



International Journal of Research in Agronomy

E-ISSN: 2618-0618
P-ISSN: 2618-060X
© Agronomy
NAAS Rating (2026): 5.20
www.agronomyjournals.com
2026; SP-9(8): 265-269
Received: 02-06-2026
Accepted: 08-07-2026

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Spatial prediction of soil organic carbon, available phosphorus and available potassium using regression kriging in Rajendranagar Mandal, Telangana, India

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DOI: <https://www.doi.org/10.33545/2618060X.2026.v9.i8Sd.6303>

Abstract

Spatial variability of soil properties is an important consideration in soil fertility assessment and nutrient management. Conventional soil sampling provides information only at specific locations, whereas spatial prediction techniques allow soil properties to be estimated at unsampled locations. The present study was conducted to predict the spatial distribution of soil organic carbon (OC), available phosphorus (P_2O_5) and available potassium (K_2O) using regression kriging in Rajendranagar Mandal of Rangareddy District, Telangana, India. A total of 109 surface soil samples were collected from 0–15 cm depth using conditioned Latin hypercube sampling. Soil organic carbon, available phosphorus and available potassium were determined using the Walkley and Black, Olsen and neutral ammonium acetate methods, respectively. The dataset was divided into 76 calibration samples and 33 validation samples. Multiple linear regression was used to establish relationships between the soil properties and environmental covariates, namely digital elevation model (DEM), normalized difference vegetation index (NDVI) and land use/land cover (LULC). The spatial dependence of the regression residuals was evaluated using experimental semivariograms, and regression kriging was subsequently used to generate continuous spatial prediction maps. The environmental variables explained 8.6, 32.6 and 40.6% of the variability in OC, P_2O_5 and K_2O , respectively. The residuals of OC were best described by a cubic semivariogram model, while spherical models were fitted for P_2O_5 and K_2O . The regression kriging validation resulted in R^2 values of 0.2317, 0.4059 and 0.1307 for OC, P_2O_5 and K_2O , respectively. The corresponding RMSE values were 0.0789%, 5.3064 kg ha⁻¹ and 71.5062 kg ha⁻¹. The spatial prediction maps revealed considerable variation in the distribution of the three soil properties across the study area. The medium classes of OC, P_2O_5 and K_2O occupied the major portion of the study area. The study demonstrates the utility of regression kriging for spatial characterization of selected soil fertility properties using environmental covariates.

Keywords: Regression kriging, digital soil mapping, soil organic carbon, available phosphorus, available potassium, spatial variability

Introduction

Soil properties exhibit considerable spatial variability due to the interaction of soil-forming factors, topography, vegetation, land use and management practices. Understanding the spatial distribution of soil properties is essential for assessing soil fertility, identifying areas with varying nutrient status and developing appropriate site-specific soil management strategies. Soil organic carbon (OC), available phosphorus (P_2O_5) and available potassium (K_2O) are important indicators of soil fertility and play major roles in maintaining soil quality and supporting crop production.

Soil organic carbon is an important component of soil quality and is associated with nutrient cycling, soil structure, water retention and biological activity. Its spatial distribution is influenced by vegetation, land use, topography and management practices. The spatial distribution of soil organic carbon has been studied using geostatistical and digital soil mapping approaches. Li *et al.* (2023) [1] demonstrated the application of predictor variables to support regression kriging for spatial prediction of soil organic carbon stocks and reported the importance of environmental predictors in explaining spatial variation.

Available phosphorus and potassium are essential plant nutrients, and their concentrations may vary substantially across agricultural landscapes. Spatial information on these nutrients can assist in identifying areas with different fertility status and support more efficient nutrient management. Kozar *et al.* (2002)^[2] used a spatial correlation model for mapping soil phosphorus and potassium, demonstrating the application of spatial modelling techniques for representing the distribution of these nutrients. Gao *et al.* (2021)^[3] also reported the application of different geospatial techniques for digital mapping of soil nutrients.

Digital soil mapping integrates soil observations with environmental information to predict soil properties at unsampled locations. Environmental covariates derived from terrain, vegetation and land-use information can provide additional information about the spatial distribution of soil properties. Regression kriging is a hybrid technique that combines regression modelling with geostatistical interpolation. In this approach, the systematic component of soil variability is explained using auxiliary environmental variables, while the spatially structured component remaining in the regression residuals is modelled using a semivariogram and interpolated using kriging.

The selection of representative sampling locations is an important component of digital soil mapping. Conditioned Latin hypercube sampling provides an efficient approach for selecting sampling locations while representing the variability of environmental covariates. Minasny and McBratney (2006)^[4] described conditioned Latin hypercube sampling as a method for sampling in the presence of ancillary information.

Considering the spatial variability of soil fertility properties and the availability of environmental information, the present study was undertaken to spatially predict soil organic carbon, available phosphorus and available potassium using regression kriging in Rajendranagar Mandal, Telangana, India.

2. Materials and Methods

The study was conducted in Rajendranagar Mandal of Rangareddy District, Telangana, India (Figure 1). The study area is geographically located at 17.321133° N latitude and 78.419063° E longitude and covers an area of 48.70 km² (4870.22 ha). It extends from 17.268024° to 17.372117° N latitude and from 78.374133° to 78.464567° E longitude. Rajendranagar Mandal experiences a semi-arid tropical climate, with hot summers and a southwest monsoon extending from June to October. The area receives an average annual rainfall of approximately 800 mm, while the mean annual temperature is

around 26°C. The elevation of the study area ranges from 498.82 to 617.79 m above mean sea level.

A total of 109 surface soil samples were collected from a depth of 0–15 cm. Sampling locations were selected using conditioned Latin hypercube sampling (CLHS) to represent the environmental variability of the study area. The collected soil samples were processed and analysed for soil organic carbon, available phosphorus and available potassium. Soil organic carbon was determined by the Walkley and Black method (1934)^[5] available phosphorus by Olsen *et al.* (1954)^[6] and available potassium by the neutral ammonium acetate method.

The dataset consisting of 109 observations was divided into 76 calibration samples and 33 validation samples. The calibration dataset was used for development of the regression kriging models, whereas the validation dataset was used for evaluating the prediction performance of the models.

Digital elevation model (DEM), normalized difference vegetation index (NDVI) and land use/land cover (LULC) were used as auxiliary environmental variables. Multiple linear regression was performed using Python to establish the relationship between each soil property and the environmental covariates. The regression component was expressed as a linear combination of the selected environmental variables. The regression residuals were calculated as the difference between the observed values and the values predicted by the regression model.

The spatial dependence of the regression residuals was examined using experimental semivariograms. Appropriate theoretical semivariogram models were fitted to the experimental semivariograms based on the spatial structure of the residuals. Regression kriging was then performed by combining the regression prediction with the kriged residual component. The geostatistical analysis was carried out using GSTools in Python, and the regression modelling, spatial prediction and map generation were implemented using Python-based computational procedures.

The prediction accuracy was evaluated using the coefficient of determination (R^2), root mean square error (RMSE), mean absolute error (MAE) and mean error (ME). The final regression kriging predictions were used to generate spatial distribution maps of OC, P₂O₅ and K₂O. Soil fertility classes were represented using the following limits: OC was classified as low (<0.50%), medium (0.50–0.75%) and high (>0.75%); available P₂O₅ was classified as low (<11 kg ha⁻¹), medium (11–25.6 kg ha⁻¹) and high (>25.6 kg ha⁻¹); and available K₂O was classified as low (<120 kg ha⁻¹), medium (120–280 kg ha⁻¹) and high (>280 kg ha⁻¹).

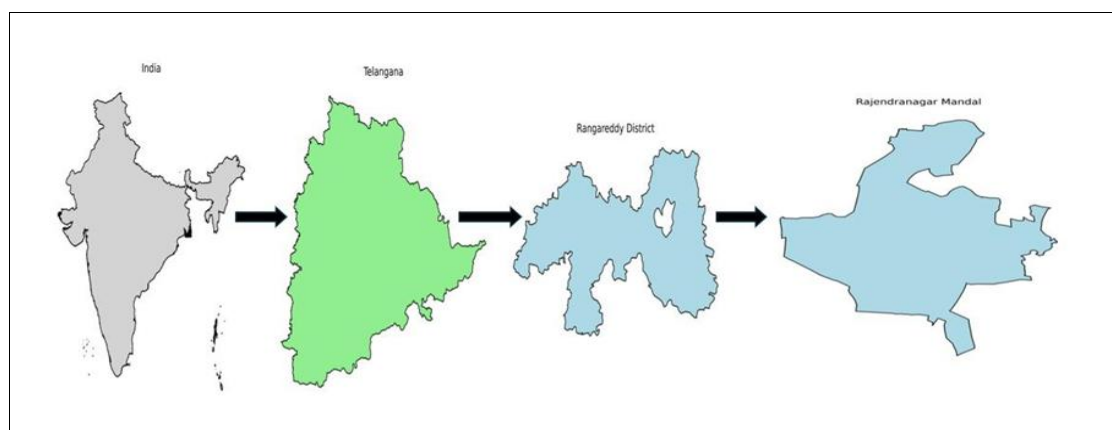


Fig 1: Location of study area

3. Results and Discussion

The regression kriging results for soil organic carbon (OC), available phosphorus (P_2O_5) and available potassium (K_2O) showed distinct relationships with the selected environmental covariates and different spatial structures of the regression residuals. The regression kriging model developed for soil organic carbon using digital elevation model (DEM), normalized difference vegetation index (NDVI) and land use/land cover (LULC) as auxiliary variables produced a coefficient of determination (R^2) of 0.086, indicating that the selected environmental variables explained 8.6% of the variability in soil organic carbon. The regression equation and coefficient of determination are presented in Table 1. The relatively low proportion of variability explained by the regression component indicates that a considerable part of the observed variation in OC remained in the regression residuals and was subsequently accounted for through the spatial component of regression kriging.

The residual spatial variability of OC was best described by the Cubic semivariogram model. The fitted experimental semivariogram is presented in Figure 2 and the corresponding parameters are given in Table 2. The model had a nugget of 0.00319, partial sill of 0.0144, total sill of 0.01759 and a range of 19,660 m. The nugget-to-sill ratio of 17.6% indicated strong spatial dependence. This suggests that a substantial proportion of the residual variation in soil organic carbon was spatially structured across the study area. Li *et al.* (2023) ^[1] also reported strong spatial dependence for soil organic carbon, indicating the importance of spatially structured factors in explaining its distribution.

The regression kriging prediction map of soil organic carbon is presented in Figure 3. The medium organic carbon class (0.50–0.75%) occupied the major portion of the study area. The low organic carbon class (<0.50%) was distributed mainly in the northern and eastern portions of the study area, whereas the high organic carbon class (>0.75%) was negligible or absent. The predominance of the medium class indicates that moderate organic carbon status characterized most of the study area, with localized areas of relatively lower organic carbon content.

The validation of the OC regression kriging model using the independent validation dataset resulted in an R^2 of 0.2317, RMSE of 0.0789%, MAE of 0.0653% and ME of -0.0191 (Table 3). The negative mean error indicates a slight tendency towards underprediction, while the relatively small magnitude of ME indicates limited systematic bias in the predictions. The validation results demonstrate the spatial prediction performance of the regression kriging model for soil organic carbon across the study area.

The regression kriging model for available phosphorus (P_2O_5) was developed using DEM, NDVI and LULC as auxiliary variables. The model produced an R^2 of 0.326, indicating that the selected environmental variables explained 32.6% of the variability in available phosphorus. The regression equation and coefficient of determination are presented in Table 1. The remaining variability was represented through the spatial modelling of the regression residuals.

The residual spatial variability of available phosphorus was best described by the Spherical semivariogram model. The fitted experimental semivariogram is shown in Figure 2. The model had a nugget of 12.37, partial sill of 15.744, total sill of 28.114 and a range of 2110.43 m (Table 2). The nugget-to-sill ratio of 44.0% indicated moderate spatial dependence, suggesting that both spatially structured and relatively unstructured components contributed to the residual variability of available phosphorus.

Gao *et al.* (2021) ^[2] demonstrated the application of geospatial approaches for spatial digital mapping of soil nutrients, supporting the use of spatial modelling techniques for representing nutrient variability.

The regression kriging prediction map of available phosphorus is presented in Figure 3. The medium available phosphorus class (11–25.6 kg ha⁻¹) occupied the major portion of the study area. The high available phosphorus class (>25.6 kg ha⁻¹) occurred as scattered patches, whereas the low available phosphorus class (<11 kg ha⁻¹) was confined to a few isolated locations. The distribution indicates spatial heterogeneity in available phosphorus, although the medium fertility class was predominant throughout the study area.

The validation results for available phosphorus showed an R^2 of 0.4059, RMSE of 5.3064 kg ha⁻¹, MAE of 4.4516 kg ha⁻¹ and ME of -0.3239 (Table 3). The relatively small magnitude of the mean error indicates limited systematic bias in the predictions. The validation results demonstrate that the regression kriging model was able to represent the spatial variation in available phosphorus across the study area.

The regression kriging model for available potassium (K_2O) was developed using DEM, NDVI and LULC as auxiliary variables. The model produced an R^2 of 0.406, indicating that the environmental variables explained 40.6% of the variability in available potassium. This represented the highest coefficient of determination among the three soil properties considered in the study. The regression equation and coefficient of determination are presented in Table 1.

The residual spatial variability of available potassium was best described by the Spherical semivariogram model. The fitted experimental semivariogram is presented in Figure 2. The model had a nugget of 1380.7, partial sill of 2857, total sill of 4237.7 and a range of 742.8 m (Table 2). The nugget-to-sill ratio of 32.6% indicated moderate spatial dependence. The relatively shorter range indicates that the spatially structured component of the potassium residuals occurred over a comparatively shorter distance within the study area. Kozar *et al.* (2002) ^[3] reported the application of spatial correlation modelling for mapping soil phosphorus and potassium, demonstrating the relevance of spatial approaches for representing the distribution of these soil nutrients.

The regression kriging prediction map of available potassium is presented in Figure 3. The medium available potassium class (120–280 kg ha⁻¹) occupied the major portion of the study area, followed by the high available potassium class (>280 kg ha⁻¹). The low available potassium class (<120 kg ha⁻¹) occurred only in a few isolated locations. The spatial distribution indicates that moderate potassium status was predominant across the study area, with localized patches of higher and lower potassium availability.

The validation results for available potassium showed an R^2 of 0.1307, RMSE of 71.5062 kg ha⁻¹, MAE of 57.8351 kg ha⁻¹ and ME of -5.443 (Table 3). The negative mean error indicates a slight tendency towards underprediction. The validation statistics indicate that the prediction performance varied among the three soil properties, reflecting differences in their relationships with the environmental covariates and the spatial structure of their residuals.

Overall, regression kriging integrated the deterministic component explained by DEM, NDVI and LULC with the spatially structured component represented by the regression residuals. The resulting prediction maps provided continuous spatial information on OC, P_2O_5 and K_2O across Rajendranagar Mandal and revealed distinct spatial patterns in the distribution of the three soil fertility properties.

Table 1. Regression equations and coefficient of determination of soil properties using regression kriging

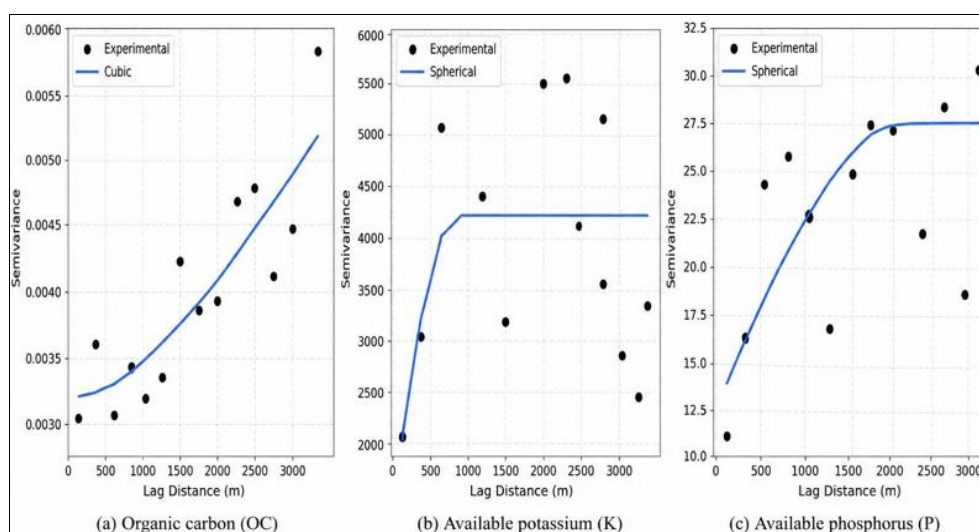
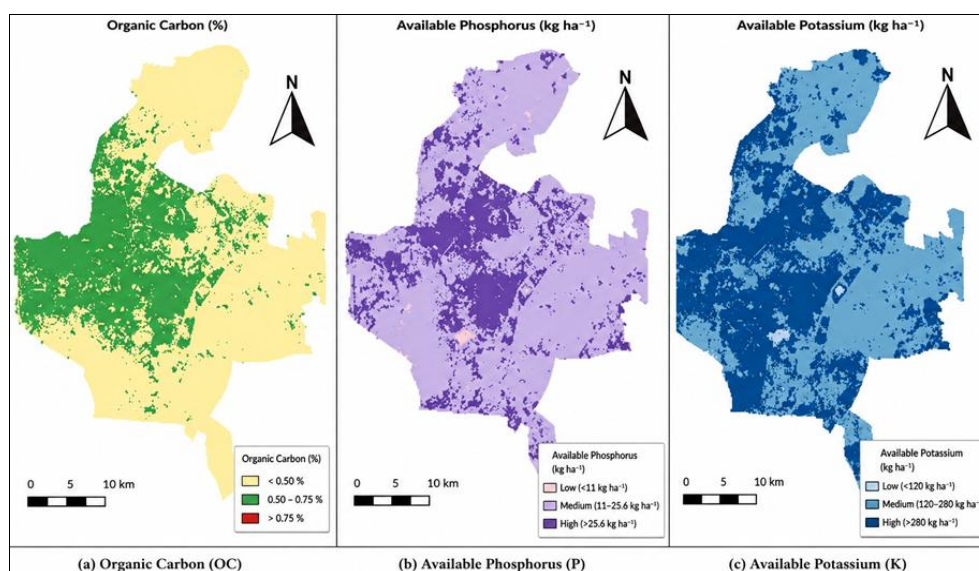
Parameter	Regression equation	R ²
Organic carbon (%)	$OC = 0.938 - 0.001 \times DEM - 0.207 \times NDVI - 0.002 \times LULC$	0.086
Available P ₂ O ₅ (kg ha ⁻¹)	$P_2O_5 = 44.749 - 0.014 \times DEM - 8.813 \times NDVI - 0.317 \times LULC$	0.326
Available K ₂ O (kg ha ⁻¹)	$K_2O = 940.380 - 0.853 \times DEM - 116.664 \times NDVI - 4.772 \times LULC$	0.406

Table 2. Semivariogram parameters of regression residuals of soil properties

Parameter	Model	Nugget	Partial sill	Sill	Nugget/Sill	Range (m)
Organic carbon (%)	Cubic	0.00319	0.0144	0.01759	0.18	19660
Available P ₂ O ₅ (kg ha ⁻¹)	Spherical	12.372	15.744	28.116	0.44	2110.43
Available K ₂ O (kg ha ⁻¹)	Spherical	1380.7	2857	4237.7	0.33	742.8

Table 3. Validation accuracy of regression kriging for selected soil properties

Parameter	R ²	RMSE	MAE	ME
Organic carbon	0.2317	0.0789	0.0653	-0.0191
Available P	0.4059	5.3064	4.4516	-0.3239
Available K	0.1307	71.5062	57.8351	-5.443

**Fig 2: Experimental and fitted semivariograms of regression residuals****Fig 3: Regression kriging prediction maps of soil properties**

4. Conclusion

Regression kriging was used to predict the spatial distribution of soil organic carbon, available phosphorus and available potassium in Rajendranagar Mandal, Telangana. The multiple linear regression models using DEM, NDVI and LULC explained 8.6% of the variability in OC, 32.6% in available P_2O_5 and 40.6% in available K_2O . The regression residuals showed strong spatial dependence for OC and moderate spatial dependence for P_2O_5 and K_2O . A cubic semivariogram model was used for OC, while spherical models were used for P_2O_5 and K_2O . The regression kriging maps showed considerable spatial variability in the three soil properties, with medium fertility classes occupying the major portion of the study area. The spatially explicit prediction maps generated through regression kriging provide useful information for characterizing the distribution of selected soil fertility properties and can support spatial assessment and management of soil resources in the study area.

References

1. Li Y, Wang X, Chen Y, Gong X, Yao C, Cao W, *et al.* Application of predictor variables to support regression kriging for the spatial distribution of soil organic carbon stocks in native temperate grasslands. *J Soils Sediments*. 2023;23:700-717.
2. Kozar B, Lawrence R, Long DS. Soil phosphorus and potassium mapping using a spatial correlation model incorporating terrain slope gradient. *Precis Agric*. 2002;3:407-417.
3. Gao L, Huang M, Zhang W, Qiao L, Wang G, Zhang X. Comparative study on spatial digital mapping methods of soil nutrients based on different geospatial technologies. *Sustainability*. 2021;13:3270.
4. Minasny B, McBratney AB. A conditioned Latin hypercube method for sampling in the presence of ancillary information. *Comput Geosci*. 2006;32:1378-1388.
5. Walkley A, Black IA. An examination of the Degtjareff method for determining soil organic matter and a proposed modification of the chromic acid titration method. *Soil Sci*. 1934;37(1):29-38.
6. Olsen SR, Cole CV, Watanabe FS, Dean LA. Estimation of available phosphorus in soils by extraction with sodium bicarbonate. *USDA Circular*. 1954;939.