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Spatial Variability of Soil Temperature in an Unreclaimed Mining Area in Ghana: Implications for Environmental Monitoring and Reclamation Efforts

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Spatial Variability of Soil Temperature in an Unreclaimed Mining Area in Ghana: Implications for Environmental Monitoring and Reclamation Efforts.

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ABSTRACT

Unreclaimed surface mining sites pose serious environmental challenges, characterized by persistent soil degradation and disrupted land surface thermal properties. While mining-related impacts on biochemistry are well documented, the spatial variability of soil temperature (ST) in these anthropogenic landscapes remains a critical knowledge gap. This study investigates ST dynamics at an abandoned mining site in the Talensi District, Ghana, by integrating high-precision in-situ surveys with drone-acquired multispectral imagery. Using both univariable and multivariable linear regression, we modeled the biophysical drivers of ST across a degraded dryland catena. Our univariable analysis revealed that bare land significantly increases ST by 0.753 °C ($p<0.01$, $R^2 = 0.152$), whereas closed shrub vegetation provides a vital cooling effect of 0.734 °C ($R^2 = 0.106$). Multivariable modeling further demonstrated that open and closed shrubs reduce ST by -1.068 °C and -1.091 °C, respectively, while unit increases in elevation and slope contribute to thermal reductions of -0.129 °C and -0.223 °C. Collectively, vegetation and terrain variables accounted for 36.7% of the thermal variance (Adjusted $R^2 = 0.367$, $p < 0.01$). These results provide a robust empirical framework for evidence-based reclamation, highlighting that strategic re-vegetation is essential for mitigating thermal pollution and facilitating ecosystem restoration in mining-disturbed arid environments.

KEYWORDS: surface mining, soil temperature, environmental monitoring, geostatistical modelling, geospatial analysis

1.0 BACKGROUND

Uncontrolled anthropogenic activities, such as urbanization, industrialization, and mining, contribute significantly to environmental degradation worldwide (1). Among these, illegal mining, commonly referred to in Ghana as galamsey, has become a major environmental concern. Illegal mining refers to the unregulated extraction of mineral resources using rudimentary tools and primitive processing techniques, often by unskilled individuals with limited awareness of their environmental impacts (2). While such activities provide short-term socio-economic benefits, including job creation and contribution to local gross domestic product (GDP), their environmental costs are severe and long-lasting (3,4). Illegal mining activities are associated with vegetation destruction, air and water pollution, and heavy metal contamination of soils. Soil pollution, together with the degradation of water bodies and vegetation cover, remains one of the most visible consequences of this operation (4).

Mining has contributed to significant landscape destruction, and this will likely negatively impact sustainable land use (5–7). The northern parts of Ghana have experienced an upsurge in both legal and illegal mining over the years, resulting in the loss of various land cover types and their distribution (8). This loss is fundamental to understanding and predicting daily-to-seasonal changes in soil temperature in situ (9). Soil temperature is an essential factor that affects every aspect of a given ecosystem's processes and functions (10,11). The Upper East Region, particularly the Talensi District, is a major center for legal and illegal mining activities, contributing greatly to local and national economies and trapping miners in poverty (12). It is reported that about 17 percent of the small-scale miners in the Talensi district are illegal operators and tend not to comply with existing mining laws due to a lack of strict enforcement, supervision, and regulations (13). The presence of gold particles in the Talensi district of Northern Ghana has attracted a large number

of unemployed youth and small-scale mining ventures to the area. The activities of illegal small-scale gold mining in the community are causing serious environmental destruction (8). Such unregulated mining activities have resulted in changes in soil temperatures in the area as a result of the negative changes that affect soil mulch, slope of the land surface, vegetative cover, organic matter content, and soil moisture content, which in turn influence soil temperature (14).

Previous studies have noted that mining legacies in the Talensi district are characterized by unreclaimed spaces, leading to widespread loss of vegetation and degraded soils (8,11,15). This has resulted in declining crop yields, reduced soil moisture, and heightened vulnerability to climate variability, producing persistent household food insecurity across northern Ghana (16,17). It is therefore crucial that current studies directly measure the spatial patterns of soil temperature and how they respond to vegetation cover. This study will fill a knowledge gap needed to address social needs (stabilizing livelihoods, reducing migration and conflicts over arable land by informing where reclamation will most quickly restore productivity), and support economic recovery (targeting reclamation and agroforestry investments to sites where shading and soil amendments will most lower temperatures, increase moisture retention, and raise crop yields and incomes). Similar to any other mining area that experiences benefits and challenges, several environmental problems exist, including altered soil properties, vegetation loss, land disturbance, and exposure of bare soil surfaces to direct solar radiation (11). Understanding how these changes affect the spatial variability of soil temperature in unreclaimed mining areas is essential for environmental monitoring and reclamation efforts. Soil temperature variations help identify degraded land, assess moisture levels, and detect pollution in unreclaimed mining areas (18). Identification of degraded lands, moisture level assessment, and detection of pollution help with the identification of soil compaction, contamination, and potential soil erosion, and as such, guide effective reclamation

efforts. Thus, understanding soil thermal properties supports sustainable land restoration and better environmental management (19).

Several studies have examined the environmental impacts of mining activities and report consistent evidence of soil degradation and land-use change (20,21). Other studies further highlight approaches that integrate soil erosion and contamination assessments within the Sustainable Development Goals (SDGs) framework (22). Some studies, for instance, have reported that artisanal mining activities contribute to severe topsoil loss, heavy metal contamination, and the conversion of vegetated lands into barren surfaces over time (20–22). For instance (23) integrated soil erosion and contamination assessment within the SDGs framework to inform sustainable land management in mining-affected areas. Also, previous studies in the Talensi District and other parts of northern Ghana (8,11,15,24,25) have extensively examined the impacts of illegal mining on vegetation, soil chemistry, heavy metal contamination, water quality, and livelihood sustainability. However, none of these studies focused on the spatial variability of soil temperature across mined landscapes, creating a critical empirical and contextual gap. More importantly, previous studies are limited by methodological gaps, often relying on non-spatial or aggregate soil property data without accounting for spatial heterogeneity in soil thermal responses to mining-induced degraded lands.

Addressing the research gap identified above is essential for developing site-specific reclamation strategies that stabilize livelihoods, improve vegetation productivity, and guide sustainable land management across degraded mining areas. This study is novel in its spatially explicit analysis of soil temperature variability within an unreclaimed mining landscape, an area largely not covered in previous studies. Also, by integrating geospatial and field-based soil temperature measurements with vegetation and terrain data, this study provides a spatially explicit assessment of how mining-

induced land cover types and topographic factors influence soil temperature patterns in an unreclaimed mining landscape. Finally, the study's ability to identify vegetation types associated with lower soil temperatures offers evidence relevant to reclamation planning and environmental monitoring in mining-affected areas. These findings contribute to globally and locally grounded information that may support sustainable land management and land rehabilitation efforts under the Sustainable Development Goals (SDGs), particularly SDG 13 (Climate Action) and SDG 15 (Life on Land).

Guided by the identified research gap and the study's objective, this study tested the null hypothesis that soil temperature has no statistically significant association with vegetation types (open grasses, closed shrubs, and open shrubs), soil moisture, topographic wetness index, elevation, and slope. This study aimed to achieve the following research objectives: (i) to examine the spatial differences in soil temperature within unreclaimed mining areas, and (ii) to analyze the influence of vegetated and bare land on soil thermal attributes. Therefore, it was guided by the following research questions: (i) How does soil temperature vary spatially across different parts of the unreclaimed mining area? and (ii) How do vegetated and bare lands predict soil temperature in the unreclaimed mining area? Addressing these questions will deepen our understanding of thermal heterogeneity in degraded ecosystems and inform evidence-based reclamation and sustainable land management strategies in post-mining environments.

2.0 MATERIALS AND METHODS

2.1 Study Area

This study used data from Ghana's Talensi District to investigate how soil temperatures vary across an unreclaimed, abandoned mining site. Why Talensi District? This area has a long history of

intense surface gold mining, and what is left behind is a landscape of leftover earth piles, bare ground, and big holes from excavations, with no post-mining reclamation conducted (15). This makes it a valuable place to explore how land surface characteristics, such as compaction, exposure, and slope, affect soil temperature, information that is pivotal for designing effective restoration strategies within the area and elsewhere.

The Talensi District is located in Ghana's Upper East Region with its capital at Tongo. It was established in 2012 after the split of the former Talensi-Nabdam District. Geographically, it lies between latitudes 10°15′-10°60′ N and longitudes 0°31′-1°0.5′ W, covering about 838 km², and has a population size of 81,194 people with a population density of 98.8 persons per square kilometer (26). The district shares boundaries with Bolgatanga to the north, Mamprusi districts to the south, Kassena-Nankana to the west, and Nabdam and Bawku West to the east. Its landscape is largely undulating with gentle slopes and rocky outcrops, underlain by Birimian, Tarkwaian, and Voltarian rock formations that contain gold deposits. The Red and White Volta Rivers drain the area, supporting dry-season farming but also causing siltation and flooding.

Talensi has a tropical climate with a short, erratic rainy season (May-October) and a long dry season (October-April). Annual rainfall averages 950 mm, with temperatures ranging from 12°C in December to 45°C in March-April. In 2024, the monthly average precipitation (which is mostly rainfall) and temperature regime in the study area exhibited a pronounced unimodal rainfall pattern, with peak precipitation occurring mid-year, alongside relatively high and moderately stable temperatures, consistent with the Talensi District's savanna climate (see Figure 2). Vegetation is mainly Guinea savannah woodland with scattered trees and grasses that dry out during the long dry season. Soils are shallow, coarse, and low in fertility, while valley soils are prone to waterlogging (27). These conditions limit crop yields, promote erosion, and drive

activities such as mining, bush burning, and charcoal production, contributing to widespread land degradation in the district (28). The study area is close to the three mining enclaves formed around 1995 (29). These include the enclaves of Kejetia (named after a big market center in Kumasi), Obuasi (named after the mining town where AngloGold Ashanti is located), and Tarkwa (named after the mining town of Tarkwa) (see Figure 1)

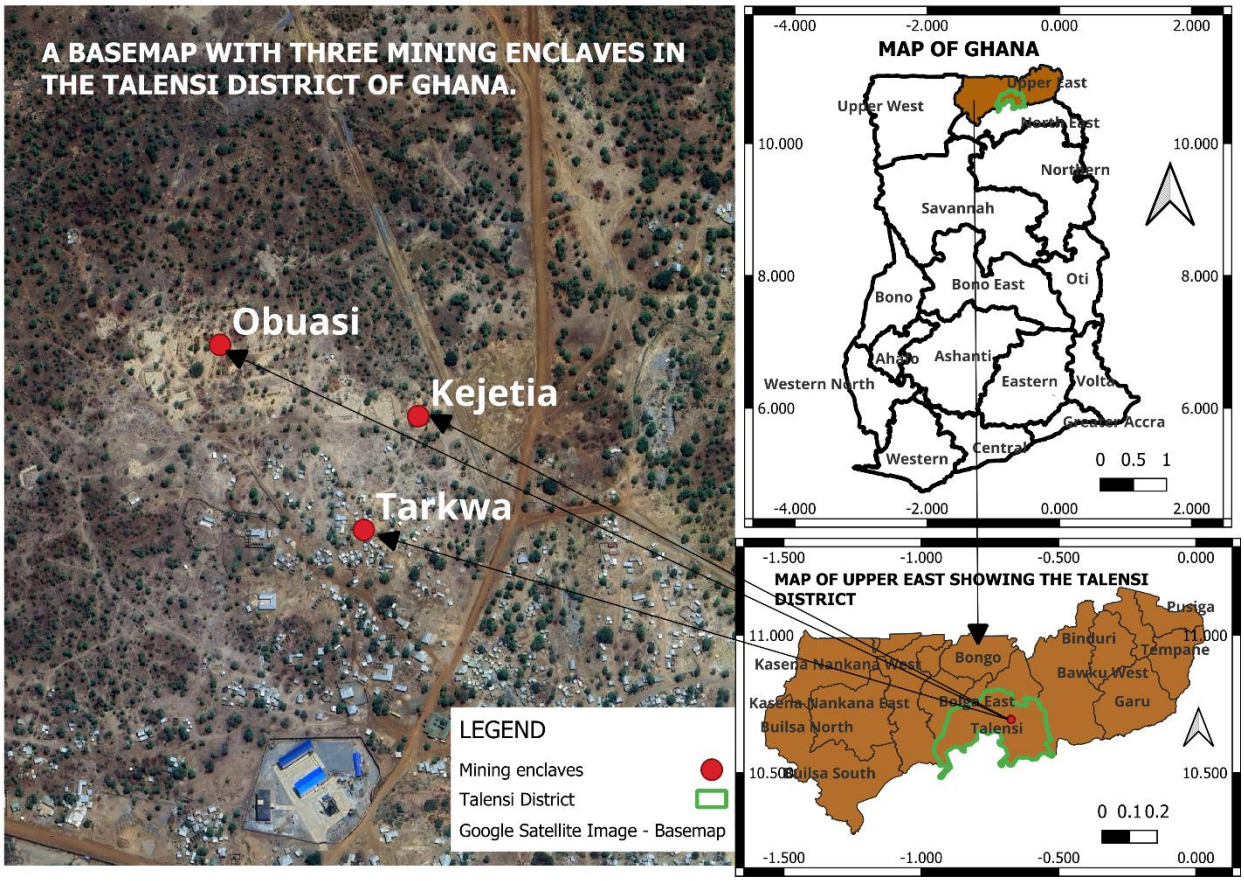


Figure 1 Study area in the Talensi District, measurement locations, and study area in the context of the Upper East region and Ghana

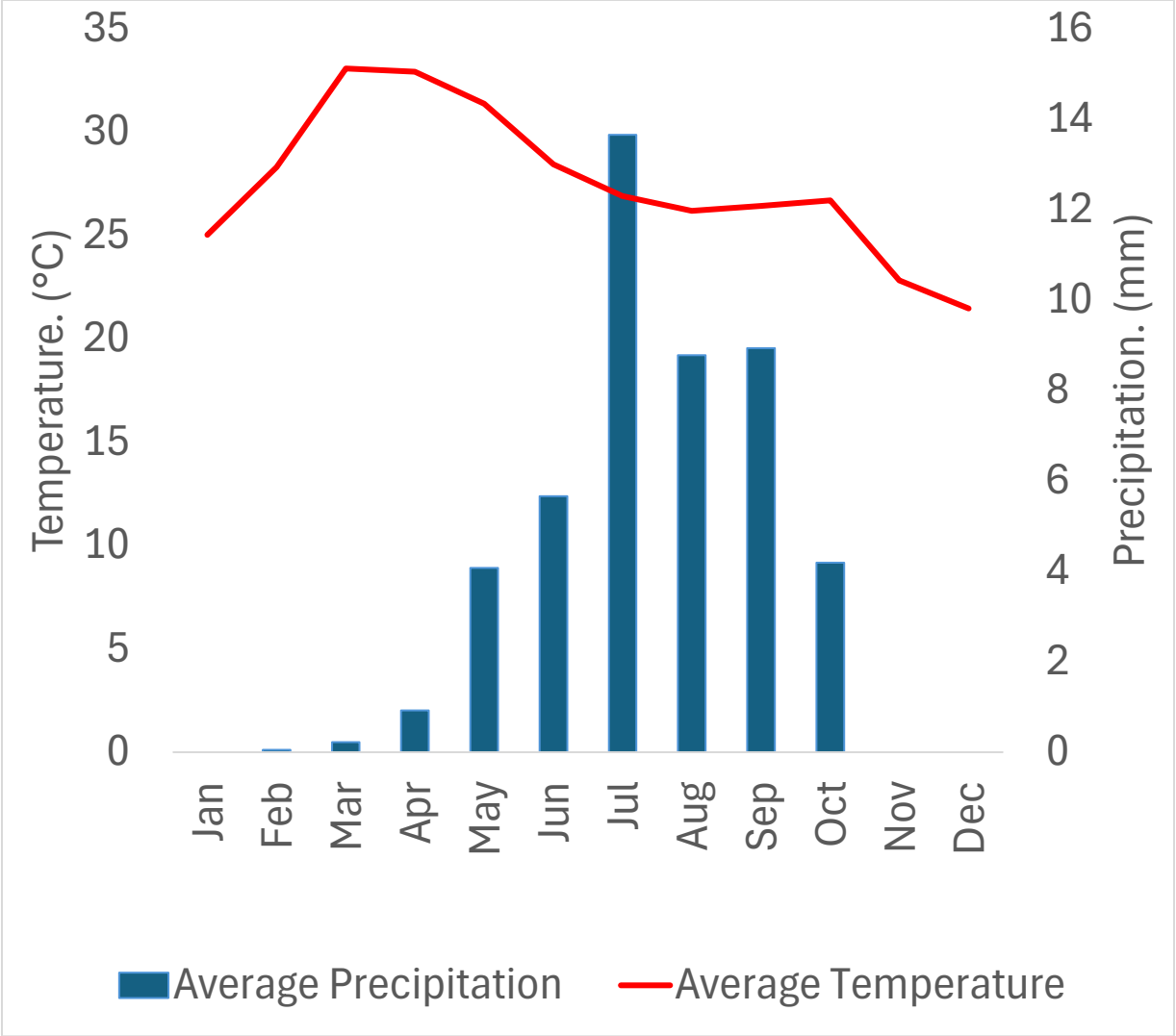


Figure 2 Average Temperature and Average Precipitation (which is mostly rainfall in the study area) in the Talensi District of Ghana, 2024.

2.2 Data and Methodological Framework

The data collection procedure for this study has been described in a previous study (30) and has been outlined as follows. We used datasets including volumetric soil water content (VSWC), vegetation cover types, soil temperature values, and the normalized difference vegetation index (NDVI). We also incorporated a 30-meter resolution digital elevation model (DEM), which we

collected from the United States Geological Survey archives. To ensure our data points accurately represented the entire area, we generated 220 random points using ArcGIS Pro, laying them out over ESRI imagery. We then went into the field to identify each location precisely, using an E1 Real-Time Kinematic (RTK)/Global Positioning System (GPS). This allowed us to achieve an accurate positioning, with an error margin of ±2.5 centimeters. On July 7, 2024, we took direct, on-site measurements of both soil temperature and VSWC. In collecting data on soil temperature and VSWC, we used a FieldScout TDR 350 from Spectrum Technologies (Aurora, IL, USA). It is important to note that in this study, when we mention soil moisture, we are referring to VSWC, which is essentially the ratio of the volume of water present to the total volume of the soil (31). This metric, widely employed in soil science, has demonstrated strong correlations with soil dielectric properties (32). The TDR 350, validated in numerous studies (33–35), facilitated accurate in situ measurements at a 20 cm depth, consistent with established protocols (36). During that same field visit, we also systematically categorized the vegetation cover. We grouped the vegetation into open grasses, open shrubs, and closed shrubs. This classification was based on how much of the ground was covered by vegetation and by soil, and we adopted a scheme originally proposed by (37). We used ArcGIS Pro to process the DEM and extracted key topographic features such as slope, aspect, and the topographic wetness index (TWI). These variables provide insight into the landscape's shape and water movement. We included them in our analysis because they can significantly affect soil temperature and moisture. Incorporating these parameters is consistent with previous studies (38–41) and allowed us to conduct a more thorough analysis of the spatial variations across the study area. The NDVI data were calculated from images captured by an unmanned aerial vehicle (DJI Mavic 3 Multispectral, DJI Sky City, Nanshan District, Shenzhen,

Guangdong, China). NDVI measures vegetation by analyzing the difference between near-infrared and red bands. NDVI was calculated in ArcGIS Pro.

2.3 Selection of Variables and Modelling Process

In this study, soil temperature, soil moisture, elevation, slope, TWI, aspect, NDVI, presence of bare land, open grasses, open shrubs, and closed shrubs were considered for modelling soil temperature. However, to reduce redundancy, we used Spearman's correlation to select significant variables (Table 1). Based on the results of the correlation analysis, soil moisture, elevation, slope, NDVI, the presence of bare land, open grasses, open shrubs, and closed shrubs (independent variables) were used in the modeling process with soil temperature (dependent variable).

To assess the reliability and performance of the models, we validated them using the coefficient of determination (R^2). The R^2 values indicate the proportion of variance in soil temperature explained by the independent variables, thereby providing a measure of model fit and explanatory power (18,42–44). Higher R^2 values suggest that the selected predictors capture a significant portion of the variability in soil temperature, while lower values imply the need to consider additional factors or non-linear relationships. This validation process ensures that the models built are both statistically sound and practically useful in interpreting soil temperature dynamics.

Insert Table 1 here

Both univariable and multivariable models were used to express the relationship between temperature and the independent variables used in the analysis. In the models, $g = (ST_K)$ is the function for the temperature of soil (*ST*), the dependent variable, at location *k;* Y_0 is the intercept or constant or baseline value for the dependent variable, *ST*, at location *k; OG* is open grasses at location *k; OS* is open shrubs at location *k; CS* is closed shrubs at location *k; EL* is elevation at location *k; SLP* is slope at location *k; NDVI* is the normalized difference vegetation index at location *k;* and *Θ* is the stochastic error term related to measurements of variables at location *k.*

$$g(ST_k) = Y_0 + Y_1 BL_k + \Theta_k \quad \text{Eqn. 1}$$

$$g(ST_k) = Y_0 + Y_1 OG_k + \Theta_k \quad \text{Eqn. 2}$$

$$g(ST_k) = Y_0 + Y_1 OS_k + \Theta_k \quad \text{Eqn. 3}$$

$$g(ST_k) = Y_0 + Y_1 CS_k + \Theta_k \quad \text{Eqn. 4}$$

$$g(ST_k) = Y_0 + Y_1 SM_k + \Theta_k \quad \text{Eqn. 5}$$

$$g(ST_k) = Y_0 + Y_1 EL_k + \Theta_k \quad \text{Eqn. 6}$$

$$g(ST_k) = Y_0 + Y_1 SLP_k + \Theta_k \quad \text{Eqn.7}$$

$$g(ST_k) = Y_0 + Y_1 NDVI_k + \Theta_k \quad \text{Eqn. 8}$$

$$g(ST_k) = Y_0 + Y_1 OG_{k1} + Y_2 OS_{k2} + Y_3 CS_{k3} + Y_4 SM_{k4} + Y_5 EL_{k5} + Y_6 SLP_{k6} + Y_7 NDVI_{k7} + \Theta_k \quad \text{Eqn. 9}$$

$$g(ST_k) = Y_0 + Y_1 OG_{k1} + Y_2 OS_{k2} + Y_3 CS_{k3} + Y_5 EL_{k5} + Y_6 SLP_{k6} + \Theta_k \quad \text{Eqn. 10}$$

$$g(ST_k) = Y_0 + Y_2 OS_{k2} + Y_3 CS_{k3} + Y_5 EL_{k5} + Y_6 SLP_{k6} + \Theta_k \quad \text{Eqn. 11}$$

3.0 RESULTS

3.1 Univariable analysis

Our univariable analysis revealed significant relationships between land cover types, environmental variables, and soil temperature (ST) (Table 2). Overall, the results from our univariable analysis suggest that vegetation cover and terrain factors influence soil temperature in opposite directions, with different magnitudes. Overall, the explanatory power of the model is modest, R^2 values ranging from 0.033 to 0.152, indicating that each factor accounts for a small but statistically significant proportion of soil temperature variability. Land-cover variables explain comparatively more variance, with bare surfaces showing the highest explanatory power (R^2 = 0.152), followed by closed shrubs (R^2 = 0.106), soil moisture (R^2 = 0.107), open shrubs (R^2 = 0.096), NDVI (R^2 = 0.091), and open grasses (R^2 = 0.077). In contrast, topographic variables contributed less to explaining soil temperature, as elevation and slope accounted for only 3.9% and 3.3% of the variance, respectively. The presence and absence of bare land, closed shrubs, open shrubs, and open grasses and their impacts on the univariable model have been expressed as follows (See Eqns. 12.1 - 19).

Bare land showed a statistically significant positive relationship with soil temperature. The univariable analysis revealed that the presence of bare land explains approximately 15.2% of the variance in soil temperature (adjusted R^2 = 0.148). The analysis revealed that the presence of bare land is associated with a 0.753°C increase in soil temperature compared to areas without bare land. The constant value of the model is 36.674°C, indicating that in the absence of bare land, the soil temperature is expected to be 36.674°C (Table 2; see Eqns. 12.1-12.3)

$$g\,(ST_k) = 36.674 + 0.753(BL_k) \quad \text{.....Eqn. 12.1}$$

For the presence of bare land, the predicted soil temperature is as follows.

$$g\,(ST_k) = 36.674 + 0.753\,(1) = 37.427°C \quad \text{.....Eqn. 12.2}$$

For the absence of bare land, the predicted soil temperature is as follows.

$$g\,(ST_k) = 36.674 + 0.753(0) = 36.674°C \quad \text{.....Eqn. 12.3}$$

The analysis revealed a significant positive relationship between open grasses and soil temperature (Table 2). The analysis showed that the presence of open grasses explains 7.7% of the variance in soil temperature. The presence of open grasses is associated with an increase in soil temperature of 0.896°C compared to areas without open grasses. With a constant value of 36.900°C associated with open grasses, the analysis showed that areas with no open grasses (bare, open shrub, and closed shrub) would have a soil temperature of 36.900°C (Table 2; also see Eqn. 13.1 - Eqn. 13.3)

$$g\,(ST_k) = 36.900 + 0.896\,(OG_k) \quad \text{.....Eqn. 13.1}$$

For the presence of open grasses, the predicted soil temperature is as follows.

$$g\,(ST_k) = 36.900 + 0.896(1) = 37.796°C \quad \text{.....Eqn. 13.2}$$

For the absence of open grasses, the predicted soil temperature is as follows.

$$g\,(ST_k) = 36.900 + 0.896(0) = 36.9°C \quad \text{.....Eqn. 13.3}$$

The results of our univariable analysis indicate that the presence of open shrubs is negatively and significantly related to soil temperature. The presence of open shrubs reduces soil temperature by 0.674°C. We found that the presence of open shrubs explains 9.6% of the variation in soil temperature. When open shrubs are absent, soil temperature is expected to be 37.160°C (Table 2; see Eqn. 14.1 - 14.3).

$g\,(ST_k) = 37.160\ -\ 0.674\,(OS_k)$ …….…… Eqn. 14.1

For the presence of open shrubs, the predicted soil temperature is as follows.

$g\,(ST_k) = 37.160\ -\ 0.674(1)\ =\ 36.486°C$ ……...……. Eqn. 14.2

For the absence of open shrubs, the predicted soil temperature is as follows.

$g\,(ST_k) = 37.160\ -\ 0.674(0)\ =\ 37.160°C$ ….……...……...…… Eqn.14.3

Our results showed that areas with closed shrubs showed a negative relationship with soil temperature. Specifically, the presence of closed shrubs is associated with a 0.734°C decrease in soil temperature. The presence of closed shrubs explains 10.6% of the variance in soil temperature. Soil temperature is expected to be 37.155°C in areas without closed shrubs (Table 2; see Eqn. 15.1 – 15.3).

$g\,(ST_k) = 37.155\ -\ 0.734\,(CS_k)$ …….……...…… Eqn. 15.1

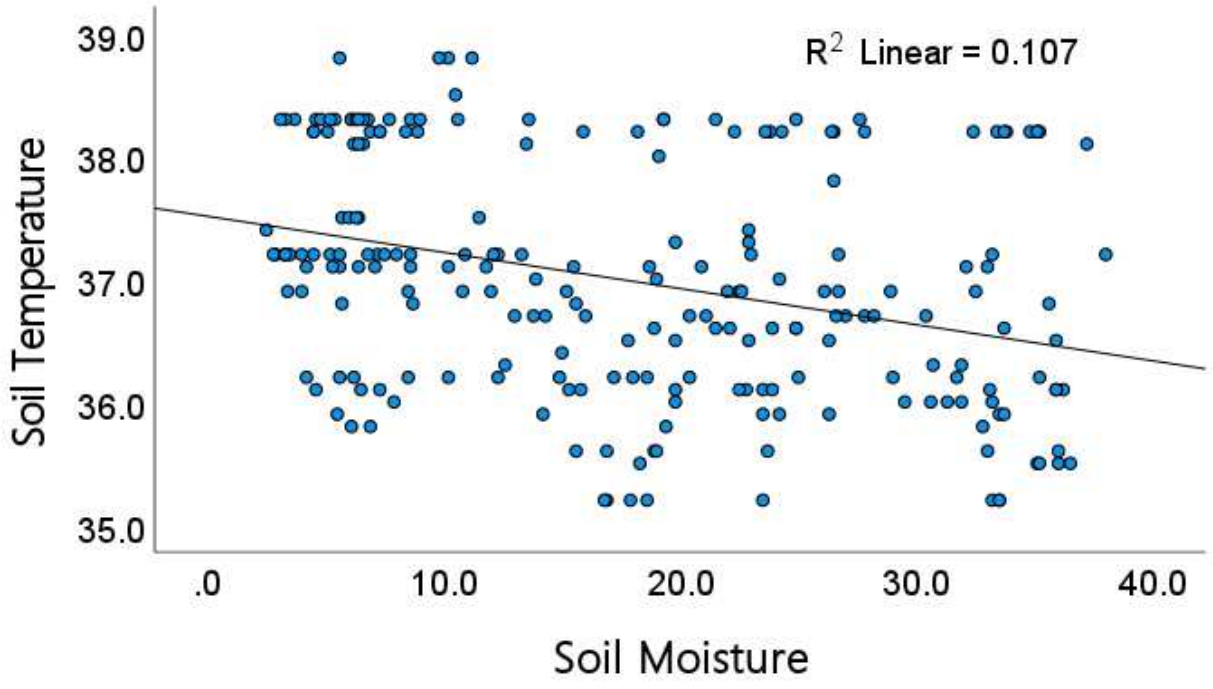
For the presence of closed shrubs, the predicted soil temperature is as follows.

$g\,(ST_k) = 37.155\ -\ 0.734\,(1)\ =\ 36.421°C$ ……...……...……. Eqn. 15.2

For the absence of closed shrubs, the predicted soil temperature is as follows.

$g\,(ST_k) = 37.155\ -\ 0.734\,(0)\ =\ 37.155°C$ ……...……..... Eqn. 15.3

The study also found a significant negative relationship between soil temperature and soil moisture. As soil temperature decreases, soil moisture increases (Figure 3). Soil moisture explains 10.7% of the variance in soil temperature. A unit increase in soil moisture is associated with a 0.630°C reduction in soil temperature. With a constant of 37.512°C, areas with low soil moisture would have higher soil temperatures (Table 2; see Eqn. 16; see Figure 3).

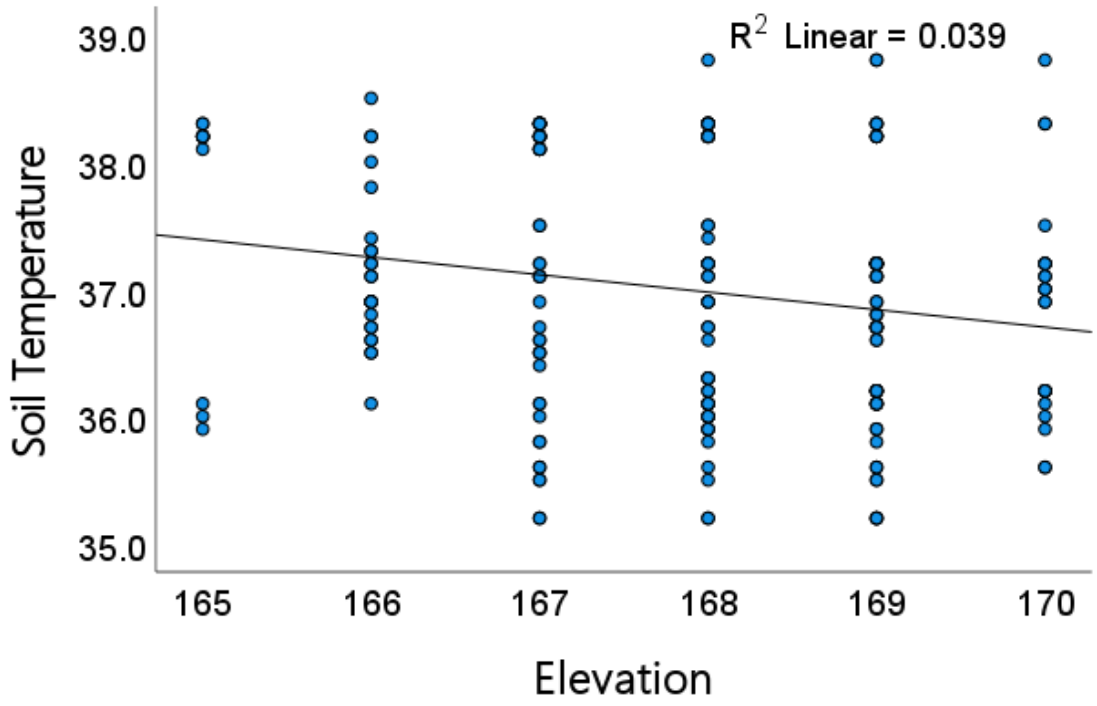


306

307 **Figure 3** A scatter plot showing the distribution of points explaining the relationship between soil
308 temperature and soil moisture (Note: R^2 on the scatter plot is 0.107, but the adjusted R^2 is 0.103)

309 $g\ (ST_k) = 37.512\ -\ 0.630\ (SM_k)$ ……...…...……...……Eqn. 16

310 The study found that elevation has a significant negative relationship with soil temperature.
311 Elevation explains a relatively small proportion of the variance in soil temperature (3.9%). Also,
312 the study found that a unit increase in elevation is associated with a $0.117°C$ decrease in soil
313 temperature (see Table 2; Eqn. 17; Figure 4)

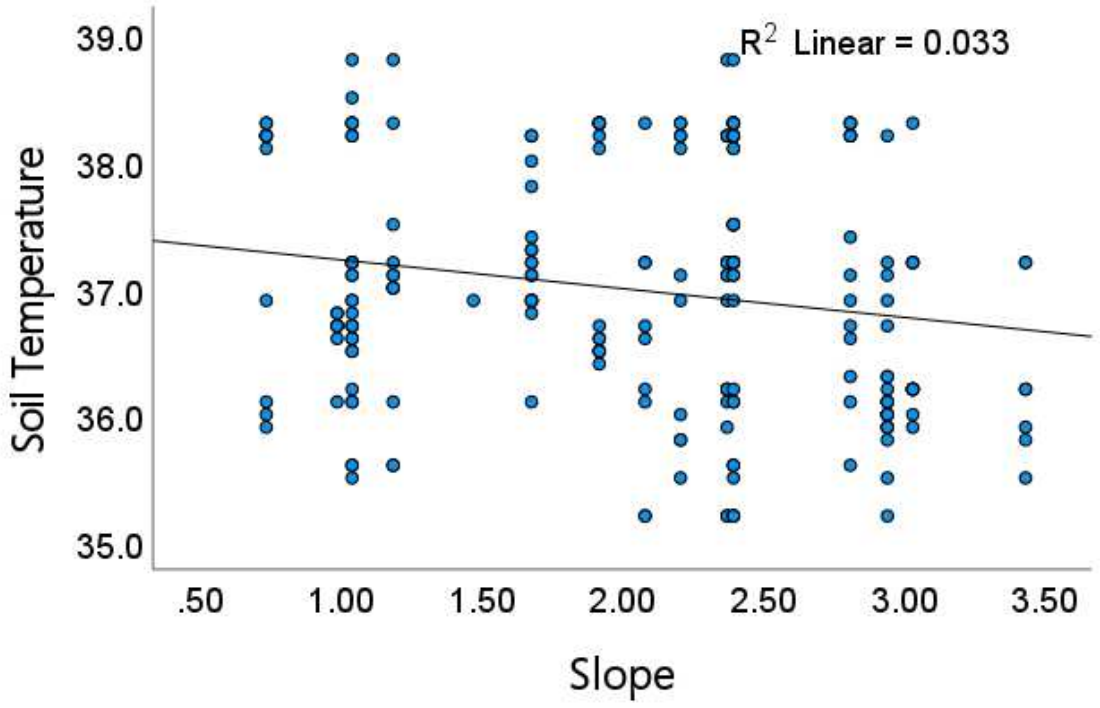


314

315 **Figure 4** A scatter plot showing the distribution of points explaining the relationship between soil
316 temperature and elevation (Note: R^2 on the scatter plot is 0.039, but the adjusted R^2 is 0.034)

317 $g\ (ST_k) = 38.883\ - 0.117\ (EL_k)$ ……..…….....Eqn. 17

318 Our results show that slope has a significant negative relationship with soil temperature. Slope
319 explains 3.3% of the variation in soil temperature. Also, the study found that a unit increase in
320 slope is associated with a 0.227 $°C$ decrease in soil temperature (see Table 2; Eqn. 18; Figure 5)

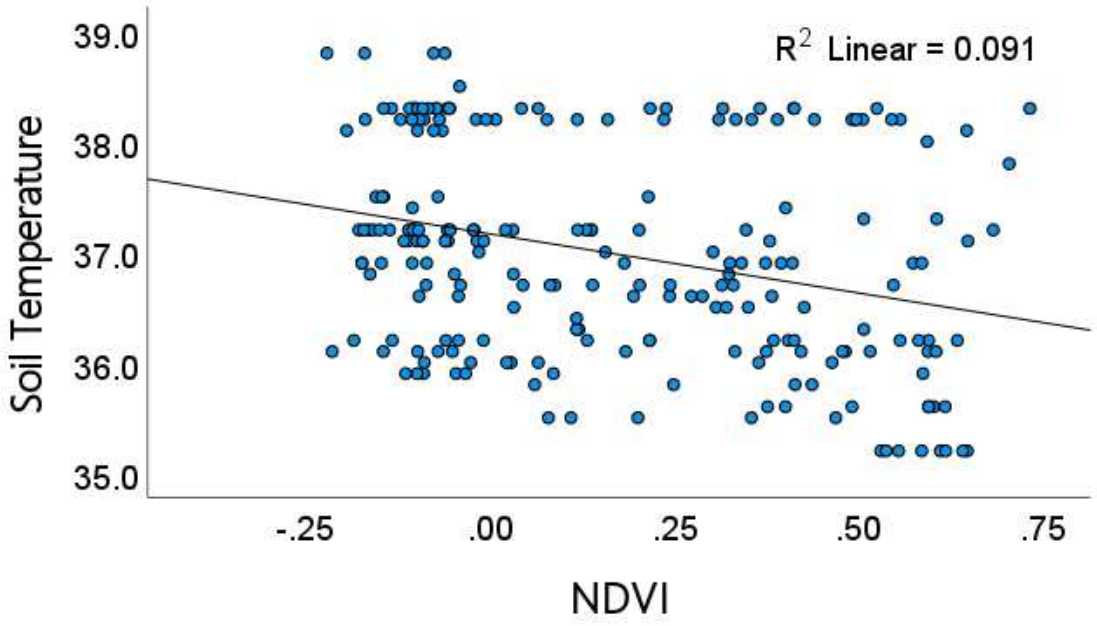


321

322 **Figure 5** A scatter plot showing the distribution of points explaining the relationship between soil
323 temperature and slope (Note: R^2 on the scatter plot is 0.033, but the adjusted R^2 is 0.028)

324 $g\ (ST_k) = 37.448\ -\ 0.227\ (SLP_k)$ …….....Eqn. 18

325 From our results, among the univariable models, NDVI shows a significant negative relationship
326 with soil temperature. NDVI explains 9.1% of the variance in soil temperature. A unit increase in
327 NDVI is associated with a 1.071°C decrease in soil temperature. The model estimated a baseline
328 soil temperature of 37.164°C, showing that increasing vegetation density is associated with a
329 reduction in soil temperature (Table 2; see Eqn. 19; see Figure 6).



330

331 **Figure 6.** A scatter plot showing the distribution of points explaining the relationship between soil

332 temperature and NDVI (Note: R^2 on the scatter plot is 0.091, but the adjusted R^2 is 0.087)

333 $g\ (ST_k) = 37.164\ -\ 1.071\ (NDVI_k)$ …….....Eqn. 19

334 Table 2 Univariable linear regression model of predicted average soil temperature based on

335 equations 1-8

Variable	Constant/Intercept	Coefficient (B)	Standard Error	t-Statistic	p-value	R-square	Adjusted R-square
Bare	36.674	0.753	0.1205	6.247	0.001*	0.152	0.148
Open grasses	36.900	0.896	0.211	4.251	0.001*	0.077	0.072
Open shrubs	37.160	-0.674	0.134	-4.818	0.001*	0.096	0.092
Closed shrubs	37.155	-0.734	0.144	-5.080	0.001*	0.106	0.102

SM	37.512	-0.630	0.058	-5.117	0.001*	0.107	0.103
Elevation	38.883	-0.117	0.039	-2.966	0.003*	0.039	0.034
Slope	37.448	-0.227	0.083	-2.722	0.007*	0.033	0.028
NDVI	37.164	-1.071	0.229	-4.671	0.001*	0.091	0.087

*Represents $p<0.01$, $p<0.05$ is statistically significant, NDVI is the normalized difference vegetation index, and SM is soil moisture

4.2 Multivariable Analysis - Step 1

A multivariable linear regression analysis assessed the combined influence of some selected environmental variables and land cover types on soil temperature (ST). Three models were developed based on equations 9 to 11. All independent variables were included in the first step of the modeling process (i.e., in equation 9). However, at the subsequent steps, some variables that did not show a statistically significant relationship with soil temperature were removed in order to build a more robust model.

In the first multivariable model (Eqn. 9), independent variables such as elevation, slope, soil moisture, and NDVI, in addition to the presence of open grasses, open shrubs, and closed shrubs, were all included as predictors. The multivariable regression results for this model are presented in Table 3. The results showed that, except for NDVI and soil moisture, all the other independent variables were statistically significant. Open grasses showed a significant positive relationship with soil temperature, but variables such as open shrubs, closed shrubs, elevation, and slope showed a negative relationship with soil temperature (see Table 3).

353 Table 3 Multivariable linear regression model parameters of predicted soil temperature based on
354 equation 9

Predictor Variables	Coefficient (B)	Standard Error	t-Statistic	p-value	Tolerance	VIF
(Constant)	36.883	6.447	9.074	0.001*		
Open grasses	0.601	0.244	2.465	0.014	0.503	1.989
Open shrubs	-0.792	0.181	-4.383	0.001*	0.411	2.430
Closed shrubs	-0.761	0.236	-3.224	0.001*	0.26	3.848
Soil moisture	-0.011	0.007	-1.52	0.130	0.464	2.156
Elevation	-0.122	0.039	-3.171	0.002*	0.932	1.072
Slope	-0.214	0.069	-3.09	0.002*	0.929	1.077
NDVI	-0.208	0.313	-0.665	0.507	0.367	2.724

355 *Represents $p<0.01$, $p<0.05$ is statistically significant, NDVI is the normalized difference
356 vegetation index, and VIF is the variance inflation factor. Note: R Square = 0.396, Adjusted R
357 Square = 0.376, and Standard Error of the Estimate = 0.753.

358 Table 4 shows that the independent variables, including open grasses, open shrubs, closed shrubs,
359 elevation, slope, soil moisture, and NDVI, explain approximately 37.6% of the variance in soil
360 temperature. The results showed that the presence of open grasses is significantly associated with
361 an increase in soil temperature by 0.601°C compared to bare land. However, the presence of open

362 shrubs means a 0.792°C decrease in soil temperature, while a unit increase in slope results in a
363 0.214°C decrease in soil temperature (Table 4). Also, closed shrubs are associated with a decrease
364 in soil temperature by 0.761°C compared to bare ground (Table 4).

365 Table 4 Multivariable linear regression model parameters of predicted soil temperature based on
366 equation 10

Predictor Variables	Coefficients	Std. Error	T	p-value	Tolerance	VIF
(Constant)	36.883	6.435	9.076	.000*		
Open Grasses	.341	.184	1.857	.065	.889	1.125
Open Shrubs	-1.004	.128	-7.839	.000*	.822	1.217
Closed Shrubs	-1.027	.132	-7.782	.000*	.833	1.200
Elevation	-.122	.038	-3.171	.002*	.940	1.064
Slope	-.230	.069	-3.336	.001*	.946	1.058

367 * Represents $p<0.01$, $p<0.05$ is statistically significant, and VIF is the variance inflation factor.
368 Note: R Square = 0.388, Adjusted R Square = 0.374, Std. Error of the Estimate = 0.754

369 **4.3 Multivariable Analysis - Step 2**

370 Equation 9 tested the relationship between soil temperature and all listed independent variables.
371 However, equation 10 tested the relationships between soil temperature and elevation, slope,
372 presence of open grasses, open shrubs, and closed shrubs. Thus, the results based on equation 10
373 test the significant variables from equation 9. Elevation, slope, presence of open grasses, open
374 shrubs, and closed shrubs explain 37.4% of the variation in soil temperature. The results, in Table

5, showed that soil temperature under open grass cover is 0.341°C higher compared to bare ground. The presence of open shrub cover reduces soil temperature by 1.004°C compared to soil temperature on bare land. Soil temperature measured under closed shrub cover is 1.027°C less than soil temperature measured on bare land (Table 5). Also, the results show that for every unit increase in elevation, soil temperature decreases by 1.22°C. Moreover, a unit increase in slope is associated with a 0.230°C decrease in soil temperature. The relationship between soil temperature and all independent variables is significant, except for open grass. At step 2, there is significantly lower multicollinearity, as indicated by VIF values that are less than 10.

Table 5 Multivariable linear regression model parameters of predicted soil temperature based on equation 10

Variable	Coefficients	Std. Error	t	p-value	Tolerance	VIF
(Constant)	36.883	6.435	9.076	.000*		
Open Grass	.341	.184	1.857	.065	.889	1.125
Open Shrub	-1.004	.128	-7.839	.000*	.822	1.217
Closed Shrub	-1.027	.132	-7.782	.000*	.833	1.200
Elevation	-.122	.038	-3.171	.002*	.940	1.064
Slope	-.230	.069	-3.336	.001*	.946	1.058

*represents $p<0.01$, $p<0.05$ is statistically significant, and VIF is the variance inflation factor. Note: R Square = 0.388, Adjusted R Square = 0.374, Std. Error of the Estimate = 0.754

388 **4.4 Multivariable Analysis - Step 3**

389 The presence of open grasses, an independent variable, is eliminated from the model at this stage
390 because it is not statistically significant, as noted in Table 5. Table 6 shows that soil temperature
391 under open shrubs is 1.068°C less compared to soil temperature measured on bare land. Also, the
392 presence of closed shrubs on the landscape reduces soil temperature by 1.091°C compared to soil
393 temperature measured on bare land, with all other variables held constant. The results showed that
394 soil temperature decreases by 0.129°C with a unit increase in elevation. Also, a unit increase in
395 slope decreases soil temperature by 0.223°C with all other variables in the model held constant
396 (Table 6; also see Eqn. 20.1 - Eqn. 20.5). The relationship between soil temperature and the
397 independent variables is significant (p-value < 0.05). More importantly, at step 3, there is
398 significantly lower multicollinearity, as shown in the VIF values of less than 10 (Table 6).

399 $$g\,(ST_k) = 36.883 - 1.068OS_{k1} - 1.091(CS_{k1}) - 0.129(EL_{k1}) - 0.223(SLP_{k1})$$..... Eqn. 20.1

400 For the presence of open shrubs and closed shrubs, soil temperature is given as

401 $$g\,(ST_k) = 36.883 - 1.068(1) - 1.091(1) - 0.129(EL_{k1}) - 0.223(SLP_{k1})$$ ..... Eqn. 20.2

402 $$g\,(ST_k) = 36.883 - 2.159 - 0.129(EL_{k1}) - 0.223(SLP_{k1})$$ ..... Eqn. 20.3

403 For the absence of open shrubs and closed shrubs, an empirical model for predicting soil
404 temperature is given as

405 $$g\,(ST_k) = 36.883 - 1.068(0) - 1.091(0) - 0.129(EL_{k1}) - 0.223(SLP_{k1})$$ ..... Eqn. 20.4

406 $$g\,(ST_k) = 36.883 - 0.129(EL_{k1}) - 0.223(SLP_{k1})$$ ..... Eqn. 20.5

407

Table 6 Model parameters of predicted soil temperature with independent variables slope, elevation, open shrub, and closed shrub based on equation 11

Variable	Coefficients	Std. Error	T	p	Tolerance	VIF
(Constant)	36.883	6.440	9.251	.000		
Open Shrubs	-1.068	.124	-8.619	.000	.887	1.127
Closed Shrubs	-1.091	.128	-8.508	.000	.893	1.119
Elevation	-0.129	.039	-3.341	.001	.949	1.054
Slope	-0.223	.069	-3.221	.001	.948	1.054

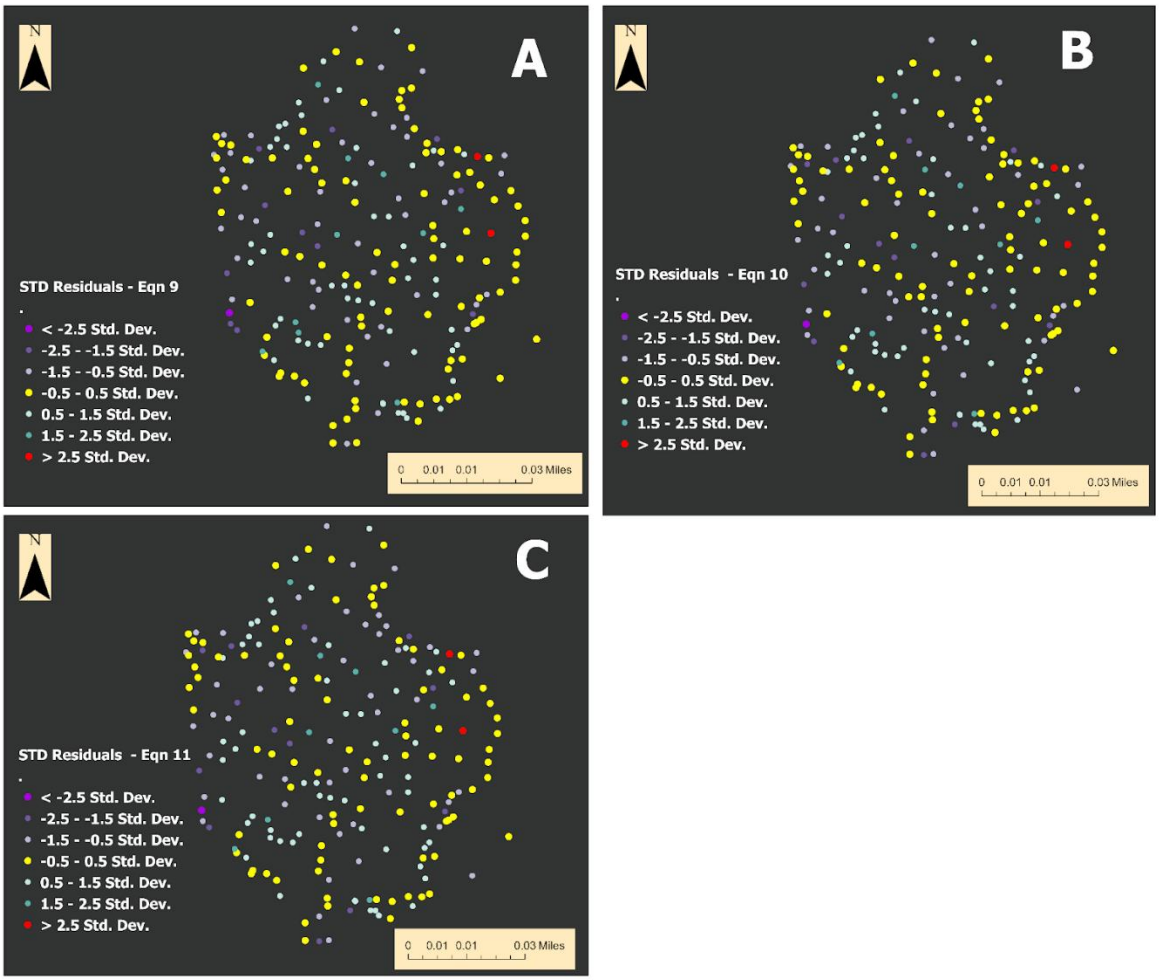
** Represents $p<0.01$, $p<0.05$ is statistically significant, and VIF is the variance inflation factor.

Note: R Square = 0.379, Adjusted R Square = 0.367, and Standard Error of the Estimate = 0.759.

In Equation 11, independent variables, including open shrubs, closed shrubs, elevation, and slope, explained 37.9% of the variation in soil temperature (Adjusted $R^2 = 0.367$). All independent variables and their coefficients were statistically significant ($p < 0.05$) and negatively related to soil temperature. VIF values ranged from 1.054 to 1.127, indicating low multicollinearity. In addition, although both models met the requirement for spatial independence, with the model results based on Equation 10 remaining robust for assessing environmental impacts on soil temperature, the model results based on Equation 11 perform slightly better in reducing prediction errors.

The standardized residuals for the spatial regression model revealed similarities and slight differences between the outcomes from Equations 9, 10, and 11 (see Figure 7). For instance, the same number of large deviations (-2.5 and 2.5) occurred at the same locations among the three multivariable models and their outcomes. However, there are slight differences in the number of

424 marginal deviations (-0.5 and 0.5). Marginal deviations based on the 3 models are outlined as
425 follows. First, based on equation 9, 96 out of 220 are almost correctly predicted. Second, based on
426 equation 10, 93 out of 220 are almost correctly predicted. Third, based on Equation 11, 86 out of
427 220 are almost correctly predicted (see Figure 7).



428

429 **Figure 7** Standardized residuals based on Equations 9, 10, and 11 [Note: Panels A, B, and C
430 correspond with Equations 9, 10, and 11, respectively. These point values indicated the degree of
431 deviation that occurred when soil moisture was predicted based on the respective independent
432 variables used in the models.

433

4.0 DISCUSSIONS

4.1 Major Findings

The initial analysis examined the relationship between individual factors, including land cover types and environmental factors, and ST in the savannah study area. Our study reported the following key findings. First, the presence of bare land is associated with higher soil temperatures. Second, areas dominated by open grasses are also linked to increased soil temperatures. This suggests that areas with less plant cover, which get more direct sunlight, tend to be hotter. In contrast, the presence of open and closed shrubs is associated with lower soil temperatures. This indicates that thicker plant cover would likely cool the soil. Additionally, soil moisture, elevation, and slope all corresponded to lower soil temperatures, meaning that as these factors increased, the soil generally became cooler. Finally, the NDVI, which measured how green or dense vegetation is, showed a significant negative correlation with soil temperatures, highlighting the significant cooling effect of greater vegetation density. The multivariable analyses offered a more comprehensive understanding of the collective effects of these factors on soil temperature.

Adding all independent variables in the first model, the results revealed that, with a couple of exceptions, most of these factors, such as open grasses, open shrubs, closed shrubs, elevation, and slope, are important for predicting soil temperature. This multivariable model explained a notable portion of the variation in soil temperature. While open grass still showed a positive impact, open shrubs, closed shrubs, and slope consistently showed a negative relationship with soil temperature. As we modified our models by removing less influential factors (open grasses, NDVI, and soil moisture), our final model, which retained open shrubs, closed shrubs, elevation, and slope, consistently showed that the more we have these factors the more soil temperature lowers, suggesting open grasses, closed shrubs, elevation and slope are crucial factors in controlling soil

457 temperature dynamics in this savannah environment, with vegetation generally having a cooling
458 effect, and higher, steeper areas also tending to record lower soil temperatures.

459 **4.2 Relationships Between Current Findings and Existing Literature**

460 Our results largely agreed with existing studies on how plants and land features affect soil
461 temperature in savannah and dry areas. It is a well-established fact that bare land gets hotter
462 because it directly absorbs more sunlight, resulting in increased temperatures (45,46). Similarly,
463 existing research has widely reported that denser plants, such as shrubs, cool the soil, thereby
464 reducing soil temperature. This is because plants provide shade and release water vapor, both of
465 which help cool the ground (47,48). Our analysis revealed an evolving relationship between open
466 grasses and soil temperature across regression models. Initially, the univariable model indicated a
467 significant positive association, which aligns with existing literature suggesting that less dense
468 vegetation leads to higher soil temperatures due to reduced shading (49,50). However, upon
469 incorporating additional environmental variables into subsequent multivariable models (e.g., open
470 shrubs, closed shrubs, soil moisture, elevation, slope), the statistical significance of open grasses
471 diminished and ultimately ceased. This observation highlights the effect of shared variance among
472 correlated predictors, where variables with stronger, more direct influences on soil temperature,
473 such as the substantial shading provided by dense shrubs cover or the thermal buffering capacity
474 of soil moisture (51), exert a more dominant explanatory role. Furthermore, topographical factors
475 like elevation and slope significantly influence soil temperature (52,53). Thus, the initial apparent
476 influence of open grasses became less discernible when considered within a more comprehensive
477 environmental context. The analysis of multivariable regression models reveals a notable shift in
478 the statistical significance of open grasses cover in predicting soil temperature.

Initially, in the comprehensive Model 1 (Table 4), open grasses showed a significant positive association with soil temperature (p=0.014). This indicated a distinct influence when considered alongside all other environmental and land cover variables (open grasses, open shrubs, closed shrubs, elevation, and slope). However, Model 2 (Table 5), a refined iteration, saw open grasses lose its statistical significance (p=0.065). This change occurred after the exclusion of soil moisture and NDVI, suggesting that the apparent effect of open grasses may have been partly accounted for by these variables, or its impact became less pronounced within the reduced set of predictors. Consequently, in the final, most concise Model 3 (Table 6), open grasses were entirely removed. This systematic elimination underscores the iterative nature of model building, where variables that do not consistently offer a unique and significant contribution are excluded to yield a more robust and interpretable model.

The negative relationship we found between soil moisture, elevation, slope, and soil temperature is in agreement with existing studies (54–56). It has been found that as soil moisture decreases, soil temperature rises because less energy is used for evapotranspiration, confirming a strong negative relationship between soil moisture and soil temperature (55). It has also been observed that soil temperature generally decreases with increasing elevation due to cooler air and reduced solar energy input at higher altitudes (54). Similarly, it has also been reported that elevation and slope position influence soil microclimate, with higher and steeper terrains showing lower soil temperatures and higher soil moisture retention (56). Our current study contributes to existing knowledge by providing additional information regarding how each factor affects soil temperature in this particular savannah region. While the general cooling or warming effects are known, the specific magnitudes of their impact provide valuable local insights. For instance, the strong cooling effect of shrubs empirically highlights their significant role in regulating local microclimates. Even

502 though other studies show slightly different results, or even contrasting ones, for specific plant
503 types or conditions (57–59). For instance, it was observed that increasing vegetation density in
504 arid areas can actually lower soil moisture through higher transpiration, sometimes resulting in
505 warmer soils, contrasting with the general cooling effect expected from vegetation cover (59).
506 Similarly, a study found that the relationship between elevation and soil temperature is not always
507 negative, as some elevation ranges and soil depths exhibit localized warming patterns (57). It has
508 also been reported that changes in surface conditions, such as vegetation loss or land disturbance,
509 can intensify soil heating beyond what topography or soil moisture alone would predict (58). These
510 differences underscore the importance of localized research, as specific conditions in each area can
511 significantly influence how these processes operate. Our findings, therefore, suggestes that in this
512 savannah, the type and density of plants, particularly the presence of shrubs, are key to managing
513 soil temperature. However, it would be important to know from future studies the type of grass,
514 whether open or closed, that is more likely to trap heat in the soil.

515 **4.3 Methodological Development and Contributions**

516 Our analysis in this study progressed from an univariable to a multivariable model. Thus, such an
517 approach provided a better understanding of the relationship between the independent variables
518 and soil temperature and helped us to present a more robust model. During the univariable analysis,
519 the individual factors explained a relatively small part of the soil temperature changes, and
520 therefore indicate that soil temperature is affected by many factors working together, a common
521 understanding in environmental science (60). By combining multiple factors in our multivariable
522 models, we significantly improved our ability to explain changes in soil temperature. Our final
523 refined model accounted for a substantial portion of the variation in soil temperature. This
524 demonstrates that the combined effects of vegetation cover types and terrain features are much

stronger than their individual impacts (61). Observing how the importance of some factors changed as we refined our models was insightful. For example, open grasses were initially significant in the first multivariable model but became less influential in the later, more refined multivariable models. This suggests that the unique effect of open grasses would likely be less pronounced when other, more dominant factors, including elevation, slope, and the presence of shrubs, present a greater linear strength of relationship with soil moisture, as insignificant variables get eliminated from the model. This method of removing less important factors is a recognized practice in research to make models clearer and more dependable (62).

We also examined statistical measures to assess the quality of our multivariable models. The R^2 value, which quantifies the proportion of variation in soil temperature explained by the independent variables, demonstrated a substantial improvement in the multivariable analysis compared to the univariable models. Specifically, the R^2 values obtained from each univariable model were considerably lower than those from the multivariable models, indicating that soil temperature is better explained by the complex interplay of multiple environmental factors rather than by isolated independent variables. However, among the multivariable models, the R^2 values marginally decreased with the sequential elimination of statistically insignificant variables. This suggests that although these variables did not meet significance thresholds in the multivariable context, their exclusion resulted in a minor reduction in the total explained variance. Nonetheless, the consistent and relatively low Standard Error of the Estimate across the multivariable steps, ranging from 0.753 to 0.759, suggests that all refined multivariable models maintain a robust predictive capability, offering stable and reliable estimations of soil temperature.

More importantly, our VIF values, which indicate if our factors are too similar to each other, have greatly improved. VIF reduced significantly in our later, more refined models. At the same time,

548 tolerance values (related to VIF) increased considerably, suggesting that the factors we retained in
549 our final models were not too closely related, making our results more reliable, as noted by other
550 studies (63). Low VIF values and high tolerance values indicate the absence of substantial
551 multicollinearity among the independent variables (64,65). This condition enhances the reliability
552 of the estimated regression coefficients, allowing for a more confident interpretation of each
553 independent variable's unique contribution to the changes observed in soil temperature. The fact
554 that open shrub, closed shrub, elevation, and slope consistently showed negative relationships with
555 soil temperature across all three models highlights their robust and lasting influence. This
556 consistency suggests that their relationships with soil temperature are fundamental and should be
557 tested in other regions, including areas that are not savannah. These independent variables came
558 with highly stable coefficients, indicating a very reliable relationship with soil temperature,
559 regardless of the presence of other variables, aligning with observations in robust regression
560 analysis.

561 **5.4 Implications for Sustainable Land Reclamation and Environmental Monitoring in**
562 **Mining-Induced Degraded Areas**

563 Our analysis of soil temperature dynamics in a mining-disturbed savannah ecosystem provides
564 valuable insights for sustainable land rehabilitation and climate regulation, directly contributing to
565 the achievement of SDGs 13 (Climate Action), 15 (Life on Land), and 12 (Responsible
566 Consumption and Production). Our findings indicate that denser vegetation, particularly shrubs, as
567 well as increased soil moisture, higher elevations, and steeper slopes, significantly reduce soil
568 temperature. Vegetation canopies provide shade and facilitate evapotranspiration, while soil
569 moisture enhances thermal buffering (66,67). While univariable models suggested that bare ground
570 and open grass areas correlated with higher soil temperatures, this effect diminished when

accounting for vegetation and terrain factors. These insights are crucial for SDG 13, demonstrating that increasing vegetative cover and conserving soil moisture can mitigate heat extremes and enhance carbon sequestration (68). Rehabilitating degraded mining lands through targeted revegetation directly supports climate adaptation efforts. Additionally, these findings support SDG 15, underscoring the need to restore native vegetation and enhance soil quality to mitigate land degradation and promote biodiversity. This aligns with initiatives under the UN Decade on Ecosystem Restoration. Moreover, employing sustainable restoration techniques, such as organic mulches and smart water-harvesting systems, supports SDG 12 by promoting resource efficiency and recycling (69). Overall, integrating vegetation restoration, moisture conservation, and terrain-sensitive management provides an effective strategy for achieving climate cooling and ecological resilience in mining-affected savannahs, advancing multiple SDGs through nature-based solutions.

5.5 Study Limitations

Although the multivariable models accounted for much of the variability in soil temperature, excluding key soil parameters such as texture and organic matter may have lowered the overall R^2 values of the models. These factors are crucial in regulating soil heat capacity and moisture retention, and their absence probably limited the models' ability to fully capture the complexity of soil-vegetation-terrain interactions. Fieldwork was also constrained by limited community cooperation, as some residents, wary of government crackdowns on illegal mining, restricted researchers' access to certain sites, which affected data coverage and spatial representation. Finally, this study was based on a single field campaign conducted during the rainy season, which limits the ability to capture seasonal variability in soil temperature. Soil temperature dynamics during the dry season, when vegetation cover is reduced, solar radiation is more intense, and surface exposure is greater, may differ substantially from those observed in this study. The cross-sectional

nature of the data collected, therefore, provides only a snapshot of spatial soil temperature patterns at one point in time. Future studies should incorporate repeated measurements across multiple seasons to provide a more comprehensive understanding of soil temperature dynamics in mining-degraded landscapes.

6.0 CONCLUSIONS

This study investigated the spatial variability of soil temperature within an unreclaimed illegal mining area in Ghana's Talensi District. These insights directly address contemporary challenges posed by escalating global warming and pervasive land degradation. The spatial variations in soil temperature serve as a vital indicator of land degradation extent, signaling heightened vulnerability to erosion and altered hydrological processes. This makes monitoring thermal patterns an efficient means to track stabilization efforts and identify areas needing urgent intervention. Furthermore, the findings are directly applicable to reclamation initiatives, advocating for the prioritized establishment of woody plant species to mitigate thermal stress and enhance soil moisture retention. The observed influence of elevation and slope suggests that reclamation plans should be tailored to specific topographic conditions. This study, therefore, offers a foundational understanding of soil temperature variability in unreclaimed mining areas, emphasizing the critical role of vegetation and topography in shaping thermal regimes. The outcomes provide a robust empirical basis for informing more effective environmental management and reclamation strategies.

DECLARATIONS

Ethics approval and consent to participate: Not applicable

Consent for publication: Not applicable

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