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Research Article

SPATIAL DISTRIBUTION OF CROP MAPPING OF NARSINGHPUR DISTRICT, MADHYA PRADESH

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Abstract- Cutting-edge remote sensing technology has a significant role for managing the natural resources as well as the any other applications about the earth observation. Crop monitoring is the one of these applications since remote sensing provides us accurate, up-to-date and cost-effective information about the crop types at the different temporal and spatial resolution. In this study, satellite data Landsat 8 for Narsinghpur district, Madhya Pradesh was classified using supervised classification. Satellite data classification accuracy was also performed and resulted in overall accuracy as 87.60%.

Keywords- Remote Sensing, GIS, Crop Map, Crop Classification.

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Introduction

Seasonal changes in day length or photoperiod act as an external temporal clue to start a series of physiological processes. As a result, certain events like growth and spawning are restricted to specific times of the year. These photoperiodically controlled reactions suggests a capacity of the organisms to distinguish between short and long days and therefore to measure physical processes and phenomena. This measurement seems to be based, at least in some species, on originating rhythms [1].

The induction of ovarian maturation and spawning of female penaeid shrimps are mainly carried out by using the unilateral eyestalk ablation technique [2]. This technique is used worldwide in hatcheries, many difficulties, such as deteriorations in spawn, larval quality and quantity over time have been joined with it [3]. Other techniques to the eyestalk ablation method, such as temperature and/or photoperiod manipulations, hormone injections have been examined in different shrimp species. [4] with *Penaeus duorarum*, and [5], with *Penaeus semisulcatus* studied the effects of temperature changes on induced maturation and spawning with a high degree of success.

In general, long photoperiods and high temperatures were reported to be required for reproduction in *Penaeus duorarum* [4]. Low temperatures less than 25°C are known to discourage mating, gonad development and spawning in *Penaeus stylirostris* [6] and *Penaeus semisulcatus* [7]. Cycling temperature fluctuations between 20 and 28°C induce maturation and spawning in *Penaeus duorarum* [4] and *Penaeus semisulcatus* [5]. The cycling temperature fluctuation has been suggested to be an effective technique in obtaining off-season reproduction in the green tiger shrimp *P. semisulcatus* [5].

A few thermal manipulating experiments have also been conducted to induce spawning in *P. trituberculatus* at 21°C [8] and *Menippe mercenaria* at 25°C [9]. However, several experiments combining altered temperature and photoperiod conditions have been performed *Penaeus merguiensis* 22°C and 27°C, 10L:14D and 14L:10D [10,11] *Penaeus semisulcatus* 20-28°C, 10L:14D and 14L:10D [5] *Penaeus esculentus* 26°C, 14L:10D [12] *Jasus edwardsii* natural vs. compressed 9 months treatment [13] *Homarus americanus* 9.8-15°C, 8L:16D and 16L:8D [14] and 13-14°C, 8L:16D [15] *Panulirus japonicus* 13°C, 19°C, and 25°C, 10L:14D and 14L:10D [16]. All cited manipulated environmental conditions resulted in some degree of successful gonadal maturation of the respected species.

The principal aim of this research was to elucidate the effects of photoperiodism and temperature mechanism that regulate the key physiological processes of maturation of gonads in *Macrobrachium dayanum* with respect to understanding reproductive biology and growth. Moreover, such knowledge is necessary reliably to egg production for aquaculture of the crustaceans. To clarify the factors affecting initiation of gonadal development, further studies on the developmental processes of gonads, particularly connected to the function of reproductive hormones, were needed because the development was primarily inhibited by the endocrine system.

Agriculture is mankind's primary source of food production and plays the key role for cereal supply to humanity. One of the future challenges will be to feed a constantly growing population, which is expected to reach more than nine billion by 2050 [1]. This will lead to an increasing demand for food, which only can be met by boosting agricultural production [2]. Critically the potential to expand cropland is limited and changes in the climate system can further exaggerate the future pressure on freshwater resources, e.g., through reshaping the pattern of water availability [3]. These trends suggest an increasing demand for dependable, accurate and comprehensive agricultural intelligence on crop production.

Agricultural production monitoring can support decision-making and prioritization efforts towards ameliorating vulnerable parts of agricultural systems. The value of satellite Earth Observation [EO] data in agricultural monitoring is well recognized [4] and a variety of methods have been developed in the last decades to provide agricultural production related statistics [5,6]. However, spatially explicit monitoring of agricultural production requires routinely updated information on the total surface under cultivation, and sometimes the spatial distribution of crops as input [4,7]. This underlines the need for developing accurate and effective methods to map and monitor the distribution of agricultural lands and crop types [crop mapping].

Monitoring crop conditions and food production from local to global scales is at the heart of many modern economic, geostrategic and humanitarian concerns.

Remote sensing is a treasured technique for assessment & monitoring agricultural crop production because it offers information that are powerfully linked with the two main components of crop production, which is crop acreage and yield [8]. Mapping the spatial distribution of crops in an accurate and timely manner is a fundamental input for agricultural production monitoring (and for derived application such as producing early warnings of harvest shortfalls), especially for systems relying on satellite EO to monitor agricultural resources [4,7]. The traditional way to retrieve such crop maps is by classifying an image, or a series of images, using one of the widely known classifier concepts and algorithms that are currently available [9].

Materials and Methods

The methodological development for the classification was achieved in three steps. In the first step ground data was collected from agricultural field. Second, was digital image classification and in the final step verification, accuracy assessment and final mapping were involved.

Study area

Narsinghpur district, spanning over an area of about 5133 km^2, lies between North latitude 23°16' and 24°36' and east longitude 78°27' and 79°40', with elevation range between 286.59 to 882.2 above MSL. The normal annual rainfall of Narsinghpur district is 1192.1mm. The study area has four tehsils fall under which is Gotegaon, Narsinghpur, Kareli & Gadarwara and the study area has further divided into six blocks namely Babai Chichali, Chawarpatha, Saikhera, Gotegaon, Kareli & Narsinghpur. The district is bounded by Seoni district on the southeast, Chhindwara in South, Hoshanghabad & Raisen in the west, Jabalpur in the northeast and Sagar in the North [Fig-1].

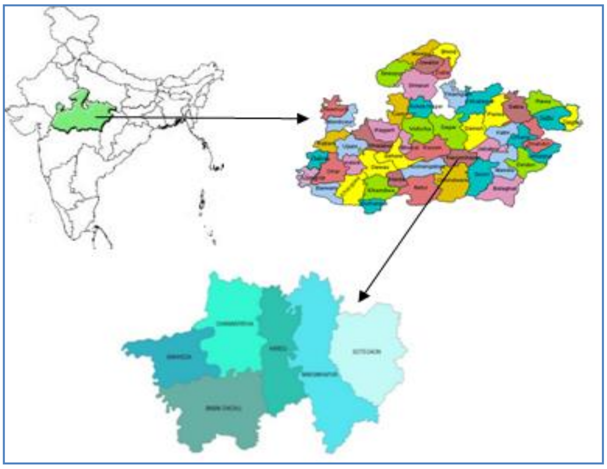

Fig-1 Location map of study area

Data Acquisition

Landsat 8 full scene geocoded satellite data for path 144 and 145 row 44 was acquired from https://earthexplorer.usgs.gov/ dated 1st February 2015 & 8th February 2015. The ancillary data Survey of India toposheet 55I and 55J on scale 1:250000 were used to perform the image processing and classification. The details of Satellite data used in the study are given in [Table-1].

Table-1 *Details of Satellite Image used for the study*

S. No.	Satellite	Spatial Resolution	Year	Source
1	Landsat 8	30 meter	February, 2015	https://earthexplorer.usgs.gov/

Preparation of Crop Map

The satellite imagery was interpreted using both digital and visual methods. The composite image was tested in order to choose the best band combination. The False Colour Composite [FCC] image of 1-2-3 [RGB] combination was used [Fig 2]. A classification scheme defines the crop classes to be considered for remote sensing image classification. Crop classification system categorizes area under different crops on season based maps. For preparation of crop map using satellite data, NRSC has developed the standard guideline. In this study, four crop classes were defined.

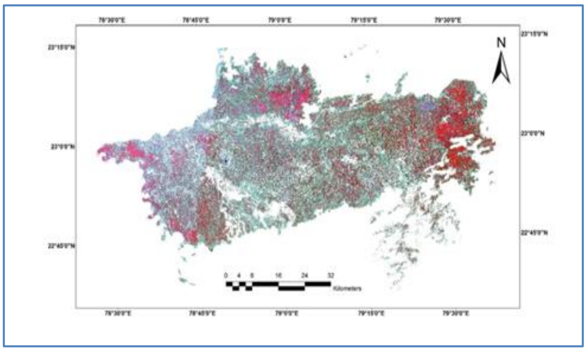

Fig-2 FCC of Agricultural Land of Narsinghpur District (Rabi Season - 2015)

Methodology of Supervised Classification

The most frequently procedure used for quantitative analysis of remote sensing data is Supervised classification; it is based upon using appropriate algorithms to mark the pixel in an image as represents the particular ground cover types or classes [10].

Selecting training fields or samples is an important step in supervised classification. In this process, there will be selections for the pixels, which represent the different patterns based on the requirements. Then supervised classification is used, with parametric setting applied to maximum likelihood and it produces very good result. In The Maximum Likelihood the program define the classification of pixels base on the probability that a pixel belongs to a particular class, assuming that probabilities are equal for all classes and that the input band have normal distribution. Image classification process is presented in [Fig-3].

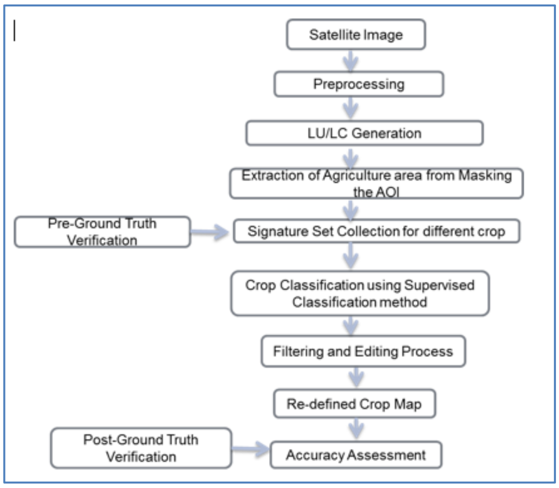

Fig-3 General Methodology adopted for Crop Classification

Classification Accuracy Assessment

To determine the accuracy of classification, a sample of testing pixels is selected on the classified image and their class identity is compared with the reference data [ground truth]. The choice of a suitable sampling scheme and the determination of an appropriate sample size for testing data plays a key role in the assessment of classification accuracy [11].

The pixels of agreement and disagreement are generally compiled in the form of an error matrix. It is a c x c matrix [c is the number of classes], the elements of which indicate the number of pixels in the testing data. The columns of the matrix depict the number of pixels per class for the reference data, and the rows show the number of pixels per class for the classified image. From this error matrix, a number of accuracy measures such as overall accuracy, user's and producer's accuracy, may be determined [12].

The accuracy of whole classification is defined as the overall accuracy [i.e. number of correctly classified pixels divided by the total number of pixels in the error matrix], whereas the other two measures indicate the accuracy of individual classes.

User's accuracy is regarded as the probability that a pixel classified on the map actually represents that class on the ground or reference data, whereas producer's accuracy represents the probability that a pixel on reference data has been correctly classified.

Accuracy assessed through comparing classified crop map with FCC using control point. Using stratified random method, where 250 points were specified as shown in [Fig-4].

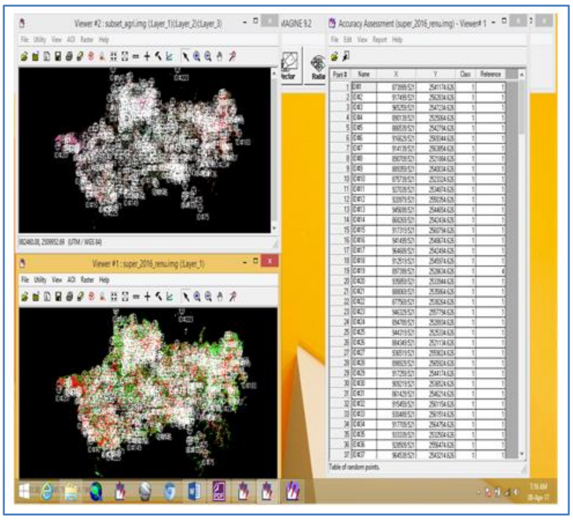

Fig-4 Random 250 points on FCC and classified image

It selects the random point from each class individually [the classes are weighted differently; hence the number of sample points differ from one class and another]. Then class value is assigned using "class value assignment option" and center value as the no majority option is used. Then, each point crop type is identified by interpreting the underlying image. The report is generated which produces overall accuracy, user accuracy, producer accuracy and error matrix.

Results and Discussion

Crop Classification

The result of classification is shown in the [Fig-5] which represents different crop classes i.e., wheat, gram, sugarcane and other crops. Wheat crop occupies [40.91%] maximum area and other crop occupies [5.20%] minimum area. Area statistics for each class obtained by the on screen visual and supervised classification of image is shown in [Table-2]. The dominant crop from crop class for Narsinghpur was found as wheat which covers 108112 ha, followed by gram [87428.6 ha], sugarcane [54997.2 ha] and other crops [13747 ha].

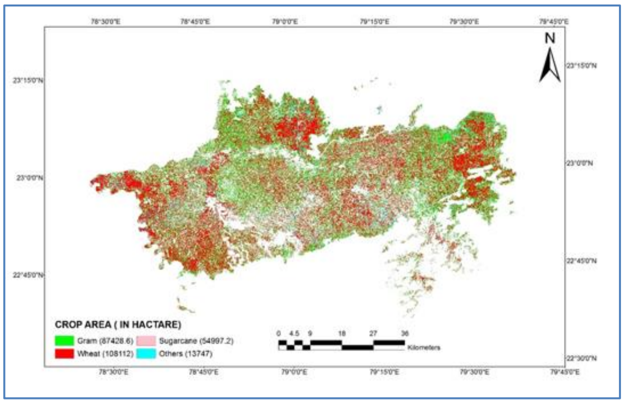

Fig-5 Crop Map of Narsinghpur District (Rabi Season - 2015)

Table-2 *Distribution of crop cover from classified image*

S. No.	Classes	Area [in hactare]	Area coverage [%]
1	Wheat	108112	40.91
2	Gram	87428.6	33.08
3	Sugarcane	54997.2	20.81
4	Others	13747	5.20
Total Area		264284.8	100

Classification Accuracy Assessment Report

An error matrix is an appropriate beginning for many analytical statistical techniques, especially discrete multivariate techniques. Discrete multivariate techniques are appropriate because remotely sensed data are discrete rather than continuous. The data are also binomially or multinomially distributed, and therefore, common normal theory statistical techniques do not apply [13].

KAPPA is a discrete multivariate technique developed by [14] and has been utilized for crop accuracy assessment derived from remotely sensed data [15-17]. The result of performing a KAPPA analysis is the KHAT statistic [an estimate of KAPPA] which is another measure of accuracy or agreement. The Values of KAPPA greater than 0.75 indicate solid agreement beyond chance, values between 0.40 and 0.79 indicate fair to good, and values below 0.40 indicate poor agreement [18]. Overall accuracy uses only the main diagonal elements of the error matrix, and, as such, it is a relatively simple and intuitive measure of agreement. On the other hand, because it does not take into account the proportion of agreement between data sets that is due to chance alone, it tends to overestimate classification accuracy [15,16,19].

KHAT accuracy has come into wide use because it attempts to control for chance agreement by incorporating the off-diagonal elements as a product of the row and column marginals of the error matrix [14]. Conceptually, k can be defined as:

$$k = \frac{(observed\ accuracy - change\ agreement)}{(1 - change\ agreement)}$$

The error matrix showing producer's and user's, and overall classification accuracy, and including the Kappa coefficients is shown in [Table-3], [Table-4] and [Table-5] respectively.

In this study, the error matrix shows that the pixel classified for each training site are wheat-67, gram-64, sugarcane-67 and others-21. The matrix of error shows that there are 9 cells which should be classified as wheat but classified as gram, sugarcane and others. There are 7 cells which should be classified as gram but classified as wheat, sugarcane and others. There are 6 cells which should be classified as sugarcane but classified as wheat and gram. There are 9 cells which should be classified as others but classified as wheat, gram and sugarcane. The total accuracy in this classification accuracy is 87.60%. This means that the training sites selected are 87.60% spectral separable, and the training areas were classified very well.

Table-3 *Classification accuracy error matrix for the crop map using reference data (ERROR MATRIX)*

Classified Data	Reference Data				
	Wheat	Gram	Sugarcane	Others	Row Total
Wheat	67	2	4	2	75
Gram	3	64	2	6	75
Sugarcane	5	2	67	1	75
Others	1	3	0	21	25
Column Total	76	71	73	30	250

Producer's accuracy represents how precisely the producer allocated the classes for the training sites. The accuracy of producers is computed by dividing the number of correctly classified pixels by the number of training sites pixels. The producer accuracy for wheat is 88.16%, gram 90.14%, sugarcane 91.78% and others 70%. User's accuracy refers to the accuracy that the pixel categorized in a certain class is truly representing that class on the ground. User's accuracy was calculated by dividing the number of correctly classified pixels by the total number of pixels that were classified in that class. For wheat user accuracy was found as 89.33%, gram 85.33%, sugarcane 89.33% and others 84%. The overall kappa statistics was found as 0.8287.

Table-4 *Producer's and User's with overall classification accuracy for the crop map using reference data (ACCURACY TOTALS)*

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Wheat	76	75	67	88.16%	89.33%
Gram	71	75	64	90.14%	85.33%
Sugarcane	73	75	67	91.78%	89.33%
Others	30	25	21	70.00%	84.00%
Totals	250	250	219		

Overall Classification Accuracy = 87.60%

Table-5 *Kappa statistics for the crop map (KAPPA [K^] STATISTICS)*

Class Name	Kappa
Wheat	0.8467
Gram	0.7952
Sugarcane	0.8493
Others	0.8182

Overall Kappa Statistics = 0.8287

Conclusion

Crop data is mostly derived from the satellite imaginary. This classified data used in wide variety of area such as planning, resource management, economic development, change detection etc. The update of this type of data is necessary. The present status of crop in the Narsinghpur district as evaluated by digital analysis of satellite data indicates that majority of area was under wheat crop i.e. 40.91%. Accuracy of assessment shows that overall accuracy was 87.60 percent which is good result and kappa statistics shows 0.8287 which shows good agreement between reference and classified image. This study clearly indicated that Remote Sensing and GIS is a novel tool to provide accurate spatial information on crop cover of a region in a time and cost effective manner.

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Author Contributions: All author equally contributed

Abbreviations: EO - Earth Observation

Conflict of Interest: None declared

References

[1] United Nations. World Urbanization Prospects (2014) The 2014 Revision; United Nations: New York, NY, USA, p. 32.
[2] Foley J.A., Ramankutty N., Brauman K.A, Cassidy E.S., Gerber J.S., Johnston M., Mueller N.D., O'Connell C., Ray D.K., West P.C., et al. (2011) *Nature,* 478, 337–342.
[3] Pachauri R.K. and Reisinger A. Climate Change (2007) Synthesis Report. Contribution of Working Groups I, II and III to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change; IPCC: Geneva, Switzerland, 2008; p. 104.
[4] Ozdogan M., Yang Y., Allez G. and Cervantes C. (2010) *Remote Sens.,* 2, 2274–2304.
[5] Carfagna E. and Gallego J.F. (2005) *Int. Stat. Rev.,* 73, 389–404.
[6] Gallego J.F., Delince J. and Rueda C. (1993) *Int. J. Remote Sens.,* 14, 3433–3445.
[7] Atzberger C. (2013) *Remote Sens.,* 5, 949–981.
[8] Justice C. and Becker-Reshef I. (2007) Report from the Workshop on Developing a Strategy for Global Agricultural Monitoring in the Framework of Group on Earth Observations (GEO); University of Maryland: College Park, MD, USA, p. 67.
[9] Tso B. and Mather P.M. (2009) Classification Methods for Remotely Sensed Data, 2nd ed.; CRC Press Taylor & Francis Group: Boca Raton, FL, USA/London, UK/New York, NY, USA.
[10] Richards J.A. (1993) Remote sensing digital image analysis: an introduction, Springer-Verlag, Berlin.
[11] Arora M.K. and Agarwal K. (2002) *Photogrammetry Journal of Finland,* 18(1), 33-43.
[12] Congalton R.G. (1991) *Remote Sensing of Environment,* 37(1), 35-46.
[13] Jensen J.R. (1996) Introductory Digital Image Processing. A Remote Sensing Perspective, Upper Saddle River, New Jersey: Prentice Hall.
[14] Cohen I. (1960) *Educational and Psychological Measurement,* 20(1), 37-46.
[15] Congalton R. and Mead R.A. (1983) *Photogrammetric Engineering & Remote Sensing,* 49(1), 69-74.
[16] Rosenfield G.H. and FitzpatrickLins K. (1986)*Photogrammetric Engineering and Remote Sensing,* 52(2), 223-227.
[17] Gong P. and Howarth P. (1990) *Photogrammetric Engineering and Remote Sensing,* 56(5), 597-603.
[18] SPSS Inc. (1998) SYSTAT - 8.0, Chicago, Illinois.
[19] Ma Z. and Redmond R.L. (1995) *Photogrammetric Engineering and Remote Sensing,* 61(4), 435-439.