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Geo-Statistical Assessment of Spatial Variability of Soil Water-holding Capacity for Optimal Irrigation under Semi-arid Vertisols in South India

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Abstract: Based on a field survey conducted in Lalgudi block, Tiruchirapalli district, Tamil Nadu, India, details pertaining to the crops grown, cropping pattern, land utilization and soil samples were collected from 20 locations under 7 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. Field capacity and wilting point are two major soil physical properties that would influence the available plant water. These parameters were estimated with the pressure plate apparatus using soil samples collected in the block. Soil texture-wise assessment was made with regard to the field capacity, wilting point and soil water holding capacity based on the observations. The locations of Lalgudi block were grouped into three categories based on the mean and standard deviation of available water holding capacity, field capacity and wilting point parameters and were statistically assessed. The groups were made by considering the

locations with values of a parameter lying under (i) $< (\text{Mean} - \text{SD})$; (ii) $(\text{Mean} - \text{SD})$ to $(\text{Mean} + \text{SD})$; and (iii) $> (\text{Mean} + \text{SD})$ limits. Geostatistics were applied for identifying the best interpolation method in order to acquire the spatial map of the available water holding capacity. An initial data exploration indicated about non-normal distribution of the available water holding capacity. Accordingly, log-transformation was made before kriging technique was used for the data. 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. An estimate of Root Mean Square Error (RMSE) based on the six models ranged from 2.1 to 2.5 for available water holding capacity parameter. The cross validation statistics indicated that Sine-Hole effect model with disjunctive kriging of available water holding capacity was superior for interpolation with minimum value of RMSE and moderate spatial dependency. The Sine-Hole effect model was found to overestimate the soil properties when interpolation was carried out and gave mean prediction error of -0.07 which indicated that the model was highly efficient. 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. Adoption of spatial algorithms for estimating the crop water requirement would greatly help the irrigation planners and water policy makers to create efficient regional plans for making precision irrigation under semi-arid vertisols.

CE Database subject headings: Available water holding capacity, Field capacity, Wilting point, Soil texture, Geostatistics, Irrigation, Semivariogram, Spatial autocorrelation, Vertisols

Introduction

Among different sectors, agriculture is the largest user of globally allocated freshwater with over 70% of water used for irrigation (Fischer *et al.*, 2007). Improving the water use

efficiency would be a critical response to overcome the growing agricultural water scarcity. In order to improve the irrigation efficiency, main factors that normally control the storage and release of water in the soil should be known. Among these factors, available water holding capacity (AWC) is a key attribute, since it would quantify the amount of water available for plants that any soil could hold under any agro-climatic condition. Soil available water holding capacity is a key soil hydraulic property, since it quantifies the amount of water available for plants that the soil could hold for a longer period. All farmers should invariably know about this important soil parameter in order to optimize the crop production under any soil and agro-climatic condition.

Obtaining a suitable measurement of AWC would therefore be useful for efficient crop management (Williams *et al.*, 2016) decisions relating to the time of sowing, crop type or level of fertiliser and other inputs. A number of farmers and advisers would be using the AWC data for crop management decisions, which in turn would be associated with the beneficial effects on crop yields (Ngwira *et al.*, 2013; and Lal *et al.*, 2015). Others would use the AWC data more informally in conjunction with the assessments of soil water (soil core, soil water monitoring device) in order to estimate the amount of plant available water. Under irrigation projects, one of the most common ways to define the quantity of irrigation water is associated with the calculation of readily available water or actual water depth (Silva *et al.*, 2011). It would be useful for precision irrigation and proper irrigation scheduling for different crops.

The spatial variation of AWC throughout the irrigated regions should be appropriately considered for efficient scheduling of irrigation. The soil properties, by nature would vary extensively over space and time in any location (Greenholtz *et al.*, 1988). The particular information on spatial variability of a soil parameter could be achieved based on geostatistical analysis. Geostatistics are useful to study the spatial distribution of soil

properties and also their inconsistency (Liu *et al.*, 2014; Behera *et al.*, 2015). Geostatistics would also help to identify the best interpolation method for acquiring the spatial map of soil parameters (Fromm *et al.*, 1993; Wigginton *et al.*, 2000; Usowicz *et al.*, 2004; Vieira *et al.*, 2007; Zheng *et al.*, 2009; Liu *et al.*, 2014). An accurate estimation of spatial distribution of different soil properties is important for precision agriculture and would be useful for the decision and policy makers to develop suitable plans and strategies.

The spatial maps of AWC parameter prepared from the best interpolation method could be used for efficiently estimating the irrigation water requirement and irrigation interval for different crops at different regions at a given point of time. This information would be very much useful for planners, irrigation engineers and decision makers to recommend and plan efficient water management strategies (De Paz *et al.*, 2015). Greenholtz *et al.*, (1988) examined about the spatial and temporal variability of hydrologic soil characteristics on Glendale clay loam soil. The authors used geostatistical techniques for characterizing the variability of wetness, tension, hydraulic conductivity and texture of a soil. They inferred that the variance of volumetric water content increased based on both depth and time. Geostatistical tools have been used to assess the spatial variation of soil moisture, texture and yield of two rainfed crops viz., vetch-oat and durum wheat (Munoz-Pardo *et al.*, 1990) in a study conducted at College of Agricultural Engineering of Medjezelbab, Tunisia. The mean error was found to significantly decrease with an increase in the sample size.

Brooker *et al.*, (1995) discussed about geostatistical analysis on the depth of topsoil and root zone readily available water at a Vineyard near Waikerie in South Australia. Using the measured semi-variograms, the spatial maps of different soil parameters were prepared for a better understanding and assessment of different soil properties in that region. Goovaerts (1998) mentioned that the basic geostatistical tools like correlogram and semivariogram could be introduced to efficiently characterize the spatial variability of each attribute

separately as well as their spatial interactions. Weller *et al.*, (2002) used different geostatistical techniques for assessing the spatial variability of soil properties. The authors expressed that Kriging technique would be better than any other interpolation technique (Robinson *et al.*, 2006).

Santra *et al.*, (2008) highlighted that estimation of spatial variation of soil properties would be important for precision farming and environmental modelling. The spatial distribution of water content at field capacity (FC) and permanent wilting point (PWP) at different zones of a farm would govern the available water for an efficient plant growth. Based on a study conducted at Indian Agricultural Research Institute, New Delhi, authors observed that Gaussian model was superior with experimental semivariogram of bulk density, silt and clay contents. The Hole-Effect model was found to be the best to fit the experimental semivariogram of organic carbon content in an alluvial soil. Camacho-Tamayo *et al.*, (2008) determined the spatial variability of different chemical properties, including soil organic carbon (SOC), soil reaction (pH), exchangeable acidity, exchangeable aluminum, available P, calcium (Ca), magnesium (Mg), potassium (K) and sodium (Na) for two Oxisols, with the purpose of identifying guidelines for site-specific agricultural practices. A greater influence of the agricultural intervention on the spatial variability was evident in the upper 10 cm of soil. A significant spatial dependence was found to exist for most of the soil properties. The information generated would form a basis to derive the guidelines for site-specific agriculture.

Jabro *et al.*, (2010) examined spatial variation of selected soil physical and chemical properties and explored their spatial correlation in the Ap horizon of a Lihen sandy loam soil (sandy, mixed, frigid Entic Haplustoll) within a field of grass-alfalfa Conservation Reserve Program (CRP) land, North Dakota. Results indicated that small to moderate spatial variability existed across the field for different soil properties studied. Nayanaka *et al.*, (2010)

explored about the spatial variability of agronomically important soil properties of a paddy growing tract in Pulasthigama in Polonnaruwa district in Sri Lanka. The authors suggested that spatial dependencies of soil properties could be used to support the spatial sampling for making a detailed soil mapping. They suggested that the management practices such as fertilizer application, irrigation and tillage operations could be fine-tuned within a field scale to maximize the rice crop production, while minimizing the detrimental effects on environment.

Sharma et al., (2014) conducted experiments on groundnut at Rajkot during *kharif* 1996 to 2006 to assess efficiency of shallow ploughing, deep ploughing every year, deep ploughing alternate years and deep ploughing once every three years. Treatments were assessed for effect on rainwater use efficiency (RWUE), soil moisture (0–15 and 15–30 cm depth), cumulative depth of infiltration, pod and straw yield, and sustainability yield index (SYI). Significantly higher pod yield of 770 kg/ha and straw yield of 2134 kg/ha were attained under yearly deep ploughing. Regression models gave coefficient of determination of 0.41 to 0.53 using monthly rainfall, and 0.71 to 0.76 using cumulative rainfall for predicting pod and straw yield. SYI ranged from 19.7 to 24.8% based on monthly rainfall and 25.6 to 30.9% based on cumulative rainfall for attaining pod yield, and 35.7 to 40.5% based on monthly rainfall and 38.0 to 44.8% based on cumulative rainfall for straw yield. Yearly deep tillage was superior to attain maximum pod and straw yield, SYI, RWUE, benefit-cost ratio and maximum depth of infiltration.

Shit *et al.*, (2016) measured different soil properties like pH, electrical conductivity, available phosphorus, potassium and organic carbon. Random samples were taken from Medinipur Sadar block of Paschim Medinipur district, West Bengal state in India. The spatial variability of these properties have been mapped using different geostatistical models. The study suggested that ordinary kriging interpolation would directly reveal about the spatial

distribution of different soil properties. Li *et al.*, (2017) examined about the temporal Irrigation Water Productivity trend of different cereal crops over the Hexi Corridor in Northwest China by employing descriptive analysis, trend analysis and change-point analysis. The spatial patterns of dry, average and wet years have been analyzed by the spatial interpolation and spatial autocorrelation methods. The results indicated that the area supported by unit of irrigation water use, fertilization and agricultural film had significant impacts during the whole period.

Elaalem (2017) examined Kriging and Inverse distance weight (IDW) methods for predicting the spatial variability of Exchangeable Sodium Percentage, Cation Exchange Capacity and Calcium Carbonate Percentage in Tripoli, Wadi Almjainin and Bin ghashir at Jeffara Plain, Libya. The study suggested about the usefulness of geostatistical methods for studying the spatial prediction for different soil proprieties. Laekemariam *et al.*, (2018) assessed the spatial variability of soil fertility and mapped the application of fertilizer types using geostatistics. The authors employed ordinary kriging method in their study. The authors have identified nutrient deficient areas and developed site-specific nutrient management based on the study.

Sanches *et al.*, (2019) investigated about the relationship between physical and chemical properties of soil and sugarcane yield, and identified the soil parameters that would efficiently determine the final productivity of a given field. The authors inferred that large volumes of both spatial and temporal data, together with the data mining techniques, allowed the extraction of knowledge and creation of specific management zones in the field in order to support the decision-making process for producers in an efficient manner. Sanches *et al.*, (2019) pointed out that adoption of precision agriculture technologies would be a promising approach to increase the agricultural yields of crops and reducing the production costs. It would comprise of several techniques and technologies for managing the spatial and temporal

variability of crops, and these approaches would improve the yield, profitability and environmental management of fields. These benefits could be essentially obtained through site-specific management that would consider the spatial and temporal variability of a given field.

In this paper, we have (i) assessed the spatial variability of soil available water holding capacity using geostatistical approach; and (ii) spatial variation in the irrigation water requirement and irrigation scheduling for major crops grown in Lalgudi block, Tiruchirapalli district, Tamil Nadu in 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 (Fig. 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 Lalgudi block has a dense dry vegetation and barren lands, while southern part is bounded by 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).

Fig.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 Fig. 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.

Fig. 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, 2004). The disjunctive kriging method provides a nonlinear unbiased estimator with the desirable property of minimum variance of errors (Yates *et al.*, 1986). 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 in many Geographical Information Systems (GIS) (Wackernagel, 1995). 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 (Yates *et al.*, 1986). 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 pentaspherical 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 a 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.*, 1998) 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

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

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) (Surendran *et al.*, 2017).

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 of 20 locations, the field capacity ranged from 10.4 to 40.0% with mean of 23.8% (CV of 34.2%). The permanent wilting point ranged from 3.1 to 36.0% with mean of 17.1% (CV of 48.4%), while the soil water holding capacity ranged from 2.5 to 10.8% with 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. But 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
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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 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 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 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 lowest field capacity of 10.4% and wilting point of 3.1%, while the soils under clay soil texture had 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 lowest capacity of 6.1%, while soils under silt loam texture had highest capacity of 10.8%.

413

414 **Fig. 3.** Field capacity, permanent wilting point and available water holding capacity under
 415 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 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 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 $(\text{Mean} + \text{SD})$. Twelve locations viz., L9, L8, L18, L3, L13, L19, L17, L20, L15, L1, L11 and L4 have fallen in the group of $(\text{Mean} - \text{SD})$ to $(\text{Mean} + \text{SD})$.

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

Parameter	Mean	SD	$< (\text{Mean} - \text{SD})$	$(\text{Mean} - \text{SD})$ to $(\text{Mean} + \text{SD})$	$> (\text{Mean} + \text{SD})$
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

434 SD: Standard deviation

435 ***Relationship between different soil parameters***

436 The estimates of correlation between different soil parameters and their effects on each other
 437 are described in Fig 4. Field capacity was found to have a positive effect on the wilting point
 438 indicating an increase in the wilting point for an increase in the field capacity. Wilting point
 439 changed by a significant coefficient of 0.980% for an unit change in the field capacity with
 440 significant predictability (R^2) value of 0.923. Field capacity had a positive effect on the
 441 available water holding capacity indicating an increase in the available water holding
 442 capacity for an increase in the field capacity. However, available water holding capacity
 443 changed by a non-significant coefficient of 0.017% for an unit change in the field capacity
 444 with non-significant predictability (R^2) value of 0.003. Wilting point had a negative effect on
 445 the available water holding capacity indicating a decrease in the available water holding
 446 capacity for an increase in the wilting point. Available water holding capacity changed by a
 447 non-significant coefficient of -0.060% for an unit change in the wilting point with non-
 448 significant predictability (R^2) value of 0.047.

449

Fig. 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 Fig. 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. This was observed based on the large difference existing between the mean and median derived for the data. The mean of available water holding capacity was 6.625% and the median was 7.045% (Fig. 5a). Since a difference existed between mean and median determined for the data, the ordinary kriging could not be applied for the dataset without carrying out a suitable data transformation.

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

Therefore, log transformation of data was made and the frequencies have been depicted in Fig. 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 median AWC of 1.951. This indicated normal distribution of the log transformed dataset of

available water holding capacity. De Paz *et al.*, (2015) observed about non-normal distribution of the field capacity and wilting point parameters and were log-transformed in order to ensure about the normal distribution of the data.

Normal QQ plots of soil properties

The Normal QQ plots without transformation of dataset and with transformation of dataset were obtained for the available water holding capacity based on the soils samples collected in Lalgudi block. Fig. 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.

Fig. 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 case of the log-transformed dataset. This indicated about 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

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

Dataset : Soil_Allpts Attribute: AWHC

485
 486 **Fig. 7.** Trend analysis of soil available water holding capacity

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

493 *Semivariogram cloud of soil properties*

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

Fig. 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 Fig 10 based on disjunctive kriging method.

(a) Circular

(b) Spherical

(c) Exponential

509 **Fig. 9.** Semivariograms for available water holding capacity in Lalgudi block using Ordinary
 510 Kriging

511 **Fig. 10.** Semivariograms for available water holding capacity in Lalgudi block using
 512 Disjunctive Kriging

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

mean of 0.1027. The sill ranged from 0.1672 based on Sine-Hole effect model to 0.1818 based on 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 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 mean of 0.58. The spatial dependency was ‘moderate’ based on all the 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 Pentaspherical model to 0.1337 for Gaussian model with 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 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 minimum dependency index of 0.61, while the Gaussian model gave 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 clearly 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 dataset of available water holding capacity had 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.*, (2015) 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.

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. In order 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.

The ME ranged from -0.1070 under Sine-Hole effect model to 0.0200 under Gaussian model with mean of -0.0235, while the RMSE ranged from 2.3993 under Sine-Hole effect model to 2.5718 under Exponential model with mean of 2.5056. The MSE ranged from -0.0921 under Pentaspherical model to -0.0658 under Gaussian model with mean of -0.0767, while the RMSSE ranged from 0.8139 under Gaussian model to 0.8417 under Pentaspherical model with mean of 0.8216 over 6 models calibrated under the Ordinary 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
Pentaspherical	-0.0877	2.4919	-0.0921	0.8417	3.0476	Overestimates
Sine-HoleEffect	-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 Exponential model to 0.1098 under Sine-Hole effect model with mean of 0.1066, while the RMSE ranged from 2.1744 under Sine-Hole effect model to 2.2980 under Exponential model with mean of 2.2594. The MSE ranged from 0.0252 under Pentaspherical model to 0.0341 under Sine-Hole effect model with mean of

0.0292, while the RMSSE ranged from 0.8077 under Sine-Hole effect model to 0.8260 under Pentaspherical 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
Pentaspherical	0.1050	2.2783	0.0252	0.8260	2.8031	Overestimates
Sine-HoleEffect	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 the six models using both methods of kriging. The best prediction method should have minimum RMSE value. Finally, it is observed that this approach gave lower RMSE values for prediction of available water holding capacity. Mardikis *et al.*, (2005) have reported a lower error value when interpolation took place only once in their study.

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, Sine-Hole effect model gave 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.*, (2008) observed about the superiority of 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. 11. The interpolated values of available water holding capacity were found to range from 4.9 to 8.2% in the study area. From Fig. 11, 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

616 into three categories and the villages coming under each category have also been described in
 617 Table 7.

618

619 **Fig. 11.** Available water holding capacity in different villages in Lalgudi block

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

628 In case of sugarcane, if it is first ratoon crop, then the irrigation interval could be
 629 prolonged since the depth of roots would be deeper and the total available water would also
 630 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

Conclusion

The goal of the agricultural producers would be to maintain the field at or near field capacity. When there is a deficit in the amount of water in the soil, the soil profile would need to be replenished by either precipitation or irrigation. Geostatistics were applied for identifying the best interpolation method to acquire the spatial map of available water holding capacity. The initial data exploration indicated about the non-normal distribution of available water holding capacity and hence log-transformation was done before using kriging method. Ordinary kriging and Disjunctive kriging have been explored with six different models viz., Circular, Spherical, Exponential, Gaussian, Pentaspherical and Sine-Hole effect model. The models have been used for the spatial prediction of available water-holding capacity. A relatively lower Root Mean Square Error was observed for all the six models which was in the range of

2.1 to 2.5. The cross validation statistics indicated that the Sine-Hole effect model with Disjunctive Kriging of available water holding capacity was superior for interpolation with minimum Root Mean Square Error value ($RMSE = 2.17$) and with moderate spatial dependency. It was found to overestimate the soil properties when interpolation was carried out. The validation of Sine-Hole effect model gave mean prediction error equal to -0.07 which indicated an efficient performance of the model. Hence, with the available water holding capacity map of Lalgudi block, the total available water, readily available water and irrigation interval of paddy, sugarcane and banana crops were estimated. The irrigation interval of paddy, sugarcane and banana varied between 1-2, 3-5 and 2-4 days respectively within the block. Finally, the block was grouped into three categories based on the available water and the villages falling in those categories have been assessed. The key would be for the farmers to understand the distinctions of the soil water holding capacity, apart from efficiently managing the water so that the crops would not be either irrigated excessively or suffer from drought condition.

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.

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