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Relationships between air relative humidity and soil temperature in open-field tomato production

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Abstract. Understanding microclimatic interactions between atmospheric and soil parameters is essential for precision agriculture and irrigation management. The present study evaluated the relationships between air temperature, relative humidity, soil temperature, and soil moisture under open-field tomato production using a portable ESP32-based monitoring system. Measurements were conducted at ten field points with three replicates per point ($n = 30$). Descriptive statistics indicated relatively stable environmental conditions during the observation period. Pearson correlation analysis revealed a statistically significant inverse relationship between air relative humidity and soil temperature ($r = -0.376$, p = 0.040), while no significant linear relationships were observed between the remaining variables ($p > 0.05$). Linear regression analysis confirmed that increasing air relative humidity was associated with decreasing soil temperature ($R^2 = 0.142$, $p = 0.040$), although the explanatory power of the model remained limited. Validation against a Meteobot® reference weather station demonstrated high accuracy of soil temperature measurements (relative error 0.74%) and acceptable performance for soil moisture (6.28%). The results indicate that low-cost IoT-based monitoring systems can reliably capture microclimatic interactions under field conditions and support their application in precision agriculture.

Key words: air humidity, microclimate monitoring, precision agriculture, regression analysis, soil temperature.

INTRODUCTION

Tomato (*Solanum lycopersicum* L.) is one of the most economically significant vegetable crops cultivated worldwide in both greenhouse and open-field production systems. Its productivity and fruit quality are strongly influenced by microclimatic parameters such as air temperature, soil temperature, relative humidity, and soil moisture (Kusumiyati et al., 2023; Tezcan et al., 2023). Even moderate deviations from optimal environmental conditions may disrupt photosynthesis, transpiration, and nutrient uptake, thereby reducing yield stability under increasing climate variability (Elahi et al., 2022).

Microclimate regulation in agricultural systems is governed by interactions within the soil-plant-atmosphere continuum. Air temperature directly affects soil heat transfer processes, while atmospheric humidity influences evapotranspiration and root-zone water balance (Allen et al., 1998; Yang et al., 2022). In open-field systems, these processes are further affected by solar radiation, wind exposure, irrigation management, and soil physical properties, resulting in pronounced spatial and temporal variability (Zhang et al., 2002; Vurro et al., 2023). Compared with greenhouse production, where environmental parameters are partially controlled, field cultivation exhibits greater heterogeneity and reduced predictability (Šalagovič et al., 2024).

The rapid development of precision agriculture has accelerated the integration of Internet of Things (IoT)-based monitoring systems for continuous environmental data acquisition (Ojha et al., 2015; Miller et al., 2025). Low-cost microcontroller platforms and distributed sensor networks have been proposed as scalable and economically viable alternatives to commercial meteorological stations (Rivera et al., 2023; Mokhtarzadeh et al., 2025). Recent studies demonstrate that portable IoT systems can reliably monitor soil moisture and temperature under agricultural conditions, provided appropriate calibration and validation procedures are applied (Bogena et al., 2017; Seyar & Ahamed 2023; Adla et al., 2024).

Parallel to hardware development, data-driven modeling approaches have been widely applied for predicting soil moisture dynamics and crop stress. Machine learning algorithms such as random forest, support vector machines, and long short-term memory (LSTM) networks have achieved high predictive performance in various cropping systems (Islam et al., 2025; Kandamali et al., 2025; Naqvi et al., 2025). However, regression-based models remain essential due to their transparency, interpretability, and practical applicability in irrigation scheduling and agronomic decision-making (Jones, 2004; Muñoz-Carpena et al., 2005). For small and medium-sized farms, simpler statistical approaches may offer more feasible implementation pathways compared to computationally intensive machine learning frameworks.

Despite substantial technological progress, most published studies focus on greenhouse cultivation or large-scale sensor networks. Fewer investigations have assessed the statistical reliability of low-cost IoT monitoring systems under real open-field vegetable production conditions, particularly in tomato cultivation (Tezcan et al., 2023; Babu et al., 2024). Moreover, rigorous validation of portable sensor platforms against certified commercial weather stations remains insufficiently documented in field horticultural systems (Bogena et al., 2017; Rivera et al., 2023).

Although numerous studies have investigated soil-atmosphere interactions, limited evidence exists regarding the strength of linear coupling under relatively stable microclimatic conditions.

Therefore, the present study aimed to evaluate the relationships between selected atmospheric and soil microclimatic parameters in open-field tomato production using a portable ESP32-based monitoring system under field conditions.

The objectives of this study were: (1) to compare the measurements obtained from the portable IoT monitoring system with those from a commercial Meteobot® weather station; (2) to assess the strength and direction of relationships between air temperature, relative humidity, soil temperature and soil moisture; and (3) to examine whether atmospheric variables can serve as statistically significant predictors of selected soil parameters under relatively stable field conditions.

This study evaluates a low-cost ESP32-based IoT monitoring system under open-field tomato cultivation and examines the relationships between atmospheric and soil microclimatic parameters. The results provide additional information on these interactions under field conditions and highlight the potential of portable IoT systems for precision agriculture.

MATERIALS AND METHODS

Study area and experimental design

The study was conducted during the 2024 growing season at the experimental field of the Agricultural University - Plovdiv, Bulgaria (42°07′58″N,24°46′01″E). The region is characterized by a transitional continental climate with warm summers and moderate precipitation during the vegetation period.

The soil at the experimental site is classified as alluvial-meadow soil, exhibiting favorable water retention capacity and good aeration properties suitable for open-field vegetable production.

The experiment was carried out in a late-season open-field tomato crop (*Solanum lycopersicum* L.), including indeterminate Bulgarian cultivars (Rila, Pink Magic, and Rugby). The total experimental area was 49.44 m² (2.40 m × 20.6 m).

Ten measurement points were symmetrically distributed across the field at approximately 2 m² intervals to capture spatial variability of microclimatic parameters (Fig. 1). At each measurement point, three consecutive replicates were recorded, resulting in a total of 30 observations per parameter.

Figure 1. Experimental field and arrangement of measurement points.

At the time of monitoring, the tomato plants were at the fruit development stage (BBCH 71-79). The crop was irrigated daily using a drip irrigation system, with approximately 4–5 L of water supplied per plant. During the monitoring period, liquid potassium-rich fertilizer was applied according to the standard cultivation practice. The soil organic matter content was approximately 1.8%.

Monitoring system and instrumentation

Two independent monitoring systems were employed:

Portable IoT-Based sensor system. A low-cost portable monitoring unit was developed using an ESP32 microcontroller platform. The system included: DS18B20 digital temperature sensors (±0.5 °C accuracy); Capacitive soil moisture sensors; DHT22 sensor for air temperature and relative humidity (±0.5 °C; ±2% RH)

The soil sensors were positioned at a depth of 7-8 cm within the active root zone. Air temperature and relative humidity sensors were mounted approximately 30 cm above the soil surface, within the crop canopy zone.

Before field deployment, all sensors were calibrated according to the manufacturers' recommendations. The capacitive soil moisture sensors were calibrated using a two-point procedure (air-dry and water-saturated reference points). The DS18B20 temperature sensors were verified using an ice-water reference (0 °C), and software offsets were applied when necessary. The DHT22 sensor was checked for temperature and relative humidity using reference measurements before installation.

Reference weather station. A commercial Meteobot® Pro automatic weather station was installed in proximity to the experimental plot. The station recorded meteorological parameters at 15-minute intervals. Data from this station were used for validation and comparative analysis of the IoT-based measurements. The Meteobot® station was installed in the experimental field of the Agricultural University – Plovdiv, close to the investigated tomato plot. Its fixed sensor configuration included above-ground meteorological sensors mounted on a metal mast, as shown in Fig. 2. Measurements from the station were matched with the field observations according to the closest recording time.

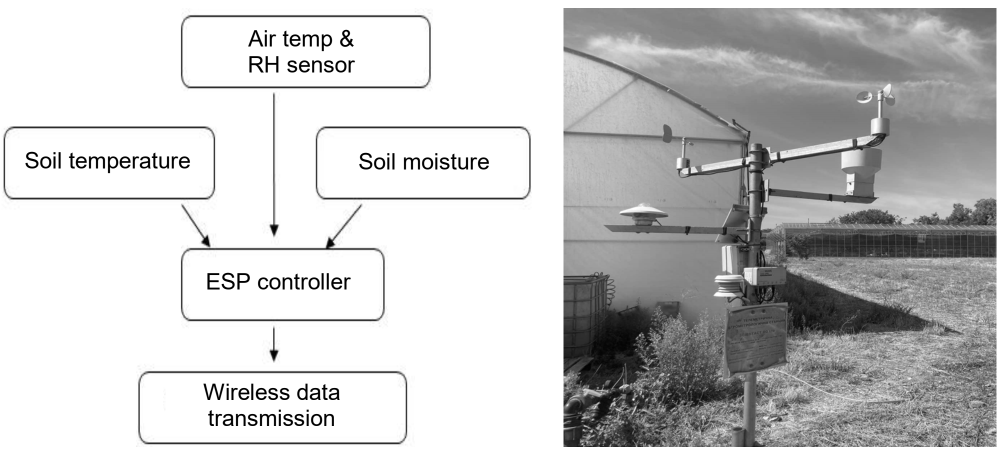

Figure 2. Experimental microclimate monitoring setup consisting of a portable ESP32-based IoT system and a reference Meteobot® weather station used under open-field conditions.

The configuration of both monitoring systems is presented in Fig. 2.

Parallel measurements from a reference Meteobot® weather station were additionally used for confirmatory comparison of selected microclimatic parameters.

Measurement protocol

Measurements of the following parameters were recorded: Air temperature (°C), Soil temperature (°C), Relative air humidity (%), Soil moisture (%).

Measurements were conducted during July 2024, when the tomato plants were at the fruit development stage (BBCH 71-79). Data were collected daily between 10:00 and 12:00 h under relatively stable weather conditions. For each measurement point, three consecutive readings were taken and averaged to reduce random measurement error.

Sensor validation and data consistency

To assess the reliability of the portable monitoring system, measurements were compared with corresponding records obtained from the Meteobot® station.

The agreement between systems was evaluated using: Mean difference (bias); Root Mean Square Error (RMSE); Mean Absolute Error (MAE)

Where applicable, paired t-tests were performed to determine whether statistically significant differences existed between the two measurement systems at $\alpha = 0.05$.

Statistical analysis

All statistical analyses were performed using the statistical package IBM SPSS Statistics 26.0.

Descriptive statistics were calculated for all variables, including the mean, standard deviation (SD), coefficient of variation (CV), and the minimum and maximum values. The coefficient of variation (CV) was also calculated to provide a relative measure of variability among the monitored parameters.

The relationships between atmospheric and soil parameters were evaluated using Pearson's correlation analysis. A simple linear regression model was fitted using the ordinary least squares (OLS) method to assess the relationship between air relative humidity and soil temperature. Model performance was evaluated using the coefficient of determination (R^2), adjusted R^2, the F-statistic, and the significance of the regression coefficients (p-values). Statistical significance was accepted at $p < 0.05$. The normality of the variables included in the regression analysis was assessed using the Shapiro-Wilk test. The assumptions of the regression model were further evaluated by examining the distribution of standardized residuals using histograms, normal probability plots, and residual-versus-predicted value plots. Ninety-five percent confidence intervals were calculated for the regression coefficients.

Study limitations. The present study was carried out during a single growing season under relatively stable weather conditions. For this reason, the findings should be considered preliminary and limited to the conditions of the experiment. Further observations over several growing seasons and under different environmental conditions are needed to confirm the observed relationships.

RESULTS AND DISCUSSION

Descriptive analysis of air and soil microclimatic variables

Descriptive statistics of the monitored microclimatic parameters are presented in Table 1. Air temperature exhibited minimal variability during the measurement period (Mean = 23.97 °C, SD = 0.25), indicating relatively stable atmospheric conditions. Soil temperature demonstrated slightly greater dispersion (Mean = 19.05 °C, $SD = 0.58$), with values ranging from 18.00 °C to 20.10 °C.

Air relative humidity remained within a narrow range (40.60-43.10%), with a mean value of 41.71% ($SD = 0.61$). In contrast, soil moisture showed the highest variability among all parameters (Mean = 71.14%, $SD = 3.37$), suggesting greater spatial or temporal heterogeneity in soil water content compared to atmospheric variables.

Table 1. Descriptive statistics of measured microclimatic parameters ($n = 30$)

Variable	Mean	*SD*	CV (%)	Min	Max
Air temperature, (°C)	23.97	0.25	1.04	23.40	24.40
Soil temperature, (°C)	19.05	0.58	3.04	18.00	20.10
Air relative humidity, (%)	41.71	0.61	1.46	40.60	43.10
Soil moisture, (%)	71.14	3.37	4.74	64.30	75.60

Pearson correlation analysis of microclimatic variables

Pearson correlation coefficients are presented in Table 2. A statistically significant negative correlation was observed between air relative humidity and soil temperature ($r = -0.376$, $p = 0.040$). No other significant correlations were detected among the measured variables.

No statistically significant relationship was found between air temperature and soil temperature ($r = 0.051$, $p = 0.791$). Similarly, correlations between atmospheric variables and soil moisture were weak and non-significant ($p > 0.05$). These findings suggest limited direct linear coupling between atmospheric temperature and soil thermal conditions during the observation period.

Table 2. Pearson correlation coefficients among measured microclimatic parameters ($n = 30$)

Variable	Soil temperature	Soil moisture
Air temperature (°C)	0.051	0.199
Air relative humidity (%)	-0.376*	-0.207

* Correlation is significant at the 0.05 level (two-tailed).

Linear regression between air relative humidity and soil temperature

Before interpreting the regression model, its main statistical assumptions were evaluated. The results of these diagnostic tests are presented in Table 3.

Table 3. Assessment of the assumptions of the linear regression model

Diagnostic procedure	Value
Shapiro-Wilk test (air relative humidity)	W = 0.957, $p = 0.259$
Shapiro-Wilk test (soil temperature)	W = 0.965, $p = 0.414$
Residual analysis	No substantial deviations observed
Homoscedasticity	Residual plots showed no evidence of heteroscedasticity
95% CI (intercept)	19.756 to 48.104
95% CI (slope)	–0.696 to –0.017

The Shapiro-Wilk test indicated that air relative humidity and soil temperature were normally distributed ($p > 0.05$). Visual inspection of the residual plots showed no substantial deviations from normality or homoscedasticity. The 95% confidence interval for the regression coefficient did not include zero, supporting the statistical significance of the fitted regression model. To further examine the observed relationship, a simple linear regression model was fitted using the ordinary least squares (OLS) method, with soil temperature as the dependent variable and air relative humidity as the predictor (Table 4).

Table 4. Linear regression analysis for soil temperature (n = 30)

Predictor	B	SE	β	t	p
Constant	33.93	6.92	-	4.904	<0.001
Air relative humidity (%)	-0.357	0.166	-0.376	-2.150	0.040

$R^2 = 0.142$, Adjusted $R^2 = 0.111$, $F(1.28) = 4.624$, $p = 0.040$.

The regression model was statistically significant ($F(1.28) = 4.624$, $p = 0.040$), with a coefficient of determination of $R^2 = 0.142$ (Fig. 3). The model indicated that each 1% increase in air relative humidity was associated with a decrease of approximately 0.357 °C in soil temperature.

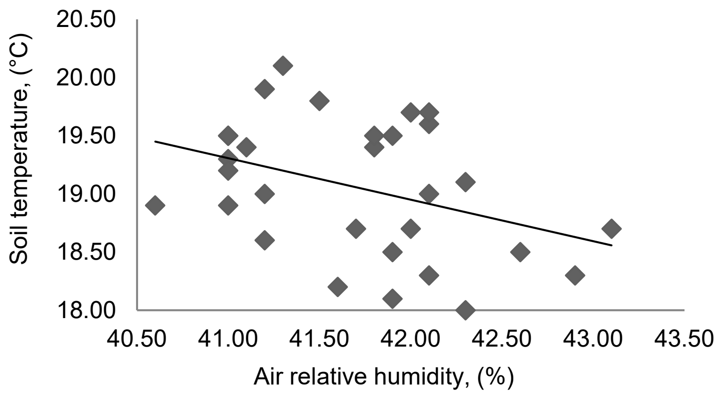

Figure 3. Relationship between air relative humidity and soil temperature showing a statistically significant inverse linear regression ($R^2 = 0.142$, $p = 0.040$).

Although the relationship was statistically significant, the correlation was weak to moderate ($r = -0.376$), and the coefficient of determination indicated low explanatory power. Air relative humidity explained only 14.2% of the observed variation in soil temperature.

The absence of a significant relationship between air temperature and soil temperature in the present study differs from the findings reported in some previous studies. This difference may be explained by the relatively stable weather conditions during the measurement period, the limited number of observations, and the specific field conditions under which the experiment was conducted. Soil temperature is influenced by several interacting factors, including solar radiation, soil moisture, soil physical properties, irrigation practices, and crop canopy characteristics. Crop canopy reduces the amount of solar radiation reaching the soil surface, while irrigation timing may also influence soil temperature by changing soil water content. These interacting factors may partly explain the relatively low coefficient of determination ($R^2 = 0.142$), indicating that air relative humidity accounted for only a small proportion of the observed variability in soil temperature. Therefore, the observed relationship should be interpreted with caution and regarded as exploratory rather than predictive.

The resulting regression equation was expressed as (Eq. 1):

$$\mathrm{T}_{soil} = 33.93 - 0.357.RH_{air} \tag{1}$$

where T_{soil} is soil temperature (°C); RH_{air} – air relative humidity (%).

This indicates that for each 1% increase in air relative humidity, soil temperature decreased by approximately 0.357 °C.

Validation of the portable IoT monitoring system

Measurements obtained from the portable ESP32-based IoT system were compared with corresponding data from the Meteobot® reference weather station in order to assess measurement accuracy under field conditions. The comparison was based on averaged values derived from three repeated measurements for each parameter. Pearson's correlation coefficient (R) and the coefficient of determination (R^2) were additionally calculated to further assess the agreement between the ESP32-based monitoring system and the Meteobot® reference station. The results of this comparison are presented in Table 5.

Table 5. Comparison between measurements obtained from the portable ESP32-based IoT system and the Meteobot® reference weather station

Parameter	Meteobot	ESP32	Absolute error	Relative error (%)	Pearson's r	R^2
Soil temperature (°C)	22.96	22.79	0.17	0.74	0.998	0.996
Soil moisture (%)	69.93	65.54	4.39	6.28	1.000	1.000

The validation results demonstrated a strong correlation between the measurements obtained from the portable ESP32-based monitoring system and the Meteobot® reference station for both soil temperature ($r = 0.998$; $R^2 = 0.996$) and soil moisture ($r = 1.000$; $R^2 = 1.000$). The low absolute and relative errors further confirmed the satisfactory performance of the developed monitoring system under field conditions. For soil moisture, a larger deviation was observed (4.39%, relative error 6.28%), which can be attributed to differences in sensor calibration, soil heterogeneity, and the inherent limitations of low-cost capacitive soil moisture sensors.

Despite these differences, the overall accuracy of the portable system remains acceptable for practical applications in precision agriculture, particularly for monitoring soil temperature.

The validation analysis was based on parallel measurements conducted under identical field conditions. Descriptive statistics presented in Table 1 reflect broader variability of the monitored parameters but were not directly used for system comparison due to differences in measurement timing.

The validation approach applied in this study can be considered as a confirmatory field test, where regression-based estimations were compared with independently measured values obtained from a reference weather station under the same environmental conditions.

The present study examined the relationships between selected atmospheric and soil microclimatic parameters under open-field tomato production during a period characterized by relatively stable environmental conditions. The descriptive statistics indicated a narrow range of variation in air temperature and relative humidity, suggesting limited short-term atmospheric variability during the measurement period. Such conditions are likely to constrain the strength of detectable statistical relationships between variables.

A statistically significant inverse relationship was identified between air relative humidity and soil temperature. This finding is physically plausible, as increased atmospheric humidity is often associated with reduced evaporative demand and altered energy exchange processes at the soil surface, potentially leading to lower soil heating. However, the relatively low coefficient of determination ($R^2 = 0.142$) indicates that air relative humidity explained only a small proportion of the observed variability in soil temperature. Consequently, the regression model should be interpreted as exploratory and not as a predictive model. This suggests that soil thermal dynamics in open-field conditions are governed by multiple interacting factors, including solar radiation, soil moisture content, irrigation practices, soil physical properties, and plant canopy effects.

In contrast, no statistically significant relationship was observed between air temperature and soil temperature. Although such a relationship might typically be expected, the absence of significance in this study can be attributed to the narrow temperature range recorded, combined with the buffering capacity of the soil and shading effects of the crop canopy. Similarly, the lack of significant correlations between atmospheric variables and soil moisture suggests that soil water content is influenced by more complex and time-dependent processes, which are not fully captured by instantaneous atmospheric measurements.

The validation analysis demonstrated a high level of agreement between the portable ESP32-based monitoring system and the Meteobot® reference station for soil temperature measurements, with a very low relative error (0.74%). This indicates that the low-cost monitoring system provides reliable temperature data under field conditions. In contrast, soil moisture measurements exhibited a higher deviation (6.28%), which is consistent with known limitations of low-cost capacitive sensors, including sensitivity to soil heterogeneity, salinity, and calibration conditions. Nevertheless, the observed accuracy remains acceptable for practical field applications, particularly in the context of precision agriculture where relative trends are often more important than absolute precision.

From an applied perspective, the results demonstrate that even simple and low-cost IoT-based monitoring systems are capable of capturing meaningful microclimatic interactions under real field conditions. This is particularly relevant for small and medium-sized farms, where the implementation of advanced monitoring technologies must balance cost, simplicity, and reliability. While the regression model presented in this study has limited predictive power, it provides useful exploratory insight into soil–atmosphere interactions and highlights the potential of accessible sensing technologies in agricultural management.

The study has several limitations that should be considered. The dataset was relatively small ($n = 30$), and measurements were conducted within a restricted time window under stable environmental conditions. Since the experiment covered only one growing season and a relatively small number of observations, the results should be regarded as preliminary. Additional studies under different climatic conditions and over longer monitoring periods are needed before these findings can be generalized.

CONCLUSIONS

The present study evaluated the relationships between selected atmospheric and soil microclimatic parameters under open-field tomato production using a portable ESP32-based monitoring system. The results indicated relatively stable environmental conditions during the observation period, characterized by low variability in air temperature and relative humidity.

Among the investigated variables, only air relative humidity showed a statistically significant inverse relationship with soil temperature. The regression analysis demonstrated that increases in atmospheric humidity were associated with decreases in soil temperature, although the explanatory power of the model remained limited ($R^2 = 0.142$). No statistically significant linear relationships were identified between air temperature and soil temperature or between atmospheric parameters and soil moisture.

The validation analysis confirmed that the portable IoT-based monitoring system provides reliable measurements of soil temperature, with a very low relative error (0.74%) when compared with a reference Meteobot® weather station. Soil moisture measurements showed higher deviations (6.28%), which can be attributed to sensor limitations and environmental variability, but still remained within acceptable ranges for practical agricultural applications.

Overall, the findings suggest that under relatively stable field conditions, soil microclimatic dynamics are influenced by multiple interacting environmental factors and cannot be fully explained by single atmospheric variables. The developed low-cost monitoring system showed good performance under the conditions of the present study and demonstrated its potential for field-scale microclimate monitoring.

The results should be interpreted as condition-specific due to the limited sample size and restricted temporal range of measurements. The findings should therefore be considered as a first step and require validation under different climatic conditions and over multiple growing seasons. Future research should focus on longer monitoring periods, increased environmental variability, and the inclusion of additional factors such as solar radiation, wind speed, irrigation practices, and soil properties in order to improve predictive performance and enhance the applicability of low-cost monitoring systems in agricultural management.

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