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Image Classification for Different Land Use and Land Covers Using Artificial Neural Network for Higher Accuracy

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ABSTRACT

In the present study, supervised maximum likelihood (ML) classification method has been used to classify images of West Champaran district of Bihar of the years 2010 and 2020 for land use and land cover (LULC) and then the same images have been classified using Artificial Neural Network (ANN) for getting better classified images and higher accuracies.Eight land use and land cover classes are taken in to consideration viz. crop land, fallow land, dense builtup, low builtup, river wetland, lakes ponds wetland, barren land and natural vegetation.Different accuracies such as producer's, user's, overall accuracies and the value of kappa coefficients have been calculated for each classified images for both ML and ANN methodologies. LULC classified images are prerequisite for better agricultural planning and getting more crop production with minimum input cost. After that comparative analysis among producer's accuracy, user's accuracy, overall accuracy and value of kappa coefficients of the various categories/ classes determined from the classification of the image 2010 and 2020 for both methodologies using confusion matrix. The result shows that crop land, fallow land, wetland, barren land exhibit better producer and user accuracy than dense built-up and low built-up area. It is also found thatoverall accuracies of the year 2010 and 2020 of ML classified images are 87.46% and 88.53% and ANN classified are 92.37% and 93.76%. The value of kappa coefficients of respective years are 0.85 and 0.87 of ML classified whereas 0.90 and 0.92 are for ANN classified images. It is finally observed that overall accuracy and kappa coefficient of ANN classified images are higher than the ML classified images. So ANN is better image classification technique than maximum likelihood technique.

Keywords: Accuracy, Image, Land use, Land cover and Supervised classification.

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INTRODUCTION

Remote sensing involves gathering information about the Earth without direct contact with its surface. This is typically done using sensors that measure the energy reflected from the Earth, with the data often presented as digital images. These sensors can be installed on satellites orbiting the Earth. In remote sensing, the process relies on the interaction between radiation and the objects being observed.

Remote sensing data, both in large and digital formats, are crucial for understanding Earth's resources. This data can be analysed through visual interpretation or computer-aided analysis, often requiring ground truth information for accuracy. Ground truth refers to verified data from the Earth's surface used to validate remote sensing observations.

Image classification in remote sensing is a multi-step process involving selecting a classification system, choosing training samples, preprocessing images, extracting features, selecting classification methods, post-processing, and accuracy assessment. The ultimate goal is to categorize all pixels in an image into specific land use or land cover classes, resulting in thematic maps showing the spatial distribution of different themes such as vegetation, water bodies, urban areas, and agricultural lands.

During image classification, visual interpretation identifies homogeneous groups of pixels representing various features, while digital image classification utilizes spectral information from one or more spectral bands. This spectral image classification categorizes pixels based on their brightness values across spectral bands, grouping similar pixels into spectral classes. However, the accuracy of image classification can be assessed using error matrices, also known as confusion matrices. These matrices enable the calculation of various measures of classification accuracy, including producer's accuracy, user's accuracy, overall accuracy, and the Kappa coefficient (Jenssen and Van der Wel, 1994). Overall accuracy and the Kappa coefficient are particularly important metrics, as they provide insight into the reliability and consistency of the classification results.

Comparing the overall accuracy and Kappa coefficient values

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obtained from different classification methodologies allows for the selection of the most effective approach for generating classified images. These classified images serve as the basis for creating maps of the study area, facilitating the visualization and analysis of land cover and land use patterns (Roy, 1991).

Image classification algorithms commonly utilize statistical methods, neural networks, or fuzzy logic approaches. When dealing with challenges like mixed pixel classification, neural networks (specifically artificial neural networks, or ANN) are often more effective compared to standard machine learning (ML) methods. The use of ANN in image classification can provide more accurate results, especially when dealing with mixed pixels where traditional ML methods struggle to differentiate between complex features. The fusion of remote sensing and GIS technology has also transformed the monitoring of changes in land use and land cover (LULC) from historical data to the contemporary era. This evolution has become increasingly indispensable due to the swift and extensive surface changes occurring across wide geographical regions. This integration has not only streamlined local monitoring efforts but has also facilitated global observation endeavors, offering significant advantages to the scientific community in comprehending Earth's dynamics and environmental transformations (Hossain *et al*., 2020; Kumari *et al*., 2022).

Furthermore, ANN classification techniques have been applied to estimate crop production (Kaul *et al*., 2005). This demonstrates the versatility of artificial neural networks in remote sensing applications, particularly in tasks related to land cover analysis, crop monitoring, and production estimation based on image data.

Keeping in view, the present study was carried out for image classification to identify different land use and land cover categories using both standard machine learning and artificial neural networks in West Champaran area for the years 2010 and 2020. Calculation and comparison of accuracies of standard supervised ML and ANN classified images has been done with the help of confusion matrix. Land use and land cover (LULC) map of West Champaran district has been created after LULC classification. This classified LULC maps may be used for better utilization of land and more crop production and ultimately it is useful to farmers to increase their crop production and income.

MATERIALS AND METHODS

Study Area

The present study focuses on the West Champaran district of Bihar, covering a geographical area with latitudes ranging from 26°16'N to 27°31'N and longitudes from 83°50'E to 85°18'E. The total area of the district spans approximately 478,727.6 hectares, with a predominantly sloping terrain from north to south. The district is characterized by four distinct physiographic units. The first unit comprises the hilly areas of Sumeswar and Dun ranges, located at the extreme north of the district and nestled at the foothills of the Himalayas. These hills are largely covered with forests. Following the hilly area is the sub-mountain tract known as the 'tarai'. Subsequently, the terrain transitions into fertile plains, which can be further categorized into two parts: one consisting of old alluvium and the other composed of recent alluvium deposited during the oscillation of the Gandakriver. The district features a total wetland area of 21,697 hectares, with an average annual rainfall of 1140 mm. Agricultural land covers a substantial portion of the district, totaling 206,038.8 hectares, while non-agricultural areas span 27,313.2 hectares. Forested areas cover 90,716 hectares, with 69,231.2 hectares of land under water bodies.

The predominant crops cultivated in the district include Bhadai, Kharif, and Rabbi crops. Bhadai crops mainly consist of maize and sugarcane, while the primary crops during the Kharif season include paddy and potatoes. Wheat, barley, and arhar are the main Rabbi crops. In the northern low-lying regions of the district, paddy cultivation predominates.

Data Used

IRS LISSIII data of study area (West Champaran) of the year 2010 and 2020 of four band (Red, Green, NIR and SWIR) having spatial resolution 23.5 m, temporal resolution is 24 daysand bandwidth ranges from 0.52-0.59 μm, 0.62-0.68μ, 0.77-0.86 μm, 1.55-1.70are used for classification of different land use and land covers using supervised maximum likelihood (ML) and artificial neural network (ANN).

Methodology

Pre-processing of satellite images has been done that includes geometric correction, atmospheric correction, radiometric calibration and radiometric rectification procedures. After preprocessing, images have been georeferencedfor defining its location in terms of map projections or coordinate systems. In present study, the satellite data of the individual years of 2010 and 2020 were georeferenced with the help of the GCPs identified on the corresponding to Survey of India toposheet number 73E/7.

The study area has heterogeneity due to occurrence of urban built-up that comprises of different types of built up areas. Different types of water bodies are also available in study area such as rivers, dams and lakes. There is a variation in vegetation also present in the study area i.e. forest area and scrub area mainly found in Northern part of the district. Agricultural land is found in the whole part of the district.

Maximum likelihood and artificial neural network classification

The maximum likelihood (ML) classification method is a commonly used supervised approach in remote sensing. It utilizes statistical principles to assign pixels to predefined classes based on their probability of belonging to each class, determined by the Bayesian probability formula. However, ML struggles with accurately classifying mixed pixels. Training data is utilized to estimate the means and variances of classes, aiding in probability estimation.The ML classification process involves developing training sites, creating spectral signatures, and refining these through correction procedures, such as replacing inadequate sites and merging overlapping ones. For the present study, eight land use/land cover classes were considered, including crop land, fallow land, dense built-up, low built-up, river wetland, lakes/ponds wetland, barren land, and natural vegetation. Dense built-up areas typically correspond to urban regions, while low built-up areas are associated with rural areas.

Following image preprocessing and georeferencing, training samples and signatures were collected, and areas of interest (AOIs) for ML and regions of interest (ROIs) for ANN were defined for each land cover class. Subsequently, LISS III images from 2010 and 2020 were classified using supervised ML, employing the training signatures. The same images were then classified using supervised artificial neural network (ANN) techniques, utilizing the same training signatures.

RESULTS AND DISCUSSION

The classification of images from West Champaran district for the years 2010 and 2020 was conducted to identify various land use and land cover classes, including crop land, fallow land, dense built-up, low built-up, river wetland, lakes/ponds wetland, barren land, and forest. This classification was carried out using both supervised maximum likelihood (ML) and artificial neural network (ANN) techniques.

After classification, the accuracy of the results was evaluated using Producer's, User's, and Overall accuracies, as well as Kappa coefficients calculated from error matrices (Table 1, 2, 3 and 4). Forested areas were primarily observed in the northern part of the district, while agricultural land and built-up areas were distributed throughout the district.

The analysis revealed that classes such as crop land, fallow land, wetlands, barren land, and natural vegetation/forest exhibited higher producer and user accuracies compared to dense built-up and low built-up areas. Moreover, the overall accuracies of ML classified images for the years 2010 and 2020 were 87.46% and 88.53%, respectively, while those of ANN classified images were 92.37% and 93.76%. The corresponding Kappa coefficients for ML classified images were 0.85 and 0.87, while those for ANN classified images were 0.90 and 0.92.

Ultimately, the results indicated that ANN classified images achieved higher overall accuracy and Kappa coefficient values compared to ML classified images. Therefore, the ANN method was deemed to be a superior image classification technique for this study.

Table 1: Producer Accuracy of different land use and land covers using standard ML and ANN methods of West Champaran during 2010 and 2020

Classes/ categories	2010		2020	
	ML	ANN	ML	ANN
Crop land	95.12	97.42	96.64	98.21
Fallow land	93.14	94.26	94.18	95.32
Dense builtup (urban)	91.37	93.78	93.17	94.54
Low builtup (rural)	84.76	85.23	88.65	90.12
River-wetland	86.92	88.54	91.90	92.34
Lakes-ponds-wetland	85.68	87.52	89.34	90.78
Barren land	83.43	84.18	84.33	86.24
Natural Vegetation	92.86	94.82	94.02	95.16

Table 2: User Accuracy of different land use and land covers using standard ML and ANN methods of West Champaran of year 2010 and 2020

Classes/ categories	2010		2020	
	ML	ANN	ML	ANN
Crop land	94.15	96.28	95.24	97.32
Fallow land	92.24	93.16	93.78	94.42
Dense builtup (urban)	90.27	92.18	91.34	93.62
Low builtup (rural)	82.42	83.71	81.75	85.24
River- wetland	87.72	88.94	88.92	90.18
Lakes- ponds-wetland	86.34	87.32	87.64	89.48
Barren land	82.41	83.62	83.73	84.94
Natural Vegetation	91.72	93.68	93.46	94.81

Table 3: Overall Accuracy of different land use and land covers using ML and ANN methods of West Champaran during 2010 and 2020

Year	ML	ANN
2010	87.46	92.37
2020	88.53	93.76

Table 4: Kappa Coefficient of different land use and land covers using ML and ANN methods of West Champaran during 2010 and 2020

Year	ML	ANN
2010	0.85	0.90
2020	0.87	0.92

CONCLUSION

The calculation of Producer's accuracy, User's accuracy, Overall accuracy, and Kappa coefficients was performed using error matrices for both classification techniques: maximum likelihood (ML) and artificial neural network (ANN), for different land use and land cover classes in West Champaran district of Bihar. The results revealed that classes such as crop land, fallow land, wetlands, barren land, and natural vegetation exhibited higher Producer's and User's accuracy compared to dense built-up and low built-up areas. Among these classes, crop land showed the highest Producer's and User's accuracy values. Furthermore, it was observed that the Overall accuracy and Kappa coefficient values of ANN classified images were higher than those of ML classified images. This is attributed to the capability of ANN to classify mixed pixels more accurately, resulting in improved classification performance. Based on the findings of this research, ANN emerges as the superior classification technique compared to ML. These Land Use and Land Cover (LULC) classified images hold significant utility for farmers, enabling better utilization of agricultural land to enhance crop production and income.

CONFLICT OF INTEREST

All the author both individually and collectively, affirms that they do not possess any conflicts of interest either directly or indirectly related to the research being reported in the publication.

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