Evaluating Spatial Soil Parameters of an Apple Orchard in 'R' Software: A Study from Kashmir Valley

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Abstract
Maintaining the ecological balance of the physical and biological environment depends greatly on the spatial variation of soil parameters across a given region and its elucidation using remote sensing and GIS applications. R software was used to apply the geostatistical methods of Ordinary Kriging and Inverse Distance Weightage to the study of the spatial distribution and variability of the soil parameters of an apple orchard in the Valley of Kashmir. Average values for available phosphorus (P), potassium (K), calcium (Ca), available nitrogen (N), and soil organic carbon (OC) were 1.15 percent, 315 percent, 22.5 kg, 221.4 kg, and 250 mg, respectively. Ordinary kriging (OK) and IDW were used to plot the spatial distribution of soil parameters using spherical (pH, OC, and Ca), steradian (EC, N, P, and K), and mean square error (MSE) values. According to the semi-variogram analysis, there was a strong to moderate spatial dependence. The interpolated maps showed various soil distribution patterns for pH (5.4-5.7), EC (0.46-0.56 DSM-1), OC (0.9-1.4 percent), N (296-335) kg ha-1, P (20-25 kg ha-1), K (221-221.8 kg ha-1), and Ca (100-400 mg kg-1) at the regional scale. This study represented a wide range of spatial soil variability. The estimation of MSE for Ordinary Kriging and IDW was used to predict the best model after performing a validation accuracy assessment. The best fit model for interpolation was the standard kriging model with low MSE. The maps of soil spatial distribution created to serve as an effective tool for policymakers and those planning farms.

Keywords: Interpolation, Geostatistics, Kriging, Inverse Distance Weightage, Soil Parameters

Introduction

Technological advancements and their applications in different disciplines of knowledge have revolutionized the contemporary world because of their applications. Among these technological advancements, Remote sensing and photogrammetry provide spatially explicit, digital data representations of the Earth's surface that can be combined with digitized paper maps in geographic information systems (GIS) to allow efficient characterization and analysis of vast amounts of data which was never possible before. Soil formation dynamics under different environmental conditions have been studied with different background knowledge. Moreover, spatial assessment of soil properties with digital interventions along with environmental factors will further alert soil science. Therefore, while devising effective soil management policies and adaptation strategies to different environmental factors, it becomes quintessential to map the soil properties at unknown locations and corroborate this with the prevailing environmental factors.

The existing digital soil data for continental and global soil systems only provides coarse-scale (1:1000000 or coarser) vector polygon maps with highly aggregated soil classes represented in the form of crisp map units derived from spatiotemporal and continuous soil and environmental data, which characterize the physiochemical, biological, and hydrological conditions of ecosystems(Grunwald et al,2011).The use of the digital soil mapping technique has allowed for the mapping of various soil parameters in numerous studies. The computer-assisted display of digital soil maps and their various properties is known in the field of soil science as digital soil mapping (DSM), also known as predictive pedometric mapping (PM), or soil mapping (PSM).It involves creating soil databases with geographic references based on quantitative relationships between spatially explicit environmental data and measurements taken in the field and the lab (McBratney et al., 2003).Digital soil maps make extensive use of cutting-edge technologies, such as GIS, GPS, spectral signatures, field scanners, DEM, RS, and computational advances like geostatistical interpolation, inference algorithm, and data mining. The maps produced to show the spatial distribution of soil class or soil properties also have the ability to document the uncertainty of soil prediction (Dharumarajan et al., 2019). Digital soil maps, as opposed to traditional soil maps, give us estimates of the accuracy and uncertainty of the prepared soil maps (Minasny & McBratney, 2016).

According to Panacherie and McBratney (2006) the three main parts of a DSM are input, process, and output. The input of a DSM is data obtained through field and laboratory observational methods, which is then "processed" through a spatial soil inference system (predictive models) to produce spatially continuous soil maps as the output. Researchers, crop planners, and policymakers are all very interested in using DSM to provide farmers with site-specific (precise) material recommendations (Xu, Y et al2018). In DSM, geostatistical approaches are frequently used and have definite advantages over alternative approaches., they allow for a change in the support, and the kriging variances directly lead to predictive uncertainty. (2002) McBratney et al and they clearly outperform the alternative techniques. They permit a change in the support, and the kriging variances directly lead to productive uncertainty (Nussbaum et al., 2018)

Geo-statistics is a branch of statistics that deals with spatial data and uses kriging as the spatial interpolator to account for spatial autocorrelation. For the purpose of creating digital soil maps, spatial interpolation of the soil samples is done using geostatistical modelling tools like kriging, semi-variance functions, and variograms. "Kriging, named after D. G. Krige, is one of the deterministic interpolation techniques" (Hasan, 2006. The theory's most basic applications presuppose that a constant local mean and a stationary variance of locational differences are separated by a specific direction and distance. The most popular geostatistical method for spatial interpolation is kriging. For this method to predict attribute values at non-sampled locations, a spatial model between two or more distinct observations is primarily used. Geographic distribution knowledge of soils aids in the assessment of environment-soil relationships, which is crucial for agronomic assessment, soil and water management, and land use planning, making it one of the precisions of kriging methods. By using spatial interpolation to combine the few soil samples from an apple orchard in the Kulgam district of the Valley of Kashmir, the study was conducted to quantify the soil variables at an unidentified location. For spatial interpolation, the soil samples were placed in an unidentified location. R software has been used to apply interpolation modelling techniques like Kriging and Inverse Distance Weightage. The mean square error was used to calculate the effectiveness of the best-fit model. QGIS was used for digitization in order to define the study area.

Review of literature

The potential for producing better soil digital maps has greatly increased as a result of technological advancements over the past few decades (McKensie et al., 2000).The spatially explicit digital data representations of the Earth's surface provided by remote sensing and photogrammetry, among other technological advancements, can be combined with digitalized paper maps in geographic information systems (GIS) to efficiently characterize and analyze massive amounts of data, which was previously impossible. Using GIS to model spatial soil variation from more easily mapped environmental variables will determine the future of soil surveys. Using GIS to model spatial soil variation from more easily mapped environmental variables will determine the future of soil surveys. The most popular geostatistical method for spatial interpolation is kriging. For this method to predict attribute values at non-sampled locations, a spatial model between two or more distinct observations is primarily used. By comparing the observations separated by specific spatial distances two at a time, Kriging methods aim to express the spatial structure in the data by taking into account more than just the distance between observations. A numerical or statistical model of the relationship between soil properties and environmental variables is developed before being applied to a geographic database to produce digital maps (Franklin, 1995). The main objectives of DSM are to produce and present data that more accurately represent soil-landscape continuity, to explicitly incorporate expert knowledge in model design, and to advance pedology and soil geography by revealing insights into soil-forming processes (Scull et al, 2003)

A branch of statistics known as geo-statistics deals with spatial data and employs kriging as the spatial interpolator to account for spatial autocorrelation. Kriging is the most frequently used geostatistical approach for spatial interpolation. This technique mostly relies on a spatial model between two or more different observations to predict attribute values at non-sampled locations. One of the precisions of Kriging methods is that they do not only regard the distance between observations but also intend to express the spatial structure in the data by comparing the observations separated by specific spatial distances two at a time. The D. G. Krige-inspired interpolation technique is called kriging (Hasan, 2006). In its most basic applications, the theory makes the assumption that differences between locations separated by a given direction and distance have a stationary variance and a constant local mean. For the analysis of this study, the estimation of soil constituents was done using the standard kriging method. Kriging fixes many of the issues with the conventional interpolation techniques used in GIS.If the theory's underlying premises are true, it is less arbitrary than other approaches. The most popular interpolation methods, IWD and regular Kriging, are mostly used in GIS applications out of all the available interpolation techniques.

Researchers (Wang et al., 2013) used terrain characteristics as independent variables for soil characteristic mapping based on environmental variables. The accuracy of the mapping that was done to measure different soil properties would have an impact on how well the soil performed and would encourage good management of the soil area. Insufficient intensive field sampling requires too much time and money, which prevents it from providing the level of precision and accuracy required for effective site management.

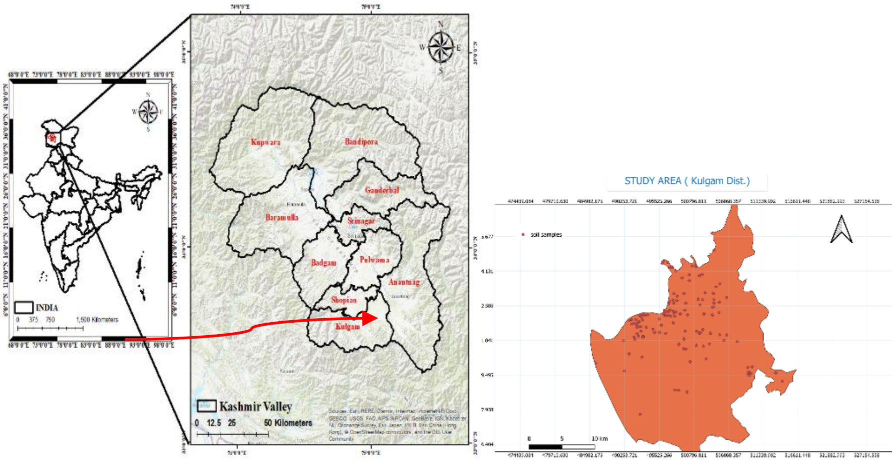
Spatial analysis is the process of modifying spatial data to draw out new information and give the original data new meaning. A Geographic Information System is typically used to analyse spatial data (GIS). GIS software enables spatial analysis tools for performing geoprocessing tasks like data interpolation and calculating feature statistics.

Material and methods

Study area

The region chosen for the study is located at an altitude of 1739 m masl, 33.5335° N latitude, and 74.9209° E longitude in the southern district of Kashmir valley (Kulgam), J&K (UT), India(fig.1). The area is located in the Northern Himalayas' temperate agroclimatic zone, which is characterized by bitterly cold winters and dry summers. The region's soils have a silty clay loam texture (Bangroo et al. 2018).[15]

Fig.1 An apple orchard in the study area



The soil sample data has been provided by the principal investigator of this study, who has done the work by collecting soil samples in an orchard field in the Kulgam district of Jammu and Kashmir.

Geostatistical analysis

R software was used to conduct geostatistical analysis for the spatial distribution of the soil parameters over the study area. QGIS was used to define the study area and create the soil sample layer. By using a weighted average of nearby samples, conventional kriging and inverse distance weightage methods were used to interpolate the values in the spatial field of unsurveyed locations.

The nugget effect and Nugget (n)/sill(s) ratio were used to determine the geographical dependence of specific soil characteristics. Strong dependence is indicated by a n/s ratio of less than 0.25, moderate dependence is indicated by 0.25-0.75, and weak dependence is indicated by greater than 0.75. We determined mean square error (MSE) to assess the precision of our predictions. The most accurate model is the one with the lowest MSE.

Results and discussions

When using R software to perform geostatistical semi variogram analysis and fitting multiple models, the spatial structure of the soil parameters is revealed. Spherical models were used to fit parameters like pH, OC, and Ca, whereas steradian models were used to fit parameters like EC, N, K, and P. Beyond this range, there was no evidence of any spatial autocorrelation or dependence in the range of the studied soil parameters, which ranged from 123.7 m (Ca) to 1050.5 m (ECIn comparison to soil qualities with larger ranges, those with a limited range are less impacted by environmental and management influences over shorter distances. Soil characteristics with a narrower range denote more diverse soils. The nugget, which represents small-scale variability, was smaller for K than for EC, pH, and other variables. The most nuggets were discovered in soil N. (Table 1). This demonstrates that N exhibited significant spatial fluctuation across a wide area.

For K and Ca, the semi variogram analysis showed a considerable spatial dependency (DSD 25%), whereas for the other soil parameters, it showed a moderate spatial reliance (25 DSD 75%). (Table 1).

The spatial dispersion of the soil characteristics reveals how the soil parameters are distributed throughout the study region. For the purpose of creating maps for certain soil properties, kriging was employed with the model parameters of the semi-variogram (Fig. a, b,c).

The research area's soil pH is distributed spatially, with a rise in pH in the area's northwest and a drop in the sections that are higher on the slope. While the northern part of the soil has a rise in EC, it is interlaced with low EC. The pH increases in the study area's extreme east and west while slightly decreasing in the study area's middle, illustrating the geographical diversity in the IDW. There are sporadic increases in the center region's OC, whereas there is a general decline on the opposite sides.

Conclusion

For pH, OC, and Ca, the best-fit model was spherical; for EC, N, K, and P, it was steradian; and the semi variogram analysis revealed that the soil parameters had a high to weak spatial dependence. Different soil distribution patterns for pH (5.7-0.64dSM-1), EC (0.57-0.64dSM-1), OC (0.9-1.4 percent), N (200-320KGha-1), P (16-21kgha-1), K (120-280KGha-1), and Ca (400-650mgkg-1) were discovered in a study conducted on an orchard field in the same study area that is kulgam.The interpolated maps showed different soil distribution patterns for N (296 - 335 kg ha-1), P (20-25 kg ha-1), K (221 - 221.8 kg ha-1), and Ca (100 - 400 mg kg-1) at regional scales. This study, which was conducted for another area in the same study area, namely Kulgam, indicated a wide range of spatial variability. Such analyses highlight the priority hotspot locations and offer information into the response to site-specific nutrient management.

Declarations

Disclosure statement

There was no potential conflict of interest reported by the authors.

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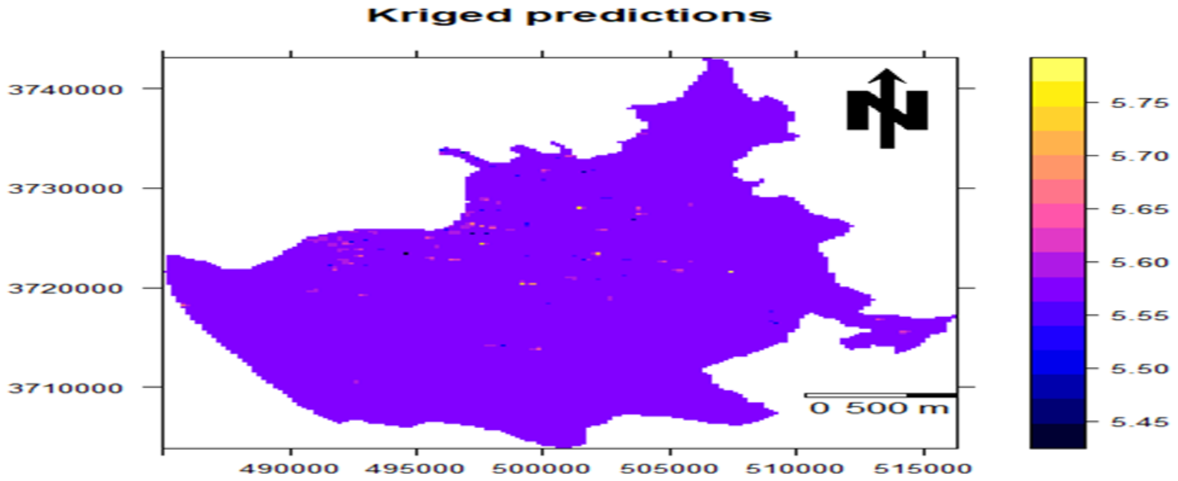
Table 1. Semi variogram parameters of selected soil properties

Soil parameters	Model	Psill	nugget	Range	Nugget/sill
pH	Spherical	0.056	0.208	177.1	3.7142
EC	steridian	0.0028	0.05	1050.5	17.857
OC	spherical	0.14	0.34	372.8	2.42
N	steridian	956.05	8101.41	826.79	8.473
P	steridian	5.29	89.94	333.41	17.001
K	steridian	15421.1	0.00	3784.44	0
Ca	spherical	30413.5	4664.1	123.746	0.1533

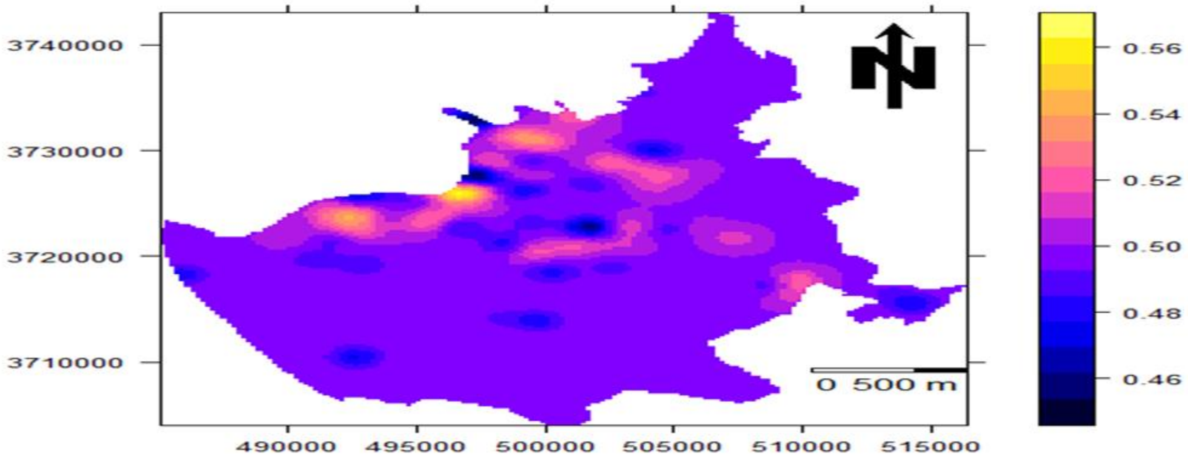
Table2. Root means square error of the Interpolation methods

Soil parameter	RMSE (OK)	RMSE (IDW)
pH	0.52	0.65
EC	0.23	0.26
OC	0.68	0.93
N	97.35	119.41
P	11.5	13.81
K	133.02	156.85
Ca	226.89	241.44

pH



EC (dS/m)



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OC (%)

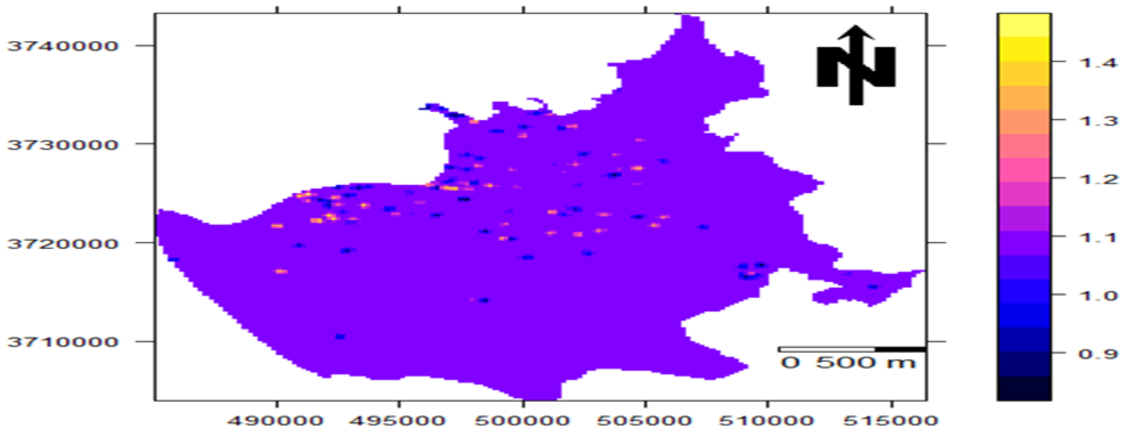
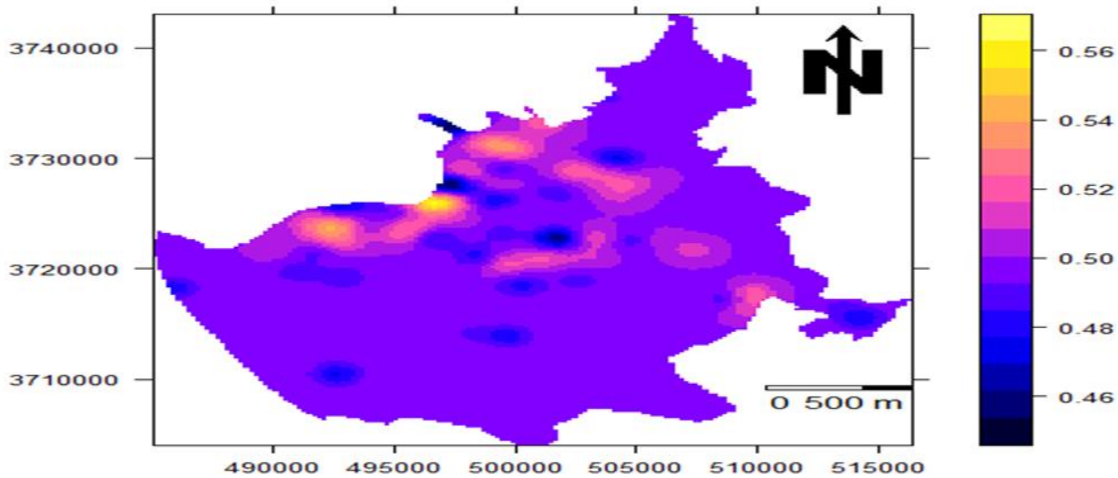
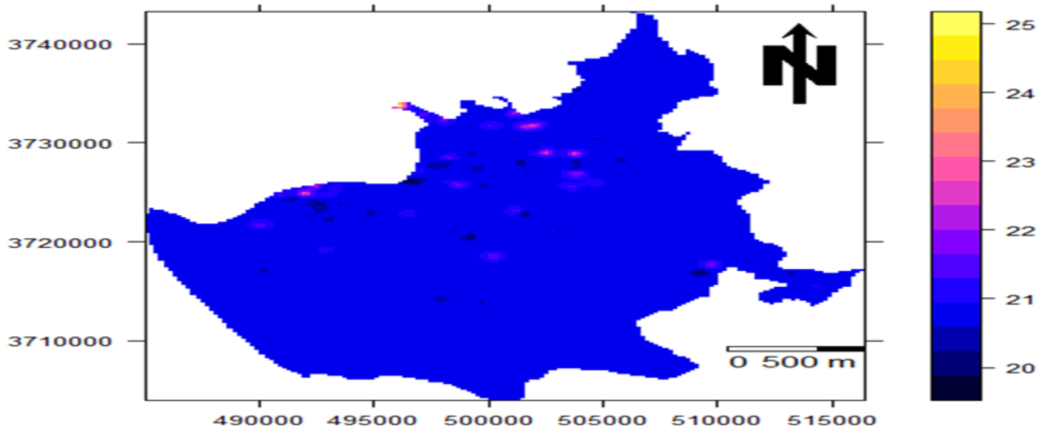


Figure 1a Spatial variability map of pH, EC and OC

N (kg/Ha)



P (kg/Ha)



K (kg/Ha)

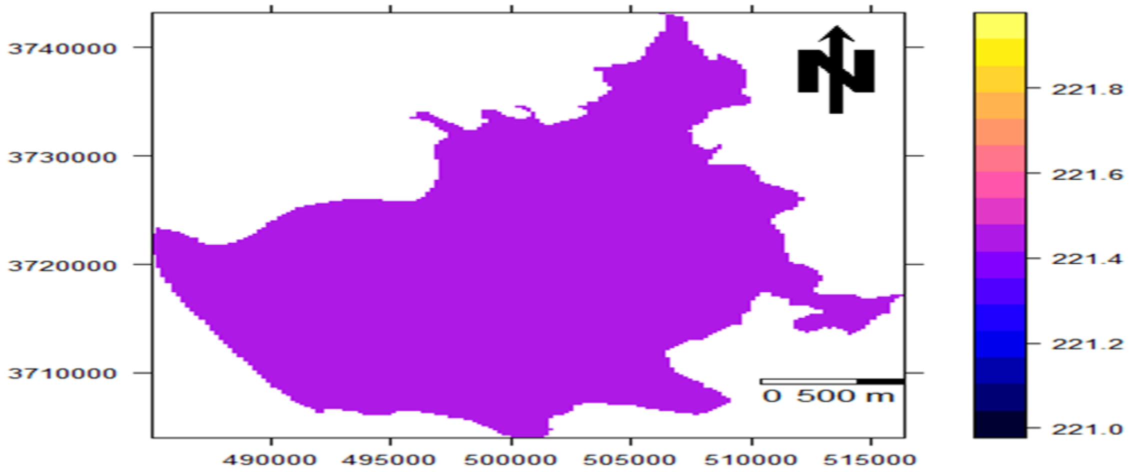
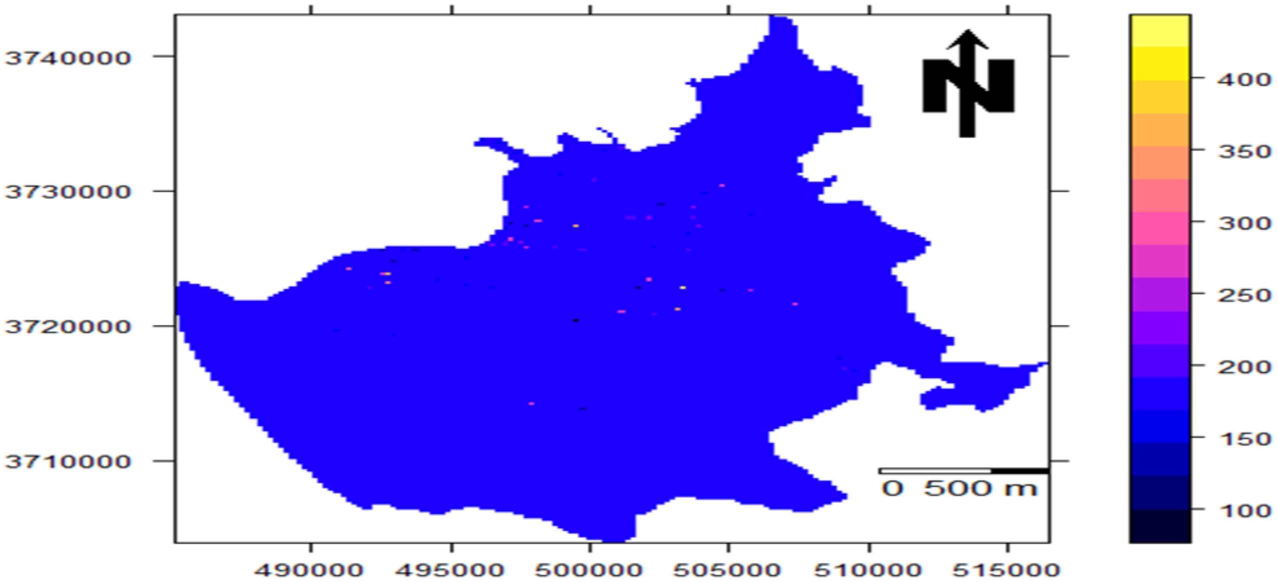
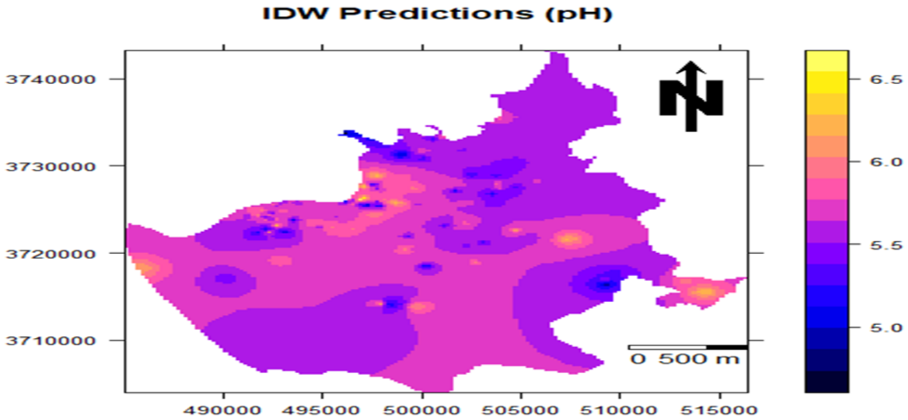


Figure 1b Spatial variability map of N, P and K

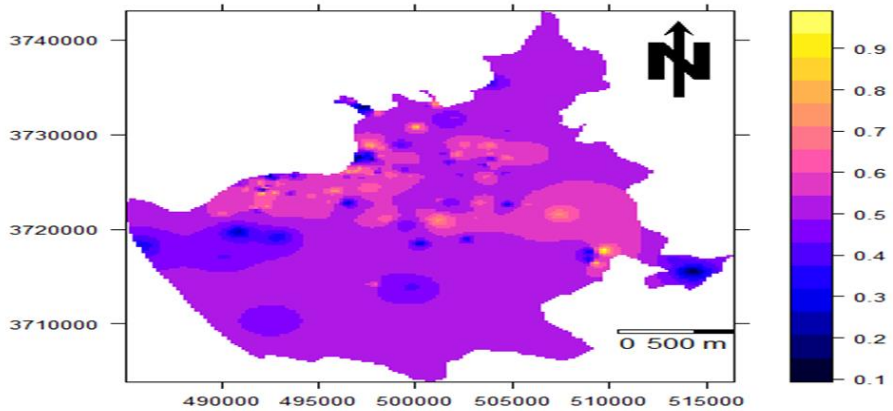
Figure 1c Spatial variability map of Ca (Kg/Ha)



pH



EC (dS/m)



OC (%)

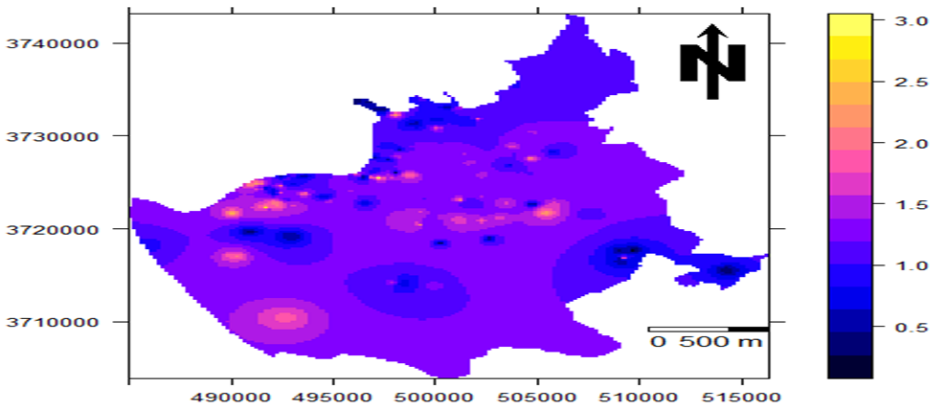
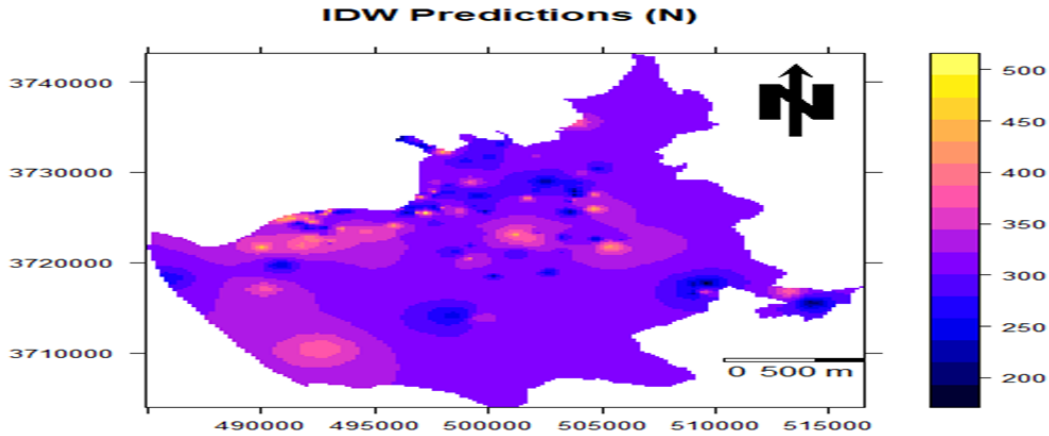
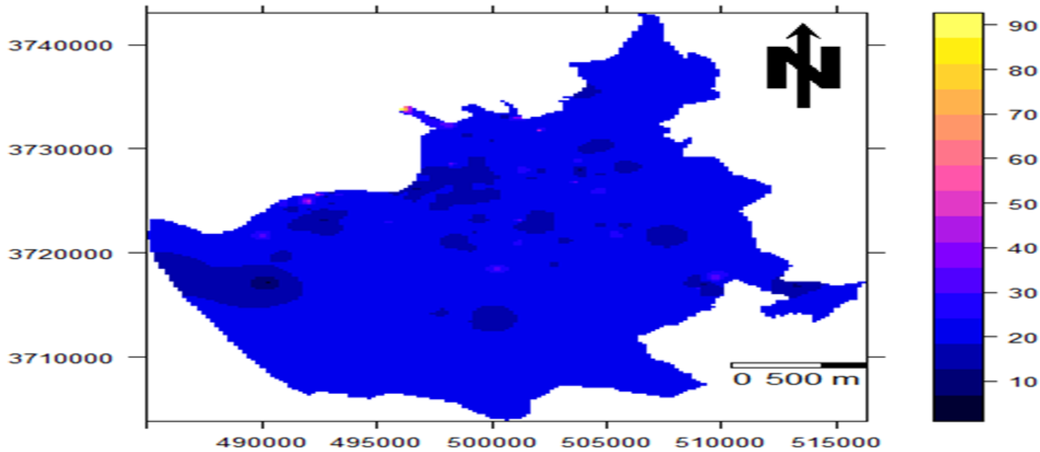


Figure 2a Spatial variability map of pH, EC and OC

N (kg/Ha)



P (kg/Ha)



K (kg/Ha)

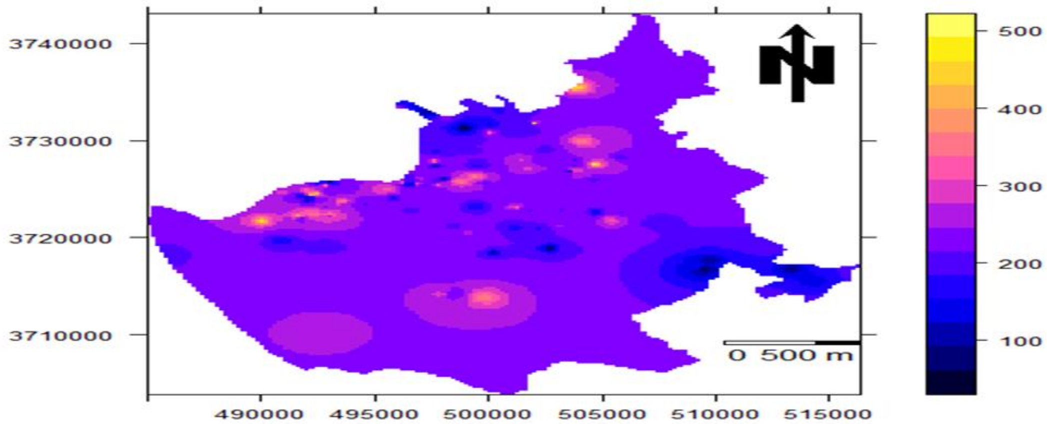
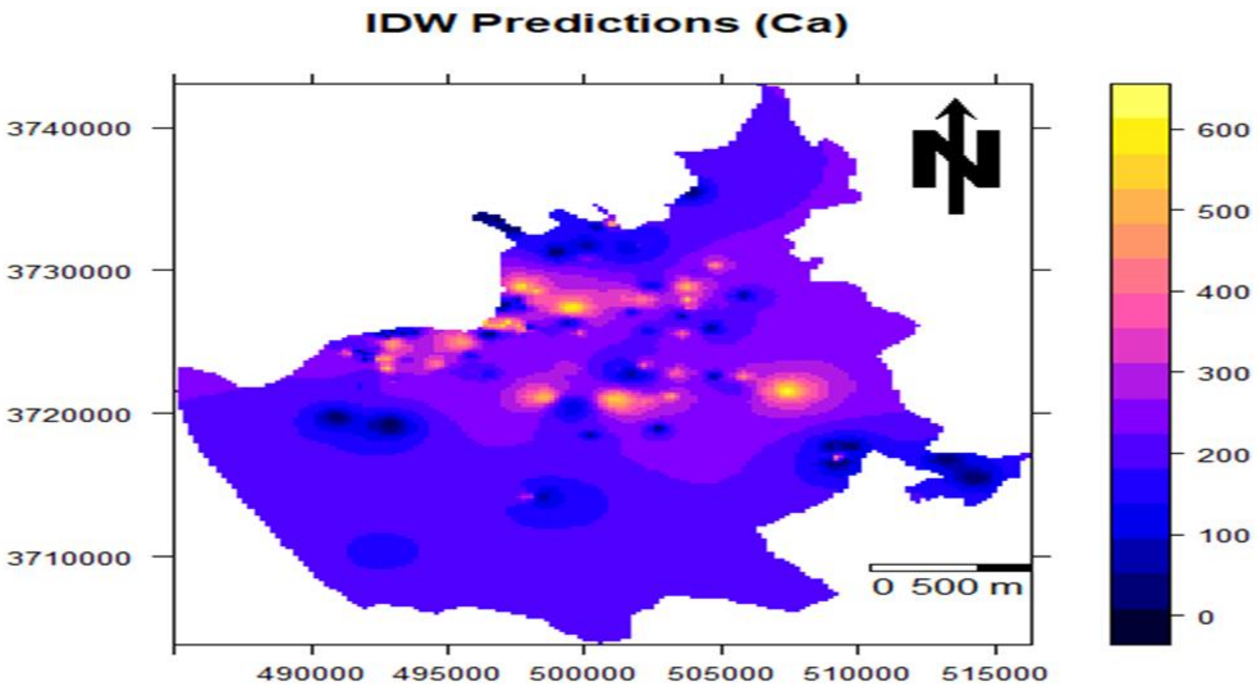


Figure 2b Spatial variability map of N, P and K


IDW Predictions (Ca)
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