value of Z is greater than the critical value, the null hypothesis is rejected in favour of the alternative hypothesis, which indicates that the trend is significant.

2.4 Correlation, Regression and Cross-Validation

The correlation analysis was employed in examining the relationship that exists between the soil temperature and the atmospheric variables used in this study before proceeding to the application of regression. To see how these variables interrelate, each of this data set was correlated with the other sets to obtain the correlation matrix. Likewise, the linear regression analysis which is one of the most widely used methods for statistical analysis when data are being analysed was also employed.

The linear regression is of the form:

$$Y = \beta_o + \beta_i X_i + \beta_j X_j + \beta_k X_k + \ \dots.. \qquad (5)$$

Where *Y* represents the predictand (soil temperature), *Xs* the predictors (in this case maximum temperature, evaporation, relative humidity at 3 pm), while ***βs*** are the constants representing the strength of the influence of *Xs* [23]. It must be recalled that when developing a statistical model, the selection of suitable predictors are crucial. Also, the most important and basic requirement to be considered for predictors is that they should be informative; that is, they should have a high predictive power. Typically, in statistical analyses, the informative predictors can be identified by correlating possible predictors with the predictands [24, 25]. Thus, as part of this procedure, the dependent variable was correlated with the various atmospheric conditions before the selection of the maximum temperature, evaporation, and relative humidity at 3pm.

In a linear regression model setting, cross-validation procedures are widely used to select an appropriate model that best fits a set of data. [26, 27]. This cross-validation is a statistical method used to evaluate and compare learning algorithms. It is one of the most used approaches for model selection and error estimation of classifiers [28]. While using cross-validation, the data were divided into two segments: one was used to learn or train a model and the other used to validate the model. In this case, the model was made to fit the training data and is subsequently assessed based on its predictions of the test data [29, 30]. Through the repeated process of this procedure for many different splits of the data, the average predictive performance of one or more models is estimated.

Different forms of cross-validation have been applied by various authors to validate regression models. However, in this work the k-fold cross-validation was employed, given its accurate performance estimation [31]. In a k-fold cross-validation the data is first partitioned into k equal (or nearly equal) parts or folds with *k* assuming the value within the range $2 \le k \le n$. Subsequently, k iterations of training and validation are performed in such a way that within each of the iteration a different segment of the dataset is held-out for validation, while the remaining k-1 folds are used for learning. However, based on choice several types of *k*-fold have been used by various authors. For instance, *2*-fold was used by [24]*,* [32] used and compared 2-fold and 3-fold, while [33, 34] used and compared 3-fold and 4-fold.

But, the most commonly used of these *k*-folds are the *5*-fold and *10*-fold. Thus, the *5*-fold cross-validation which is widely recognised for assessing model performance was utilised in this work. The dataset were divided into five subsets in which four of these subsets were used to iteratively train the model and the remaining one subset was used for the validation. This mitigates overfitting and provides a detailed evaluation of the model's predictive abilities.

3. RESULT AND DISCUSSION

The boxplots (Figure 1) indicate that all the variables contained outliers. While both soil temperature and relative humidity have extreme values at both sides (i.e. highest and lowest outliers), maximum temperature and evaporation have the lowest and highest outlier values, respectively. As a result of the detected outliers (Figure 1), winsorization was utilised in removing successfully all the outliers in the variables considered (Figure 2).

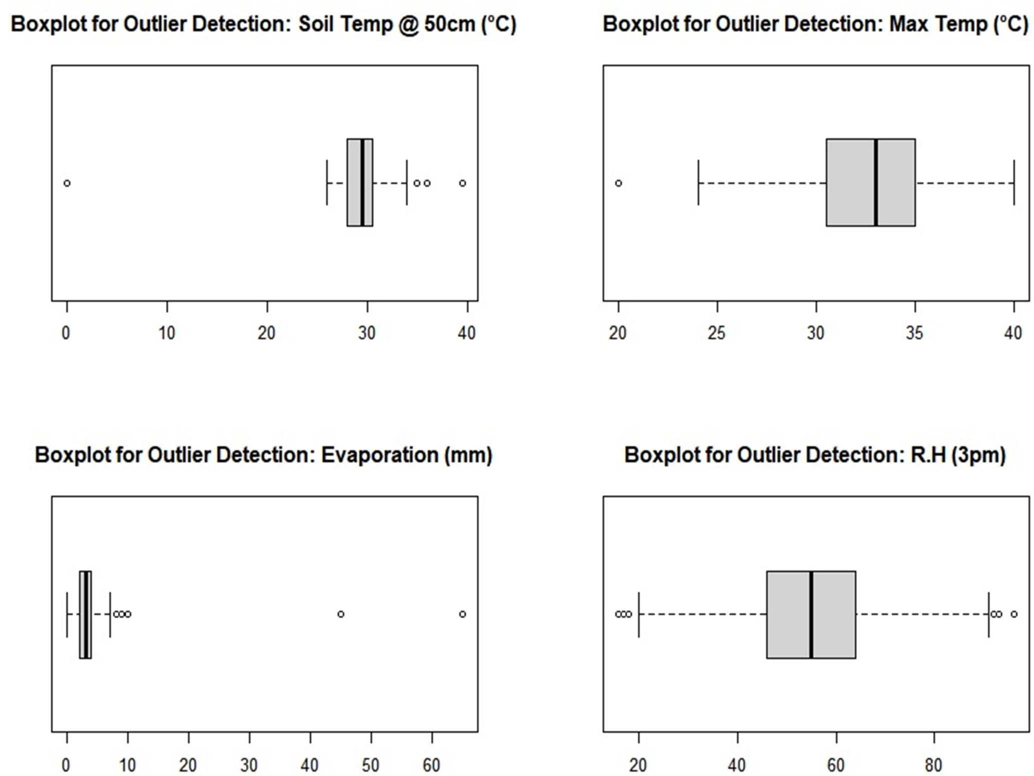

Figure 1: Boxplots for Outlier Detection.

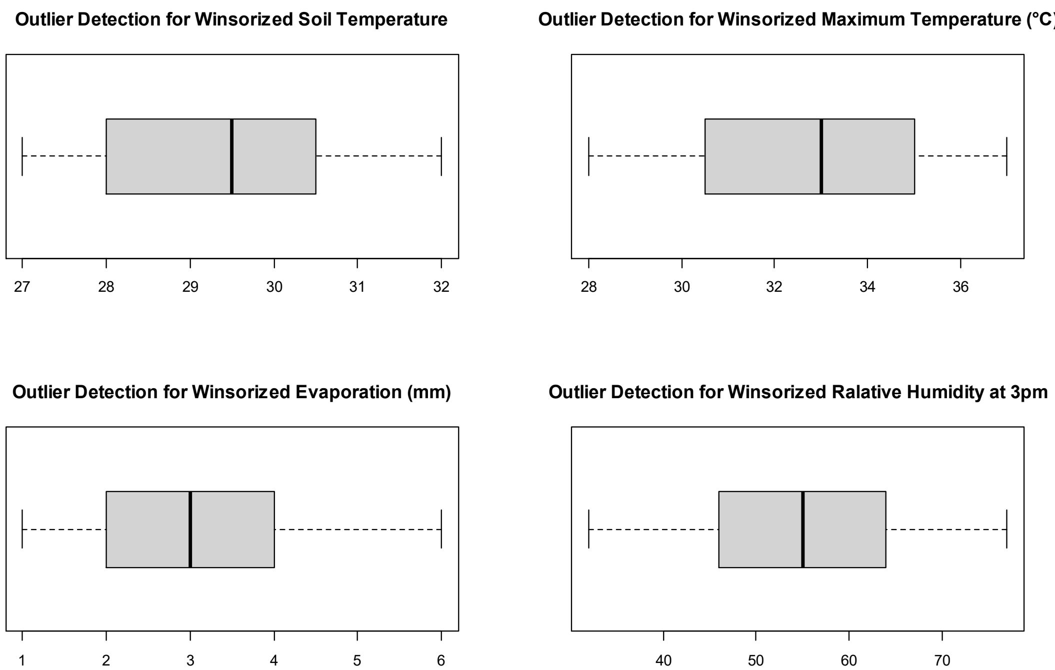

Figure 2: Boxplots of Winsorized Variables

Moreover, the applicability of the MK trend analysis was first carried out on the different atmospheric parameters considered, to ascertain that the analysis meets the non-parametric conditions required since MK test is not applicable in autocorrelated data [13, 19]. However, the results of the analysis showed that all the four variables were autocorrelated (Figure 3). Thus, there is the need to conduct prewhitening before the MK test could be applied.

Prewhitening all the four datasets makes none of the data set to be autocorrelated as many of their lags fall below the significant band with no consistent pattern in their autocorrelation (i.e. no downward or upward pattern across the lags on the horizontal axis) (Fig. 4). Thus, the dataset do not have significant autocorrelations and the MK test can now be applied to analyse the variability of each dataset.

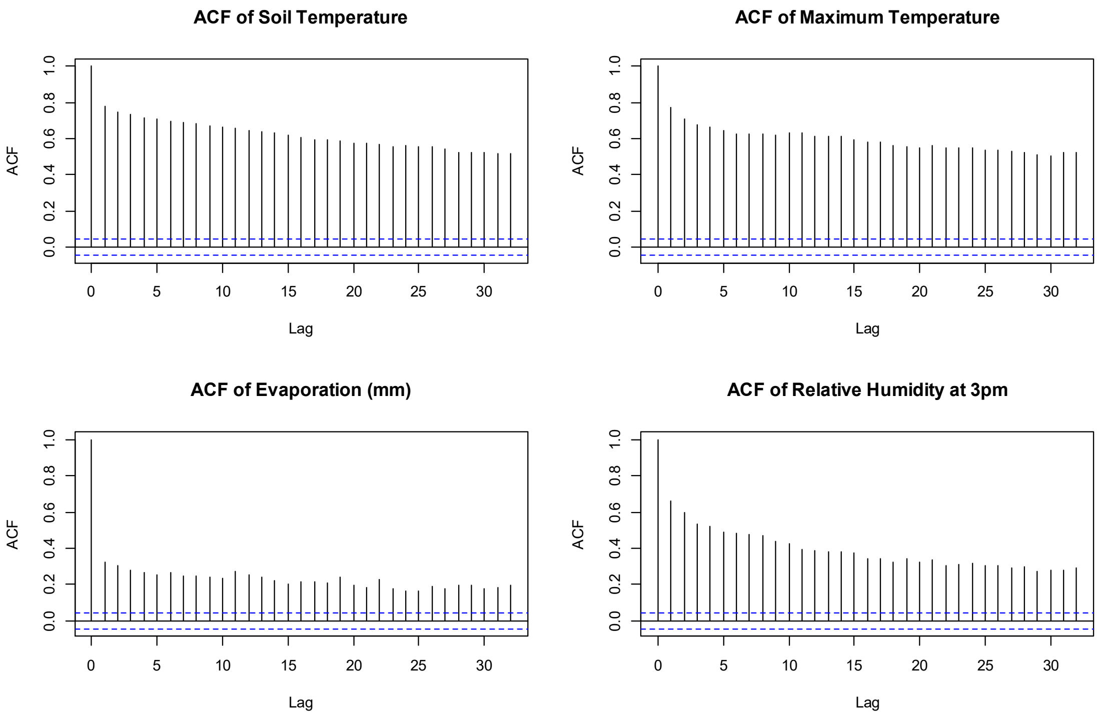

Figure 3: Autocorrelation test of the precipitations of the variables.

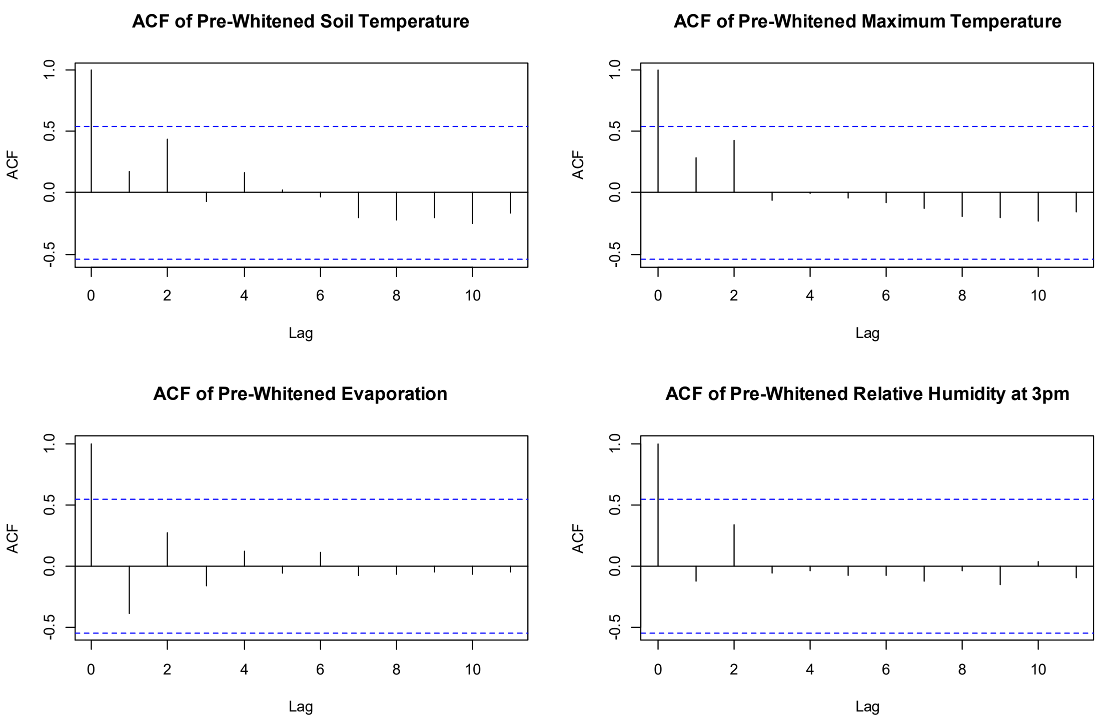

Figure 4: Autocorrelation Test of the Pre-Whitened Datasets.

With the exception of relative humidity which has no significant trend (p-values > 0.05), the results of the MK test analysis (Table 1) revealed the strong significant trend increase in all the variables (Figure 5); they show the sign of variability within the short period of term.

However, only soil temperature and maximum temperature were significant at both 95% and 99% confidence levels as buttressed by their small p-values (< 0.05 and < 0.01) and large positive *tau* values. As for the evaporation, the trend is only significant at 95% confidence level, but at 99% confidence level the trend shows no sign of significance since its p-values > 0.01.

The correlation analysis (Table 2) shows a strong relationship between the soil temperature and the atmospheric variables used, indicating strong and significant associations. The results show that higher air temperatures and evaporation rates tend to increase soil temperature, while higher relative humidity is linked to cooler soil conditions. This highlights the sensitivity of soil systems to surface climate parameters. Table 3 shows a very strong relationship between these variables, with air temperature; evaporation and soil temperature are all positively correlated while relative humidity is the only variable that is negatively correlated with others.

The 5-fold cross-validation applied to the regression procedure yielded the result of average Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Coefficient of Determination (R^2) values across the five folds (Table 4). The RMSE and MAE give low error values meaning that the model's predictive power or performance presents a high degree of accuracy. Both RMSE and MAE indicate that, on the average, the model's predictions deviate from the actual value of soil temperature by approximately 0.49 and 0.39 units, respectively. Buttressing this is the R^2 value which indicates that about 81.74% of soil temperature can be explained by the combined effects of maximum air temperature, evaporation, and relative humidity at 3 PM. This shows how significant the influence of these atmospheric conditions has on soil temperature dynamics.

The strong relationship obtained between these three atmospheric conditions and soil temperature aligns with existing literature. For instance, studies have demonstrated that increases in air temperature bring about an increase in atmospheric demand for water, thereby enhancing soil evaporation rates [35]. Furthermore, the outcome of this study indicates that air temperature and relative humidity are influential factors that affect soil temperature, since they are both positively correlated with soil moisture [36] which also has a direct influence on soil temperature The application of 5-fold cross-validation employed in this context is consistent with various best practices in atmospheric and environmental modelling, because of its provision for a reliable assessment of model performance and ensuring that the findings are robust and generalizable [30].

Table 1: Mann-Kendal Test and Measure of dispersion variable

			Mann-Kendal Test		
Variables	Mean	SD	tau	P-value	Trend
Soil Temperature	29.44	1.5	0.711	0.00111	Rising
Maximum Temperature	32.67	2.61	0.805	0.00019	Rising
Evaporation	3.11	1.53	0.5	0.02278	Rising
Relative Humidity at 3pm	54.78	12.08	0.245	0.27124	No trend

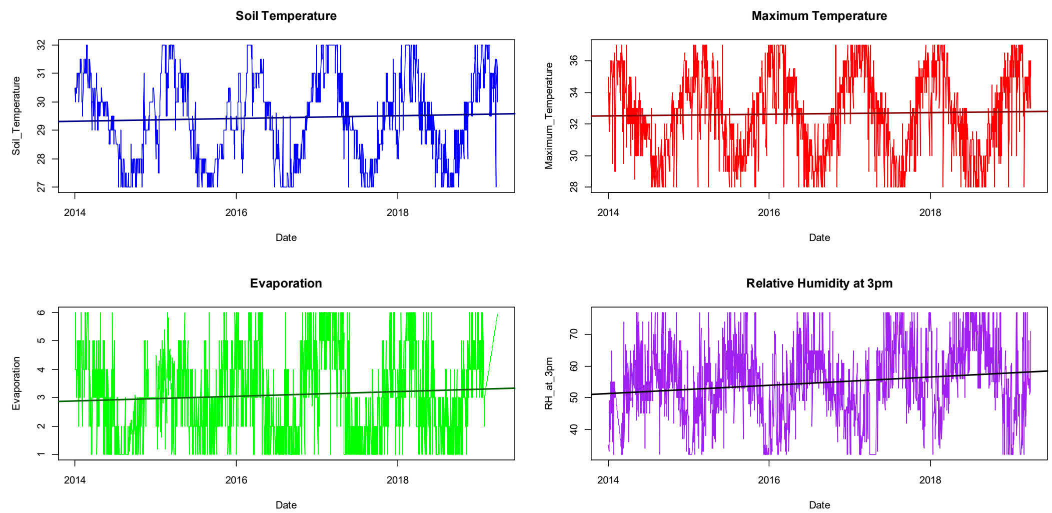

Figure 5: Tend variability of the variables.

Table 2: Correlation of Soil Temperature with Atmospheric Conditions

Atmospheric Conditions	Correlation
Maximum Temperature	0.7570
Evaporation	0.5956
Relative Humidity at 3pm	- 0.4808

Table 3: Correlation Matrix of all the variables

	Soil temperature	Maximum air temperature	Evaporation	Relative Humidity at 3PM
Soil temperature	1.000	0.757	0.596	-0.481
Maximum air temperature	0.757	1.000	0.548	-0.521
Evaporation	0.596	0.548	1.000	-0.388
Relative Humidity at 3PM	-0.481	-0.521	-0.388	1.000

Table 4: Result of 5-fold Cross-Validation

	Metrics value
Coefficient of Determination (R^2)	0.8174
Root Mean Squared Error (RMSE)	0.4889
Mean Absolute Error (MAE)	0.3939

4. CONCLUSION

This study emphasises the intricate relationships between atmospheric conditions and soil temperature. The regression analysis, validated through 5-fold cross-validation as performed in this study, confirms that the soil temperature responds significantly to short-term atmospheric changes. The analysis revealed that the atmospheric conditions i.e. the maximum air temperature, evaporation, and relative humidity at 3 PM can serve as reliable predictors of soil temperature due to high explanatory power and low prediction error of the model.

The model indicates its potential applicability in forecasting variations in soil temperature. As observed in this study, changes in soil temperature, an essential factor that plays a significant role in soil formation through a geological process, is a potential early indicator of climate change. Therefore, this study is very important and useful for land management system, ecological health, and agricultural productivity. Understanding soil temperature dynamics and variability could help us, especially in selecting appropriate sites and crops for cultivation in agriculture. Following the outcome of this study, we therefore recommend that soil temperature data could be integrated into climate adaptation strategies, and the analyses of this kind should be extended to long-term datasets and different climatic zones to get a holistic view.

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