NONPARAMETRIC CROP SYSTEM IDENTIFICATION USING LISS-3 SATELLITE DATA

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Abstract : ***Agriculture resources are among the important renewable dynamic natural resources. Comprehensive, reliable and timely information on agricultural resources is very much necessary for a country like India whose mainstay of the economy is agriculture. Efficient crop management practices require accurate timely and rapid information about crop distributions. Since agricultural crops are dynamic, it is often useful to observe their development over time. Therefore, multi-temporal data was used for crop discrimination. In present study, data from LISS-3 sensor of Indian Remote Sensing (IRS) satellite was acquired during Rabi season (from early December to late January) of 2004 to 2017. The LISS-3 data of 24m resolution, as well as with Green, Red, NIR and SWIR band is used to derive NDVI (Normalized Difference Vegetation Index) images. Total 41 cloud free set of data were taken and stacked together to form a time series data. Hybrid approach is used for the classification of multi-date NDVI data set. Association rules are used for crop prediction. This paper demonstrates results of developed non-parametric methodology for identifying crop sowing pattern over Madhya Pradesh region.***

Index Terms - System Identification, Association Rules, LISS-3, Multi temporal Series, NDVI.

I. INTRODUCTION

Agriculture resources are among the important renewable dynamic natural resources. Comprehensive, reliable and timely information on agricultural resources is very much necessary for a country like India whose mainstay of the economy is agriculture.

Remote Sensing data has a unique potential in monitoring crop acreage and production at regional level due to synoptic and repetitive coverage. Estimation of crop yield and acreage are very important for crop production forecasting.

Accurate and efficient crop management practices require accurate and rapid information about crop distributions. Generally multispectral remotely sensed images are used to distinguish crop types on the basis of their spectral properties. However, such analysis involving single-date images has the drawback that, since maximum discrimination between different crop types occurs at different stages in the growth cycle, not all differences are incorporated in the procedure. In addition, the temporal “profile” of the spectral reflectance curve of each crop is not taken into the account. Such profiles may be difficult to distinguish at certain points in the growth cycle. Finally, since agricultural crops are dynamic, it is often useful to observe their development over time. Therefore, multi-temporal data was used for crop discrimination.

In this paper, multidate LISS-3 data was acquired during Rabi season from early December to late January from year 2004 to 2017. The LISS-3 data is used to derive NDVI (Normalized Difference Vegetation Index) images. Total 41 cloud free set of data were taken and stacked together to form a time series data. Hybrid approach will use for the classification of multidate NDVI data set. Further Association rules are used for crop prediction.

Association rule learning is a rule-based machine learning method for discovering interesting relations between variables in large databases. It is intended to identify strong rules discovered in databases using some measures of interestingness.

II. ASSOCIATION RULES

Association rule learning is a rule-based machine learning method for discovering interesting relations between variables in large databases. It is used to identify strong rules in databases using some measures of interestingness. Association rules are useful for discovering regularities between products in large-scale transaction data recorded by point-of-sale (POS) systems in supermarkets. Associations are used in retail sales to identify patterns that are frequently purchased together. This process refers to the process of uncovering the relationship among data and determining association rules.

For example, a retailer generates an association rule that shows that 70% of time milk is sold with bread and only 30% of times biscuits are sold with bread.

In this research study we have used association rules to find the correlations between crop sawing systems. By using association rules we have found some strong rules for crop sawing system from these rules we can predict the next year’s crop for the same place with 60% to 65% accuracy.[1]

III. DATA

In this paper multi-dated LISS-3 data of ResourceSat-1 and ResourceSat-2 satellite from year 2004-2017 were used which were ordered from NRSC (National Remote Sensing Centre) site.

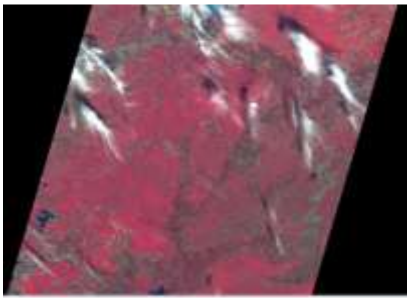

Figure 1 [RS-1 Data]

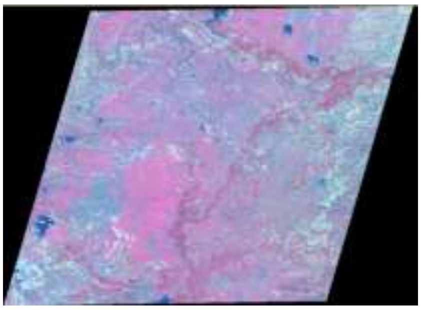

Figure 2[RS-2 Data]

IV. STUDY AREA

Table 1[Study Area]

Study Area	**Vidisha**
Latitude	23.5251° N,
Longitude	77.8081° E
Path	98
Row	55
Year	From:2004 To: 2017
Satellite	Resourcesat-1 and Resourcesat-2
Sensor	LISS-3

Here we were working on Madhya Pradesh with 98 path and 55 row number which covers the Tikamgarh, Bhopal, Chatarpura, Guna, Sagar, Vidisha, Raisen and Lalitpur talukas partially or fully. We have selected the Vidisha taluka as in the given data it covers the whole area of it. Following figure shows the talukas boundary of scene.

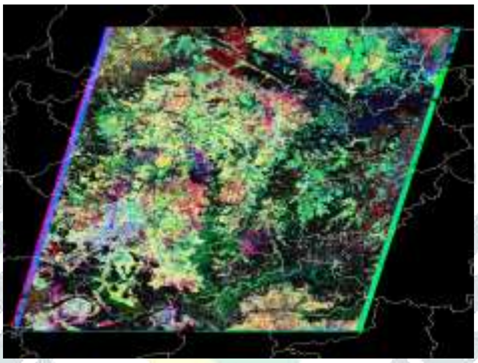

Figure 3[Taluka Boundary of scene]

V. RESEARCH METHODOLOGY

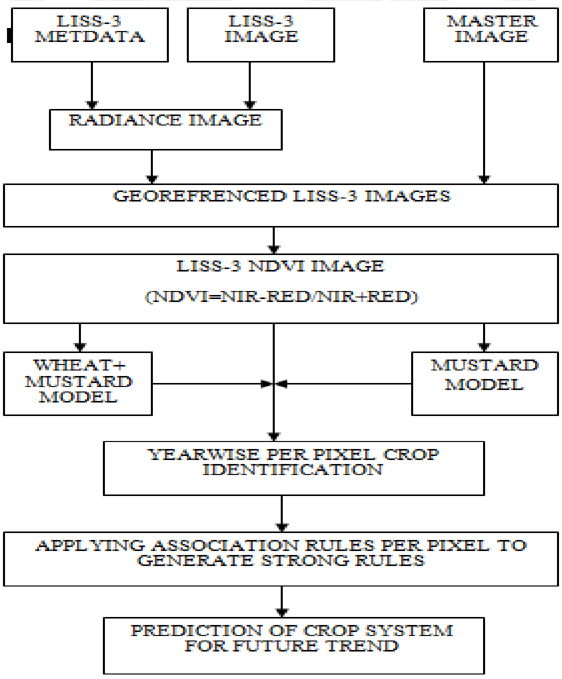

Figure 4[RESEARCH METHODOLOGY]

In the research study LISS-3 images of 2004 to 2017 year were used as raw data. With the highest standard deviation one image was selected as master image. After generating radiance image we have done georeferencing of all images using ERDAS Imagine 2015 software with the reference of master image. Following figure shows the georeferenced image.

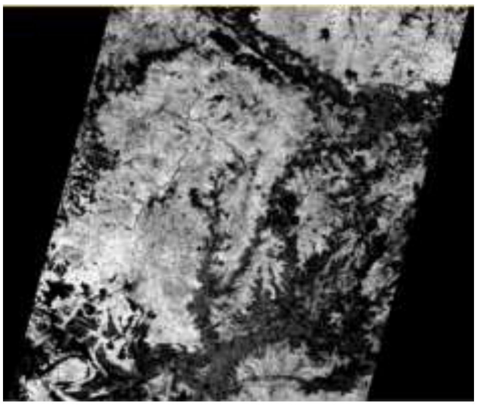

Figure 5[GEOREFRENCED IMAGE]

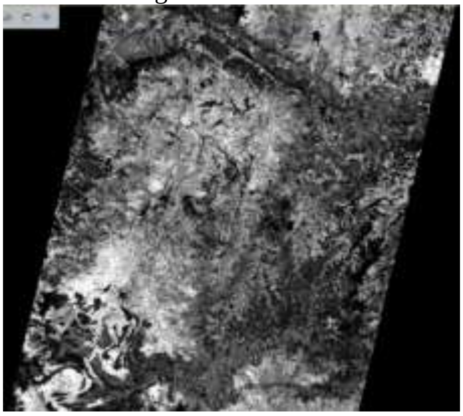

Figure 6[MASTER IMAGE]

NDVI of georeferenced images was done. Where, NDVI is Normalized Difference Vegetation Index which is a standard index allowing you to generate an image displaying greenness (relative biomass). This index takes advantage of the contrast of the characteristics of two bands from a multispectral raster dataset the chlorophyll pigment absorptions in the red band and the high reflectivity of plant materials in the near infrared (NIR) band. Following figure shows the georeferenced NDVI images. [3]

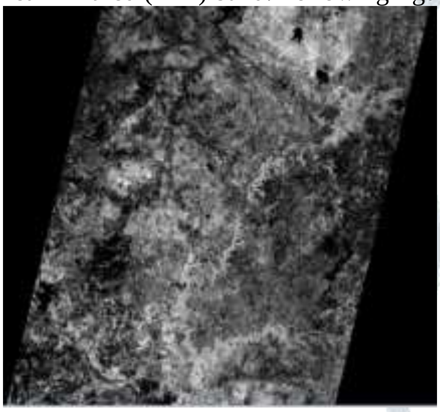

Figure 7 [GEOREFRENCED NDVI]

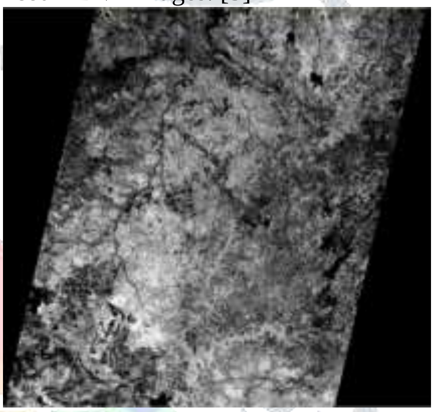

Figure 8[GEOREFRENCED NDVI]

Mustard model and Mustard + Wheat model were applied on georeferenced NDVI images to identify the crop system per pixel. Then output images were given to thematic model as input which gives the thematic output from which one can identify the crop per pixel even though one is not aware from the basics of the crop system. Following figure shows the thematic crop identified image.

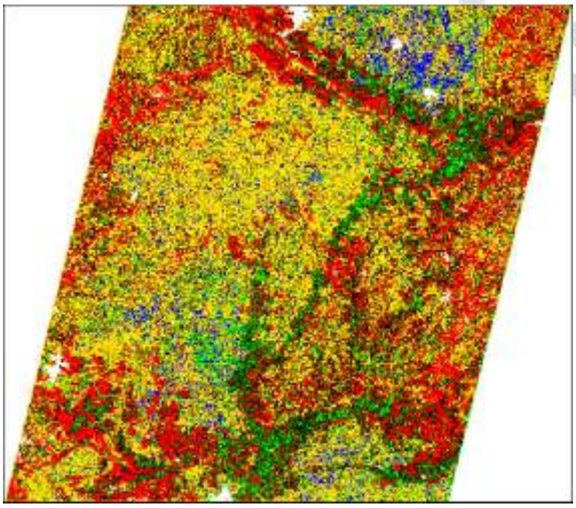

Figure 9[THEMATIC CROP IDENTIFIED IMAGE]

Here, in the image white colour pixels are for no data value,
red for no vegetation,
blue for forest,
yellow for mustard,
golden for probably mustard,
light green for wheat and
dark green colour for probably wheat.

After identifying crop system per pixel the Association rules were applied to find the strong rules for the prediction of crop system for future trend.

VI. LITERATURE REVIEW

1. SPADE: An Efficient Algorithm for Mining Frequent Sequences.

In this paper we present SPADE, a new algorithm for fast discovery of Sequential Patterns. The existing solutions to this problem make repeated database scans, and use complex hash structures which have poor locality. SPADE utilizes combinatorial properties to decompose the original problem into smaller sub-problems that can be independently solved in main-memory using efficient lattice search techniques, and using simple join operations. All sequences are discovered in only three database scans. Experiments show that SPADE out performs the best previous algorithm by a factor of two, and by an order of magnitude with some pre-processed data. It also has linear scalability with respect to the number of input-sequences, and a number of other database parameters.

VII. RESULT

Following table displayed the row number, column number, number of unique values per pixel and unique pixel values.

Row Number	Column Number	Year	Number of Unique Values	Unique Values
85	1409	2004 2005 2006 2007 2009 2010 2011 2012 2013 2014 2015 2016	1 3 2 3 1 1 1 1 1 2 1 3	11 03 11 21 11 22 11 21 22 21 21 21 22 21 03 11 21 03 21 22
228	1615	2004 2005 2006 2007 2009 2010 2011 2012 2013 2014 2015 2016	1 2 2 2 2 1 2 1 2 2 1 1	11 21 22 21 22 02 22 21 22 21 21 22 02 11 12 03 11 01 21 01 21

For the more accuracy we have took around 1000 samples of raw and column which gives the year wise unique value for single pixel.

On these output we had taken different support counts to find the accuracy of the research work and to identify strong association rule. Following table shows one of the final outputs with 66% accuracy.

Support value	Number of Rules	Temporal Rule	Rule
0.5	4	11,3,21,22	21,22
0.4	3	11,21,22	21,22
0.3	2	21,22	21,22
0.2	2	21,22	21,22

From the output we can predict the next year's crop i.e. wheat with 66% accuracy. The prediction of crop system comes with 66% accuracy which is desirable though this research work doesn't use any historical data such as soil moisture data or weather report. This research work is a nonparametric crop system identification using LISS-3 satellite data with 60% -66% accuracy.

REFERENCES

[1] https://en.wikipedia.org/wiki/Association_rule_learning

[2] MOHAMMED J. ZAKI "SPADE: An Efficient Algorithm for Mining Frequent Sequences" Machine Learning, 42, 31–60, 2001 °c 2001 Kluwer Academic Publishers. Manufactured in The Netherlands.

[3] https://en.wikipedia.org/wiki/Normalized_difference_vegetation_index