Research Article
Journal of Vocational Institute of Agriculture Vol. 7 ● No. 1 • January – June 2023

Soil Moisture Prediction via a Multiple Linear Regression Model for Stainless Steel Tube Sensor

Warapol Kasemsan[1] and Atirat Maksuwan[1*]

Received: 15 August 2022
Revised: 31 August 2022
Accepted: 31 August 2022

ABSTRACT

In soil moisture measuring system, a type of soil moisture sensor was developed using stainless steel tubes. The electrical contact resistance of stainless steel arose as a result of the dense protective oxide layer. Generally, the measurement of the soil moisture using advanced analytical instruments is costly and difficult. In current study, the researchers developed a multiple linear regression model to predict soil moisture via environmental parameters using analytical instruments through stainless steel tube sensor. The results showed a low prediction root mean squared error (RMSE) and stable model performance. This modeling approach contributes to efficient and low-cost for soil moisture estimation and understanding of the soil moisture based on the environmental parameters.

Keywords: Soil Moisture; Multiple Linear Regression; Stainless Steel Tubes Sensor

[1]Department of Environmental Technology and Applied Science, Faculty of Science and Technology, Pathumwan Institute of Technology, Bangkok 10330
*Corresponding author e-mail: atirat.maksuwan@gmail.com

Introduction

A key element to understanding the nature of global change is the ability to model the two-way interaction between land and atmosphere. Perhaps the most important role that the land surface component performs is the partitioning of incoming radiative energy into sensible and latent heat fluxes. There have been a number of modeling studies, demonstrated the sensitivity of soil moisture anomalies to climate[1-2]. Shukla (personal communication) for instance, reports that soil moisture is the second most important forcing function, second only to the sea surface temperature in the mid-latitudes, and it becomes the most important forcing function in the summer. The role of soil moisture is equally important at smaller scales. Recent studies with mesoscale atmospheric models have similarly demonstrated sensitivity to spatial gradients of soil moisture. For example, Fast and McCorcle[3] have shown that moisture gradients can induce thermally induced circulations similar to sea breezes. Chang and Wetzel[4] have concluded that the spatial variations of vegetation and soil moisture affect the surface baroclinic structures through differential heating which in turn indicate the location and intensity of surface dynamic and thermodynamic discontinuities necessary to develop severe storms. In yet another study, Lanicci et.al.[5] have shown that dry soil conditions over the southern Great Plains can dynamically interact to alter pre-storm conditions and subsequent convective rainfall patterns. More recently, Betts et al.[6] demonstrated that the initialization of the Global Climate Model Weather Forecast (GCMWF) weather predictions with current soil moisture values can lead to improved rainfall predictions. In addition to the role of soil moisture in the interactions between the land surface and the atmosphere, soil moisture is a storage of water timewise between rainfall and evaporation that acts as a regulator to one of the more fundamental hydrologic processes, infiltration and runoff production from rainfall and which must be accounted for in any water and energy balances. Soil moisture content may be determined via its effect on dielectric constant by measuring the capacitance between two electrodes implanted in the soil[7-10]. Where soil moisture is predominantly in the form of free water (e.g., in sandy soils), the dielectric constant is directly proportional to the moisture content[11-12]. The probe is normally given a frequency excitation to permit measurement of the dielectric constant. The readout from the probe is not linear with water content and is influenced by soil type and soil temperature[13]. Therefore, careful calibration is required and long-term stability of the calibration is questionable. In soil moisture measuring system, type of soil moisture sensor was developed using stainless steel tubes. The electrical contact resistance of stainless steel arises as the result of the dense protective oxide layer. The measurement of the soil moisture by advanced analytical instruments is costly and difficult. In current study, we develop the multiple linear regression models to predict soil moisture via environmental parameters by analytical instruments through stainless steel tubes sensor. Results here show a low prediction root mean squared error (RMSE) and stable model performance. This modeling approach contributes to efficient and low-cost for estimations of soil moisture estimations and understandings of the soil moisture based on environmental parameters.

Materials and Methods

Conceptual framework of this research in Figure 1.

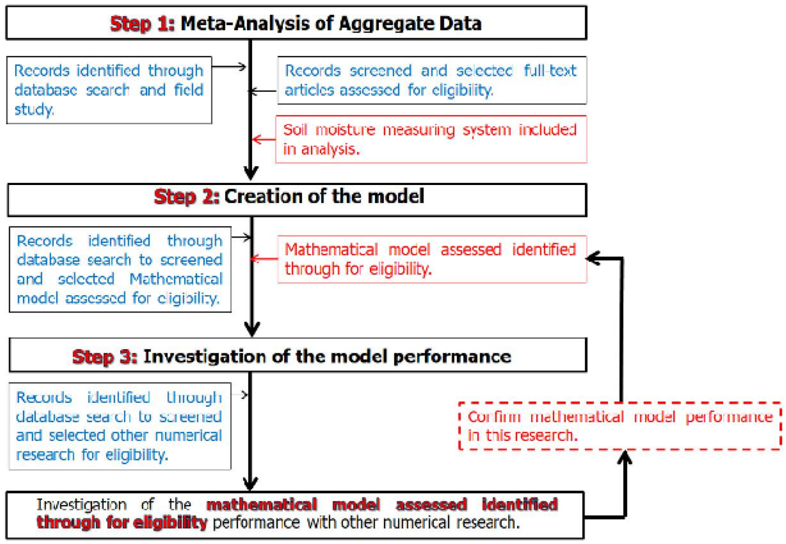

Figure 1 Conceptual framework of this research

The researcher used a prospective framework for adaptive meta-analysis to reduce the bias in the selection of studies, assessment the risk of bias, definition of results and timing and planned analysis execution[14-15]. The researcher was modified the following framework from Chrisanthi et al.[16]. The key principles of adaptive meta-analysis are follows (1) Initiate a systematic literature review process to find all soil moisture measurement systems included in the analysis; (2) Comprehensive search for published trials unpublished and eligibled; (3) Working with co-authors to understand the conceptual framework for adaptive meta- analysis; (4) Reliable prediction of feasibility and duration of meta-analysis; (5) Interpretation of results taking into account available and unavailable data, and the valuation of systematic reviews and meta-analysis. For the completeness of the search for soil moisture measurement systems included in the analysis. Additionally, the researcher did a comprehensive search on soil moisture measurement systems for analysis, both published in academic databases and official documents of the Department of Agricultural Extension. In this research, all documents obtained were cataloged and analyzed. Summarizing the finding from this relatively large dataset requires documenting the organization of Gaber's seven criteria[17] to make it easier to refer to the material, which are different from the most meta-analytic techniques using an extensive number of criteria to organize documents. For example, Rosentahl[18] use more than 70 criteria to analyze documents in his meta-analysis. Therefore, the seven criteria used in this research provided an easy way to refer documents to free up their time, the researchers closely analyzed each document received. Then, gathered data, according to seven criteria, to find confluence by comparing findings from papers and research papers gleaned from the narrative and vote counting process to achieve a holistic understanding[19]. The seven criteria used to summarize the data for each document are shown in Table 1.

Table 1 Criteria for abstracting reviewed assessments[19]

Criteria	Purpose
Author	Name, address, and phone number; so, they can be contacted for additional questions
Title	Title of document and ID number if applicable
Date	To see how the findings in the report compare to earlier or later reports on the same topic
Methods	Identification of the research strategy used to obtain information
Data	Type of data (qualitative/quantitative) generated from the research
Findings	Identification of primary research results
Recommendations	Short description of primary policy recommendations

Most soil moisture problems, based on environmental factors, are multivariate. Therefore, an invariant approach to research analysis is often flawed and may produce inaccurate prediction coefficients quantitatively or qualitatively, and an inaccurate conclusion with inference testing[20-21] often requires a multivariate approach.

Multiple linear regression is a useful technique for simulating many phenomena in soil moisture based on environmental parameter research[22-24]. For data sets that meet the necessary assumptions, It has a well-developed layout that can often be fixed for sure, yielding estimates of the predictor variable coefficients and standard error or uncertainty[25-26]. This can lead to a better understanding of the associated effects and the significance of the compelling predictors, and allows the investigator to predict the outcome of future data. Applications in soil moisture based on environmental parameters include modeling to consider, it an effective technique for collecting spatial data relevant to irrigation system design. The multiple linear regression models are built on the same simple linear regression, and the four fundamental assumptions made with simple linear regression must also be true for multiple linear regression[27-29]. However, in addition to the concepts discussed so far for simple linear regression, which is remain applicable, a new concepts set has to be introduced. This discussion will focus on situation where there are two predictor and one outcome variable. With all three variables, three-dimensional figure can be used to visualize data. Models with more predictive variables follow the same principle, but difficult to visualize. The equation for the regression model now represents the plane. Let the multiple linear regression model (MLR Model). We consider multiple regression and linear relation as follows,

$$Y = XB + V \tag{1}$$

in which,

$$Y = \begin{bmatrix} y_1 \\ y_2 \\ \dots \\ y_n \end{bmatrix}, X = \begin{bmatrix} 1 & x_{11} & x_{12} & \dots & x_{1m} \\ 1 & x_{21} & x_{22} & \dots & x_{2m} \\ \dots & \dots & \dots & \dots & \dots \\ 1 & x_{n1} & x_{n2} & \dots & x_{nm} \end{bmatrix}, B = \begin{bmatrix} b_0 \\ b_1 \\ \dots \\ b_m \end{bmatrix}, V = \begin{bmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \dots \\ \varepsilon_m \end{bmatrix}$$

We develop a multiple linear regression model to predict soil moisture via environmental parameters from an analytical instrument through stainless pipe sensor using linear regression with natural logarithmic transformation (LRNLT Model). Start by considering the nonlinear regression problem is as follows,

$$y = ae^{bx}U \tag{2}$$

With the parameters a and b and the multiplication error term U. If we find the natural logarithm of both sides, this will becomes

$$\ln(y) = \ln(a) + bx + u \tag{3}$$

in which, $u = \ln(U)$.

Development of the LRNLT model was supported by Suchane[30] experimental data to demonstrate the correlation between accuracy of stainless steel tubes sensor for measurement of soil moisture content by gravimetric method and environmental parameter that showed in Figure 2 and Table 2 - 6 .

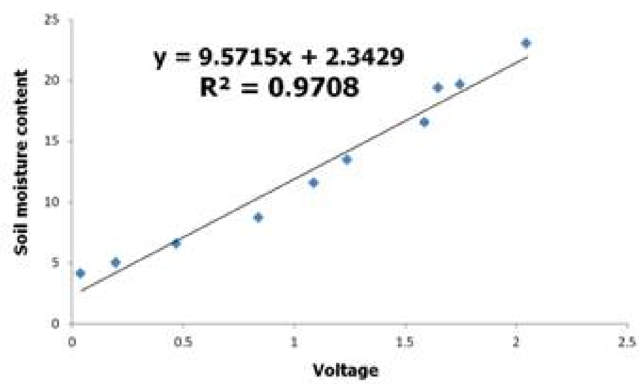

Figure 2 Accuracy of stainless steel tubes sensor for measurement of soil moisture content by gravimetric method.

Table 2 Descriptive statistics of actual of soil moisture content by stainless steel tubes sensor from measurement of soil moisture content by gravimetric method.

	N	Minimum	Maximum	Mean	Std. Deviation
Voltage	10	.04	2.05	1.0920	.68999
Soil Moisture Content	10	4.10	23.06	12.7950	6.70277
Valid N (listwise)	10				

Table 3 Correlations of actual of soil moisture content by stainless steel tubes sensor from measurement of soil moisture content by gravimetric method.

		Voltage	Soil Moisture Content
Voltage	Pearson Correlation	1	.985**
	Sig. (2-tailed)		.000
	N	10	10
Soil Moisture Content	Pearson Correlation	.985**	1
	Sig. (2-tailed)	.000	
	N	10	10

**. Correlation is significant at the 0.01 level (2-tailed).

Table 4 Descriptive statistics of actual of soil moisture content via environmental parameters in study area by stainless steel tubes sensor

	N	Minimum	Maximum	Mean	Std. Deviation
Soil Moisture Content	196	10.27	14.38	10.6629	.57073
Air temperature	196	21.90	34.40	26.3893	3.59042
Relative Humidity	196	14.90	99.90	78.8026	27.86853
Valid N (listwise)	196				

Table 5 Correlations of actual of soil moisture content via environmental parameters in study area by stainless steel tubes sensor

		Soil Moisture Content	Air temperature	Relative Humidity
Soil Moisture Content	Pearson Correlation	1	.264**	-.215**
	Sig. (2-tailed)		.000	.002
	N	196	196	196
Air temperature	Pearson Correlation	.264**	1	-.901**
	Sig. (2-tailed)	.000		.000
	N	196	196	196
Relative Humidity	Pearson Correlation	-.215**	-.901**	1
	Sig. (2-tailed)	.002	.000	
	N	196	196	196

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6: Descriptive Statistics creation of the model between MLR and LRNLT predications with actual of soil moisture content via environmental parameters in study area by stainless steel tubes sensor

	N	Minimum	Maximum	Mean	Std. Deviation
Actual	196	10.27	14.38	10.6629	.57073
MLR	196	10.45	15.67	10.7081	.44314
LRNLT	196	10.36	11.07	10.6876	.20250
Air temperature	196	21.90	34.40	26.3893	3.59042
Relative Humidity	196	14.90	99.90	78.8026	27.86853
Valid N (listwise)	196				

We then tested the LRNLT model's effectiveness from Eq. (3) Compared to other studies with experimental and material science experimental data to show that the LRNLT model can be applied widely.

Results and Discussion

The result of calculation from LRNLT model was supported experimental data by Suchane[30]. We could find a good agreement in Figure 3 with accuracy creation of the model presented by root mean square error (RMSE) between MLR and LRNLT predications via environmental parameters.

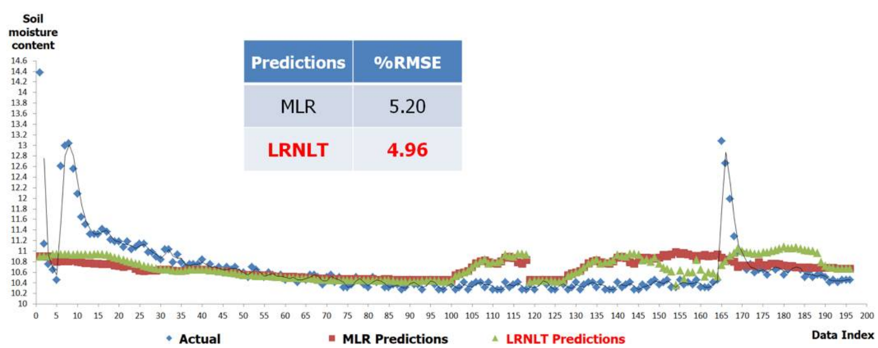

Figure 3 Accuracy creation of the model presented by %RMSE between MLR and LRNLT predications via environmental parameters

These results show that accuracy creation of LRNLT predication higher than MLR predication presented by lower prediction root mean square error. Modeling correlations between MLR and LRNLT predications with actual of soil moisture content via environmental parameters in the study area by stainless steel tubes sensor are shown in Table 7.

Table 7 Correlations from creation of the model between MLR and LRNLT predications with actual of soil moisture content via environmental parameters in study area by stainless steel tubes sensor

		Actual	MLR	LRNLT	Air temperature	Relative Humidity
Actual	Pearson Correlation	1	.060	.372**	.264**	-.215**
	Sig. (2-tailed)		.401	.000	.000	.002
	N	196	196	196	196	196
MLR	Pearson Correlation	.060	1	.233**	.318**	-.205**
	Sig. (2-tailed)	.401		.001	.000	.004
	N	196	196	196	196	196
LRNLT	Pearson Correlation	.372**	.233**	1	.678**	-.539**
	Sig. (2-tailed)	.000	.001		.000	.000
	N	196	196	196	196	196
Air temperature	Pearson Correlation	.264**	.318**	.678**	1	-.901**
	Sig. (2-tailed)	.000	.000	.000		.000
	N	196	196	196	196	196
Relative Humidity	Pearson Correlation	-.215**	-.205**	-.539**	-.901**	1
	Sig. (2-tailed)	.002	.004	.000	.000	
	N	196	196	196	196	196

**. Correlation is significant at the 0.01 level (2-tailed).

The results here show a high correlation coefficient from generating a significantly higher LRNLT predicate at the 0.01 level. Performance of the proposed LRNLT model in Eq. (3) was evaluated using the root mean square error (RMSE) and correlation coefficient against other studies with experimental data in both environmental and material science, respectively. In environmental science, we focus on the study of soil moisture. The result of calculation from LRNLT model was supported experimental data by Zhiqi et al.[31] in Figure 4.

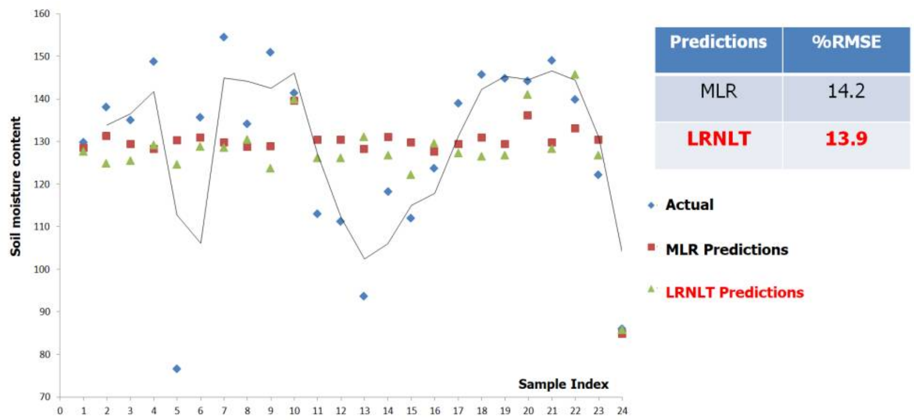

Figure 4 Investigation of the model performance presented by %RMSE in soil moisture prediction via environmental parameters between MLR and LRNLT predictions at Loess Plateau, China

These results show that the generation accuracy of LRNLT is higher than that of the MLR predicate presented by the squared error of the lower predictive root mean. However, root mean square error is greater than 10% on both LRNLT and MLR predication. The reason is standard deviation (S.D.) of soil moisture content (outcome variable) mean in Table 8 have a very wide range. Because the sample size used in the analysis was too small.

Table 8 Descriptive statistics actual of soil moisture content via environmental parameters at Loess Plateau, China

	N	Minimum	Maximum	Mean	Std. Deviation
Soil Moisture Content	24	76.60	154.36	128.5908	20.99895
Air temperature	24	9.86	18.59	10.7308	1.67884
Relative Humidity	24	5.44	19.69	8.6138	3.85978
Valid N (listwise)	24				

The correlation coefficient between outcome variables and predictor variables in Table 9 were highly significant at the 0.01 level but one pair less than 0.6. Therefore, the variance of the data is very large. In material science, we focus on assessed mathematical model identified the eligibility performance in regression model using support vector machines (SVM) technique.

Table 9 Correlations actual of soil moisture content via environmental parameters at Loess Plateau, China

		Soil Moisture Content	Air temperature	Relative Humidity
Soil Moisture Content	Pearson Correlation	1	-.443*	-.178
	Sig. (2-tailed)		.030	.405
	N	24	24	24
Air temperature	Pearson Correlation	-.443*	1	.622**
	Sig. (2-tailed)	.030		.001
	N	24	24	24
Relative Humidity	Pearson Correlation	-.178	.622**	1
	Sig. (2-tailed)	.405	.001	
	N	24	24	24

*Correlation is significant at the 0.05 level (2-tailed).

**Correlation is significant at the 0.01 level (2-tailed).

The results of the study were divided into 3 cases as follows: The first, result of calculation from LRNLT Model was supported experimental data by Zhang and Xu[32] in Figure 5.

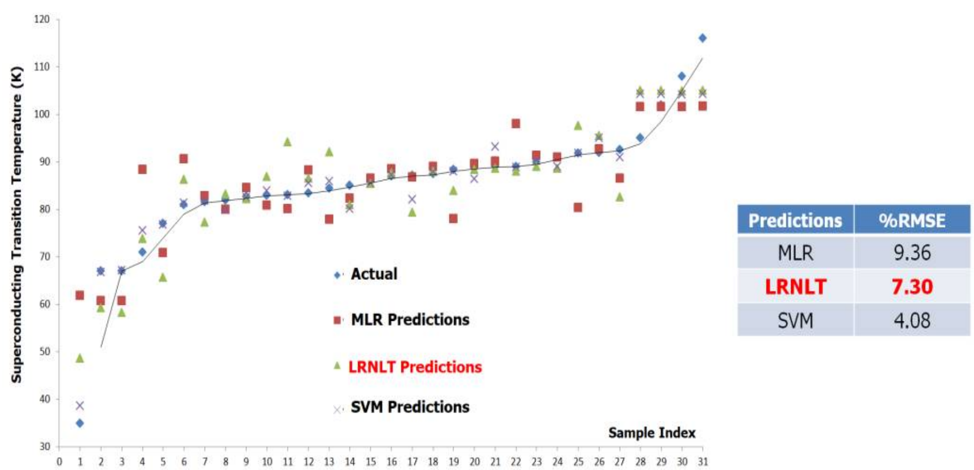

Figure 5 Investigation of the LRNLT model performance presented by %RMSE in predicting YBCO superconductor critical temperature from lattice parameters

These results show that accuracy creation of SVM higher than LRNLT and MLR, respectively. The lowest root mean square error was created by SVM. The reason of high root mean square error create by LRNLT model was standard deviation (S.D.) of superconducting transition temperature (outcome variable) mean in Table 10.

Table 10 Descriptive statistics actual of YBCO superconductor critical temperature from lattice parameters

	N	Minimum	Maximum	Mean	Std. Deviation
Superconducting transition temperature	31	35.00	116.00	85.3045	13.69135
Lattice paprameters a	31	3.77	3.87	3.8261	.02139
Lattice paprameters b	31	3.74	3.89	3.8624	.03753
Lattice paprameters c	31	11.48	11.79	11.6380	.09679
Valid N (listwise)	31				

The Standard deviation (S.D.) had a very large range compared to lattice parameters a, b and c (predictor variables). Because the sample size used in the analysis was too small. Even though, the correlation coefficient between outcome variable and predictor variables was significantly higher at the 0.01 level in Table 11, But the correlation coefficient was still low (less than 0.6), indicating that the variance in the data was large.

The second, result of calculation from LRNLT model was supported experimental data by Zhang and Xu[33] in Figure 6, the lowest root mean square error was created by SVM.

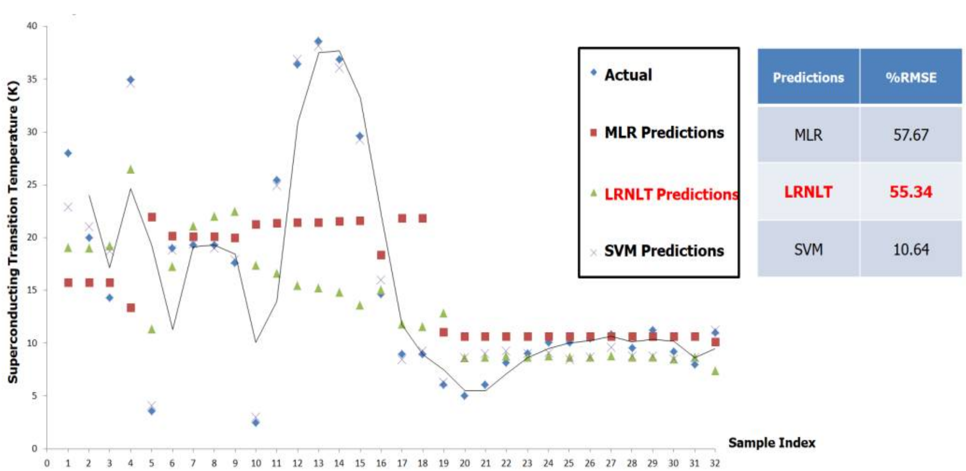

Figure 6 Investigation of the LRNLT model performance presented by %RMSE in predicting Fe-based superconductors critical temperature from lattice parameters

Table 11 Correlations actual of YBCO superconductor critical temperature from lattice parameters

		Superconducting transition temperature	Lattice parameters a	Lattice parameters b	Lattice parameters c
Superconducting transition temperature	Pearson Correlation	1	-.474**	.197	-.461**
	Sig. (2-tailed)		.007	.287	.009
	N	31	31	31	31
Lattice parameters a	Pearson Correlation	-.474**	1	.589**	.532**
	Sig. (2-tailed)	.007		.000	.002
	N	31	31	31	31
Lattice parameters b	Pearson Correlation	.197	.589**	1	.348
	Sig. (2-tailed)	.287	.000		.055
	N	31	31	31	31
Lattice parameters c	Pearson Correlation	-.461**	.532**	.348	1
	Sig. (2-tailed)	.009	.002	.055	
	N	31	31	31	31

**. Correlation is significant at the 0.01 level (2-tailed).

These results show that accuracy creation of SVM higher than LRNLT and MLR, respectively. In addition, root mean square error creates by LRNLT Model higher than the first case. The reason of high root mean square error is very wide range standard deviation (S.D.) of superconducting transition temperature (outcome variable) mean compared to lattice paprameters a and c (predictor variables) in Table 12. So that, the sample size used in the analysis was too small. The correlation coefficient between outcome variables and predictor variables in Table 13 were highly significant at the 0.01 level, there is only one pair and less than 0.6 so the variance in the data is huge.

Table 12 Descriptive statistics actual of Fe-based superconductor critical temperature from lattice parameters

	N	Minimum	Maximum	Mean	Std. Deviation
Superconducting transition temperature	32	2.50	38.60	15.6937	10.45198
Lattice parameters a	32	2.88	4.04	3.8150	.21404
Lattice parameters c	32	5.18	13.84	9.2188	3.61565
Valid N (listwise)	32				

Table 13 Correlations actual of Fe-based superconductor critical temperature from lattice parameters

		Superconducting transition temperature	Lattice parameters a	Lattice parameters c
Superconducting transition temperature	Pearson Correlation	1	.131	.471**
	Sig. (2-tailed)		.476	.007
	N	32	32	32
Lattice parameters a	Pearson Correlation	.131	1	.137
	Sig. (2-tailed)	.476		.455
	N	32	32	32
Lattice parameters c	Pearson Correlation	.471**	.137	1
	Sig. (2-tailed)	.007	.455	
	N	32	32	32

**. Correlation is significant at the 0.01 level (2-tailed).

The third, result of calculation from LRNLT model was supported experimental data by Zhang and Xu[34] in Figure 7, the lowest root mean square error was created by LRNLT model.

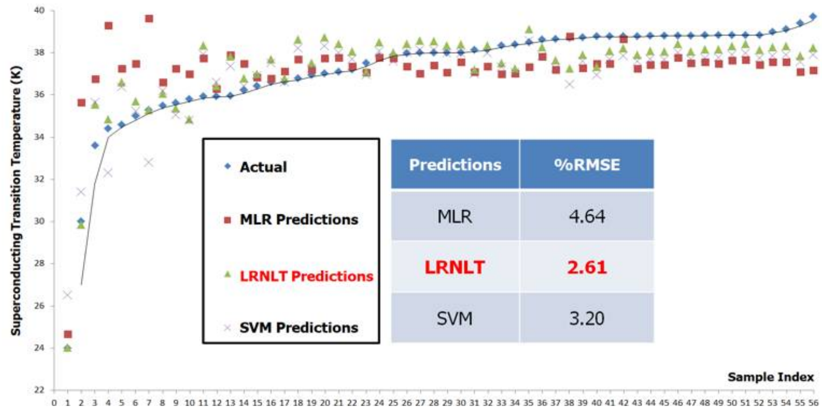

Figure 7 Investigation of the LRNLT model performance presented by %RMSE in predicting doped MgB_2 superconductor critical temperature from lattice parameters

These results show that accuracy creation of LRNLT higher than SVM and MLR, respectively. The reason of the lowest root mean square error was a small range standard deviation (S.D.) of superconducting transition temperature (outcome variable) mean compared to lattice parameters a and c (predictor variables) in Table 14. Furthermore, the standard deviation (S.D.) of the outcome variable mean in this case was the smallest compared to the previous two cases. The correlation coefficient between outcome and predictors variables in Table 15 was 0.6 or higher for all pairs of high significance at the 0.01 level. Therefore, the variance of the data was small.

Table 14 Descriptive statistics actual of MgB_2 superconductor critical temperature from lattice parameters

	N	Minimum	Maximum	Mean	Std. Deviation
Superconducting transition temperature	56	24.00	39.70	37.2018	2.51314
Lattice parameters a	56	3.06	3.52	3.0903	.05896
Lattice parameters c	56	3.05	3.55	3.5181	.06367
Valid N (listwise)	56				

Table 15: Correlations actual of MgB_2 superconductor critical temperature from lattice parameters

		Superconducting transition temperature	Lattice parameters a	Lattice parameters c
Superconducting transition temperature	Pearson Correlation	1	-.671**	.695**
	Sig. (2-tailed)		.000	.000
	N	56	56	56
Lattice parameters a	Pearson Correlation	-.671**	1	-.994**
	Sig. (2-tailed)	.000		.000
	N	56	56	56
Lattice parameters c	Pearson Correlation	.695**	-.994**	1
	Sig. (2-tailed)	.000	.000	
	N	56	56	56

**. Correlation is significant at the 0.01 level (2-tailed).

Conclusions

In summary, the multiple linear regression models are developed to predict soil moisture by using stainless steel tube sensors based on environmental parameters. The result of this research showed that by using LRNLT model depending on the group of the soil moisture data or outcome variable, it had a low standard deviation (S.D.) and the correlation between soil moisture data and all environmental parameters data or predictor variables was significant at the 0.01 level (Highest significant). We then tested the LRNLT Model's effectiveness from Eq. (3) with other studies. The results showed that low prediction root mean square error and stable model performance suggest that the correlation coefficient between outcome and predictors variables was 0.6 or higher for all pairs of high significance at the 0.01 level. Because the variance of the data was small. A small variance indicates that the data points tend to be very close to the mean. So, the multiple linear regression model for modeling and understanding the relationship between soil moisture temperature and relative humidity. The modeling exercise might also contribute to environmental friendly technology.

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