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Intelligent Regional Soil Feature Approximation Based Geospatial Image Classification for Plant Growth Estimation Using Fuzzy Rule Sets and Data Mining

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ABSTRACT

This paper discusses about the enhancement of plant growth estimation which can be initiated through the classification of geo spatial images. There are number of methods has been discussed for the classification of geospatial images as well as to perform plant growth estimation. To overcome the deficiency present in earlier methods, the proposed method uses region based soil feature approximation which considers various features of soils like dryness, humidity, grindness and more. The method splits the entire geospatial image into number of sectors of small region and for each region of image the method extracts the features of soil and performs approximation about the class support. Similarly the method maintains number of rules which are generated from the classified images of trained set and using them the method compute the plant growth support for each class with the help of fuzzy rules. Based on plant growth support the class of image is identified and the plant growth estimation is performed based on the rules available under the same class. The method generated efficient result on plant growth estimation and image classification.

Index Terms: Geospatial Image, Plant Growth, Soil Feature Approximation, Fuzzy Rules, Data Mining.

INTRODUCTION

The technology development has been adapted for many problems like wind flow identification, which estimates the rainflow of any geographic region. Similarly the geographic image taken from the satellites can be used to perform many activities. The geospatial image captures the environmental image which has the features of soil image like plant fetures, water particles and soil patterns. Such images can be applied to solve many problems like agricultural growth. To perform agricultural growth the researchers search for the places where the particular plant can be cultivated and where the plant has more growth factors. Each plant has their own features of growth and they need different environmental conditions like some of them need more water content, some of them need more humidity and few of them need no humidity but dryness. Simialrly based on the captured image, the agricultural research organizations perform many activities using them.

The plant growth is the factor which represents the result of cultivation and the final yield of any plant being cultivated. Not all the plants grows in all the soil patterns and each of them need different soil patterns where the particular plant can be cultivated. The plant growth is estimated based on various features like dryness, humidity, grindness, color values, water suspension and more. Based on the above mentioned features of soil which are extracted from the geospatial images, the plant growth factor can be computed. The plant growth factor represents the support of soil for the growth of the plant.

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How the features of any soil can be converted to guage the growth of the plant is by performing approximation. The soil feature approximation is the process of estimating the support of soil for the plant. Based on each soil feature, the growth factor can be estimated, for example, the water content present in the soil image can be used to perform approximation. 'For any plant the presence of water is more essential and the level of water required to cultivate the plant varies according to the plant being cultivated. The water level has more impact than the other features of the soil. Similarly the grindness and the color values has more impact on the plant growth, by including them in approximating the plant growth will produce effective results.

The application of fuzzy rule has great impact in various problems and the same can be applied in the problem of plant growth estimation. By extracting the features of soil image obtained through the satellites, and making them into the form of rules and the plant growth achieved in any point of time can be converted into rules. So by collecting and generating such rules at different time domain could help to generate ,more number of rules. By maintaining more number of rules the average values and range values can be obtained at each features based on which the plant growth can be estimated.

To obtain the time domain values and to perform estimation of growth factor, the data mining techniques can be used. In this paper, we combine an approach of image processing with data mining technique to perform plant growth estimation. We discusse the proposed approach in the next coming section in detail.

Related Works

The plant growth estimation has been performed in different methods and we discuss some of the methods here in this section related to the problem of plant growth estimation.

Effects of soil texture by soil addition on the growth and quality of oriental melon [1], investigate the effects of soil amendment with different characteristics on plant growth, fruit yield and quality of oriental melon for continuous cropping under protected cultivation. Humus layers in arable soil was disturbed because soil amendment from hillside to oriental melon field was continued to resolve problems for continuous cropping. Water potential and hardness of soil was decreased in sandy loam with lower clay contents compared with loam and silty clay. Leaf length and area, fresh and dry weight of plant at earlier growing stage were higher, but chlorophyll contents of leaves were dropped in sandy loam compared with silty clay soil.

Soil texture classification algorithm using RGB characteristics of soil image [3], proposes the potential of soil texture classification using RGB histograms was investigated. Seven sites representing major Korean paddy soil series were selected, 4-6 core samples up to a 50-cm depth were obtained from each site, and each sample was segmented by 5-cm intervals. For each segmented soil sample, four surface images were taken using a miniaturized CCD camera, and texture fractions were determined by the pipette method. Scatter plots showed linear patterns between silt content and histogram variables such as brightness, skewness, and mode - brightness. When 5% averaged silt content was linearly regressed with mode - brightness, R2, RMSEC, and RMSEP were 0.96, 2.2%, and 6.3%, respectively. When soils were classified using USDA criteria, the laboratory method and the in-situ image processing method produced the same results for 48% of the samples.

Classification of Soil Textures Based on Law's Features Extracted from Preprocessing Images on Sequential and Random Windows [4], Texture analysis has been used for recognizing synthetic and natural textures. Textures are one of the important features in computer vision for image classification and retrieval. An important approach to region description is to quantify its texture content. In this paper ,the Soil images has been analyzed using various image pre processing tasks such as Gray level thresholding, Low pass filter, Edge enhancement using Prewitt's Horizontal filtering and then Feature extraction using 3x3 Law's mask convolution. The features are constructed on preprocessed methods applied on the Soil texture image by considering different types of windows. These features offer a better classification rate. The experimental results on various Soil textures clearly demonstrate the efficiency of the proposed methods.

Origin of the soil texture classification system used in Japan [5], reviewed the origin of the Japanese classification systems for soil particle size ranges and soil texture. The size range system was adopted from International Society of Soil Science (ISSS) standards. The soil texture classification system was introduced by Tommerup in his paper at the ISSS Commission I (Soil Physics) meeting in 1934. This soil texture classification system was modified by Yamanaka in 1955, and was henceforth adopted as the conventional soil texture classification system in Japan. This ISSS-defined soil texture classification system has been in use since that time.

Exploring plant growth promoting potential of non rhizobial root nodules endophytes of Vigna radiate [6], plant growth promoting traits of 26 non rhizobial and one fungal endophyte previously isolated from Vigna radiata root-nodules were assessed for IAA and siderophore production, phosphate solubilization and hydrolytic enzymes production. Most bacterial endophytes improved seedling vigor index while fungal endophyte (Macrophomina phaseolina) lacked all PGP traits. Endophytes Ml, M10 and M15 were most influential in improving Seedling Vigor Index. Three endophytes having multiple PGP traits with maximum siderophore production: 46.77 µg mL–1 (Bacillus anthracis; Ml), IAA production: 10.81 µg mL–1 (Paenibacillus taichungensis; M10) and phosphate solubilization: 134.483 µg mL–1 (Paenibacillus xylanilyticus; M15) significantly increased root length (RL), shoot length (SL), number of lateral roots (NLR) and plant dry weight (DW) when inoculated/co inoculated with E. adhaerens (native rhizobia) to V. radiata in a small field trial. M10 inoculation produced longest RL while Ml when coinoculated with E. adhaerens produced highest SL and NLR. Ml inoculation or coinoculation was most effective in improving dry weight of mature plants. Most of the endophytes coinoculated with E. adhaerens improved growth parameters. We report that non rhizobial endophytes with PGP traits in combination with native rhizobia can be prospective candidates for use as biofertilizer.

A Regularized Particle Filter EM Algorithm Based on Gaussian Randomization with an Application to Plant Growth Modeling [12], study a specific data and parameter augmentation method which gives us the opportunity to estimate more easily the parameters of the initial model. For this reason, the notion of Gaussian randomization of a model with respect to some of its parameters is introduced. The initial model can be regarded as a submodel of the resulting extended incomplete data model. Under the assumption that the initial model has a unique maximum likelihood estimator (MLE) and that the likelihood function is continuous we prove that the extended model has a unique MLE with common values for the parameters of the MLE which correspond to the initial model. We also prove the reverse direction. Moreover, an appropriate stochastic version of an EM (Expectation-Maximization) algorithm is suggested to make parameter estimation feasible. In particular, we describe how the regularized particle filter of Musso and Oudjane (1998) can be used in this frequentist-based approach to perform the Monte Carlo E-step at each iteration of the stochastic EM algorithm. This regularized version is particularly adapted to the framework of Gaussian randomization since the last iterations of the EM algorithm are characterized by low variance in the parameter distributions. A toy example with available analytic solutions, a synthetic example and a real data application with scarce observations to the LNAS (Log-Normal Allocation and Senescence) model of sugar beet growth are presented to highlight some theoretical and practical aspects of the proposed methodology.

Parametrization of five classical plant growth models applied to sugar beet and comparison of their predictive capacities on root yield and total biomass [13], propose the evaluation and comparison of five plant growth models that rely on a similar energetic concept for the production of biomass, but with different levels of description (individual-based or per square meter) and different ways to describe biomass repartition (empirical or via allocation): Greenlab, LNAS, CERES, PILOTE and STICS. The models were all programmed on the same modelling platform, calibrated on a first set of data, and then their predictive capacities were assessed on an independent data set. First, a sensitivity analysis was carried out on each model to identify a subset of parameters to be estimated, to reduce the variability of the models. We were able to reduce the number of parameters from 10 to 4 for Greenlab, and from 16 to 1 for STICS. Three criteria were then used to compare the predictive capacities of the models: the root mean squared error of prediction and the modelling efficiency for the total dry matter production and the dry matter of root, and the yield prediction error.

All the above discussed methods uses minimum factor to estimate the growth and perform soil classification, but suffers with the problem of accuracy in soil classification and plant growth estimation.

REGIONAL SOIL FEATURE APPROXIMATION BASED GEOSPATIAL IMAGE CLASSIFICATION

This paper discusses about the process of soil feature approximation performed at each region of the image to classify them against number of classes. Also the paper focuses on the plant growth estimation based on the rule sets being generated. The entire process has been split into number of stages namely Image Enhancement, Regional Soil Feature Extraction, Rule Set Generation, Soil Feature Approximation, Soil Classification and Plant Growth Estimation.

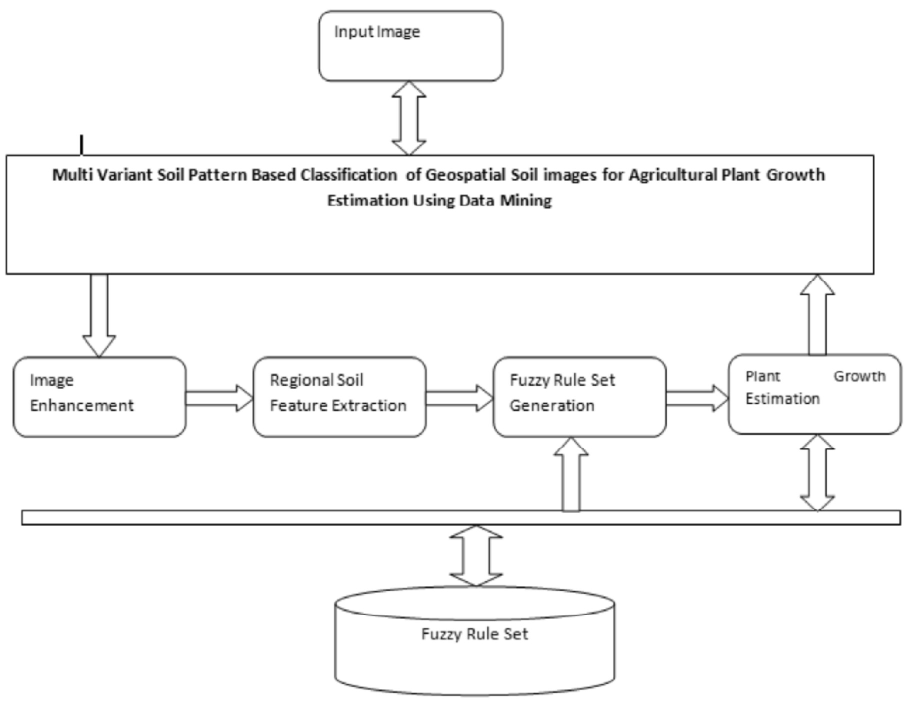


Figure 1: Proposed System Architecture

The Figure 1, shows the architecture of the proposed approach and its functional components

Image Enhancement: The geospatial image captured through the satellite has more noise which is introduced by the satellite camera which has to be removed before proceed into the next stages. The method applies the gabor filter with different orientation to remove the noise from the input image. The noise removed image will be used to perform the feature extraction.

Regional Soil Feature Extraction: At this stage the method first splits the entire image into number of sectional image. The entire image is converted into regional image. In the second stage, the method extracts various features of geo spatial regional image like water,humidity,dryness,grindness,color and so on. The feature extraction is performed for each regional image obtained in the previous stage. The extracted features are converted into feature vector which will be used to perform feature approximation.

Psuedo Code of Feature Extraction

Algorithm:

Input: Enhanced Sectional Image Img

Output: Soil Feature Vector Fv.

Start

Extract Color values of regional image Img.

Cv = $\int_{i=1}^{size(Img)} \int_{j=1}^{3} \sum Img(i,j)$

Compute Histogram of Green Pixels.

Hg = $\int_{i=1}^{size(Cv)} \sum Cv(i)(2) \nexists Hg$

Compute Histogram of Blue Values.

Hb = $\int_{i=1}^{size(Cv)} \sum Cv(i)(3) \nexists Hg$

Identify pixels with white colors.

Hw= $\int_{i=1}^{size(Cv)} \sum Cv(i)(1) > 200$

Convert image into gray scale.

Rimg = Convert Img into gray scale.

Compute Grindness value.

Gv = $\int_{i=1}^{size(Rimg)} StdDev(\sqrt{Dist\big(Rimg(i), Rimg(i+1)\big) > 10})$

Compute Humidity

Hv=

$\int_{i=1}^{size(Rimg)} StdDev(\sqrt{(Rimg(i), Rimg(i+1)) > 200)\&\& Dist\big(Rimg(i), Rimg(i+1)\big) > 10})$

Compute Water Source Factor Wsf.

Wsf = $\frac{\sum Hb}{size(Img)}$

Compute Plant Factor Pf.

Pf = $\frac{\sum Hg}{size(Img)}$

Generate Feature Vector Fv.

Fv = {Hv,Wsf,Pf,Gv}.

Stop.

The above discussed algorithm extracts the features from the enhanced image and generates the soil feature vector.

Algorithm:

Input: Feature Vector Set Fvs.

Output: Rule R

Start

Compute range value for Humidity factor

Min,Max = Compute Minimum and max values of humidity.

For each feature Fi from Fvs

$$\mathrm{Min} = \int_{i=1}^{size(Fvs)} \mathrm{Min}(\min, \mathrm{Fvs}(\mathrm{Hv}))$$

$$\mathrm{Max} = \int_{i=1}^{size(Fvs)} \mathrm{Max}(\max, \mathrm{Fvs}(\mathrm{Hv}))$$

End

Compute min max value of water source factor.

For each feature Fi from Fvs

$$\mathrm{WMin} = \int_{i=1}^{size(Fvs)} \mathrm{Min}(\min, \mathrm{Fvs}(\mathrm{Wsf}))$$

$$\mathrm{WMax} = \int_{i=1}^{size(Fvs)} \mathrm{Max}(\max, \mathrm{Fvs}(\mathrm{wsf}))$$

End

Compute min max value of Plant factor.

For each feature Fi from Fvs

$$\mathrm{PMin} = \int_{i=1}^{size(Fvs)} \mathrm{Min}(\min, \mathrm{Fvs}(\mathrm{Pf}))$$

$$\mathrm{PMax} = \int_{i=1}^{size(Fvs)} \mathrm{Max}(\max, \mathrm{Fvs}(\mathrm{Pf}))$$

End

Compute min max value of Grindness.

For each feature Fi from Fvs

$$\mathrm{GMin} = \int_{i=1}^{size(Fvs)} \mathrm{Min}(\min, \mathrm{Fvs}(\mathrm{Gv}))$$

$$\mathrm{GMax} = \int_{i=1}^{size(Fvs)} \mathrm{Max}(\max, \mathrm{Fvs}(\mathrm{Gv}))$$

End

For each attribute Ai of feature vector

Split the range into N ranges.

$$\mathrm{Rvs} = \int_{i=1}^{4} \mathrm{Split}(\mathrm{Min}, \mathrm{Max})/4$$

End

For each range values

Generate rule Ri.

Ri = {Range(A_1), Range(A2), Range(A3), Range(A4),GF}

Add to Rule set.

End

Stop.

Fuzzy Rule Set Generation: The fuzzy rules are about generating a set of range values for each attribute being considered from the result of feature extraction phase. First the method generates the small scale images through the feature extraction phase and then for each feature vector obtained the method computes the range values for each attribute or measure being considered. In the training phase the method generates such rules with the values of plant growth which is also an input for the system. By generating range values the method generates number of rules which will be used to perform plant growth estimation.

The above presented algorithm computes range values from the feature vector given and based on the values the method generates rule to perform plant growth estimation.

Soil Feature Approximation: The soil feature approximation is the process of computing plant growth factor based on various features given and the rule sets available. The method computes plant growth support factor for each attribute present in the feature vector. Based on computed support factors of each factor considered the method performs approximation of plant growth. The approximated value will be used to compute the plant growth estimation.

Algorithm:

Input: Feature Vector Fv

Output: Multi Feature Support Factor MFSF.

Start Hv,Wsf,Pf,Gv

Compute Humidity Support Factor HSF.

$$HSF = \int_{i=1}^{size(Rs)} \frac{(\sum Hv(Rs(i)) <> Fv.Hv).Pg}{size(\sum Hv(Rs(i)) <> Fv.Hv)}$$

Compute water support factor WSF.

$$WSF = \int_{i=1}^{size(Rs)} \frac{(\sum WSF(Rs(i)) <> Fv.wsf).Pg}{size(\sum Wsf(Rs(i)) <> Fv.wsf)}$$

Compute Plant Support Factor PSF.

$$PSF = \int_{i=1}^{size(Rs)} \frac{(\sum Pv(Rs(i)) <> Fv.Pv).Pg}{size(\sum Pv(Rs(i)) <> Fv.Pv)}$$

Compute Grindness Support Factor

$$GSF = \int_{i=1}^{size(Rs)} \frac{(\sum Gv(Rs(i)) <> Fv.Gv).Pg}{size(\sum Gv(Rs(i)) <> Fv.Gv)}$$

Compute Multi Feature Support Factor MFSF.

$$MFSF = \frac{PSF}{WSF} \times \frac{HSF}{GSF}$$

Stop

The above discussed algorithm computes the multi feature support factor for the plant growth which is used to estimate the plant growth.

Soil Classification: The method computes the multi feature support factor for each class with the given input feature vectors. Based on the multifeature support factor computed the method decides the class of image to perform soil classification.

Algorithm:

Input: Soil Feature Fv, Rule Set Rs.

Output: Class C.

Start

For each class Ci from Soil Class Sc

Compute Multifeature Support Factor.

End

Choose the most valued support factor and class Ci = Max(MFSF).

Stop.

The above psuedocode computes the multi feature support factor for each class to select the class with maximum support factor.

Plant Growth Estimation: The plant growth estimation is performed by computing the plant growth support on each attribute considered. The method computes multi feature support factor for each class and choose the class of image and then the method computes the plant growth factor using the computed MFSF value and the values of growth obtained earlier.

Algorithm:

Input: MFSF

Output: Estimated Growth GF.

Start

Read MFSF value.

Compute Growth Factor GF = $\text{MFSF} \times \frac{\sum GF(Ci)}{size(Ci)}$

Stop.

The above discussed algorithm computes the plant growth using the computed multi feature support factor.

RESULTS AND DISCUSSION

The proposed method has been implemented using matlab and the efficiency of the proposed method in plant growth estimation and soil classification has been evaluated using number of data sets of spatial images. The result shows that the proposed method has produced efficient result in soil classification and plant growth estimation with more accurate results.

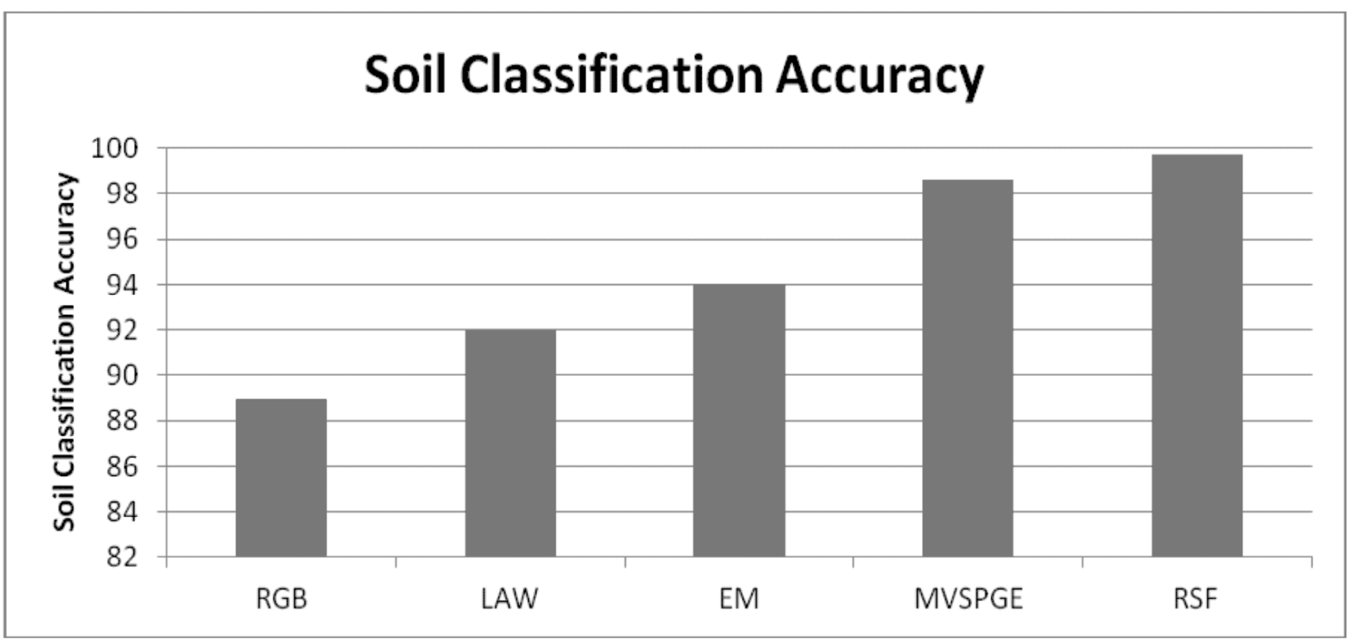
Table 1
List of soil types considered

Symbol	*Soil Type*
S	Sand
Sicl	Silty Clay Loam
Sic	Silty Clay
C	Clay
Sl	Sandy Loam
Cl	Clay loam
Sil	Silty Loam
L	Loam
LS	Loamy Sand
SCL	Sand Clay Loam
Sc	Sand Clay

Table 2
Comparison of different parameters of soil classification

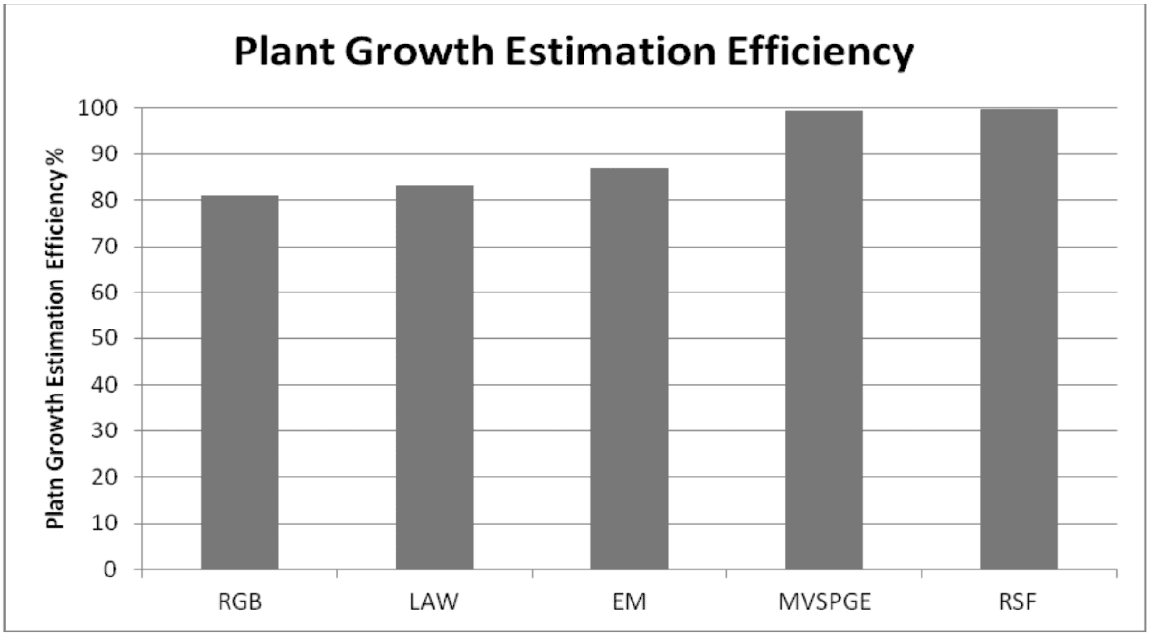
Method	*Classification Accuracy*	*False Classification*	*Plant Growth Estimation Ratio*
RGB	87	11.6	84.7
LAW	89	9.4	87.6
EM	91	7.3	89.3
MVSPGE	97.8	1.3	96.9
RSF	99.4	0.7	98.7

The Table 2, shows the comparative result on soil classification and plant growth estimation produced by proposed method on different soil type.



Graph 1: Comparison of soil classification accuracy

The graph 1, shows the comparative result on soil classification produced by different methods and the result shows that the proposed method has produces more classification accuracy.



Graph 2: Comparison of plant growth estimation efficiency

The Graph 2 shows the comparative result of plant growth estimation produced by different methods and it shows clearly that the proposed method has produces more estimation efficiency than other methods.

CONCLUSION

We proposed a regional soil feature approximation based soil classification algorithm for the estimation of plant growth of different soils using the images obtained from the satellite. The method enhances the input image quality by applying the gabor filter and generates number of small scale images. From each mall scale image, the method extracts the features like water flow, color, humidity, grindness. Using the features being extracted the method generates the rule set from the earlier trace of feature being identified and plant growth estimated. Using the fuzzy rule generated, themethod computes the multi feature support factor to estimate the plant growth. The proposed method produces efficient results in plant growth estimation and improves the classification ratio.

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