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Review Article

Spatial Data Mining- A tool for Spatial Decision Support System in Agriculture Management

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Abstract

Agriculture and its allied sectors have been generating a huge amount of big data. This data includes the different forms such as structured, semi-structured and unstructured real time data. This has led to impose challenges to mine knowledge. Data Mining has left a vast scope for decision making in government and enterprises. The gap has been bridged by several techniques. Data mining is one of the such technique. The recent advanced information technology techniques such as spatial information technology has the capability of analyzing the wider range of agriculture related resources. The different agriculture related parameters include soil, climatic conditions, irrigation and water availability pattern and various socio-economic variables. The paper aims to systematically review the current researches on geospatial information for making better decisions in agriculture. The study also summarizes the application of geospatial data mining techniques and algorithms in agriculture. The study is an initiative in the current era for building a decision support system in agriculture sector.

Keywords: Geospatial data, Geoinformatics, Spatial Data Mining, Algorithm, Agriculture

1. Introduction

Agriculture has been a very important element for the development of a country. India has been producing good number of fruits, cereals, vegetables and allied items. The production of agriculture commodities is involved with several agriculture practices which somewhere drives different risks for the producers. Agriculture sector has been facing several challenges since times. There is a sufficient data in agriculture sector starting from production to marketing. With time, researches are trying to bridge the knowledge gap through different advanced information technology techniques like geospatial information and data mining. With so many challenges agriculture sector has started focusing on advanced data techniques like data mining, data analytics including descriptive, predictive and prescriptive analytics. The research question for the present study is that what is the current scenario of research on the applications of spatial data analytics methods/algorithms for a better decision making in agriculture sector. This drives the research to explore the researches and literature on several spatial data mining techniques for building decision support system for agriculture. The current study is divided into literature review, different spatial data mining algorithms and how these algorithms have improved the agriculture management and conclusion.

2. Spatial Data Mining

Spatial data mining (SDM) which is also called as geographic knowledge discovery emerged to extract information from datasets of millions of observations with hundreds of variables and complex data collected from different data sources. The data collected from different sources have diversity in the form of space, time changes, inclusion of different variable connections, explicit and implicit spatial relations and interactions. SDM is the process of discovering interesting and previously unknown, but potentially useful patterns from large spatial datasets. The spatial data contains the Map objects. Some objects in the spatial database are defined on points, lines and polygons. The objects represented in the spatial database have specific area and volume. The knowledge extracted from the spatial data sets is helpful for solving the specific problems. The process of extraction of knowledge includes identifying the data patterns, associations between different attributes of the datasets, and by determining the relationships between them. This process is also termed as Knowledge Discovery from databases (KDD) ([1],[2]). SDM identifies the patterns in the data by identifying the spatial neighborhood relations between the objects. The spatial analysis tools such as spatial statistics, analytical cartography, exploratory data analysis and different traditional data mining algorithms such as classification, clustering, association rule mining, data visualization and visual analytics [3] are widely used in SDM process.

3. Application of SDM techniques in agriculture

The following section explains the application of SDM techniques in different agriculture management activities.

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3.1 Spatial Cluster Analysis

The organization of the data into groups is termed as clustering. Spatial clustering is nothing but identification of similarity of spatial objects and group them into one region or a cluster[3]. The spatial clustering is nothing but grouping of similar objects into clusters so that inter-cluster similarity is more and intra-cluster similarity is less. The spatial cluster analysis is also called as "Hot -Spot" analysis [36]. The K-means clustering and hierarchical clustering are the main techniques of cluster analysis. The K-means clustering is one of the spatial clustering algorithms in which first K number of objects are selected randomly. Each object is called as cluster. The clusters are formed on the basis of inter cluster similarity. The objects in the cluster are similar to each other. Each cluster is considered as a class and programming language Java is used to analyze the data.

The cluster analysis technique from spatial data mining have been used to evaluate the multi-crop yield stability for a field. The multiple crops were planted on the same land area for over a time period. It is observed that if the same pattern of crops is repeated over the time then yield stability exists in the cropping pattern. The different parameters such as soil elevation, slope, aspect, curvature is considered for the yield stability. It is observed that regression analysis R^2 values of a field are the functions of elevation, aspect, curvature and slope [4]. The agricultural meteorology plays very important role in increasing the crop yields and reduction of crop loses. K-means algorithm was also used to analyze the meteorological spatial data on temperature and rainfall. This clustering approach for the spatial data mining was used on two-dimension map format data. The cluster analysis led to the "Association Rule Mining Analysis" which helped to analyze the Agriculture Meteorological Data [5].

Land suitability analysis is very important to increase the agriculture productivity. GIS based K-means and Hierarchical clustering algorithms were effectively used to identify the suitable area clusters based on biophysical and socioeconomic parameters from a raster image for scaling improved crop varieties and good agro economic practices. It was observed that K-means clustering performed better than the hierarchical clustering[6].The study conducted in Bekaa valley the researcher has, applied the modified clustering algorithm such as Trust Region Model for estimating the crop yield by considering various factors so that an overall model can be made. For the study largest agricultural area in Lebanon known as Bekaa valley with an area size of more than 1200 km^2 was selected[7].

3.2 Decision Tree

Decision tree is an inductive method in the data mining.Decision tree approach in spatial data mining is widely used in agriculture land grading. This approach of SDM uses the classification rule to form the group of instances. These group of instances are shown in tree like structure format. The decision tree approach is widely used in agriculture land grading .The agriculture land grading is nothing but integrated assessment of agriculture land in the region to analyze the natural factors, soil factors and economic factors that affect the land quality. Different attributes such as cropping index, rainfall, irrigation, roadway connection, thickness of soil, density of population etc. are considered while constructing the decision tree. Decision tree helped in predicting and classifying the spatial data. The Bayesian Networks are used provide the relationships between the attributes combing the results of classification produced by decision tree [8]. Also, with the help of the Graphical User Interface Development Environment (GUIDE) in MATLAB this decision tree model performs better than the traditional methods of land grading [9].The study [10] Marcio Pupin Mello et al. 2013, in Mato Grosso, Brazil, used Bayesian Networks for Raster Data (BayNeRD) for making a probability image for the growth of soybean. He further used this probability image to make a thematic map. Also, the overall accuracy achieved was greater than 90%.

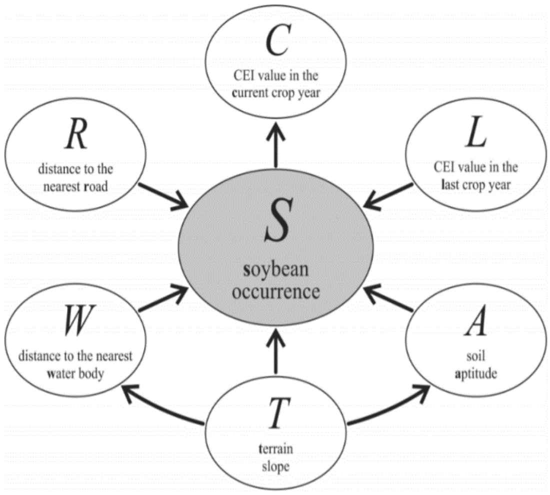


Fig. 1. The acyclic graph representation of BayNeRD[10]

The Soil Map Modelling was effectively used for monitoring and utilization of agricultural land. This approach uses the region's natural resources such as soil, condition of the environment. The decision tree approach was used to achieve the best soil map model and the spatial contextual information was extracted based on the different environmental variables[11].

3.3 Classification and Regression

Precision agriculture technology is widely used all around the globe to maximize the crop production. Precision agriculture focuses on precise and direct application of agriculture resources such as water, seed, fertilizer for the optimized farm returns. It majorly focuses on applying the right thing, in the right way, at the right place and time. Data mining algorithms such as decision tree, artificial neural networks (ANN) are successfully applied in precision agriculture. The decision tree model derived from classification and regression tree (CART) approach was applied for the scheduling irrigation, fertilizer application rate to maintain weed control for corn farms. By applying CART tree algorithm with 12 treatment combinations the best validation results were obtained under three different stages of development with 75-100% accuracy. The two factor and single factor analysis was also used by varying only two and one factor out of three (irrigation, weed control and nitrogen) and it was observed that accuracy is highest ([11][12]).

In such process where hierarchical methods are used, criteria such as entropy or information gain is used, E represents entropy and information gain is a function of E represented by I.

Δ=I(E)−∑i=1 to k (|Ei|/|E|)*I(Ei)

Principle component analysis (PCA) and Support vector machine (SVM) were also used in classification. These algorithms are commonly used in pattern recognition [13]. When considering a multi-sensored data, for detecting the different objects in field, it becomes difficult and fails many times in detecting various patterns. But the system combined PCA based algorithm with SVM for pattern detection gives a highly accurate result. When we take the satellite data for study, sometime crop mapping also plays an important role. In 2013 researchers wanted to find the different fields of crops such as, Cotton, Rice, Fallow, Maize, Wheat, alfalfa, Melons using hyper-spectral and multi-sensor approach. For which four sites in middle Asia were chosen. Random forest (decision tree classification), PCA, Support Vector Machine (SVM) with the help of many indices been used for this. Afterword study showed that SVM appear as a computationally effective and very accurate means for agricultural crop identification [14].

The linear regression model is developed for forecasting winter wheat yield in Kansas and Ukraine. The NASA's Moderate resolution Imaging Spectro-radiometer (MODIS) is used to take the earth observations. These were combined with official crop statistics is used to develop an empirical and generalized approach to forecast the wheat yields. It is observed that regression based forecast model closely matched in Kansas with 7% error and in Ukraine it matched with 10% error. This simple model has limited data requirements and it offers prediction of winter wheat production prior to harvest. The model also can be easily generalized and can be directly applied at the state and national levels [15]. For optimizing a remote sensing production efficiency model for macro-scale GPP and yield estimation in agro ecosystems [16] used Production Efficiency Model Optimized for Crops (PEMOC). The crops chosen were corn, soybean, wheat, pea, canola. The models were made for macro-level data with the help of remotely sensed data, in US. Also, micrometeorological data, climate and rainfall data, etc. were acquired, used marginal distribution sampling for selecting the data.

The models for the crop yield have been made and being in use since 1970's. At Netherland in 1992 B.A.M. Bauman,1995 was from one of the people who consider the GIS application of remotely sensed data in crop yield estimation. Remote sensing data was taken from satellite as well as optically remote sensing data was taken. He considered optical remote sensing also and vegetation index for the crop growth model. With taken the work of Bauman, in 1994 J. G. P. W. Clevers used optical remote sensing, for the simple growth model (using FPAR) for sugar beet where LAI was used as a key variable[17].

Anup K Prasad et al. 2005, estimated the crop yield for corn and soybean at Iowa, US, with the help of difference vegetation index and various land parameters, using piecewise linear regression method. The model helped to reduce the errors in the crop yield prediction [17].

Piecewise linear regression is also known as segmented linear regression where the equations have one or more breakpoint each interval having its own equation. In the given study the breakpoint is in days represented as 'm' giving two equations:

crop yield=(c1+(a1*NDVI) +(a2*SM) +(a3*ST) +(a4* RF)),{for crop yield<breakpoint m}

OR

(c2+(b1*NDVI) +(b2*SM) +(b3*ST) +(b4*RF)), {for crop yield>breakpoint m}

The classification and Regression Tree Model are also used to analyze the factors that influence the sugarcane yield in Northern Argentina. The data mining CART algorithm was applied on five years sugarcane yield data from 1999 to 2005. The author has used the K-means cluster algorithm and decision tree to study the yield of sugarcane [18].

Anikó Kern et al. in 2018, presented a statistical model for the estimation of crop yield by taking account of climate data, remote sensing data. The crops considered were winter wheat, rapeseed, maize and sunflower. By considering as many variables as possible a stepwise linear regression method was used by taking the survey site in Hungary with an area of about 93,030 square km. This model was better in compare to the other statistical model in central Europe. Further it was also used to predict the yield the same crop in 19 national counties (NUTS-3 regions) based on meteorology and remote sensing information [19].

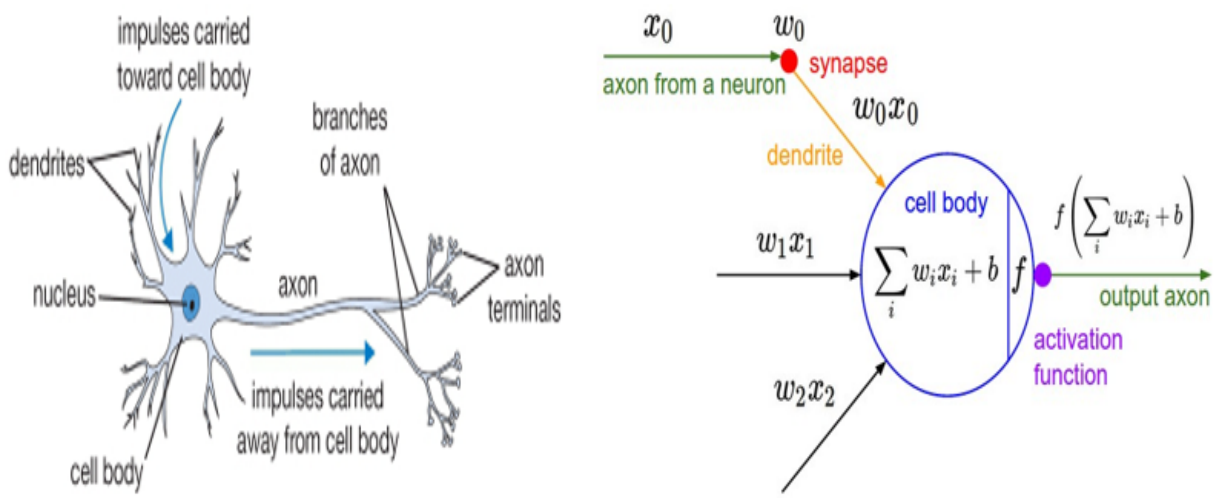
The spatial data analysis methods are also used to study the regional agricultural economy. The variable such as per capita agricultural total output value is taken as the index variable, and the township as the basic analysis unit. Based on the Exploratory Spatial Data Analysis method (global and local spatial autocorrelation) of spatial data mining theory, including Moran I index, Moran Scatter Plot and LISA spatial distribution of the agricultural economy is studied of Beijing townships in 2005[20].

Jing Feng Huang et al., in 2013 presented Rice Yield Prediction model using Multi-Temporal NDVI Data taken from 1979 to 2006 in China. It is very difficult, because many things to be considered for the rice. The method of moving average with the time series analysis with crop yield predictive model was used. The testing was done afterword giving the minimum error of 10% to the range of 19%[21].

3.4 Artificial Neural Network

The one of the important and powerful tools for data processing and data analysis is Artificial neural network (ANN). ANN provide a way to emulate biological neurons to solve complex problems in the same manner as human brain. Each of the neurons is autonomous, independent and works asynchronously [22].

ANN is widely used in eastern w for in season yield mapping and forecasting of corn. The hyper-spectral images of corn plots under different fertilization levels and weed management levels were examined. It is observed that results obtained from ANN models are quite efficient than the regression models to predict the relationship between crop yield and spectral reflectance values [23]. ANN models are applied to predict climatic data in tomato greenhouse in Agadir area, Morocco. To increase tomato yield it is required to maintain the temperature and humidity in greenhouse. The predictions for climatic data for greenhouse given by ANN are much better than Multi-level regression [24]. ANN is also applied for weed control for sunflower farms. It is applied to differentiate between 2-3 weeks old sunflower and common cocklebur weed. Application of ANN along with image processing was used. The study was carried out on production fields of Trakya University in Tekirdag in 2001. The back-propagation algorithm with three hidden layers was used to differentiate between sun flower plant and weed, plant and soil combinations. It was observed that higher accuracy is obtained in plant and soil image recognition than other. The model developed is for images acquired over 2h periods when sun was at or near to zenith. The model further can be extended with a training data set which covers images obtained at various conditions [25]. Application of ANN for weed control is also performed for sunflower farms in Andalusia, south- ern Spain, at Matabueyes and at Santa Cruz, in 2003 and 2004, respectively. Both fields were naturally infested by Ridolfia Segetum weed. The product unit neural network approach is applied discriminate the areas affected by the ridolfia segetum weed [26]. In Oakes, North Dakota, USA for corn, four crop yield prediction models were built. Various vegetation indexes were taken into consideration and the method of Back-Propagation Neural Network (BPNN) was used[27]. The pool model was accurate with tested rate of 93% and standard error of 5%.



Source: http://cs231n.github.io/neural-networks-1/, Retrieved on 05/01/2020
Fig. 2. Representation of ANN Model.

Back Propagation(BP) algorithm was effectively applied for GIS based land suitability analysis in Wuhan area of China. The model were also compared with Analytic Hierrachy Process (AHP) and PCA. The study concluded that BP algorithm gave more accuracy over AHP[28].

The researchers, generated model for crop yield prediction, which can be used anywhere for soybean. Based on remote sensing and techniques as deep Gaussian Process, Neural Network (NN), LSTM were considered. The model was used for real time forecasting throughout the year, which was useful for the places where survey is not possible[29][30].

ANN model is also used in Marylan USA for soybean and Maryland corn crop yield prediction under the typical climatic conditions at state, regional and local levels. Weekly rainfall, soil rating, plant growth data was used as a parameter. It was observed that ANN models consistently produced accurate results. It is also observed that a result at regional level, at coastal plain was accurate with 85% R^2 value [31][32].

In 2019 Petteri Nevavuori et al., used vegetation index and true colour composite (i.e. RGB) for the prediction of crop yield, of wheat and malting barley. By the help of Convolution Neural Network (CNN), the prediction is to be done on early stage by RGB and NDVI[33]. At growing season of 2017, 9 crop fields located in vicinity of the city of Pori, with area of approximately 90 ha. was selected. At early stage RGB was giving better result than NDVI, but not at later stage([34][35].

Table 1. Summary of Crop Estimation models developed using SDM techniques

Reference	Goal	Model used	Crop and Location
B.A.M. Bauman 1992	to construct a crop growth model with the help of remote sensing	Monte-carlo method	winter wheat in Netherland
J. G. P. W. Clevers 1994	how to make model for sucrose estimation in sugar beet	simple growth model based on FPAR	sugar beet in Netherland
Anup K Prasad et al. 2005	take the help of Vegetation index for improving model	piecewise linear regression method	corn, soybean in Iowa, US
Sudhanshu Sekhar Panda et al. 2010	to make a model by using various vegetation indexes	back-propagation NN (BPNN)	corn in Oakes, North Dakota, USA

Jing Feng Huang et al. 2013	to estimate the rice yield as close as possible	moving average with crop-yield predictive model	rice in China
Marcio Pupin Mello et al. 2013	probability image for the growth of soybean	Bayesian Networks (BayNeRD)	soybean in Mato Grosso, Brazil
F. Löw et al 2013	to identify the different fields of crops and present them on thematic map	SVM, PCA	Cotton, Rice, Fallow, Maize, Wheat, alfalfa, Melons at Four test sites in Middle Asia
Jiaxuan You et al. in 2015	to make a model that can be used world wide	Deep Gaussian Process, NNs and LSTMs	soybean in US
Michael Marshall et al. 2018	model for a macro level data	Production Efficiency Model Optimized for Crops (PEMOC)	corn, soybean, wheat, pea, canola in US
Anikó Kern et al. in 2018	to make a crop yield model for different crops by considering as many variables as possible	stepwise regression model	winter wheat, rapeseed, maize and sunflower in Hungary (with an area of 93,030 km2)
Mohamad M. Awad 2019	estimating the yield by considering various factors so that an overall model can be made	Trust Region Method	potato at largest agricultural area in Lebanon known as Bekaa valley with an area size of more than 1200 km2
Petteri Nevavuori et al. 2019	predict the crop yield at early stage by RGB and NDVI	Convolutional Neural Network	wheat and malting barley at 9 crop fields located in vicinity of the city of pori, with area of approximately 90 ha.

4. Conclusion and Future Research Direction

It is observed that both supervised and unsupervised techniques of spatial data mining are applicable in agriculture domain. The data mining techniques are applied in different areas of agriculture such as improvement in crop yield, green house management, weed control, soil mapping and micro level planning. It is also observed that the results obtained for crop yield prediction are highly accurate by using ANN model as compared to decision tree and also by using traditional vegetation indices. There is strong need to have artificial intelligence-based application such as machine learning that is artificial neural networks which will automate the decision procedure for the farmer's in India. There are number of challenges in data exploiting, in data mining for improving the crop productivity. Another key problem in agricultural information systems is that data availability and quality are often poor and need to be assured before exploitation. Atmospheric factors such as clouds gives error in data when the satellite remotely sensed data is considered. The lack of literacy in the farmers generally leads to wrong selection of crops depending upon the soil, soil properties, nutrients, drought conditions and climatic conditions of the area. There is a strong need to design and develop web-based framework based on spatial data mining which will help farmers to take decision for the selection of crops, fertilizers, crop diseases and pest management and water management altogether which will increase the crop productivity and in turn the food grain production.

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