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Image Classification for Different Land Use and Land Covers Using Fuzzy Logic for the Improvement of Accuracies

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Abstract

The aim of present research is to classify the satellite images of Ranchi area using fuzzy logic for different land use and land covers. An IRS-LISS III (Linear Imaging Self Scanning Sensor) image has been used for classification. Fuzzy logic is relatively a new theory. Now, fuzzy logic is widely used in the classification of remotely sensed images, for various land use and land cover classes. Classification of images includes pervious and impervious categories. Pervious categories contain mainly standing water bodies, natural vegetation and agricultural lands. Impervious categories contain dense built-up, moderate built-up and low density built-up area. The images of Ranchi area has been classified using standard maximum likelihood (ML) as well as fuzzy techniques using supervised method of classification using ERDAS IMAGINE 9.1. After classification of images, producer's accuracy, user's accuracy, overall accuracy and kappa coefficient values have been calculated with the help of confusion / error matrix. Result shows that in pervious category, standing water body exhibits highest accuracy (100%), then natural vegetation and agricultural land exhibits lowest accuracy. Standing water exhibits highest accuracy due to more clear pixels. Among the impervious categories, low density built-up area exhibits highest producer's accuracy due to small area, dense built-up has second highest and moderate built-up has lowest producer's accuracies. Comparison among accuracies have been done for both techniques and it is observed that the fuzzy logic is a better classification methodology than the standard ML method because overall accuracy and kappa value are higher for fuzzy classified images.

Keywords: classification, fuzzy logic, producer's accuracy, user's accuracy, overall accuracy

1. Introduction

Image classification is a process to assemble groups of identical pixels found in remotely sensed data into classes that match the required categories of user by comparing pixels to one another and those of known identity (Palaniswani et al., 2006). Fuzzy logic is a relatively new theory, the areas of applications are process control, management and decision making, operations research, economics and for this research, the most important, pattern recognition and classification. Fuzziness often occurs due to the presence of mixed pixels, which are not completely occupied by a single, homogeneous category. Mixed pixels occur because the pixel size may not be fine enough to capture detail on the ground necessary for specific applications (Campbell, 1984). They may also occur where the ground properties, such as vegetation and soil types, vary continuously (Wood & Foody, 1993). Standard classification methods such as maximum likelihood technique is sometimes not able classify mixed pixels accurately. A traditional hard classification technique does not take into account this continuous change in land cover classes and only assigns the single class level which dominates in a pixel, it leads to loss of information (Kumar et al., 2007). Fuzzy or soft classification methods are able to classify mixed pixels or land cover is not clearly visible. In the remote sensing Fuzzy C-Means (FCM) clustering algorithm has been widely used to classify satellite images with vague land cover classes (Zhang & Foody, 1998), which decompose the pixel into its class proportions. Earlier in contextual FCM classification of remotely sensed data, it was found that the contextual information could be useful to map the real world phenomena more accurately (Dutta et al., 2008).

Fuzzy classification may be more appropriate than representing reality through sharp objects and crisp classes (Cheng et al., 2001). Fuzzy classification methods assign gradual membership of pixels of classes measured as degrees in [0, 1]. This gives the flexibility to represent pixels that belong to more than one class. The concept of these membership degrees is based on the definition and interpretation of fuzzy sets (Zadeh, 1965). A fuzzy set is a set whose elements have degrees of membership. An element of a fuzzy set can be a full member or a partial member. The membership value assigned to an element is no longer restricted to just two values, but can be 0, 1 or any value in between 0 and 1. But crisp logic has only two values i.e. 0 or 1. So, fuzzy logic is more accurate method than the crisp logic. Land use and land cover are two different terminologies (Dimyatri et al., 1996). Land cover refers to the physical materials on the surface of a given parcel of land e.g. natural vegetation/ forest, barren land, natural water bodies, etc. while land use refers to the human activities that takes place on or make use of land, e.g. residential, industrial, commercial, agricultural land (Longley et al., 2001). Classification has been done for different land use and land covers. Classification accuracy is usually evaluated. It shows a relation between the predicted and the actual classes of membership for a set of pixels. With the help of confusion matrix, it is possible to obtain several measures of classification accuracy, such as producer's accuracy, user's accuracy, overall accuracy and the Kappa coefficient (Jenssen & Van der wel, 1994).To adapt to the fuzziness prevalent in natural phenomena, fuzzy approaches have been proposed (Wang, 1990). So, the objective of this study is to classify images of Ranchi area for land use and land covers applying standard and fuzzy logic methods of classification of LISS III image of the year, 2008, calculation and comparison of accuracies of standard supervised and fuzzy classified images with the help of confusion matrix, error matrix or contingency matrix of all classes. Overall accuracy and value of kappa (KHAT) have also been calculated for both methodologies of classified images and comparison has been done for getting better classified images and methodology.

2 Materials and Methods

2.1 Materials

2.1.1 Study Area

The area considered for present research includes Ranchi city and its surrounding. Ranchi is located on the southern part of Chotanagpur plateau forms the eastern part of the Deccan plateau. Ranchi is the capital of Jharkhand state. Ranchi is located at 23º23′N and 85º23′E. The area of interest is situated in between 23º24′N to 23º53′N and 85º24′E to 85º54′E. The study area has heterogeneity due to occurrence of urban built-up that comprises of different types of built up areas such as densely populated area, moderate populated area and less populated area with more vegetation and more open area. Different types of water bodies are also available in study area such as dams and lakes. There is a variation in vegetation also present in the study area i.e. dense forest area, open forest area and scrub area. Due to rapid urbanization, agricultural lands are being utilized in making different types buildings and markets.

2.1.2 Data Used

IRS LISS III data of October 2008 of 4 bands have been used for classification of images by both the techniques i.e. standard maximum likelihood and fuzzy logic methods. Spatial resolution of LISS III data is 23.5 m, and bandwidth ranges from 0.52-0.59 μm, 0.62-0.68 μm, 0.77-0.86 μm, 1.55-1.70 μm and temporal resolution is of 24 days that enables proper identification of land use and land covers.

2.2 Methods

Selection of training samples, image preprocessing, feature extraction, selection of suitable classification approaches, post classification processing and accuracy assessment are the main steps of image classification. In general, image classification approaches can be grouped as supervised and unsupervised, standard maximum likelihood (ML) and soft (fuzzy, Artificial Neural Network, etc.) classification. Classified maps also known as the thematic maps because they contain the various themes of the ground features (Arnoff, 1982).

Supervised classification technique has been considered in this study because the pixel categorization process is done after specifying the sample training areas. Moreover, sophisticated supervised classification technique with fuzzy logic has been applied to get much more accurate result than the standard hard classification. Six types of land use and land covers namely Standing water (SW) bodies, natural vegetation (NV), Agriculture land (AG) with and without crop, dense built-up (DB), moderate built-up (MDB) and low density built-up (LDB) has been identified in the study area. Pervious categories contains Standing Water (SW), Natural Vegetation(NV) and Agriculture (AG) and impervious categories contains Dense built-up (DB), Moderate built-up and Low density built-up (LDB). Natural Vegetation includes dense forest, open forest and scrub. In the present research, after preprocessing and training dataset/ signature collection, AOI (Area of Interest) creation, the LISS III images of

year 2009 has been classified using training signatures to follow standard supervised maximum likelihood technique. After that the same images were classified using training signatures to follow fuzzy supervised techniques.

Fuzzy classification has been done to take two classes per pixel to classify mixed pixels where standard ML classification technique is unable to classify mixed pixels. After classification of images, producer's accuracy, user's accuracy, overall accuracy and the value of kappa (KHAT) coefficients have been calculated with the help of confusion/ error matrix for training signatures for pervious and impervious categories. At last comparison has been done among all accuracies to get better classified images and better classification technique. The producer's accuracy and user's accuracy are determined in percentage by using following formula (Lillesand & Keifer, 1994; Townsnend, 1981):

$$\text{Producer's Accuracy} = \frac{\text{Number of correctly classified pixels of a particular class}}{\text{Number of reference pixels of the same class (column total)}} \text{X } 100$$

$$\text{User's Accuracy} = \frac{\text{Number of correctly classified pixels of a particular class}}{\text{Number of reference pixels of the class (row total)}} \text{X } 100$$

3. Result and Discussion

First of all image of the year 2008 has been classified through supervised standard and fuzzy techniques using training signatures. After classification of images, confusion/ error matrices are created and utilized to assess the accuracies including producer's accuracy, user's accuracy and overall accuracy of all classified images. Kappa (KHAT) coefficient is also calculated in this study.

Comparative analysis among producer's accuracy, user's accuracy, overall accuracy and kappa coefficients have been done. It has been observed that the overall accuracies of images classified using fuzzy technique are more than the accuracies of images using standard supervised classification technique. The value of kappa coefficients of fuzzy classified images is also higher than the standard classified images. Among pervious categories, standing water exhibits 100% producer's and user's accuracy for both fuzzy and standard techniques, natural vegetation exhibits second higher producer's accuracies and agriculture has lowest producer's accuracies among pervious categories Table 1 and Figure 1.

Among the impervious categories, low density built-up area exhibits highest producer's accuracy due to small area, dense built-up has second highest and moderate built-up has lowest producer's accuracies Table 1 and Figure 1. Moderate built-up, exhibits lowest producer's accuracy because there is mix up of some pixels with other categories such as agriculture, etc.

Table 1. Producer's Accuracy for both classification techniques for LISS III imagery of year 2008 for training signatures of pervious and impervious categories

Categories	ST	FL
SW	100	100
DB	89.84	90.33
MDB	73.64	74.53
LDB	90.25	92.25
NV	80.89	83.33
AG	75.64	76.01

SW: Standing Water; DB: Dense Built-up; MDB: Moderate Built-up; LDB: Low Density Built-up; NV: Natural Vegetation; AG: Agriculture; ST: Standard/ hard; FL: Fuzzy Logic.

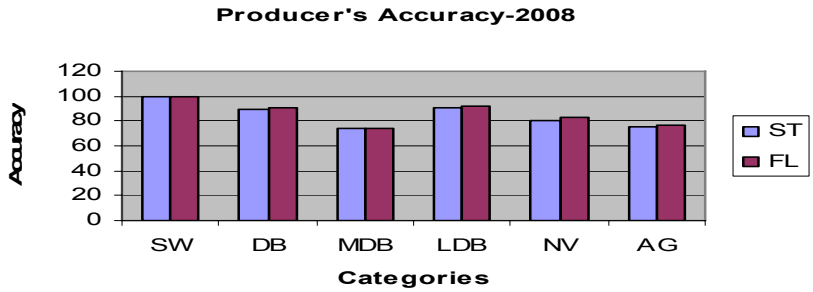

Figure 1. Producer's Accuracy for both classification techniques for LISS III imagery of year 2008 for training signatures of pervious and impervious categories

User's accuracy for standing water is 100% and it is the highest among pervious categories. Natural vegetation exhibits second highest user's accuracies and agriculture has the lowest user's accuracies for the year 2008 in pervious categories for both, standard and fuzzy techniques Table 2 and Figure 2.

Among the impervious categories, low density built-up also exhibits highest user's accuracy, dense built-up has the second highest and low density built-up has the lowest user's accuracies in standard as well as fuzzy classification method due to less area of low density built-up and more mixing of pixels in moderate built-up with other categories Table 2 and Figure 2. But overall, the fuzzy classified images have more accuracy than the standard ML classified images because mixed pixels are more clearly classified in fuzzy methods.

Table 2. User's Accuracy for both classification techniques for LISS III imagery of year 2008 for training signatures of pervious and impervious categories

Categories	ST	FL
SW	100	100
DB	80.62	86.14
MDB	74.24	84.33
LDB	89.53	89.53
NV	78.01	84.09
AG	72.18	75.41

SW: Standing Water; DB: Dense Built-up; MDB: Moderate Built-up; LDB: Low Density Built-up; NV: Natural Vegetation; AG: Agriculture; ST: Standard/ hard; FL: Fuzzy Logic.

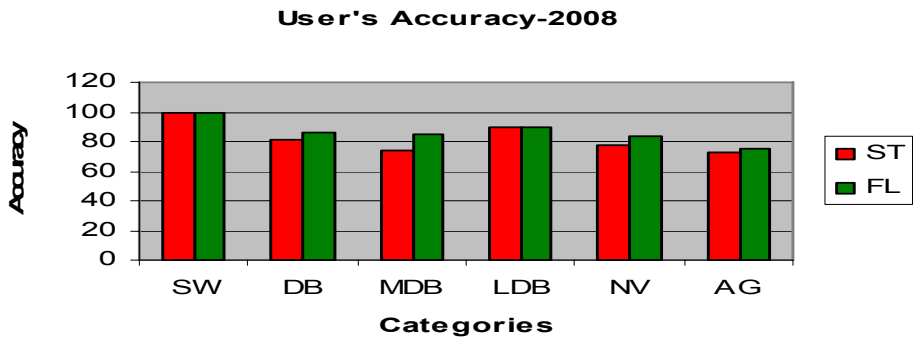

Figure 2. User's Accuracy for both classification techniques for LISS III imagery of year 2008 for training signatures

Overall accuracy of fuzzy classified images is more than the standard maximum likelihood (ML) classified images for year 2008 Table 3 and Figure 3. So it is observed that the fuzzy classification technique is a better technique than the standard technique.

Table 3. Overall Accuracy for both classification techniques for LISS III imagery of year 2008 training signature

Year	ST (Standard ML method)	FL (Fuzzy Logic)
2008	78.98	83.56

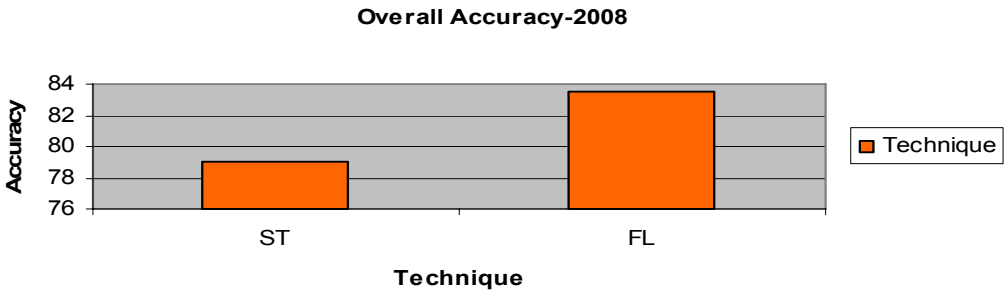

Figure 3. Overall Accuracy for both classification techniques for LISS III imagery of year 2008 for training signatures

Value of kappa coefficients is higher for fuzzy classified images than the standard classified images Table 4 and Figure 4. So it is clear from above observations that the fuzzy logic method is the better classification tool than the standard supervised classification methods.

Table 4. Kappa coefficient value for both classification techniques for LISS III imagery of year 2008 for training signatures

Year	ST (Standard ML method)	FL (Fuzzy Logic)
2008	0.73879 (73.9%)	0.7592 (75.9%)

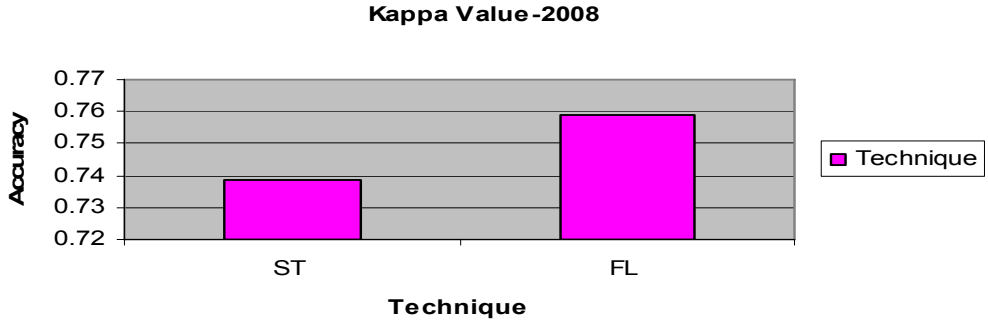

Figure 4. Kappa coefficient value for both classification techniques for LISS III imagery of year 2008 for training signatures

4. Conclusion

Producer's, User's, Overall accuracies and the value of kappa have been calculated for each classified images for both standard and fuzzy techniques with the help of error/ confusion matrix. After that comparative analysis among producer's accuracy, user's accuracy, overall accuracy and value of kappa coefficients of the various pervious and impervious categories determined from the classification of the image 2008. Supervised Standard maximum likelihood and fuzzy supervised classification methodologies have been used to classify images. It is observed from tables and figures, fuzzy logic method produced the higher accuracies than the accuracies classified by using standard maximum likelihood techniques.

From these investigations, following conclusions are drawn:

1) Standing water exhibits 100% producer's and user's accuracy determined from the classification of image of the year 2008 among pervious categories due to significantly considerable spectral

homogeneity of the training signatures extracted for these categories from which producer's accuracy and user's accuracy are determined.

2) Natural vegetation exhibits second highest producer's accuracy and user's accuracy and agriculture have the lowest producer's and user's accuracy among pervious categories.

3) Built-up areas classified by using fuzzy technique exhibit higher producer's, user's accuracy and overall accuracies than the standard ML technique in impervious categories.

A general trend is observed in the present study is that the producer's accuracy, user's accuracy' overall accuracy and the value of kappa coefficients are higher for fuzzy classified images than the images classified by standard supervised methods. So the fuzzy classification technique is a better classification technique than the standard supervised classification methodology.

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