Geospatial Analytical Framework for Soil Fertility Management

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Abstract
The soil fertility and fertilizer recommendation through the geospatial modeling and geo-data analytics is the prime concern of current agriculture automations. The current process involved in getting soil nutrients encompasses a static process and consumes enormous time on various agricultural activities. Hence, this jeopardy is resolved by implementing the proposed framework. This geospatial framework provides quick and dynamic soil nutrients on individual agricultural land and further offers predictive datasets for various agricultural activities. The framework also depicts spatial variations on soil properties for both macro and micro nutrients. This implementation of geospatial thematic maps creates density and variations on all the available soil nutrients of a selected land region. These spatial variations are displayed with adequate color properties based on the categorisation of agricultural land size like marginal, small, semi-medium, medium and large farming lands. The framework is beneficial to the farming community and the e-governance for distributing the fertilizers on a need basis across taluk/district of every state in India.

1. Introduction

The current Indian farming methods involve the legacy fertilizer distribution on farming lands and the distribution/calculation of fertilizers is done using homogeneous practices (Basavaraja et al., 2016). The traditional approach over the decades is the prime cause for not accomplishing the productive utilization of land, crops and fertilizer deployment. The efficient usage of geospatial variability in determining the site-specific nutrient management technique benefits the Indian agriculture (Patil et al., 2011 and Suri et al., 2014). The site-specific fertilizer recommendation portrays the spatial variability on cultivation land by adopting the advanced techniques like Geographical Information System (GIS) and Global Positioning System (GPS) related to yield constraining components (Andrienko and Andrienko, 2011).

The use of Global Navigation Satellite System (GNSS) in the field of agriculture encompasses an interactive tool to classify the agricultural land into various management regions for gathering, storing, retrieving, transforming and reproducing the yield potentials (Andrienko and Andrienko, 2012). These technologies formulate and explore the geospatial variations on soil fertility maps and they are constructed on the estimations of soil properties (Santra et al., 2008). The proposed framework mainly emphasizes on geospatial agricultural data, thematic map components and interactive geospatial analytical model, this model is utilized to determine the soil nutrients based on farming land size categorization. This geospatial analytical framework benefits the farming community in obtaining the best recommendation of fertilizer utilization in the form of Soil Health Card (SHC). The proposed framework illustrates the study of soil nutrients and its spatial variability by creating intuitive graphical interfaces on varieties of soil nutrients. The application framework proposes an approach to examine the vast quantities of spatial soil nutrients and performs the statistical nutrient analysis on their utilization.

The prime objective of the proposed research is to provide the optimum fertilizer recommendation by using the cloud based GIS framework and Decision Support System (DSS). This is achieved by analyzing the spatial patterns with soil nutrient distribution. The important aspect of this paper is exhibited in the following order: (1) To analyze and model the various geospatial scenarios of soil fertility management, (2) to introduce an interactive framework to build the entire process of geospatial analysis on soil nutrients, (3) to construct the proposed model with interactive geospatial analytical tools.

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2. Literature Review

The literature study of geospatial modeling on soil fertility management and prediction methods are performed in chronological order. The study aims to evaluate various geospatial techniques, spatial variability's, agricultural management practices, geo-informatics and the decision support systems. To analyze these unstructured data, we started studying the machine learning methods in agriculture studies, at first we discovered an integration of machine learning is implemented in most of the current research studies to acquire statistics on geo-coordinates (Tittonell et al., 2005 and Hengl et al., 2015). This study of statistics on geo-coordinates involved a large capacity of data and hence to support this, clustering technique is proposed. The study now added the concept of clustering technique along with machine learning method. The clustering technique is implemented to band the geo-coordinate positions proved in most of the research studies (Anuar et al., 2008 and Tahir et al., 2016). These suitable statistical methods are applied to respective geo-coordinates. The study moved further in understanding the environmental parameters, tools used and current practices.

The study of authors (Brannon and Hajek, 2001 and Andrienko and Andrienko, 2011) recognized the agricultural management activities with various environmental parameters and natural resources that relay on evident spatial features. The framework further demonstrates the analysis of time series and modeling by using the interactive visual analytical tools. The authors (Patil et al., 2011 and Raghupathi and Srinivas, 2014) illustrate the efficient usage of spatial variability in defining the site-specific nutrient management practices. This highly benefits the farmers in fertilizer utilization, cost-effective farming and in preserving the soil health. The lack of heterogeneous knowledge on soil fertility management among Indian farmers is leading to inadequate practices of fertilizers on various soil types. The researcher (Suri, 2011) showed the heterogeneity in economic returns reveals limited technology adoption by the farmers. However, the paper lacks to monitor soil fertility management in the proposed model. After studying the framework and analytical tools the study continued to research on GNSS techniques.

The study by authors (dos Santos et al., 2017) investigated the lack of GIS and GPS techniques to model the agricultural data and to visualize the outcomes. In order to solve the distinctive hindrances in soil fertility management, an enhanced and integrated geospatial modeling is required for Decision Support Systems (DSS). This increases the nutrient efficiency and geospatial variability in cultivated lands. Another study (Antwi et al., 2016) on African soil health consortium illustrated the understanding of spatial variability on cultivated lands. The prime benefits identified are, refining the agricultural management practices for effective land utilization and dynamic recommendations of site-specific nutrients. These refined benefits are considered as one of the building blocks for designing the proposed geospatial analytical framework. However, the research studies (Jones et al., 2003 and Keating et al., 2003) reported the limited use cases of decision support tools with GIS for analyzing and evaluating soil fertility. The research study (Sarkar et al., 2017) stated the roles of geo-informatics (RS, GPS, and GIS) in the implementation of site-specific nutrient management (SSNM) for an efficient use of fertilizers. This processing approach guaranteed the increase of food production growth in Indian agriculture. The tools like Decision Support System for Agro-Technological Transfer (DSSAT), Agriculture Land Suitability Evaluator (ALSE) (Ranya et al., 2013) and Agricultural Production System Simulator (APSIM) is pooled with research studies of crop yield prediction. Further, the remote sensing applications are also integrated with GIS tool to evaluate and examine the spatial distribution of few soil nutrients. These techniques are used as the prediction methods for interpolating the geo-coordinate data on a continuous surface at unknown locations (Bhatt and Joshi, 2012). The research work (Paz-Kagan et al., 2016, Santra et al., 2008 and Ramzan et al., 2016) adopted the geo-statistical tools on soil properties at smaller spatial scales.

The literature study concludes with two major research gaps: at first, an innovative technique needs to be implemented to analyze and model the various geospatial scenarios in soil fertility management. Most of the studies have focused on very few soil nutrients on limited spatial scale but not on the integrated approach to monitor the soil quality on enormous spatial scales. Secondly, an interactive framework needs to be integrated with the entire process of geospatial analysis in constructing geospatial analytical tools.

3 Geospatial Analytical Modeling

In our proposed framework, GIS technique is used to construct the geospatial model to display the spatial distribution maps and to represent the geospatial variability of soil nutrients. The geospatial soil nutrient variations are exemplified in different color variations for macro soil nutrients like Nitrogen (N), Potassium (K), and Phosphorous (P) contents. Further, to cleanse and structure the enormous agricultural datasets, an effective clustering method is implemented. In this method, spatial analytics is performed on soil nutrients by using the Spatial Analyst control from the ArcGIS 10.2.1 tool. The framework is described in Figure 1, this comprises of techniques like re-grouping, data exchange, filtering of geospatial data and cluster based channels for implementing statistical analysis. The following geospatial components are involved in development of the proposed framework and each component is explained in detail.

Data Storage: At first, the data is collected in spreadsheets and interpreted using the ArcGIS tool. The study experiment used Tumkur district map of Karnataka State for interpretation and obtained the interpreted values in the form of TIFF picture format for each soil nutrients. Further, when we converted these files into raster points then we received 98 lakhs of dataset for each geo-coordinates of Tumkur district. Subsequently, these data are exported into CSV file format and they are imported into the cloud database server. The interpreted data is successfully mapped to geo-coordinates and soil nutrients of Tumkur district farmer table data sets.

Computational Tools: In this computational tool the study implemented the horizontal shading technique to optimize the data storage as the datasets were huge. The study discovered that storage of farmer and related data are concatenated with village and the farmer reference string. For example, Farmer_Kunigal, Farmer_Gubbi, in order to achieve quick search and transactions on data. A cloud based software service is developed and deployed to perform all these data import and export activity. The development is powered using the Microsoft .Net Framework with MVC technology to process the data. Further a dynamic intelligence is built within the application to compute STCR equations. The privilege of application is customized to role based activities in order to benefit the dynamic STCR equation creation and modification.

Visual Tools: The visual tool contains the GIS and other information system services. In this approach, we integrated the GIS services to display the map. Further, it is also used to represent the spatial distribution of each soil nutrients using ArcGIS 10.2.1 tool. The spatial soil nutrients variations are represented in color variations for each available soil nutrient (N, P, and K).

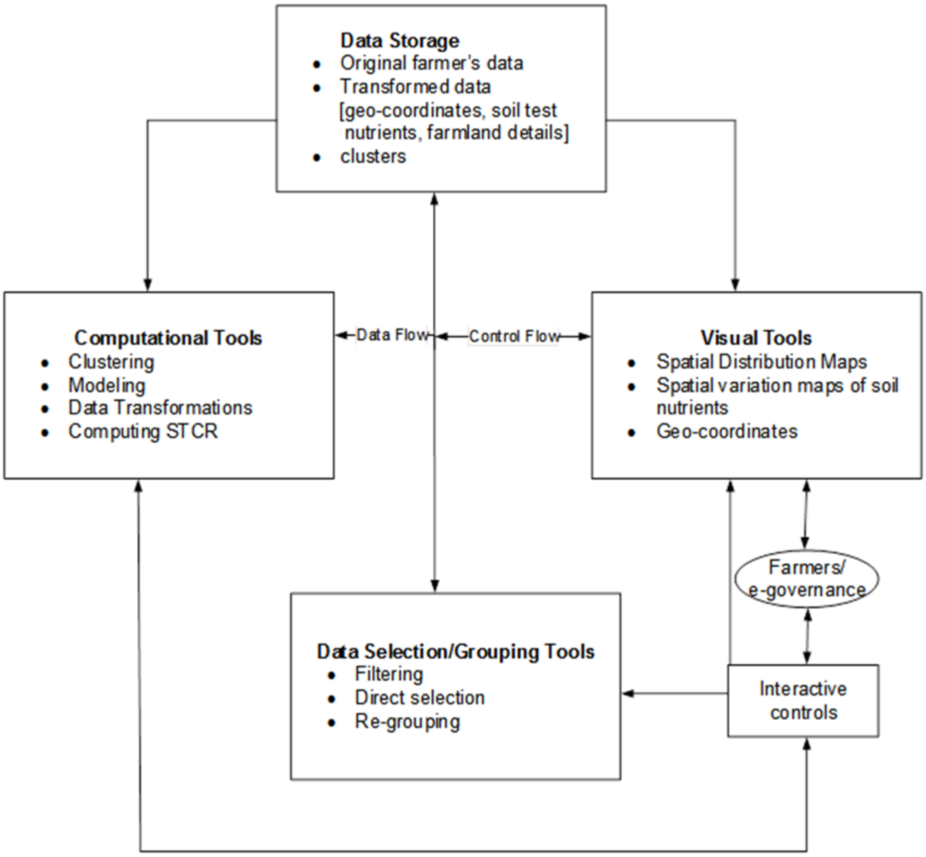

Figure 1: Representation of Geospatial Components

Data Selection/Grouping Tools: To cleanse and structure the huge datasets the study used effective clustering methods. A novel algorithm is created and deployed through the application software to cluster the database and to improve the performance by creating the indexes in the table. The data partitioning and optimization were done to achieve quick application access within clusters and the prediction analysis is done using the ArcGIS. This tool is used for analyzing the soil nutrient variations and to categorize the farmers operational land holdings. Apart from these fundamental components, a statistical analysis is done on intelligent re-grouping like adjustment of computational clusters, data exchange, filtering of the data including spatial and cluster-based filters.

3.1 Data Flow Analysis

This subsection illustrates the data flow analysis of the geospatial soil nutrients with different spatial locations of farmer's land, basically, data-flow analysis is an integral design part of the framework. Figure 2 describes the data flow analysis in four sequential processes, each process is explained in chronological order. The first process starts with the data collection, second in pre-processing of the data, third with data storage and the last in analyzing, monitoring and demonstrating the data through spatial analytical model by using GIS cloud based server.

Step 1: The soil samples collected are processed in varying geospatial locations like low, medium and high range locations of farmer's land by considering the macro and micro nutrients. A particular color shade for each classification on soil nutrient is mapped and displayed on thematic map (Piotrowska et al., 2016). At least two gatherings are displayed in the thematic maps that are comparative in soil type and land positions, these classifications are visualized in order to categorize and recognize each pattern.

Step 2: The framework examines the geospatial nutrient variations in each of the soil classifications by using the thematic graphs. The characterization of soil nutrients is done periodically based on the season and by making the visual examinations but few scenarios are picked based on the variations in nutrient and climate. In order to make the fertilizer recommendations, framework integrates the dynamic Soil Test Crop Response (STCR) equations based on the crop type, season, soil type and seed variety. These equations are formulated to provide the fertilizer recommendations for individual farmer land. A prediction model is built on soil nutrients for recommending the fertilizer based on the result sets (Maro et al., 2014).

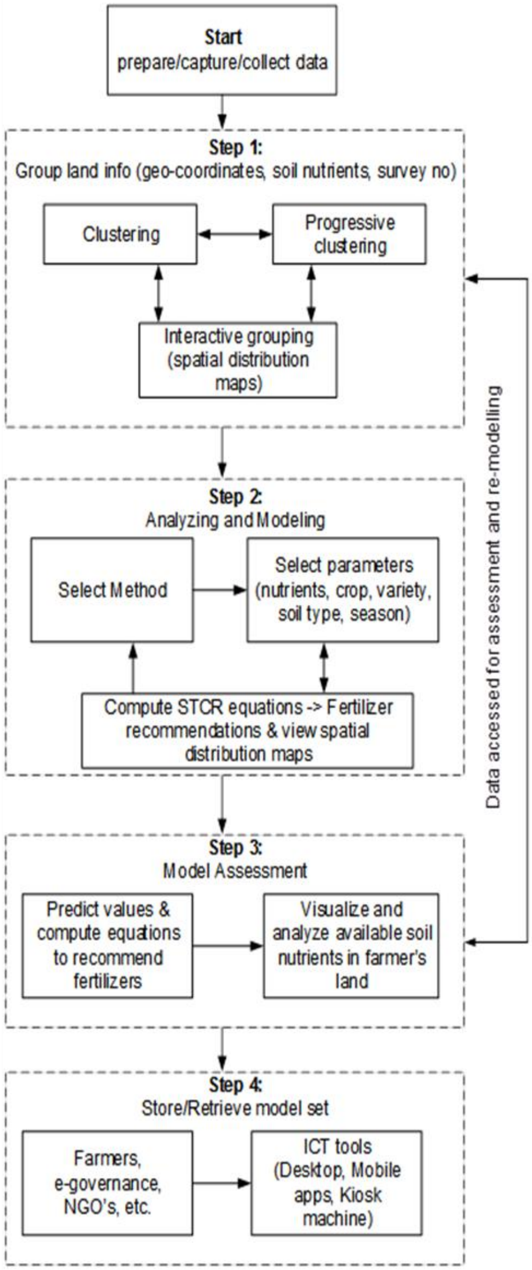

Figure 2: Data Flow Analysis of the proposed Framework

Step 3: Once the model is built then the framework is evaluated based on the historical geospatial data. The variation and allocations of period data are explored through the maps due to lack of the exact spatial variations. The predicted soil nutrients are broadly visible because they are based on the categorization of similar features of spatial variations (Bhatt and Joshi, 2012).

Step 4: The last stage of the model is defined to store analytical model data onto cloud based GIS server. This data is useful for farmers and e-governance and can be accessed through ICT enabled services like website, Kiosk machine and mobile apps (Premasudha and Leena, 2016) on spatial maps. The large volume of farmer's information on cloud service will highly benefit in various services.

3.2 Geospatial Prediction Model

The key aim of this framework is to build a single soil nutrient variation model for a cluster of similar soil nutrients, soil type and land size for different farmers (Liu et al., 2009). We selected one of the best prediction model known as predictive modeling technique. In our approach, we used this method to predict the datasets to recommend fertilizers with soil nutrients. This model technique involves the machine learning methods, computational procedures and mathematical methods on agricultural datasets on defined objects like soil, fertilizer, geo-coordinates and crops. This approach implements an equation-based model to consider the prediction procedures in the anticipated areas. The mathematical equations are defined to forecast and generate nearby datasets of macro soil nutrients for recommending the fertilizers on various scale of farming land.

The predictive model consists of various parameters such as season, soil type, crop types, fertilizers, and farm data to forecast the outcomes based on current datasets. The predictive computational model method diverges from other mathematical and relational model approaches because it basically relies on the data formulated equations. This approach of calculation is also known as black box because it maps the source datasets to the predicted output datasets with a linear method. Irrespective of the method implemented, the process involved in integrating the predictive model on agricultural prediction is listed below.

1. Treat the missing data by cleaning the outlier data
2. Recognise a parameter on unavailable datasets by predictive model approach
3. Use the equations to pre-process the data into a suitable form
4. Train the predictive model by recognising the data subsets
5. Estimate the parameters on each source dataset
6. Verify the performance/accuracy of model generated data
7. Calibrate the original datasets against the predicted data sets using model accuracy
8. Repeat the procedure if prediction falls with higher numbers

In this paper, we consider predictive model on agriculture datasets to generate the unsampled geo-coordinate soil nutrients values for Tumkur district farmers. We have integrated this model in our approach in a specific village so that we can gather and evaluate the prediction results quickly with the help of soil scientist. We have chosen the Tumkur district as our pilot source of activity and performed the prediction activity and the obtained soil nutrients are evaluated with the guidelines of the Soil Science Scientist (UAS, GKVK, Bangalore). The results found to be marginally close to the actual datasets established by the soil scientist and team. The proposed geospatial predictive model was successful in generating the soil nutrients based on land scales like low, medium and high. The results obtained are discussed in Figure 3 prediction model of Tumkur district.

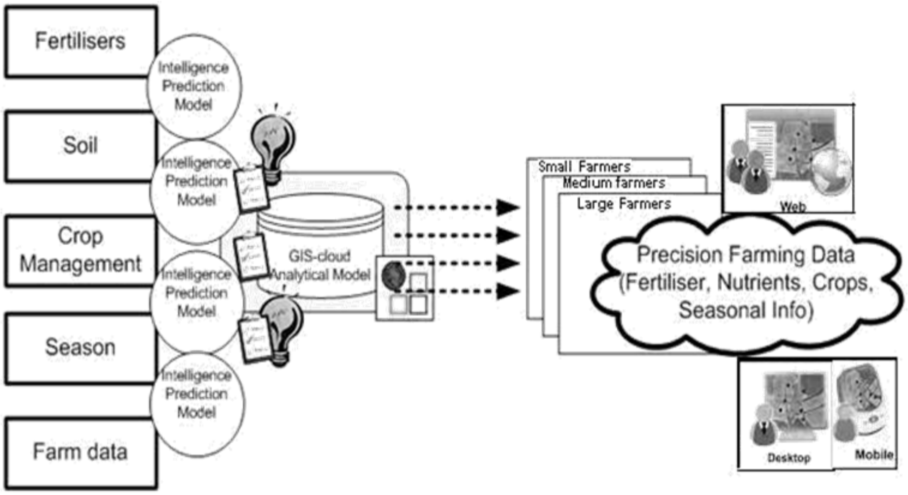

Figure 3: Illustration of the prediction model of soil nutrients

The core blocks of machine learning and equation models are encapsulated in GIS-Cloud analytical model, this model is created by using the Microsoft .Net MVC framework architecture and the intelligence of predictive model linear equations are associated with the smart program modules. The various agricultural modules like fertilizers, soil, crop management, season and farm data are created using the dynamic creation methods i.e., the software intelligence allows flexibility of model creation at any point of time. Each created module is automatically plugged into the intelligence prediction model and to the core block by default. The scale of farmers illustrated in the figure like small, medium and large are the end users identified as farmers. The land scale of the farmer and his information data sets are formerly created using the latitude and longitude coordinates. Whenever a farmer makes a transaction through the cloud software service http://krishiganaka.sit.ac.in, the intelligence will perform lookup on the datasets and based on the retrieval data the prediction module generates the data. The model framework is evaluated using the equations, let us begin with equation 1

$$\text{Soil Nutrient Index} = \frac{(\text{SNL} * 1 + \text{SNM} * 2 + \text{SNH} * 3)}{\text{SNT}}$$

Equation 1

Where SNL, SNM and SNH are the sample number of soil nutrients categorized as low, medium and high respectively and SNT is total number of soil samples. This correlation of soil nutrients is computed using Pearson's equation (Johnson and Wichern, 2007) to reveal the predicted soil nutrients.

$$SN = FM_i - M1 \quad N_{low} = \frac{FM_i - FS_i}{M1 - S1}, N_{high} = \frac{H1_i - FM_i}{L1 - M1}$$

Equation 2

Where S1, M1 and L1 are the small, medium and large farmers for the predicted values used for the classification of farmers per ha *I*. Consider the soil level nutrients as SN and two scale factors N_{low} and N_{high}. Let FS_i, FM_i and FL_i be the small, medium and large farmers for the actual value allocation in the soil samples tested for the area (per ha) *i*. Consider S^n be the predicted value from an arbitrary soil nutrients step *n* (the value *n* is common for all classification members). The distinct values for farmer's land *i* and soil nutrient *n* as in equation (2) is calculated based on the below mentioned formula:

$$S_i^n = \begin{cases} M1 + N_{low}.(S^n - M1) + N, if\ S^n < M1 \\ M1 + N_{high}.(S^n - M1) + N, otherwise \end{cases}$$

Equation 3

The remainder values are calculated based on the variations between the actual values and the individually adjusted predicted values. In the model assessment step, the predicted values are processed and executed as per the above equations. The results are visualized based on the evaluation in the form of spatial distribution maps.

4. Case Study

This section deals with the implementation of the proposed framework in GIS cloud server and developing the cloud software service for providing site-specific fertilizer recommendations using the spatial distribution maps. In coordination with University of Agricultural Science (UAS), GKVK, Bangalore, INDIA the developed framework and software solutions are transacted on Kestur village of Tumkur district, Karnataka, INDIA.

4.1 Study Area and Data Collection

The data was collected from the team of AICRP on Soil Test Crop Response (STCR), UAS, GKVK, Bangalore. The team of Soil Science has carried out an extensive research to discover the spatial variability in macro and micro soil nutrients by randomly selecting 223 villages soil samples out of 2708 villages of Tumkur district (Basavaraja et al., 2016) covering 8% to 10% of the total number of villages. We have considered Tumkur district, Karnataka, India as our pilot study for evaluating the framework and software service on agriculture dataset. The geographical area of Tumkur district is 1059.7 hectares with the annual rainfall of 622.0 mm is obtained with an estimated 32 rainy days. This topographical environment contains red and sandy soil like cretaceous red loamy, red sandy loam, sandy clay loam, loamy soil, sandy soil.

The district yields various crops like ragi, paddy, maize, etc., and few plantation crops like areaca and coconut. Around 1,332 soil samples are collected randomly and tested by AICRP on STCR team at UAS Soil Test laboratories to determine the available soil nutrients for both micro and macro nutrients across ten taluks of Tumkur district. The three major nutrients Nitrogen (N), Phosphorus (P) and Potassium (K) data are used for interpolation using ArcGIS software 10.2.1. We have compared the results for various interpolation techniques such as Inverse Distance Weighting (IDW), Ordinary kriging (OK), Radial Basis Function (RBF), etc., based on the cross validation methods using root mean square error (RMSE) and the mean error (ME) available in ArcGIS tool. The RMSE and Mean Error shown in Table 1 were validated based on the least error for each nutrients and the obtained results showed the OK interpolation method produced least error compared to other kriging methods.

Table 1: Comparison of performance of the four interpolation methods based on RMSE and ME

Interpolation Methods	N		P		K	
	RMSE	ME	RMSE	ME	RMSE	ME
OK	50.62	0.04	16.81	0.12	139.61	-1.08
IDW	53.78	-1.02	17.52	0.39	145.84	-0.18
RBF	50.99	-0.43	16.81	0.03	139.98	-1.50
GPI	56.16	-0.00	17.91	-0.00	146.29	-0.04

The OK interpolation method was considered to be the best method for interpreting the soil nutrients for proposed framework. To perform the geospatial analytical model, we required the detailed information of individual farmer's operational holdings along with geo-coordinates. The above samples are insufficient to perform statistical model as the farm size data was unavailable. To perform the analytical model, we selected a small village of Tumkur district as a pilot study. Kestur village is located in Tumkur taluq, Kora hobli of Tumkur district in Karnataka, India. The total geographical area of village is 435.57 hectares. Kestur has a total population of 2,326 peoples. Tumkur is nearest town to Kestur which is approximately 18km away.

In order to obtain details like land, survey number, khata number and land size of each farmer in the kestur village we had to interact with legacy services run by government of Karnataka. The current software system called Bhoomi is in practice for processing the agriculture data, this application software database contains 20 million digitized records pertaining to 6.7 million of farmer's land ownership of the state. Further, it contains the Record of Rights, Tenancy and Crops (RTC) is made available for individual farmer's land. The software generates several types of reports based on land ownership details, land size, soil type, crop details, and owner's name. This is beneficial in making decisions for e-governance and in providing the agricultural inputs in various activities. Using this software, we manually collected the information for the total 188 survey numbers of the village in spreadsheet and further data was used for classification and analysis. This job was tedious since the application was limited to process single survey number and other design limitations of processing the bulk data sets. Hence, it consumed more than sufficient time in fetching complete survey numbers of one village in a single spread sheet.

4.2 Data Classification

The data classification is done by collecting the soil samples from varying land dimensions i.e., more than one hectare along with geo-coordinate values. This is essentially required in analyzing and implementing the site-specific balanced fertilizer recommendation and to understand the current status of soil fertility in spatial distribution maps. In the proposed framework, the data collection and filtering process are involved to simplify the process.

1. Examining geospatial soil sample variations for small land scales (<= 1 hectare)
2. Examining geospatial soil sample variations for large land scales (> 1 hectare)

Initially, the agricultural dataset is exported to database in order to generate reasonable decisions for further analysis. The data is further categorized based on the land areas owned by farmers. As per highlights of Indian agriculture census (Agriculture Census 2015-16), the land areas used for agricultural production is defined as operational land holdings and are classified into five categories as shown in Table 2. The distribution of soil sample points in Tumkur District and classification of land holdings along with soil sampling in Kestur village of Tumkur district as demonstrated in Figure 4.

Table 2: Classification of operational land holdings and number of soil samples for each holding

Farmer's Category	Hectare	No of Soil Samples (One sample/hectare)
Marginal	<1 ha	1
Small	1>=2 ha	2
Semi-Medium	2>=4 ha	4
Medium	4>=10 ha	10
Large	>10 ha	One sample/hectare

5. Results and Discussion

The Figure 5 represents the web interface designed using ASP.NET, SQL Server 2015 and ArcGIS 10.2.1. This interface is hosted on a private cloud setup and is accessible through the URL www.krishiganaka.sit.ac.in. This cloud service benefits to individual farmers of Tumkur district to obtain the optimum fertilizer recommendations based on geo-coordinate of their farming land (Leena et al., 2016).

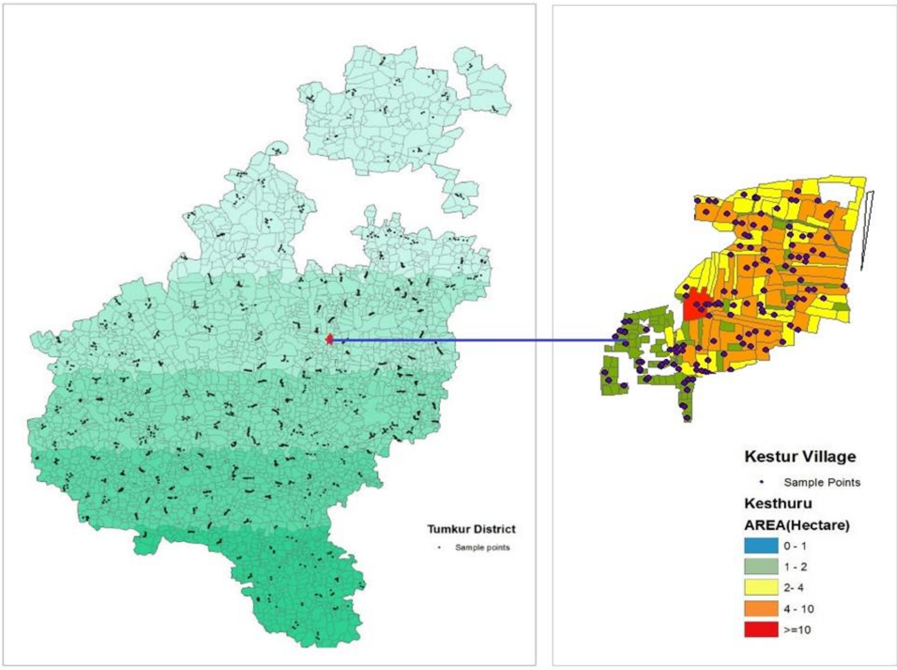

Figure 4: Distribution of soil sample points in Tumkur District and classification of land holdings along with soil sampling in Kestur village of Tumkur district

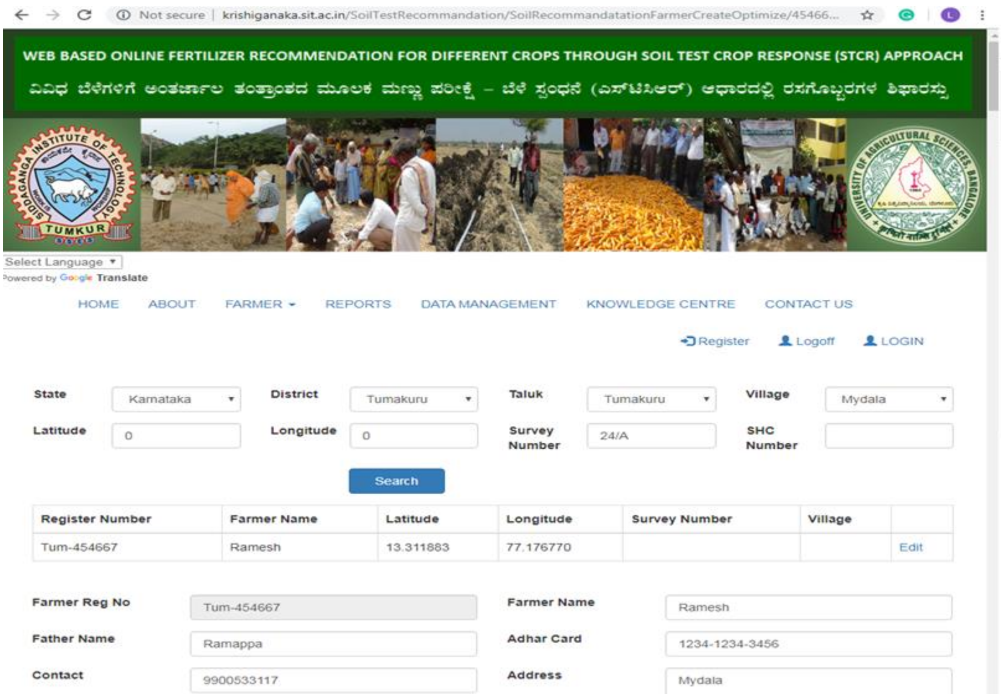

Figure 5: Web Interface for online fertilizer recommendation system

The tentative geospatial analytical technique determines the average degree of variations between un-sampled and nearest actual soil samples collected values. The geospatial variability of soil nutrients based on the soil samples collected from UAS, GKVK, and Bangalore is demonstrated for soil nutrient N in Figure 6. The spatial distribution maps were generated using the ordinary kriging geo-statistical technique through ArcGIS 10.2 software for soil nutrients N, P and K. The color variations shown in spatial distribution map for soil nutrient N in the Figure 6 explains the region of high, medium and low nutrient content. This distribution benefits the farmers/e-governance to distribute the fertilizers based on the availability of soil nutrients. The classification of operation land holdings of Kestur village is demonstrated in Figure 7. The classification is based on farm holding size and is explained in Table 2. As per the survey, Kestur village soil is highly variable in nature and properties. The spatial distribution of soil nutrients benefits in distributing the fertilizers. The e-governance can distribute the fertilizers to small hold farmers by providing maximum subsidies on fertilizers. This helps farmers to get maximum yield and to improve their economic growth.

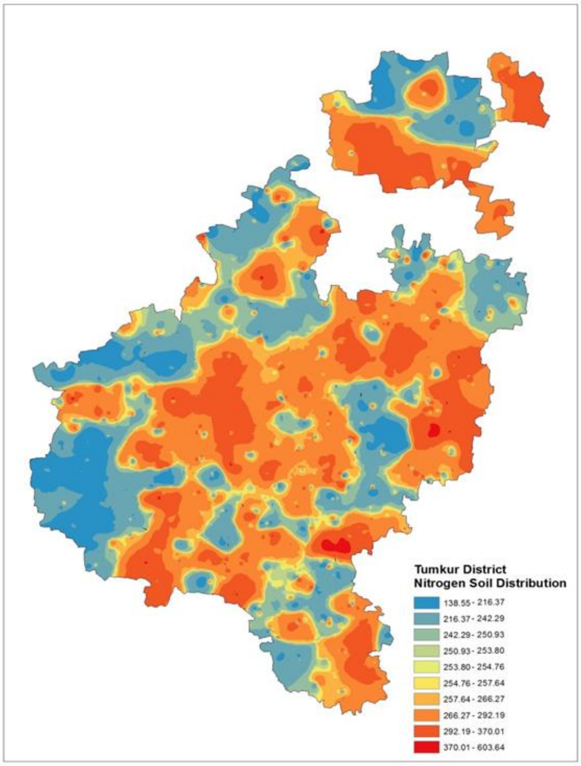

Figure 6: Spatial distribution of nitrogen (N) soil nutrient for Tumkur district

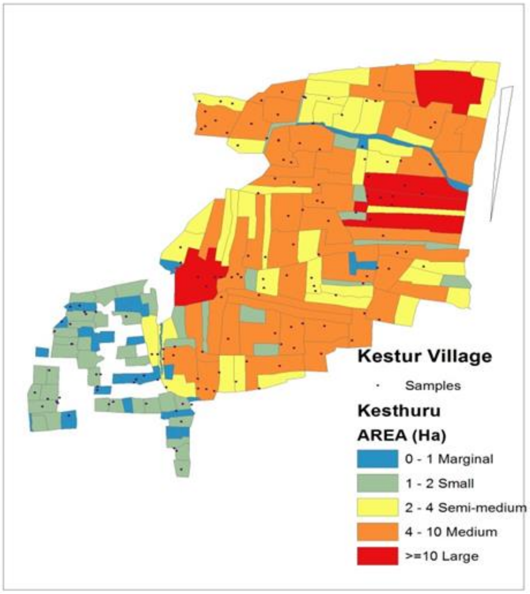

Figure 7: Classification of Operational Land Holdings for Kestur village

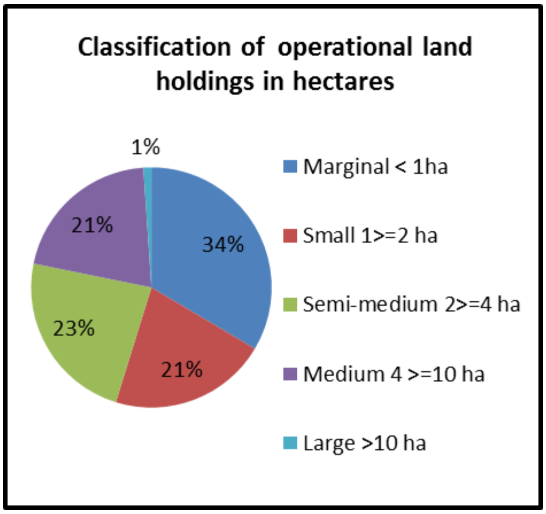

Figure 8: Statistics of classification of Operational Land Holdings for Kestur village

The classification of operational land holdings in hectares is shown in Figure 8. The statistics demonstrates the maximum population in the village holds marginal and small operational holdings. This analysis benefits the e-governance to distribute the fertilizers at nominal or free of cost for marginal and small scale farmer's based on the data and thus helps to improve the economic growth. Further, the spatial analytical model aids to analyse the available soil nutrients and to estimate the exact amount of required fertilizers

6. Conclusion

The proposed framework is aided in modelling and analyzing the geospatial agricultural datasets on all unexpected dynamic occurrences of soil nutrients for varying farming land holdings. The framework enabled a GIS cloud service capable of storing the enormous agricultural datasets and to predict the adequate fertilizer recommendation to farmers and e-governance systems. The proposed framework strongly relies on Pearson's mathematical computations for geospatial analytics. To achieve much effective result these approaches are combined with the interactive clustering and spatial techniques for soil fertility management. Given these innovative characteristics of the framework, lack of agricultural data fails to perform effective spatial analytics and some of the following areas were identified as requirement for further research study.

1. Lack of consolidated agricultural data access to perform spatial analytics.
2. A centralised repository system related to agricultural datasets is required for interdisciplinary analysis.
3. Implementation of the proposed framework on large scale will benefit the farmers and e-governance in distribution of fertilizers based on the operational holdings.

Acknowledgments

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