

Geo-statistical assessment of spatial variability of soil water-holding capacity for optimal irrigation under semi-arid vertisols in South India

J Ramachandran^{1#}, R Lalitha², S Vallal Kannan³ and K Sivasubramanian⁴



Summary

Based on a field survey conducted in Lalgudi block, Tiruchirapalli district, Tamil Nadu, India, details about the crops grown, cropping pattern, land utilization and soil samples were collected from 20 locations under seven different soil textures of semi-arid vertisols. Using the data, efficient geostatistical models have been explored to study the spatial variation of irrigation water requirement of paddy, sugarcane and banana grown in the study area. Geostatistics was applied to identify the best interpolation method to acquire the spatial map of the available water holding capacity. Ordinary kriging and Disjunctive kriging were explored with six models viz., Circular, Spherical, Exponential, Gaussian, Penta-spherical and Sine-Hole effect models and were used for spatial prediction. The cross-validation statistics indicated that the Sine-Hole effect model with disjunctive kriging of available water holding capacity was superior for interpolation with a minimum value of RMSE and moderate spatial dependency. With the available water holding capacity map of Lalgudi block, total available water, readily available water and irrigation interval of paddy, sugarcane and banana were estimated. The irrigation interval of paddy, sugarcane and banana were found to vary between 1-2, 3-5 and 2-4 days respectively within Lalgudi block. The adoption of spatial algorithms for estimating crop water requirements would greatly help irrigation planners and water policymakers create efficient regional plans for precision irrigation under semi-arid vertisols.

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Introduction

More than 70% of the freshwater used worldwide is utilized for irrigation, making agriculture the major user of water Fischer et al. (1). One of the most important ways to combat the developing agricultural water shortage would be to increase water use efficiency. One important soil hydraulic parameter is soil accessible water holding capacity (AWC), which measures how much water plants can get and how much the soil can retain over time. Thus, determining an appropriate AWC measurement would be helpful for effective crop management decisions regarding the type of crop, amount of fertilizer, and other inputs Williams et al. (2). The AWC data would be used by several farmers and advisors to make decisions about crop management, which would then be linked to the positive impacts on crop yields Ngwira et al. (3); and Lal et al. (4).

Any location's soil characteristics would naturally fluctuate greatly over time and place Greenholtz et al. (5). Geostatistical analysis could provide specific information on the geographical variability of a soil characteristic. For effective irrigation scheduling, the geographical variation of AWC across the watered regions should be properly taken into account.

The spatial distribution of soil qualities and their inconsistencies can be studied with the help of geostatistics Liu et al. (6); Behera et al. (7). The optimal interpolation technique for obtaining the spatial map of soil properties would also be determined with the use of geostatistics Fromm et al. (8); Wigginton et al. (9); Usowicz et al. (10); Vieira et al. (11); Zheng et al. (12); and Wei et al. (13). To effectively define the spatial variability of each variable independently as well as their spatial relationships, Goovaerts (14) suggested introducing basic geostatistical methods such as the semivariogram and the correlogram. Weller et al. (15) evaluated the spatial variability of soil parameters using a variety of geostatistical approaches. The Kriging methodology would be superior to all other interpolation methods, according to the authors Robinson et al. (16) and Sudaria et al. (26).

Precision agriculture depends on a precise assessment of the spatial distribution of various soil characteristics, which also helps policymakers and decision-makers create appropriate plans and strategies.

¹Teaching Assistant, Department of Soil and Water Conservation Engineering, Agricultural Engineering College and Research Institute, Tamil Nadu Agricultural University (TNAU), Coimbatore-641003, Tamil Nadu, India

²Professor, Department of Soil and Water Conservation Engineering, Agricultural Engineering College and Research Institute, TNAU, Kumulur-621712, Trichy, Tamil Nadu, India

³Associate Professor (Agronomy) and Head, Coastal Saline Research Centre, TNAU, Ramanad, Tamil Nadu, India

⁴Professor (ENS), Department of Agronomy, TNAU, Coimbatore-641003, Tamil Nadu, India

[#]Corresponding author: J Ramachandran, E-mail: eeesurya.tnau@gmail.com

It is possible to effectively estimate the irrigation water requirement and irrigation interval for various crops in various places at a particular point in time by using the spatial maps of the AWC parameter created using the optimal interpolation approach. Planners, irrigation engineers, and decision-makers would find this information extremely helpful in suggesting and organizing effective water management techniques De Paz et al. (17) and Kaur et al. (27). According to Santra et al. (18), environmental modelling and precision farming would benefit from the estimate of regional variation in soil parameters.

According to Sanches et al. (19), implementing precision agriculture technologies could be a viable strategy to boost crop yields and lower production costs. It would include a number of methods and tools for controlling the temporal and spatial variability of crops. By using these strategies, fields' environmental management, yield, and profitability would all be enhanced. In essence, site-specific management that takes into account the temporal and spatial variability of a particular field could yield these benefits. This paper

presents two analyses: (i) the use of a geostatistical approach to assess the spatial variability of soil available water holding capacity; and (ii) the spatial variation in irrigation water requirement and irrigation scheduling for major crops grown in Lalgudi block, Tiruchirapalli district, Tamil Nadu, India.

Materials and Methods

Details of the study area

The research study was conducted during 2017-19 in Lalgudi block of Tiruchirapalli district, Tamil Nadu, India (Figure 1). Lalgudi block is situated at 10°52'27" North latitude and 78°48'57" East longitude and located at 70 m above the mean sea level. The northern part of the Lalgudi block has dense dry vegetation and barren lands, while the southern part is bounded by the Coleroon river. Around 45 villages and two town panchayats exist in this block. Panguni river and Pullambadi canal flow through the block. The total geographical area of the block is 20558 hectares. The soils in Lalgudi block are vertisols with semi-arid climate with long-term average annual rainfall of 877 mm (mean of 22 years).

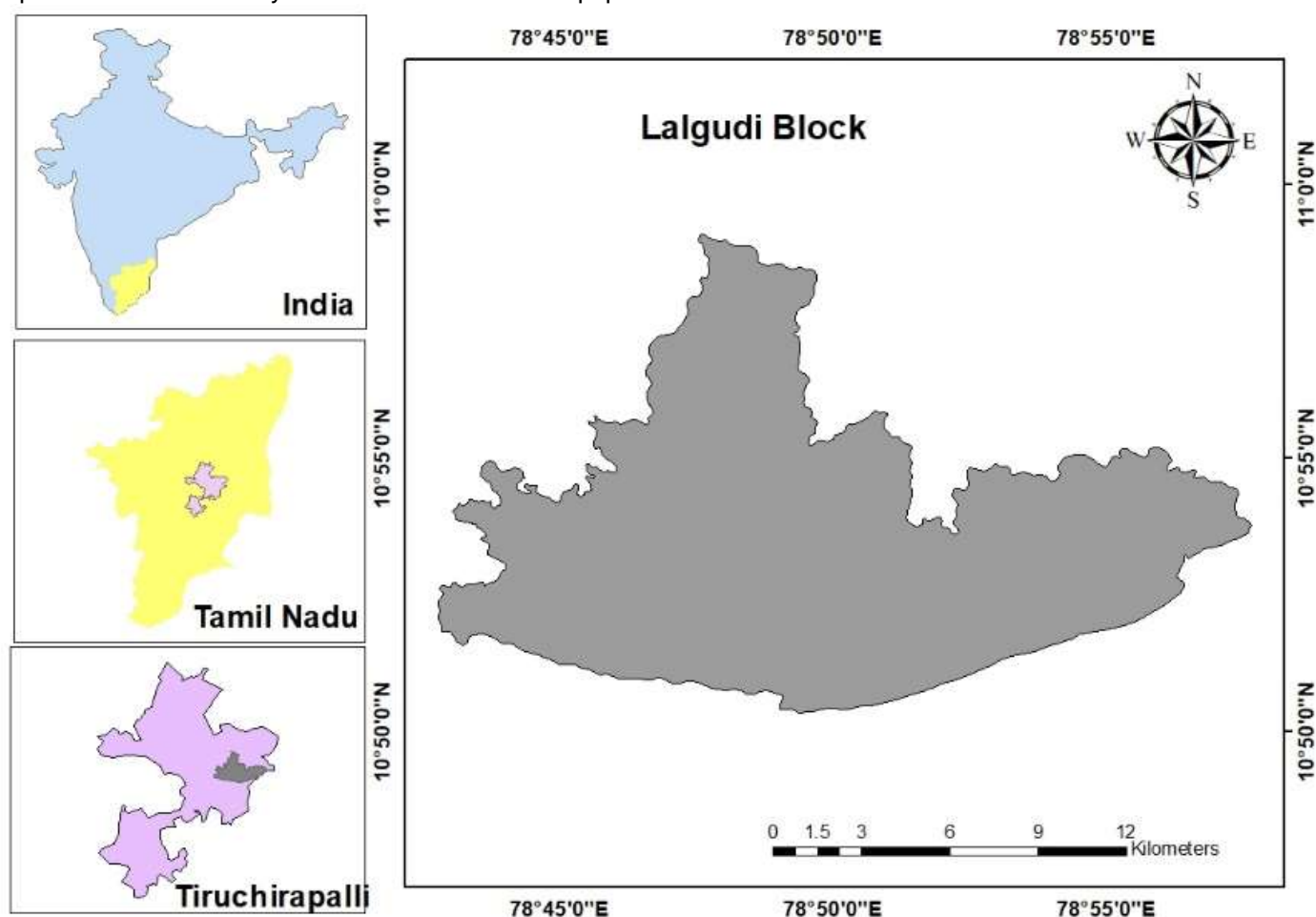


Figure 1. Location of the study area – Lalgudi block

Soil analysis

Initial soil samples were collected from different parts of Lalgudi block at a soil depth of 30 cm. Twenty samples were collected in the study area at random locations which include the fields of paddy, banana, sugarcane and forest area. Geo-positioning of the sampling locations was recorded with a handheld Global Positioning System

(GPS). The location of sampling sites is depicted in Figure 2. The soil texture was identified using the International Pipette Method or Robinson Pipette Method. The parameters of field capacity and wilting point were determined using the Pressure Plate Apparatus. The difference between field capacity and wilting point would indicate about the available water

holding capacity. The experiment was conducted for two years during 2017-18 and 2018-19.

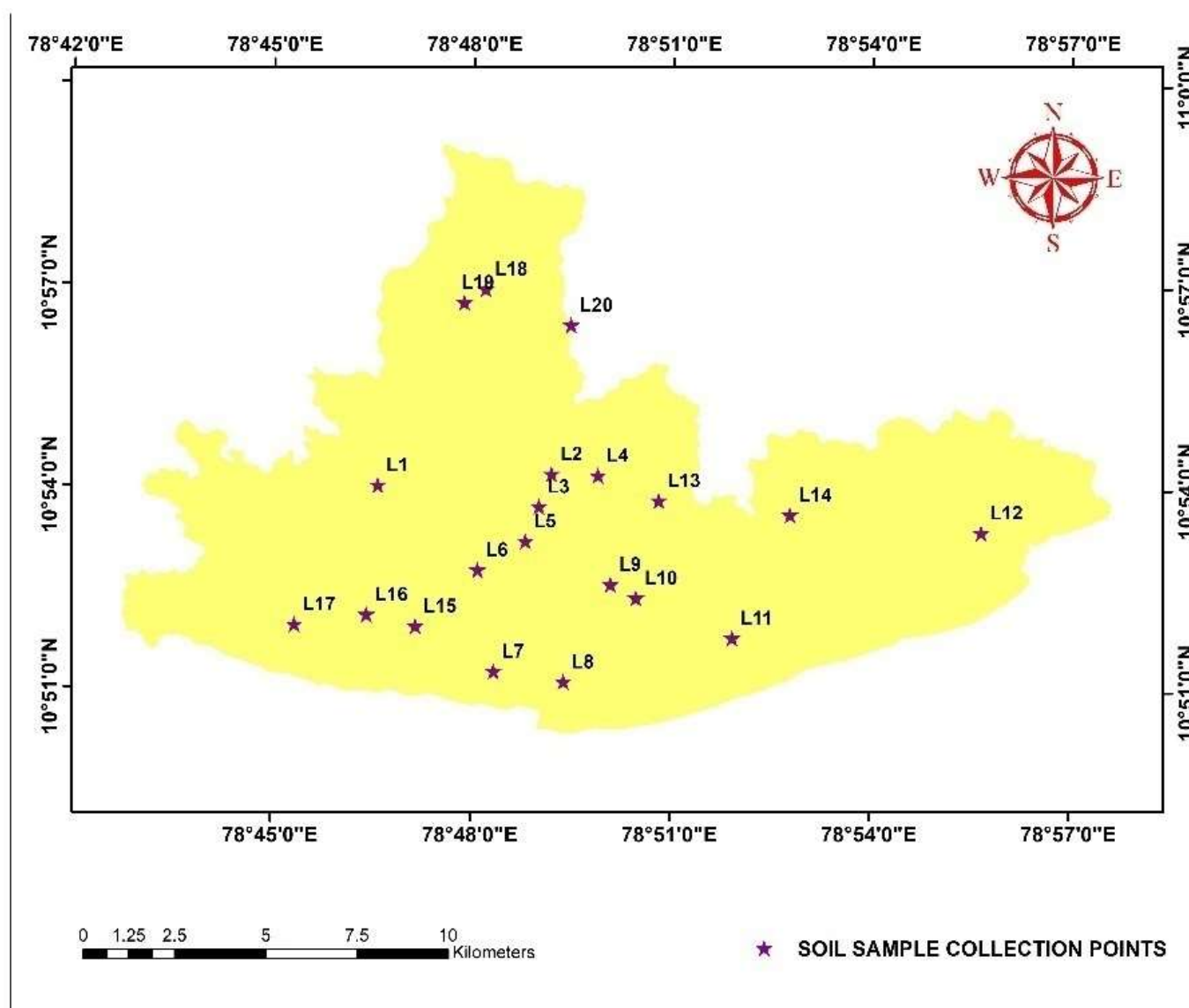


Figure 2. Location of the study area and sampling sites in Lalgudi block

Geostatistical analysis

Exploratory Spatial Data Analysis of soil parameters

The exploration of data was done by (i) examining the distribution of dataset; (ii) identifying the trends in the dataset; (iii) assessing the spatial autocorrelation and directional influence of the dataset. In order to carry out the exploration, a new point shape file was created in ArcGIS which included all the soil sample collection points and their corresponding values of field capacity, wilting point and available water holding capacity as records in the attribute table.

The 'Histogram' tool was used to display the frequency distribution of the dataset and summary statistics. The 'Normal QQPlot' tool was used to get the Quantile-Quantile (QQ) plots. It is a graph on which the quantiles from two distributions could be plotted relative to each other. The 'Trend Analysis' tool would help to identify the trends in the input data set and provide 3-dimensional perspective of the data. A unique feature of the 'Trend Analysis' tool is that the values could be projected onto x,z plane and y,z plane as scatter plots. Polynomials could be fitted to the scatter plots on the projected planes. If the curve through the projected

points is a flat one, then no trend would exist. Semivariogram modeling would be a key step between the spatial description and spatial prediction. The empirical semivariogram would provide desired information on the spatial autocorrelation of datasets.

Kriging methods

Kriging is the most common interpolation technique adopted by many research workers. It is an advanced geostatistical procedure that provides an estimated surface from scattered set of points with z-values. Ordinary kriging could be considered as an exact interpolator in the sense that the interpolated values or their local average would coincide with those values at the sampled locations Burrough and McDonnell, (20). The disjunctive kriging method provides a nonlinear unbiased estimator with the desirable property of minimum variance of errors Yates et al., (21). It is better than different linear estimators with respect to the exactness of estimation. In this study, ordinary kriging and disjunctive kriging have been considered for carrying out the interpolation of dataset.

Ordinary Kriging

The ordinary kriging has been widely used in the interpolation due to its simplicity as well as its availability Wackernagel, (22). It provides a smoothed surface and an inexact interpolation. When the dataset follows normal distribution, ordinary kriging could be used. The standard model for using ordinary kriging is given as

$$Z(s) = \mu(s) + \varepsilon(s) \quad (1)$$

where $Z(s)$ is the variable of interest, decomposed into a deterministic trend $\mu(s)$ and a random, autocorrelated errors form $\varepsilon(s)$.

Disjunctive Kriging

Disjunctive kriging is a non-linear type in which the original dataset would be transformed using a series of additive functions. Therefore, the standard model could be altered and can be given as

$$F(Z(s)) = \mu(s) + \varepsilon(s) \quad (2)$$

Where $F()$ is an arbitrary function of $Z(s)$. In general, the disjunctive kriging would try to do more than the ordinary kriging for any data set.

Experimental Semivariogram

Let Z be an intrinsic random variable function and let $Z(X_i)$, for $i = 1, 2 \dots N$, be a sample of size N . The semivariogram of the random function could be given as

$$\hat{\gamma}(h) = \frac{1}{2n(h)} \sum_{i=1}^{n(h)} [Z(X_i + h) - Z(X_i)]^2 \quad (3)$$

Where $n(h)$ indicates the number of pairs at the lag distance h apart. This is known as the experimental semivariogram.

Characteristics of Semivariogram

A semivariogram is a graphical representation of the semivariance and lag distance. The distance at which the semivariogram first flattens out is known as the 'range'. It is the distance after which the variogram levels off. The sample locations that are separated by distances smaller than the range are spatially autocorrelated, whereas the locations farther apart than the range are not spatially autocorrelated. The value of a semivariogram at the range on the y-axis is called 'sill'. The 'nugget' is the value at which the semivariogram intercepts the y-value. In practical terms, the nugget represents the small-scale variability of the data. A portion of that short range variability would be the result of measurement error. The partial sill is the 'sill' minus the 'nugget'. Theoretically, at zero separation distance (lag = 0), the semivariogram value would be '0'. However, at an infinitesimally small separation distance, the semivariogram would exhibit a nugget effect, which is greater than '0'. All parameters were estimated using the Geostatistical Tool in ArcGIS software.

Dependency Index

The spatial correlation of parameters was estimated by measuring the Dependency Index (DI). It is determined as ratio of values of Nugget (N) and Sill (C) and is given as

$$D = \frac{N}{C} \quad (4)$$

when DI is less than 0.25, then there is a strong correlation; when DI lies between 0.25 and 0.75, there is a

moderate correlation; and when DI is greater than 0.75, there is a weak correlation based on a given dataset.

Semivariogram models

A semivariogram would depict about the spatial autocorrelation of the measured sample points. Once each pair of locations has been plotted, a model could be fit through them. A geostatistical analyst would provide several semivariogram functions to model the empirical semivariogram among which the following six models were used in this study.

Circular model

The circular semivariogram was estimated by the following model:

$$\gamma(h) = \begin{cases} \frac{2c}{\pi} \left(\sin^{-1}(h) + h\sqrt{1-h^2} \right), & h \leq 1 \\ 1, & h > 1 \end{cases} \quad (5)$$

Spherical model

A spherical semivariogram is a line in shape near the origin. It could be estimated by the following model:

$$\gamma(h) = \begin{cases} c \left(\frac{3}{2} \frac{h}{a} - \frac{1}{2} \left(\frac{h}{a} \right)^3 \right), & 0 \leq h < a \\ c, & a \leq h \end{cases} \quad (6)$$

The model is said to be transitive because it would reach a finite sill at a fine range. The spherical model is given as a default model in some packages.

Exponential model

The exponential semivariogram could be estimated based on the following model:

$$\gamma(h) = c \left(1 - e^{-\frac{3h}{a}} \right) \quad (7)$$

Here, the sill could be approached asymptotically. The exponential model would be useful when there is a larger nugget and a slow rise to the sill.

Gaussian model

The Gaussian semivariogram could be estimated based on the following model:

$$\gamma(h) = c \left(1 - e^{-3 \left(\frac{h}{a} \right)^2} \right) \quad (8)$$

The model would approach the sill asymptotically. A graph model has a parabolic form near the origin. It would provide an S-shaped curve.

Pentaspherical model

The pent-aspherical semivariogram could be estimated based on the following model:

$$\gamma(h) = \begin{cases} c \left(\frac{15}{8} \frac{h}{a} - \frac{5}{4} \left(\frac{h}{a} \right)^3 + \frac{3}{8} \left(\frac{h}{a} \right)^5 \right), & 0 \leq h < a \\ c, & a \leq h \end{cases} \quad (9)$$

Sine Hole Effect model

The Sine Hole effect semivariogram could be estimated based on the following model:

$$\gamma(h) = c \left(1 - \frac{\sin\left(\pi \frac{h}{a}\right)}{\pi \frac{h}{a}} \right) \quad (10)$$

The model is not monotonic. It would reach a global maximum and then it would continue a damped oscillation around the sill. Each model could be designed to fit different types of phenomena in an accurate manner. The following cross validation statistics were used to identify the best model for the data set.

Cross validation statistics

In order to study the interpolator performance, mean error (ME), root-mean-square error (RMSE), average standard error (ASE), mean squared standard error (MSE) and root-mean-square standardized error (RMSSE) have been determined as

$$ME = \frac{1}{n} \sum_{i=1}^n \varepsilon_i \quad (11)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \varepsilon_i^2} \quad (12)$$

$$ASE = \sqrt{\frac{1}{n} \sum_{i=1}^n \sigma(s_i)} \quad (13)$$

$$MSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \frac{\varepsilon_i}{\sigma(s_i)}} \quad (14)$$

$$RMSSE = \sqrt{\frac{1}{n} \sum_{i=1}^n \left(\frac{\varepsilon_i}{\sigma(s_i)} \right)^2} \quad (15)$$

Generally, the best prediction model would be the one which has standardized mean closer to zero, the smallest root-mean-square prediction error, the average standard error closer to the root-mean-square prediction error and the standardized root mean square prediction error closer to one.

Validation of interpolation

A part of sample dataset was removed for the purpose of validation and this data set is known as the 'test dataset'. The remaining data set which is known as the 'training dataset' was used to develop the trend and autocorrelation models which are used for the purpose of prediction.

In Geostatistical Analyst, the test and training datasets could be created using the 'Subset Features' tool. About 50% of the soil samples were considered as sub-set points for validation. Using these points and the validation option in the Geostatistical Wizard, interpolation method could be validated. The Mean Prediction error could be used to quantify the validation process which is given as

$$\text{Mean Prediction Error} = \frac{\sum_{i=1}^n Z^*(x_i) - Z(x_i)}{n} \quad (16)$$

Where $Z^*(x_i)$ are the predicted values and $Z(x_i)$ is the computed value at the location of validation points. If the prediction errors are unbiased, the mean prediction error would be closer to zero.

Spatial estimation of available water for different crops

Using the best prediction model, the Total Available Water (TAW) and Readily Available Water (RAW) were estimated for paddy, banana and sugarcane crops. The Total Available Water for a crop could be given as

$$TAW = (\theta_{FC} - \theta_{WP}) * Z_r * 1000 \quad (17)$$

Where TAW is the total available soil water [mm] in the root zone, θ_{FC} is the water content at the field capacity [$\text{m}^3 \text{m}^{-3}$], θ_{WP} is the water content at the wilting point [$\text{m}^3 \text{m}^{-3}$], Z_r is the rooting depth of a particular crop [m].

$$RAW = TAW * p \quad (18)$$

Where RAW is readily available soil water in the root zone [mm], p is the average fraction of Total Available Soil Water (TAW) that could be depleted from the root zone before the moisture stress (reduction in ET) occurs [0 - 1]. The rooting depth for paddy could be considered as 30 cm, while it is 45 cm for sugarcane and 30 cm for banana. The values of p for paddy, sugarcane and banana were taken from crop evapotranspiration guidelines Allen et al. (23) as 0.20, 0.65 and 0.45 respectively. The computations were done using the 'Raster Calculator' tool in ArcGIS software.

Spatial estimation of the irrigation interval

The irrigation interval could be estimated as

$$I_I = \frac{TAW}{\text{Peak } ET_{\text{crop}} + \text{Other Water Losses}} \quad (19)$$

The Peak ET could be calculated as the maximum of crop evapotranspiration that was estimated using CROPWAT 8.0 software. It was assumed that the other water losses were 1 mm day^{-1} for sugarcane and banana, while the percolation loss for paddy was 5 mm day^{-1} (except end stage).

Results and Discussion

Analysis of soil samples

The descriptive statistics of field capacity (%), permanent wilting point (%) and available water holding capacity (AWC) based on the analysis of 20 soil samples collected at different locations under different soil textures are described in Table 1. Based on the analysis of data from 20 locations, the field capacity ranged from 10.4 to 40.0% with a mean of 23.8% (CV of 34.2%). The permanent wilting point ranged from 3.1 to 36.0% with a mean of 17.1% (CV of 48.4%), while the soil water holding capacity ranged from 2.5 to 10.8% with a mean of 6.6% (CV of 34.6%). The available water holding capacity (%) was found to vary with the soil texture. Under coarse textured sandy soils, the AWC was significantly lower due to lower field capacity. Under fine-textured clay soils, the AWC was significantly lower because of a higher wilting point. However, under medium textured silt and loam soils, higher field capacity and lower wilting point were found to provide a significantly higher water holding capacity in the study area.

Table 1. Soil parameters observed in different locations in Lalgudi block

Locations	Soil texture	Field capacity (%)	Wilting point (%)	Available water holding capacity (%)
L1	Clay	34.1	26.1	8.0
L2	Sandy Loam	18.4	15.2	3.2
L3	Sandy Clay	28.1	21.8	6.3
L4	Silty Clay Loam	29.5	20.7	8.7
L5	Clay	40.0	36.0	4.0
L6	Sandy Loam	14.2	10.8	3.5
L7	Sandy Loam	18.5	9.5	9.0
L8	Sandy Loam	16.9	10.8	6.0
L9	Sandy Loam	18.1	12.3	5.8
L10	Silt Loam	27.5	16.7	10.8
L11	Sandy Clay Loam	22.2	13.5	8.6
L12	Sandy Clay Loam	23.4	19.6	3.8
L13	Clay	34.3	27.5	6.8
L14	Sandy Clay	31.7	29.1	2.5
L15	Sandy Clay Loam	27.4	19.8	7.6
L16	Sandy Clay	31.4	21.7	9.7
L17	Sandy Loam	18.6	11.3	7.3
L18	Sandy Loam	14.8	8.8	6.1
L19	Loamy Sand	10.4	3.1	7.3
L20	Sandy Loam	16.1	8.6	7.5
Mean		23.8	17.1	6.6
SD		8.1	8.3	2.3
CV (%)		34.2	48.4	34.6

SD: Standard deviation CV: Coefficient of variation (%)

Soil texture-wise variability in different parameters

The 20 locations (L1 to L20) were found to have 7 soil textures viz., clay, sandy clay, sandy clay loam, sandy loam, silty loam, silty clay loam and loamy sand textures. Under clay soil texture existing in 3 locations (L1, L5, L13), field capacity ranged from 34.1% (L1) to 40.0% (L5) with mean of 36.1% (CV of 9.3%); while wilting point ranged from 26.1% (L1) to 36.0% (L5) with mean of 29.9% (CV of 17.9%); and available water holding capacity ranged from 4.0% (L5) to 8.0% (L1) with mean of 6.3% (CV of 32.8%). Under loamy sand soil texture existing in one location (L19), field capacity was 10.4%, while the wilting point was 3.1% and available water holding capacity was 7.3%.

Under sandy clay soil texture observed in 3 locations (L3, L14, L16), field capacity ranged from 28.1% (L3) to 31.7% (L14) with mean of 30.4% (CV of 6.6%); while wilting point ranged from 21.7% (L16) to 29.1% (L14) with mean of 24.2% (CV of 17.5%); and available water holding capacity ranged from 2.5% (L14) to 9.7% (L16) with mean of 6.2% (CV of 58.4%). Under sandy clay loam soil texture existing in 3 locations (L11, L12, L15), field capacity ranged from 22.2% (L11) to 27.4% (L15) with mean of 24.3% (CV of 11.2%); while wilting point ranged from 13.5% (L11) to 19.8% (L15) with mean of 17.6% (CV of 20.3%); and available water holding capacity ranged

from 3.8% (L12) to 8.6% (L11) with mean of 6.7% (CV of 38.0%).

Under sandy loam soil texture existing in 8 locations (L2, L6, L7, L8, L9, L17, L18, L20), field capacity ranged from 14.2% (L6) to 18.6% (L17) with mean of 17.0% (CV of 10.3%); while wilting point ranged from 8.6% (L20) to 15.2% (L2) with mean of 10.9% (CV of 19.7%); and available water holding capacity ranged from 3.2% (L2) to 9.0% (L7) with mean of 6.1% (CV of 32.5%). Under silt loam soil texture observed in one location (L10), field capacity was 27.5%, while the wilting point was 16.7% and available water holding capacity was 10.8%. Under silty clay loam soil texture existing in one location (L4), field capacity was 29.5%, while the wilting point was 20.7% and available water holding capacity was 8.7%. The mean values of field capacity, wilting point and available water holding capacity under different soil textures are described in Fig 3. The analysis indicated that soils under loamy sand soil texture had the lowest field capacity of 10.4% and wilting point of 3.1%, while the soils under clay soil texture had the highest field capacity of 36.1% and wilting point of 29.9% under different locations in Lalgudi block. In case of soil water holding capacity, the soils under sandy loam soil texture had a lowest capacity of 6.1%, while soils under silt loam texture had highest capacity of 10.8%.

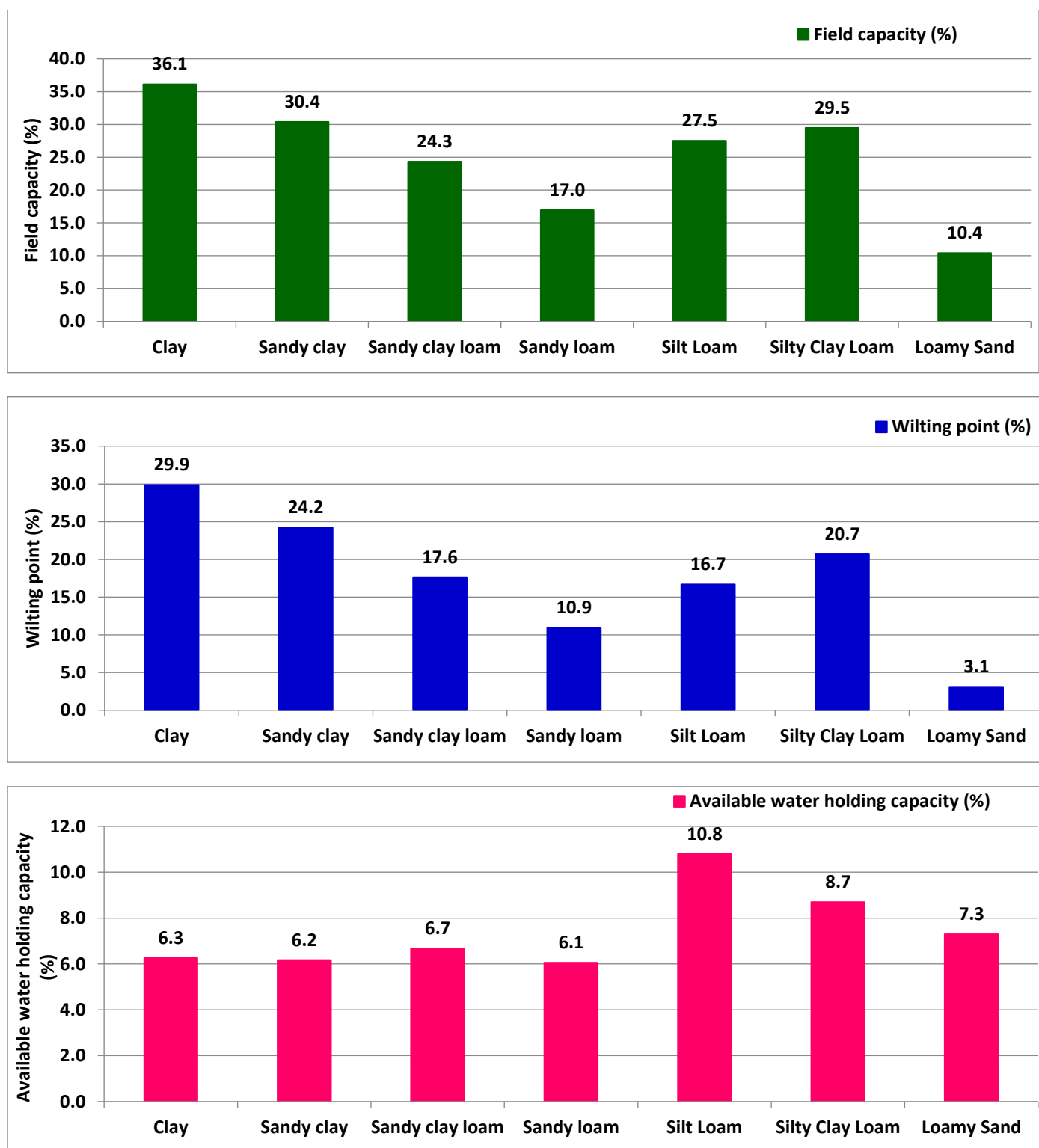


Figure 3. Field capacity, permanent wilting point and available water holding capacity under different soil textures in Lalgudi block

Grouping of locations based on mean and standard deviation of soil parameters

A grouping of different locations into 3 groups was made based on a mean and standard deviation of field capacity, wilting point and available water holding capacity and is described in Table 2. The 3 groups have values falling under (i) $< (\text{Mean} - \text{SD})$; (ii) $(\text{Mean} - \text{SD})$ to $(\text{Mean} + \text{SD})$; and (iii) $> (\text{Mean} + \text{SD})$. In case of field capacity, 3 locations of L19, L6 and L18 have fallen in the group of less than $(\text{Mean} - \text{SD})$, while 3 locations of L1, L13 and L5 have fallen in the group of more than $(\text{Mean} + \text{SD})$. Fourteen locations viz., L20, L8, L9, L2, L7, L17, L11,

L12, L15, L10, L3, L4, L16 and L14 have fallen in the group of $(\text{Mean} - \text{SD})$ to $(\text{Mean} + \text{SD})$.

In case of wilting point, 3 locations of L19, L20 and L18 have fallen in the group of less than $(\text{Mean} - \text{SD})$, while 4 locations of L1, L13, L14 and L5 have fallen in the group of more than $(\text{Mean} + \text{SD})$. Thirteen locations viz., L7, L6, L8, L17, L9, L11, L2, L10, L12, L15, L4, L16 and L3 have fallen in the group of $(\text{Mean} - \text{SD})$ to $(\text{Mean} + \text{SD})$. In the case of available water holding capacity, 5 locations of L14, L2, L6, L12 and L5 have fallen in the group of less than $(\text{Mean} - \text{SD})$, while 3 locations of L7, L16 and L10 have fallen in the group of more than $(\text{Mean} + \text{SD})$.

+ SD). Twelve locations viz., L9, L8, L18, L3, L13, L19, L17, L20, L15, L1, L11 and L4 have fallen in the group of (Mean – SD) to (Mean + SD).

Table 2. Grouping of locations based on mean and standard deviation of parameters

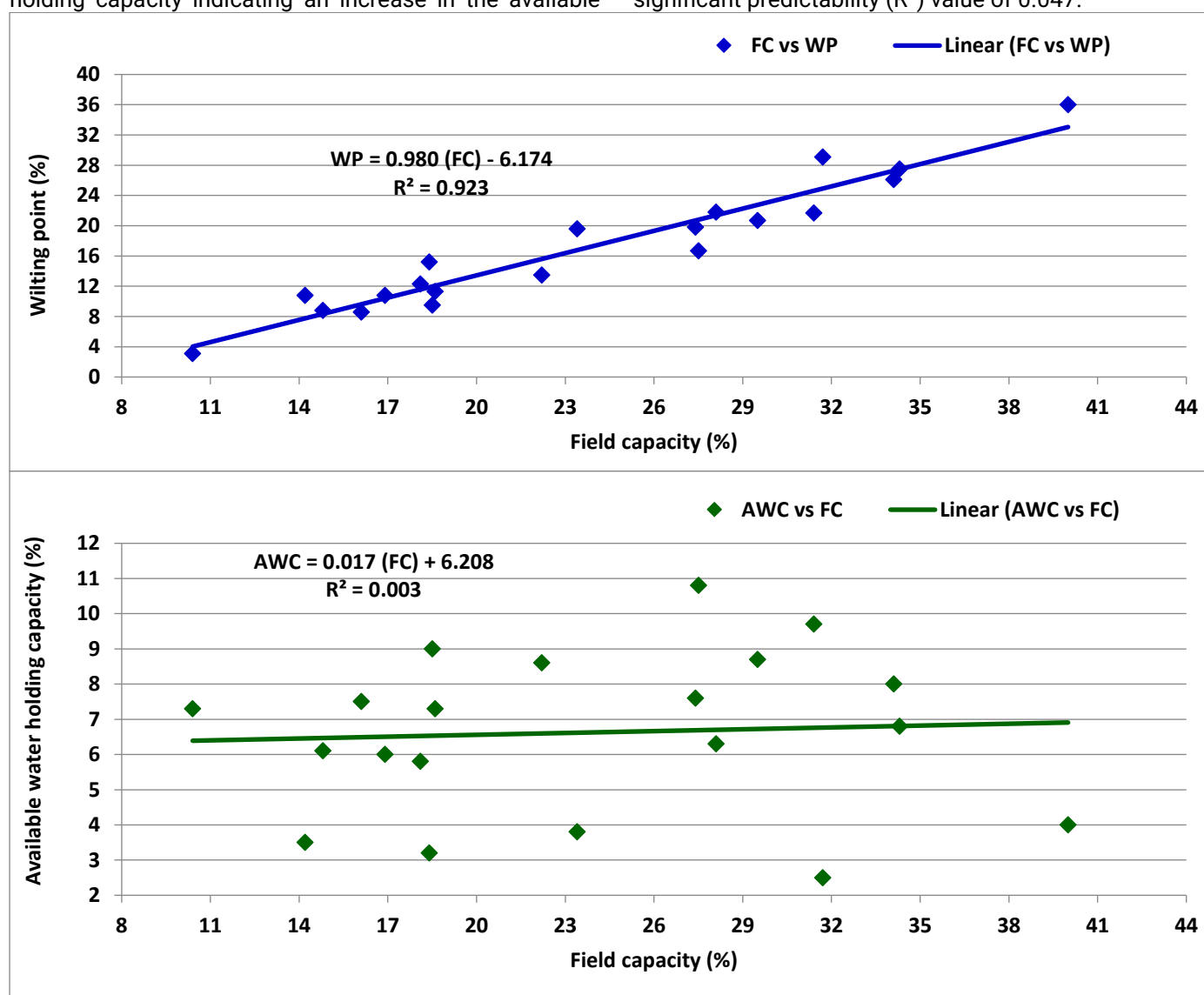
Parameter	Mean	SD	< (Mean - SD)	(Mean - SD) to (Mean + SD)	> (Mean + SD)
Field capacity (%)	23.8	8.1	L19 < L6 < L18	L20 < L8 < L9 < L2 < L7 < L17 < L11 < L12 < L15 < L10 < L3 < L4 < L16 < L14	L1 < L13 < L5
Wilting point (%)	17.1	8.3	L19 < L20 < L18	L7 < L6 < L8 < L17 < L9 < L11 < L2 < L10 < L12 < L15 < L4 < L16 < L3	L1 < L13 < L14 < L5
Available water holding capacity (%)	6.6	2.3	L14 < L2 < L6 < L12 < L5	L9 < L8 < L18 < L3 < L13 < L19 < L17 < L20 < L15 < L1 < L11 < L4	L7 < L16 < L10

SD: Standard deviation

Relationship between different soil parameters

The estimates of the correlation between different soil parameters and their effects on each other are described in Figure 4. Field capacity was found to have a positive effect on the wilting point indicating an increase in the wilting point for an increase in the field capacity. The wilting point changed by a significant coefficient of 0.980% for a unit change in the field capacity with a significant predictability (R^2) value of 0.923. Field capacity had a positive effect on the available water holding capacity indicating an increase in the available

water holding capacity for an increase in the field capacity. However, available water holding capacity changed by a non-significant coefficient of 0.017% for a unit change in the field capacity with a non-significant predictability (R^2) value of 0.003. The wilting point harmed the available water holding capacity indicating a decrease in the available water holding capacity for an increase in the wilting point. Available water holding capacity changed by a non-significant coefficient of -0.060% for a unit change in the wilting point with a non-significant predictability (R^2) value of 0.047.



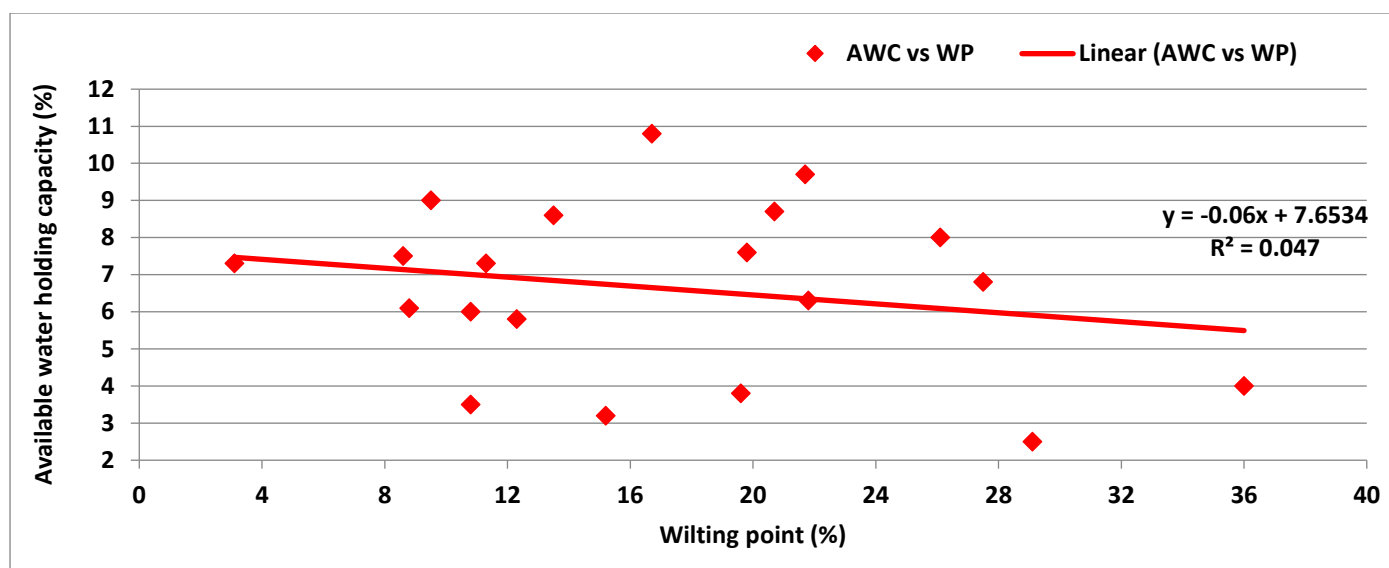


Figure 4. Relationship between different parameters in Lalgudi block: (a) FC vs WP (Top); (b) AWC vs FC (Middle); (c) AWC vs WP (Bottom)

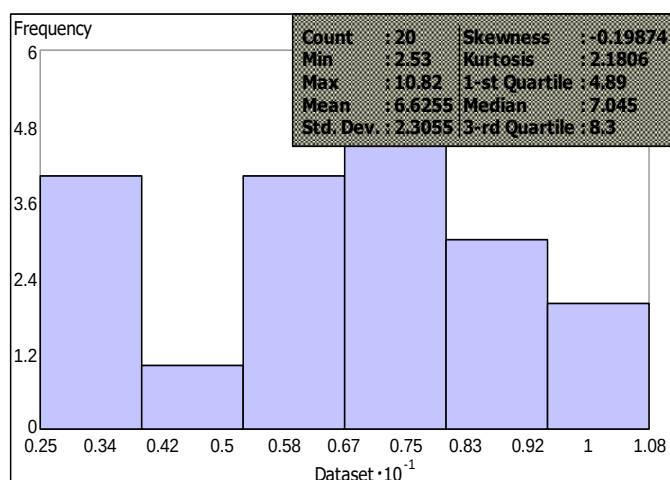
Geostatistic analysis

Assessment of soil parameters

The descriptive statistics viz., minimum, maximum, mean, median, standard deviation and coefficient of variation (%) of soil parameters are given in Table 1 and are depicted in Figure 5. The available water holding capacity in the soil based on the soil samples collected in 20 locations were found to be non-normally distributed.

Histogram

Transformation: None

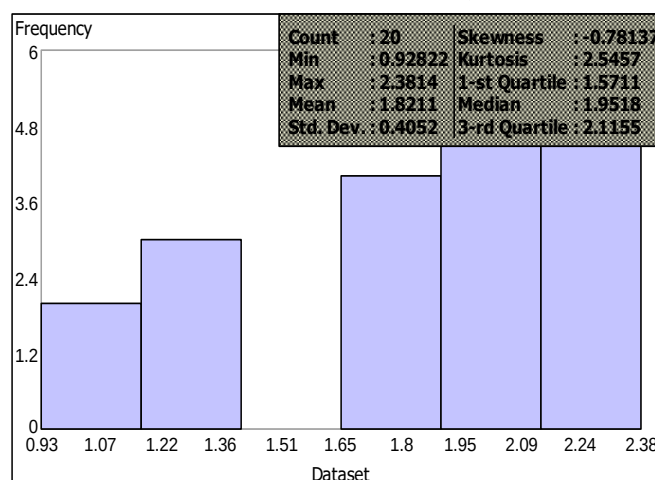


Dataset : Soil_Allpts Attribute: AWHC

a) Without data transformation

Histogram

Transformation: Log



Dataset : Soil_Allpts Attribute: AWHC

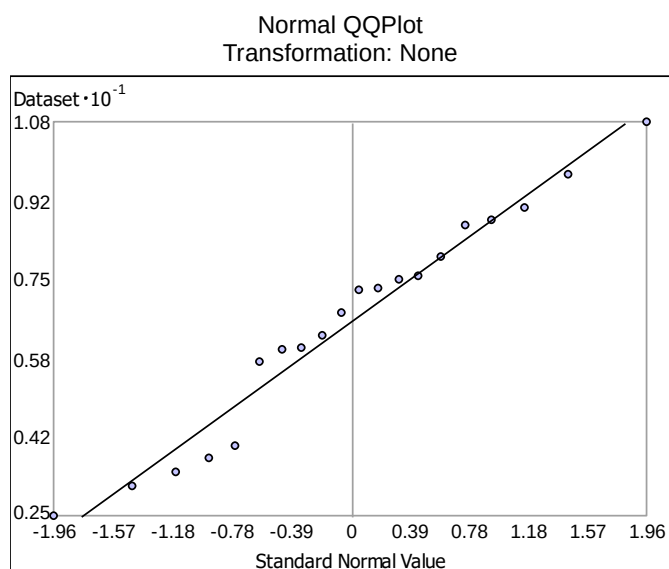
b) With log transformation

Figure 5. Assessment of soil available water-holding capacity in Lalgudi block

Therefore, a log transformation of data was made and the frequencies have been depicted in Figure 5b. The mean and median of the log-transformed dataset were found to be closer to each other. The transformed data was found to have a mean AWC of 1.821 and a median AWC of 1.951. This indicated a normal distribution of the log-transformed dataset of available water-holding capacity. De Paz et al. (17) observed about non-normal distribution of the field capacity and wilting point parameters which were log-transformed in order to ensure the normal distribution of the data.

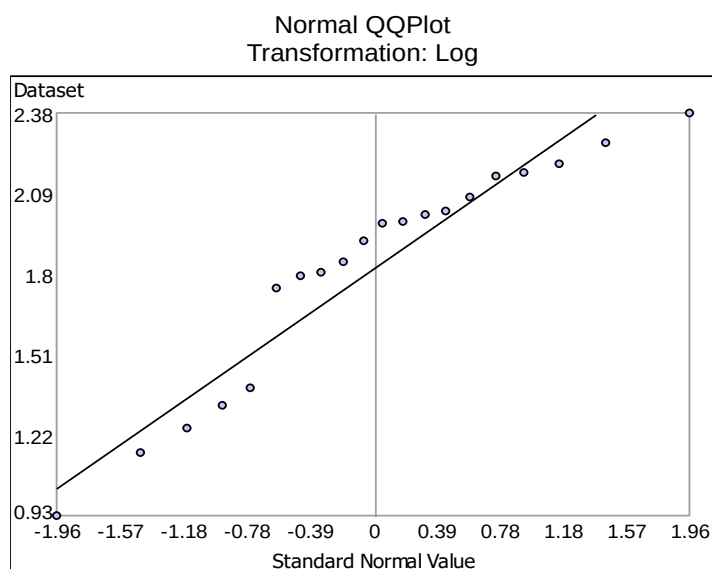
Normal QQ plots of soil properties

The Normal QQ plots without transformation of the dataset and with transformation of the dataset were obtained for the available water holding capacity based on the soil samples collected in Lalgudi block. Figure 6 (a) depicts about the QQ plots of available water holding capacity without transformation, while Fig. 6 (b) depicts about the QQ plots of available water holding capacity with log transformation respectively.



Dataset : Soil Allpts Attribute: AWHC

a) Without data transformation



Dataset : Soil Allpts Attribute: AWHC

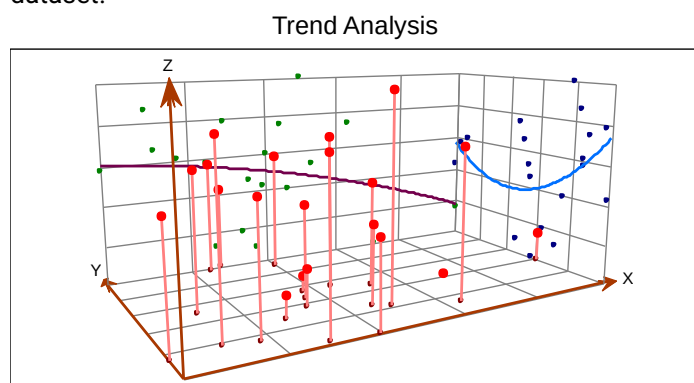
b) With log transformation

Figure 6. Normal QQ plots of soil available water-holding capacity in Lalgudi block

The analysis indicated that the sample data points were closer to the normal straight line in the case of the log-transformed dataset. This indicated the closeness of the dataset to be normally distributed when the data transformation was done compared to the non-transformed data.

Trend analysis of soil parameters

Trend analysis was carried out for the data of soil parameters. The trend exhibited by the soil available water holding capacity is depicted in Figure 7 which would help in identifying the presence of trend in the dataset.



Dataset : Soil Allpts Attribute: AWHC

Figure 7. Trend analysis of soil available water holding capacity

The polynomial curve (blue line on the xz-plane) indicated the existence of a trend. The available water holding capacity was found to have an upside-down U-shape curve which indicated that it had a significantly higher influence from the boundaries towards its center. The curve through the projected points in the yz-plane was found to be flat in all three datasets which indicated that there was no trend in the yz-plane for the sample dataset considered in the study.

Semivariogram cloud of soil properties

The semivariogram cloud would provide information on spatial autocorrelation of the dataset, apart from giving scope for identifying outliers in the dataset. The semivariogram cloud for available water holding capacity is depicted in Fig 8.

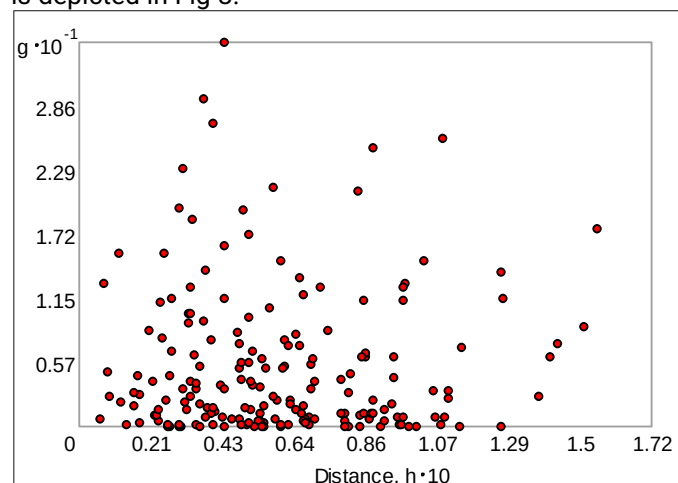


Figure 8. Semivariogram cloud for soil AWC in Lalgudi block

Each red dot would indicate about the empirical semivariogram value of the two soil samples plotted against the distance of separation. Based on Fig.8, most of the points were found to be close to one another. This indicated that the points are alike with each other. When closely examined, it is observed that as the distance increases, the pair of points of available water holding capacity were found to be far apart.

Characteristics of semivariograms

The experimental semivariogram fitted with six models viz., Circular, Spherical, Exponential, Gaussian, Pentaspherical and Sine-Hole effect and two kriging methods viz., ordinary and disjunctive methods for the available water holding capacity are depicted in Fig. 9 based on ordinary kriging and Figure 10 based on disjunctive kriging method.

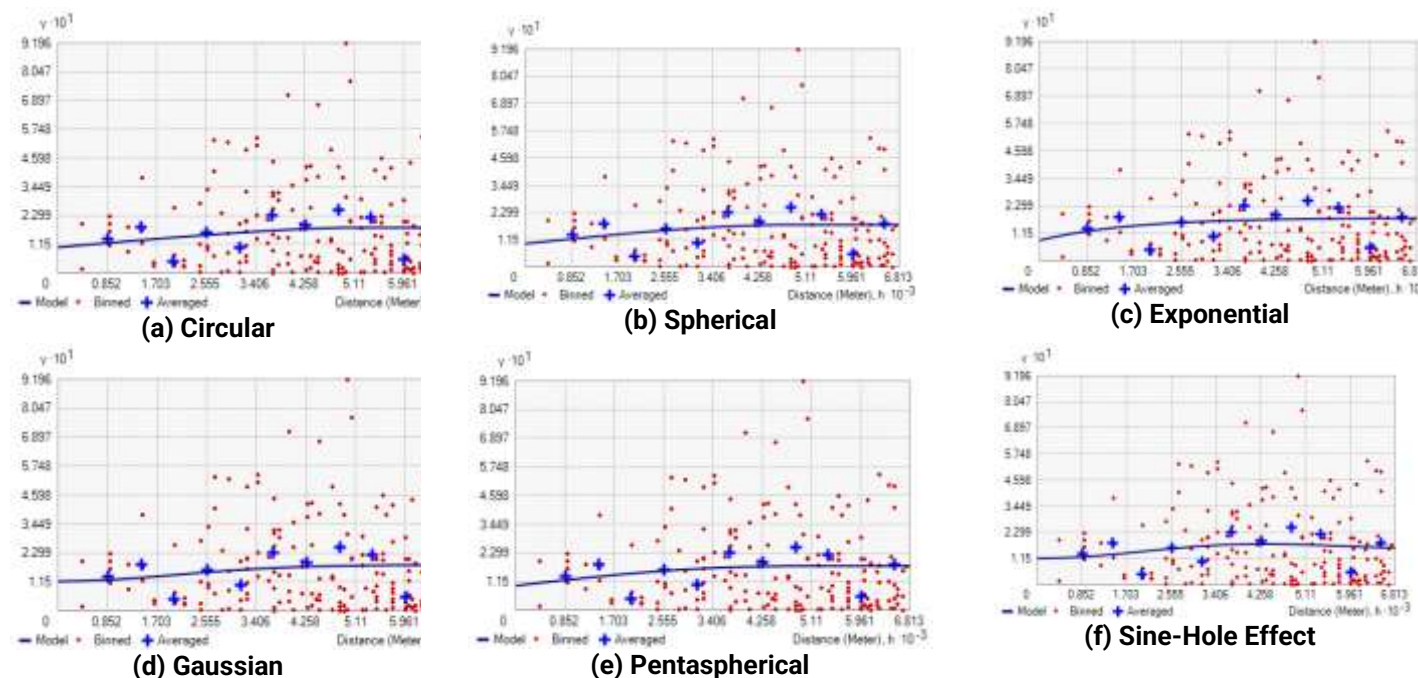


Figure 9. Semivariograms for available water holding capacity in Lalgudi block using Ordinary Kriging

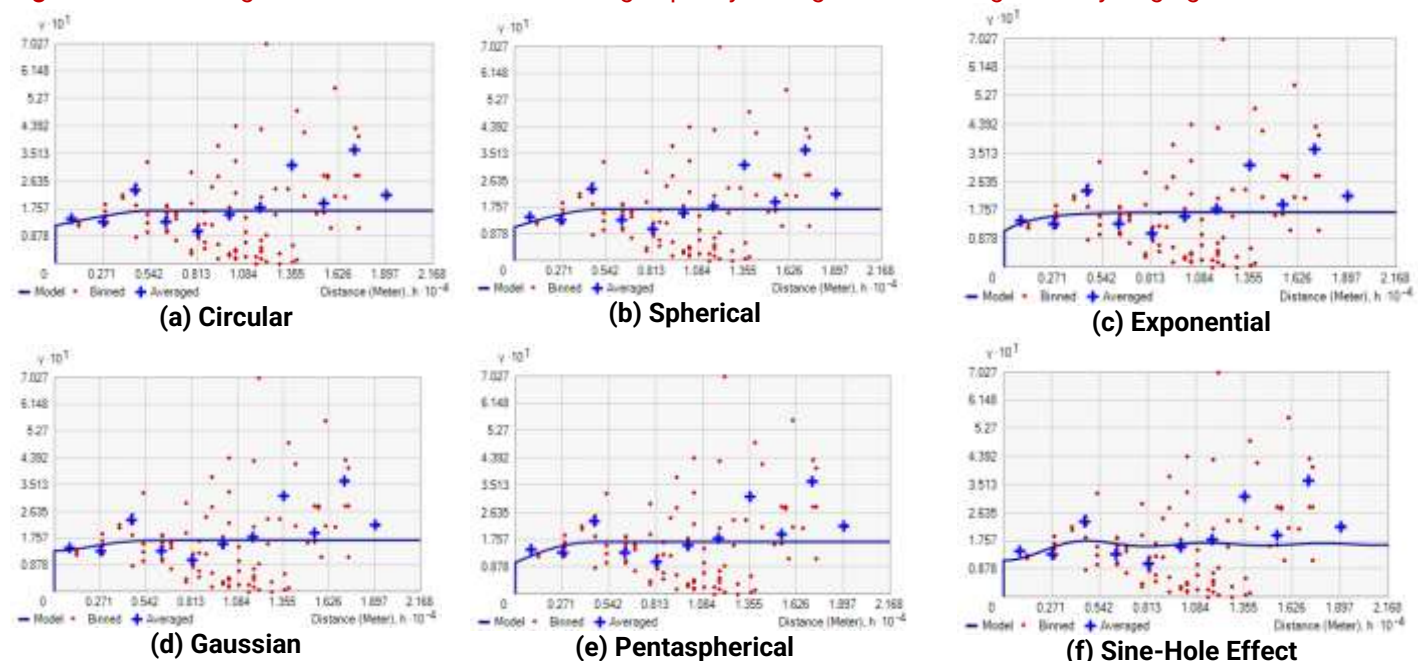


Figure 10. Semivariograms for available water holding capacity in Lalgudi block using Disjunctive Kriging

Based on the semivariograms, the characteristics of a semivariogram like nugget, sill and range were estimated for the available water holding capacity and are given in Table 3 based on ordinary kriging and Table 4 based on disjunctive kriging. The dependency index of each model was estimated and the nature of the spatial dependency of each dataset is indicated in the respective Tables. Under the Ordinary Kriging method, a range of 4957 m was observed. The nugget ranged from 0.0854 for the Exponential model to 0.1168 for the Gaussian model with a mean of 0.1027. The sill ranged from 0.1672

based on the Sine-Hole effect model to 0.1818 based on the Gaussian model with mean of 0.1775, while the partial sill ranged from 0.0519 based on Sine-Hole effect model to 0.0944 based on the Exponential model with mean of 0.0748. Based on the analysis, the dependency index ranged from 0.47 under the Exponential model to 0.69 under the Sine-Hole effect model with a mean of 0.58. The spatial dependency was 'moderate' based on all 6 models calibrated for the data of available water holding capacity under vertisols located in Lalgudi block.

Table 3. Characters of available water holding capacity semivariograms with Ordinary Kriging

Model	Nugget	Partial Sill	Range (m)	Sill	DI	Spatial Dependency
Spherical	0.0980	0.0801	4957	0.1781	0.55	Moderate
Circular	0.1025	0.0783	4957	0.1808	0.57	Moderate

Exponential	0.0854	0.0944	4957	0.1798	0.47	Moderate
Gaussian	0.1168	0.0650	4957	0.1818	0.64	Moderate
Pentaspherical	0.0979	0.0792	4957	0.1771	0.55	Moderate
Sine-Hole Effect	0.1153	0.0519	4957	0.1672	0.69	Moderate
Mean	0.1027	0.0748		0.1775	0.58	

Under the Disjunctive Kriging method, a range of 5199 m was observed. The nugget was found to range from 0.1016 for the Pentaspherical model to 0.1337 for the Gaussian model with a mean of 0.1153. Compared to this, the sill ranged from 0.1642 based on the Sine-Hole effect model to 0.1688 based on the Spherical model with a mean of 0.1677, while the partial sill ranged from 0.0347 based on the Gaussian model to 0.0661 based on the Pentaspherical model with mean of 0.0525. The

Pentaspherical model gave a minimum dependency index of 0.61, while the Gaussian model gave a maximum dependency index of 0.79 compared to the mean value of 0.69. The spatial dependency was found to be 'weak' under Gaussian model, while it was 'moderate' under all the remaining 5 models calibrated for the data of available water holding capacity under vertisols located in Lalgudi block.

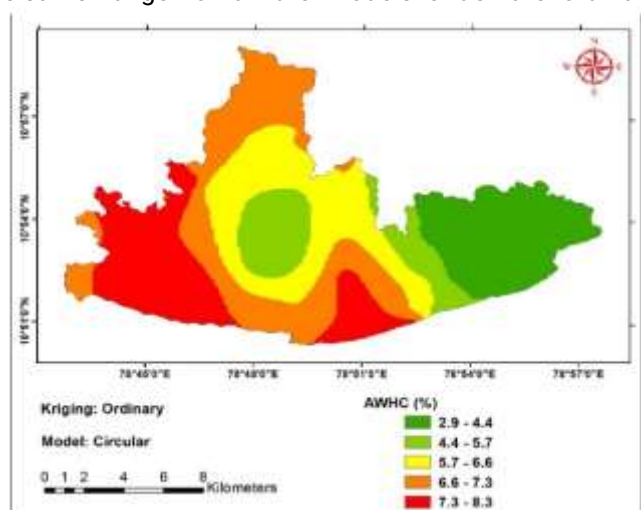
Table 4. Characters of available water holding capacity semivariograms with Disjunctive Kriging

Model	Nugget	Partial Sill	Range (m)	Sill	DI	Spatial Dependency
Spherical	0.1096	0.0592	5199	0.1688	0.65	Moderate
Circular	0.1217	0.0470	5199	0.1687	0.72	Moderate
Exponential	0.1114	0.0572	5199	0.1686	0.66	Moderate
Gaussian	0.1337	0.0347	5199	0.1684	0.79	Weak
Pentaspherical	0.1016	0.0661	5199	0.1677	0.61	Moderate
Sine-Hole Effect	0.1135	0.0507	5199	0.1642	0.69	Moderate
Mean	0.1153	0.0525		0.1677	0.69	

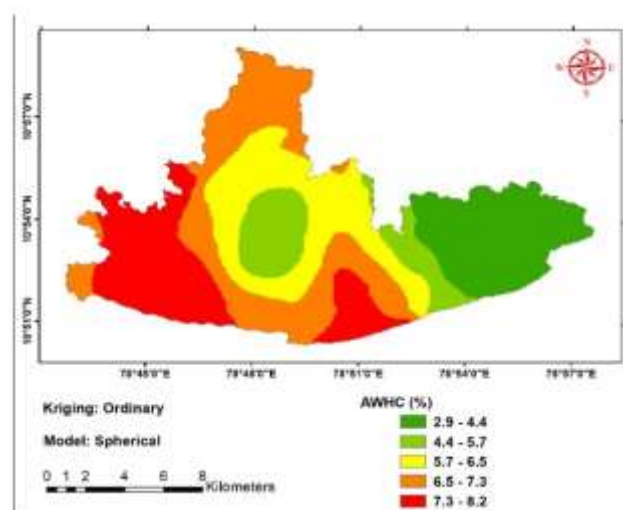
Based on the analysis of data of available water holding capacity, the Gaussian model under disjunctive kriging alone exhibited weak spatial dependency, whereas all the remaining models exhibited moderate spatial dependency. The results indicated that the theoretical models have satisfactorily represented the spatial variability of available water-holding capacity based on the soil samples collected in the study area. The spatial interpolation of available water holding capacity using ordinary kriging and disjunctive kriging with six models is shown in Figures 11 and 12 respectively.

The dataset of available water holding capacity had the same range for all the models under the ordinary

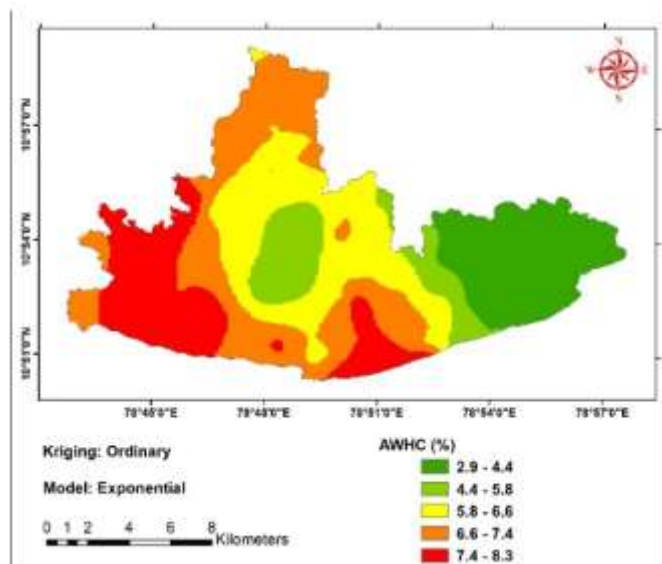
kriging (4957 m) as well as under the disjunctive kriging (5199 m). The higher range value under disjunctive kriging indicated better continuity and smoother spatial variability of the soil property compared to the ordinary kriging method. De Paz et al. (17) reported that the range was between 3000 and 5200 m for field capacity and permanent wilting point parameters respectively. In the present study, the dataset based on 20 locations exhibited a higher range indicating a smoother spatial variability and also about the sufficiency of the number of samples collected for carrying out interpolation within the block.



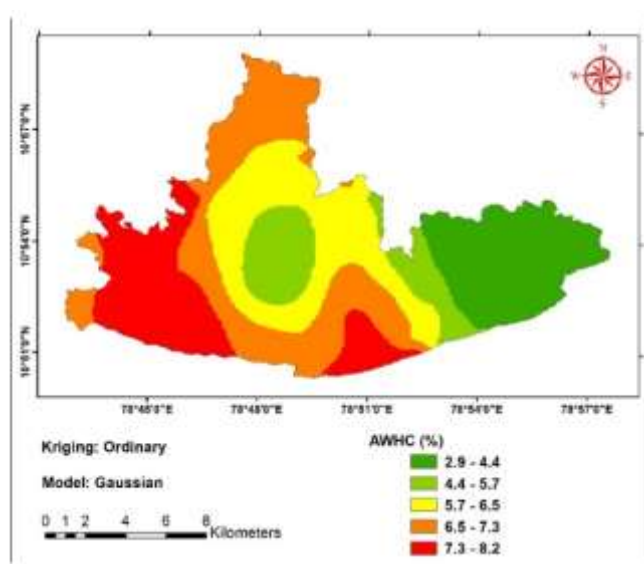
(a) Circular



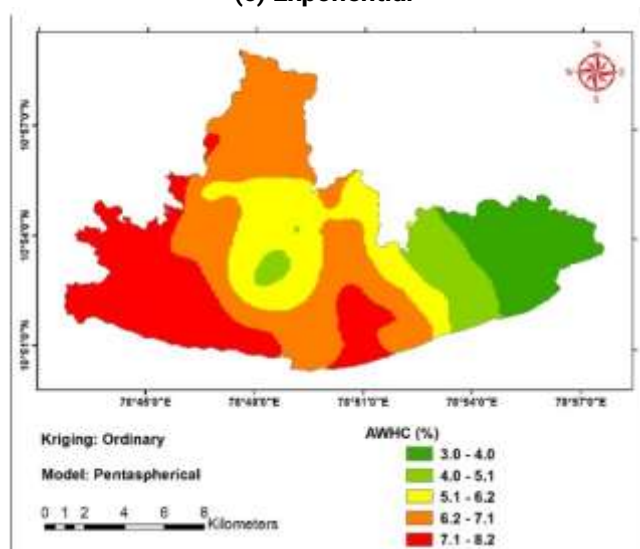
(b) Spherical



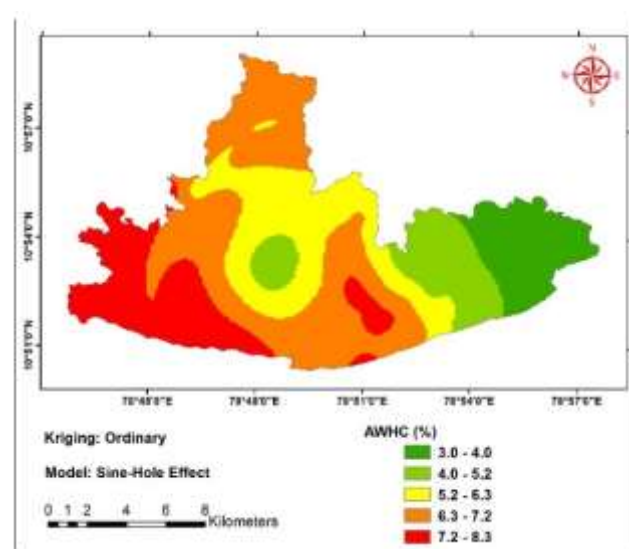
(c) Exponential



(d) Gaussian

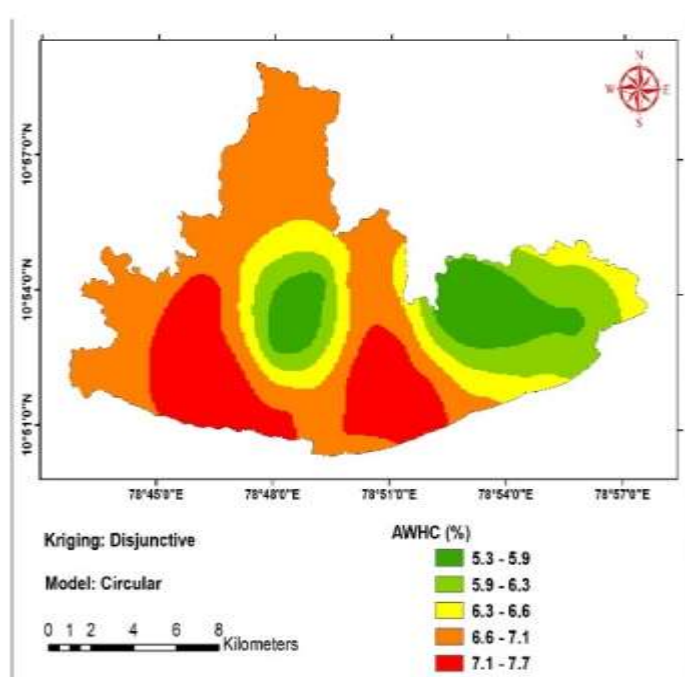


(e) Pentaspherical

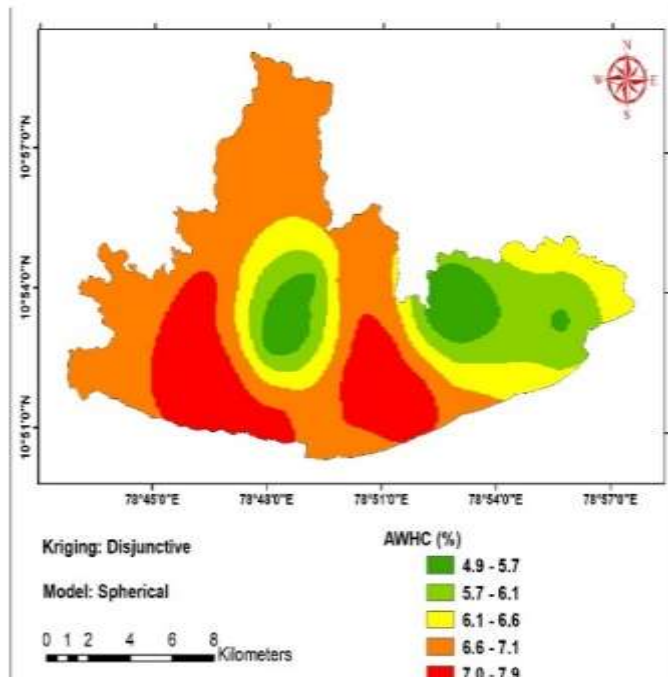


(f) Sine-Hole Effect

Figure 11 a-f. Spatial Interpolation of Available Water Holding Capacity using Ordinary Kriging



(a) Circular



(b) Spherical

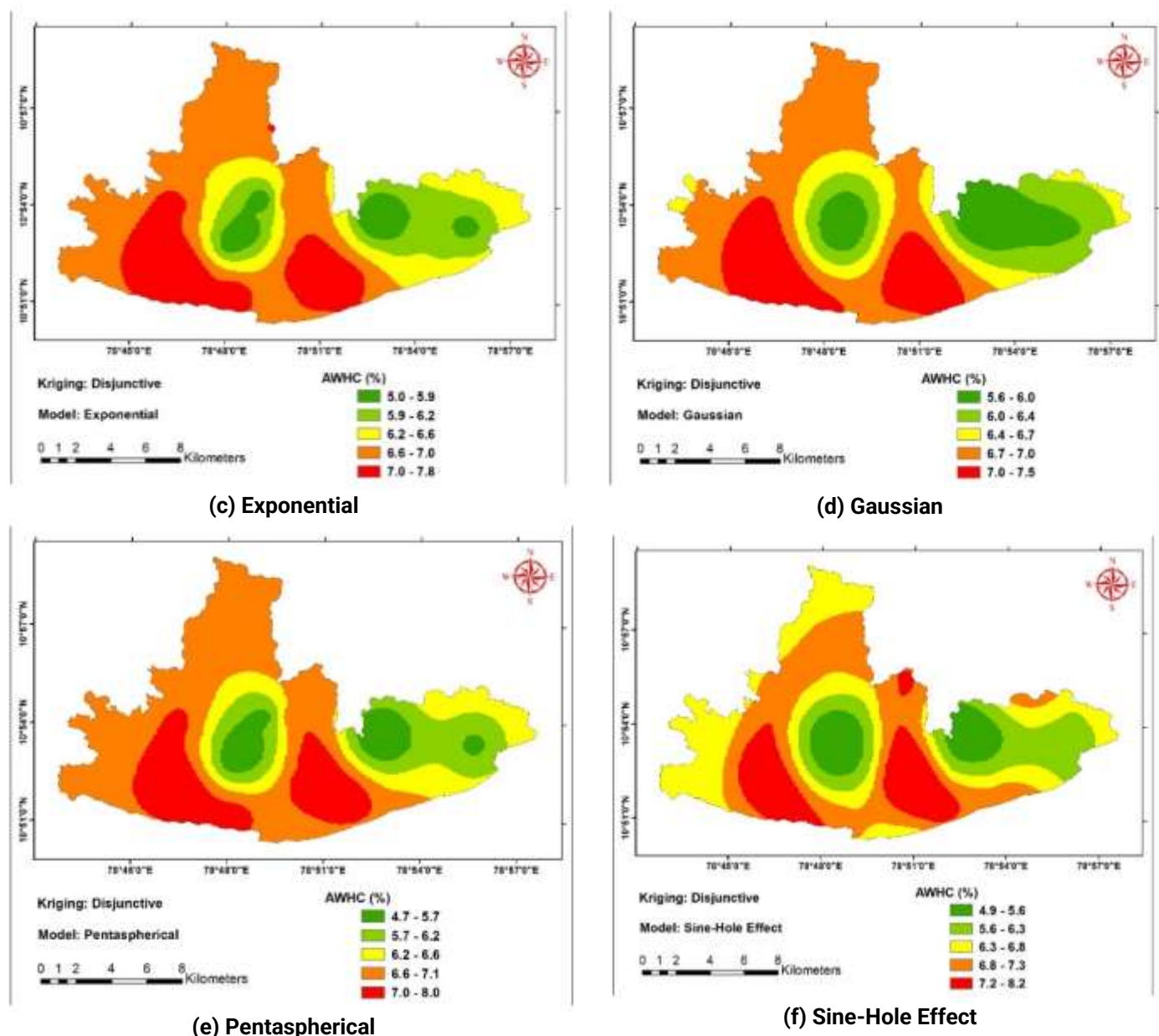


Figure 12 a-f. Spatial Interpolation of Available Water Holding Capacity using Disjunctive Kriging

Cross-validation statistics of semivariograms

The cross-validation statistics determined were found to be useful for predicting the best-performing model for interpolation of water-holding capacity data in the study area. To study the interpolator performance, the results of cross-validation parameters like mean error (ME), root-mean-square error (RMSE), average standard error (ASE), mean squared standard error (MSE) and root-mean-square standardized error (RMSSE) are given in Table 5 based on Ordinary Kriging method and Table 6 based on Disjunctive Kriging method.

Table 5. Cross-validation statistics of available water holding capacity with Ordinary Kriging

Model	ME	RMSE	MSE	RMSSE	ASE	Remarks
Spherical	0.0123	2.5403	-0.0722	0.8222	3.1664	Overestimates
Circular	0.0088	2.5118	-0.0691	0.8157	3.1456	Overestimates
Exponential	0.0127	2.5718	-0.0734	0.8215	3.1939	Overestimates
Gaussian	0.0200	2.5186	-0.0658	0.8139	3.1604	Overestimates

The ME ranged from -0.1070 under the Sine-Hole effect model to 0.0200 under the Gaussian model with a mean of -0.0235, while the RMSE ranged from 2.3993 under the Sine-Hole effect model to 2.5718 under the Exponential model with mean of 2.5056. The MSE ranged from -0.0921 under the Pentaspherical model to -0.0658 under the Gaussian model with a mean of -0.0767, while the RMSSE ranged from 0.8139 under the Gaussian model to 0.8417 under the Pentaspherical model with mean of 0.8216 over 6 models calibrated under the Ordinary Kriging method.

Pentaspheical	-0.0877	2.4919	-0.0921	0.8417	3.0476	Overestimates
Sine-Hole Effect	-0.1070	2.3993	-0.0876	0.8148	3.0214	Overestimates
Mean	-0.0235	2.5056	-0.0767	0.8216	3.1200	

The ME ranged from 0.1038 under the Exponential model to 0.1098 under the Sine-Hole effect model with a mean of 0.1066, while the RMSE ranged from 2.1744 under the Sine-Hole effect model to 2.2980 under the Exponential model with a mean of 2.2594. The MSE ranged from 0.0252 under the Pentaspheical model to

0.0341 under the Sine-Hole effect model with a mean of 0.0292, while the RMSSE ranged from 0.8077 under the Sine-Hole effect model to 0.8260 under the Pentaspheical model with mean of 0.8152 over 6 models calibrated under the Disjunctive Kriging method.

Table 6. Cross-validation statistics of available water holding capacity with Disjunctive Kriging

Model	ME	RMSE	MSE	RMSSE	ASE	Remarks
Spherical	0.1087	2.2700	0.0280	0.8210	2.8039	Overestimates
Circular	0.1061	2.2658	0.0302	0.8117	2.8156	Overestimates
Exponential	0.1038	2.2980	0.0268	0.8161	2.8341	Overestimates
Gaussian	0.1059	2.2697	0.0310	0.8089	2.8266	Overestimates
Pentaspheical	0.1050	2.2783	0.0252	0.8260	2.8031	Overestimates
Sine-Hole Effect	0.1098	2.1744	0.0341	0.8077	2.7566	Overestimates
Mean	0.1066	2.2594	0.0292	0.8152	2.8100	

For any model, if (i) RMSE is less than ASE and (ii) RMSSE is less than 1, then the model would overestimate the given dataset. Based on the results, it is observed that the available water holding capacity was overestimated by all six models using both methods of kriging. The best prediction method should have a minimum RMSE value. Finally, it is observed that this approach gave lower RMSE values for the prediction of available water holding capacity.

While comparing the ordinary kriging and disjunctive kriging carried out for the available water holding capacity, it is observed that the models calibrated under disjunctive kriging gave lower RMSE values (Table 4 and Table 5). Among the six models calibrated under disjunctive kriging, the Sine-Hole effect model gave a lower RMSE value indicating the superiority of the model for predicting the available water-holding capacity.

Hence, for any further spatial estimation of the water requirement of crops, the interpolated available water-holding capacity map with disjunctive kriging has been used. Santra et al. (18) observed the superiority of the Sine Hole-effect model. They observed that this model was the best fit for the experimental semivariogram of the soil organic carbon content.

Validation of the best prediction model

In order to validate the best prediction model, 50% of the dataset was considered as a subset and mean prediction error was estimated. It was found that the Sine-Hole effect model under Disjunctive Kriging gave a prediction error of -0.07 which is closer to zero compared to other models. Hence, the spatial estimation of available water holding capacity with the Sine-Hole effect model under Disjunctive Kriging would be superior for making interpolation of the available water holding capacity.

The available water holding capacity map for Lalgudi block prepared with the Sine-Hole effect model under Disjunctive Kriging is depicted in Fig. 13. The interpolated values of available water holding capacity were found to

range from 4.9 to 8.2% in the study area. From Figure 13, it is observed that most of the areas in Lalgudi block had available water holding capacity in the range of 6.1 to 7.0%. Thus, the map would be useful for (i) making an efficient spatial estimation of the water requirement for different crops; and (ii) grouping the villages based on the crop water requirement.

Spatial available water and irrigation interval for different crops

Using the available water holding capacity map prepared by considering the Sine-Hole effect model calibrated under Disjunctive Kriging, the total available water, readily available water and irrigation interval have been estimated for paddy, banana and sugarcane crops and are given in Table 7. The available water content observed in different villages has been grouped into three categories and the villages coming under each category have also been described in Table 7.

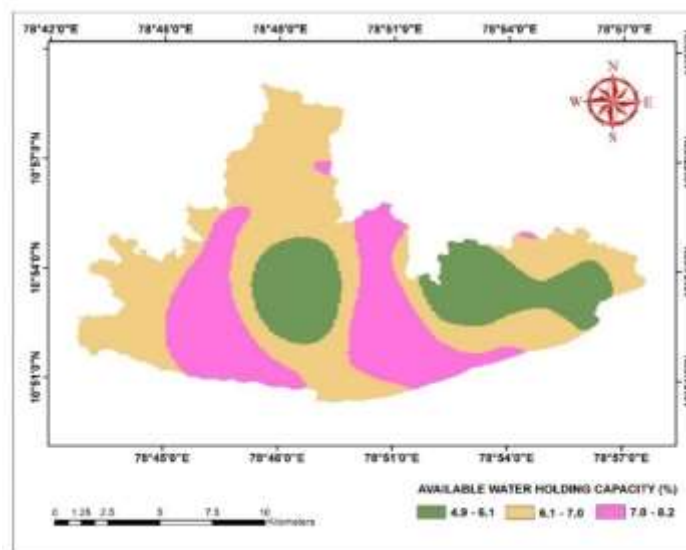


Figure 13. Available water holding capacity in different villages in Lalgudi block

The results obtained based on the geostatistical analysis of the data were similar to the observations made by farmers when interacted with them during the field visit. The paddy growers reported that the standing water depth could be maintained for paddy crop by irrigating the field once in two days at Edayathamangalam, Kuhoor, Kelanbil, and every day at Nagar, Angarai, Thirumangalam and Sembarai villages. The sugarcane farmers expressed that irrigation has to be provided either once in three days or five days for sugarcane crop. Farmers in Marudhur reported that irrigation will be

provided to sugarcane at a maximum interval of five days.

In case of sugarcane, if it is first ratoon crop, then the irrigation interval could be prolonged since the depth of roots would be deeper and the total available water would also be more. Similarly, it could be adopted for banana crop since banana growers would go for either first or second ratoon in banana. Hence, the spatial interpolation of soil properties was highly consistent with the actual practice adopted by farmers in the study area.

Table 7. Available water and irrigation interval for different crops in Lalgudi block

Villages	Crops	TAW (mm)	RAW (mm)	Irrigation Interval (Days)
Agalanganallur, Nagar, Angarai, Thirumangalam, Sembarai, Mettupatti, Thinniyam, T.Kalvikudi, AlangudiMahajanam	Paddy	14-18	2-3	1
	Sugarcane	22-27	14-18	3
	Banana	14-18	6-8	2
Thachakurichi, Magilambadi, Puthuruthamanur, Neikuppai, Edayathamangalam, Kuhoor, Kelanbil, Ariyur, NathamMangudi, Madakudi, Thalakudi, Appadurai, Esankorai, Pudukudi	Paddy	18-21	3-4	2
	Sugarcane	27-31	18-20	4
	Banana	18-21	8-9	3
R.Valavanur, Marudhur, Sirumarudhur, Valadi, Pamparamchutti, Thirumanamedu, Sevanthinathapuram	Paddy	21-24	4-5	2
	Sugarcane	31-37	20-24	5
	Banana	21-24	9-11	4

Similarly, geostatistical soil textural maps have been generated based on Kriging tools and these would be utilized for Land Use Pattern, precision agriculture, conservation practices, as well as land management in the research region Rajalakshimi et al. (24). Spatial variability maps of various soil physical properties will be useful for site-specific farming, for example, variable rate irrigation Rajalakshimi et al. (25).

Conclusion

Agricultural producers operate their fields at a near-field capacity. Soil water depletion is refilled by either precipitation or irrigation. Geostatistical analysis aids in definition of the available water-holding capacity and is useful for guiding irrigation. Preliminary analysis was non-normal and therefore needed log-transformation before kriging techniques. Ordinary and disjunctive kriging were compared on the basis of six models: Circular, Spherical, Exponential, Gaussian, Pentaspherical, and Sine-Hole. The fit produced better RMSE with the Sine-Hole effect model using disjunctive kriging at a mean prediction error of -0.07 and moderate spatial dependency. However, the fitting did slightly overestimate the properties of soil. According to the derived water-holding capacity map of Lalgudi block, the irrigation intervals determined for paddy, sugarcane, and banana are 1-2, 3-5, and 2-4 days, respectively. The block was divided into categories according to the availability of water, which helped farmers differentiate between soils and provide irrigation in optimal amounts, preventing both overwatering and drought levels.

Data Availability Statement

a. Some or all data, models, or code that support the findings of this study are available from the corresponding author upon reasonable request.

b. All data, models, and code generated or used during the study appear in the submitted article.

Author contribution

All the authors have given their equal contribution

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