Improvement of User’s Accuracy Through Classification of Principal Component Images and Stacked Temporal Images

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Abstract The classification accuracy of the various categories on the classified remotely sensed images are usually evaluated by two different measures of accuracy, namely, producer’s accuracy (PA) and user’s accuracy (UA). The PA of a category indicates to what extent the reference pixels of the category are correctly classified, whereas the UA of a category represents to what extent the other categories are less misclassified into the category in question. Therefore, the UA of the various categories determines the reliability of their interpretation on the classified image and is more important to the analyst than the PA. The present investigation has been performed in order to determine if there occurs improvement in the UA of the various categories on the classified image of the principal components of the original bands and on the classified image of the stacked image of two different years. We performed the analyses using the IRS LISS III images of two different years, i.e., 1996 and 2009, that represent the different magnitude of urbanization and the stacked image of these two years pertaining to Ranchi area, Jharkhand, India, with a view to assessing the impacts of urbanization on the UA of the different categories. The results of the investigation demonstrated that there occurs significant improvement in the UA of the impervious categories in the classified image of the stacked image, which is attributable to the aggregation of the spectral information from twice the number of bands from two different years. On the other hand, the classified image of the principal components did not show any improvement in the UA as compared to the original images.

Keywords producer’s accuracy; user’s accuracy; principal components; classification; stacked image

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Introduction

The measurement of the accuracy of the classified images generated from the classification of the original digital images is the most vital component of the remote-sensing-based mapping of the land use and land cover categories in an area. The accuracy of the various categories, which is otherwise referred to as the classification accuracy, basically indicates to what extent a category is correctly mapped on the remotely sensed data or images with reference to its geographic location on the ground. If all the pixels classified from the remotely sensed data show correct geographic position of the various land use and land cover categories, the classified map is considered to be 100 percent correct. The classified maps are also referred to as thematic maps since they portray the various themes of the ground features.[1]

In literature, there exists several formulas for measuring the classification accuracy of the various categories, such as producer’s accuracy, user’s accuracy,
and Kappa accuracy that are used for individual categories, whereas for the assessment of the accuracy of the entire image, two popular accuracy measures exist, namely, overall accuracy and average accuracy.\textsuperscript{[2,3]} In the estimation of the accuracy of an individual category, the basic principle involved is the number of the correctly classified pixels of that category on the classified image vis-à-vis its exact geographic location on the ground. This is estimated by dividing the number of the correctly classified pixels of a category on the classified image by the number of the reference pixels or training pixels selected from the original image for that category.\textsuperscript{[4]} This is also called producer’s accuracy (PA). The training pixels are also referred to as the training signatures.

In practice, the accuracy estimation is done from a matrix referred to as Error Matrix, Confusion Matrix, or Contingency Matrix. In such matrix, the reference data (usually represented by the columns of the matrix) are compared with the classified data (usually represented by the rows). The major diagonal indicates the agreement between these two datasets. Overall accuracy for a particular classified image is then calculated by dividing the sum of the entries that form the major diagonal (i.e., the number of correct classifications) by the total number of samples taken. The producer’s accuracy of a particular category is determined by dividing the number of correct pixels in that category by the total number of pixels of the same category represented as the reference data in the error matrix. The producer’s accuracy measures how well the reference pixels have been classified. It includes the error of omission, which refers to the proportion of the observed features on the ground that is not classified in the map. The more errors of omission exist, the lower the producer’s accuracy.

The primary aim of the present investigation is to determine if for the same reference signature of the individual land use and land cover categories, there occurs improvement in the user’s accuracy of the various categories through the classification of the principal components of the original images of the individual years and stacked image generated by stacking the original images of two different years, respectively.

Among the various image enhancement techniques, PCA has proved to be significantly helpful in depicting the various land use and land cover features more conspicuously than the original bands because of their properties of redistributing the original information in the bands. Therefore, it is expected that classification of the PCs generated from the original bands would provide better discrimination among the various land use and land cover categories than the original bands.\textsuperscript{[6]} On the other hand, the stacked image generated by stacking the multispectral images of two different years aggregates the spectral information of the various land use and land cover categories from twice the number of bands from two different years and, therefore, is expected to provide better classification accuracies of the categories.

\section{Study area}

The area considered for performing the present investigation includes Ranchi city and its surroundings, which is also the capital of Jharkhand state, India, and is bounded by 23° 16' 28" N to 23° 27' 34" N and 85° 18' 14" E to 85° 26' 54" E (see Fig. 1). The study area forms part of the Chotanagpur region and is located at an altitude of 654 m above the mean sea level. The area is traversed by Subarnarekha river and its major tributaries, namely, Jumar, Potpoto, Sapahi, etc., and is characterized by the occurrence of dense dendritic
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Fig.1  Study area

The type of forest found in this region is Dry Peninsular and includes important trees like Sal, jack, bamboo thickets, etc. In Ranchi, the forest cover is dwindling very fast because of the clearing of the jungles by the aboriginals for cultivation. Geographically, the study area is largely heterogeneous, which resulted from the occurrence of the urban built-up agglomerate of varying density and types of dwellings, agricultural lands, barren lands, natural vegetation comprising forest, shrub, etc., and numerous standing water bodies, such as ponds. In the study area, large tracts of land are left barren, which are highly fertile for the cultivation of pulses and vegetables. Paddy dominates the present cropping pattern followed by pulses, maize, and wheat. The main problems facing at present in the study area are rapid, unscientific, and unsustained urbanization at the expense of the fertile agricultural lands and natural vegetation. This has caused drastic modification in the landscape in addition to triggering many adverse effects, such as increase in the extent of the impervious features, decrease in the rain water recharge, lowering of the ground water table, and rising of temperature.

If the present pace of urbanization persists, the ecological paradigm of the study area will worsen to such extent that it will be nearly impossible to restore its pristine status. In order to carry out quantitative assessment of the ecological status of the study area and implement effective remedial strategy, it is imperative to carry out spatio-temporal monitoring and assessment of the land use and land cover dynamics employing reliable techniques, such as the digital classification of multispectral remote sensing data.[7]

2  Materials and methods

The satellite data of the individual years were georeferenced with the help of the ground control points (GCPs) identified on the corresponding Survey of India toposheet No. 73E/7. In the present study, we have used the IRS LISS III data (Path 105–Row 055) of December 1996 and February 2009, respectively, covering the area selected for performing the investigation; the former representing the pre-capital formation period, and the latter the post-capital formation period. Ranchi was formed as the capital of the Jharkhand state in November 2000. The LISS III data is characterized by four spectral bands, such as green (0.52-0.59 µm), red (0.62-0.68 µm), NIR (0.77-0.86 µm), and SWIR (1.55-1.70 µm) and nominal spatial resolution of 23 m.[2] We have selected the images of these two years with a view to assessing the impacts of urbanization in the post-capital period on the classification accuracy of the various pervious and impervious categories. The datasets used in the present study are, namely, (1) the original images of two individual years, i.e., 1996 and 2009, (2) principal components determined from the original images of the individual years, (3) stacked images of these two years, and (4) principal components of the stacked image. The stacked image generated by stacking the images of 1996 and 2009 would aggregate the spectral information from two different years and is expected to provide better discrimination of the various impervious categories on the classified image as compared to the images of the individual years.

Supervised maximum likelihood classifier was employed for performing classification of the differ-
ent pervious and impervious categories by considering their training signatures extracted from the different types of datasets as mentioned above. The various pervious categories identified in the study area are standing water bodies, agricultural land, natural vegetation, and barren land. On the other hand, we considered three impervious categories, such as dense built-up, moderate built-up and low-density built-up. In the study area, dense built-up category comprises the closely connected residential and commercial clusters. On the other hand, all the newly constructed buildings and the old buildings that occur in isolated and scattered form throughout the study area are categorized as low-density built-up. The moderate built-up category comprises the residential and commercial buildings, which are located close to each other but are interspersed with the open barren lands and smaller patches of agricultural lands and shrubs. The dense built-up category is largely devoid of vegetation and plantation; the moderate-density built-up is associated with the vegetation including plantation; while the low-density built-up is largely devoid of vegetation since they are developed by clearing the vegetation and through the consumption of the agricultural lands.

In the next step, the error matrixes from the classification of the different datasets were generated. From the error matrixes, the producer’s accuracy and user’s accuracy of the different categories were determined. These accuracy measures are traditionally expressed in percentage. Finally, comparative analyses were performed between the producer’s accuracy and user’s accuracy of the various categories and among the user’s accuracy of the individual categories generated from the different datasets in order to determine the dataset(s) that provide considerably higher user’s accuracy so that they could be used subsequently for better interpretation of the various land use and land cover categories.

The producer’s accuracy and user’s accuracy in percentage are determined by using the following formulas:

\[
\text{Producer’s Accuracy} = \frac{\text{Number of correctly classified pixels of a particular class}}{\text{Number of reference pixels of the same class}} \times 100
\]

\[
\text{User’s Accuracy} = \frac{\text{Number of correctly classified pixels of a particular class}}{\text{Number of classified pixels in the class}} \times 100
\]

### 3 Results and discussion

The producer’s accuracy and user’s accuracy of the various pervious and impervious categories determined from the original images of 1996 and 2009 and stacked image of these two years are shown in Table 1, while those determined from the principal components of the abovementioned images are presented in Table 2.

Comparative analyses between the producer’s accuracy and user’s accuracy reveal that the user’s accuracy is noticeably higher than the producer’s accuracy for the various categories determined from the classification of the different images considered for performing the present investigation. All the pervious categories except the natural vegetation exhibit nearly the same producer’s and user’s accuracy in the classified images of the various datasets considered. For the natural vegetation category, the user’s accuracy is found to be reasonably higher than its producer’s accuracy in the classified images of the individual years as well as in the classified stacked image. The occurrence of the similar producer’s and user’s accuracy of the three pervious categories, such as the agricultural land, standing water bodies, and barren land, is attributable to the prevalence of significantly considerable spectral homogeneity in them, while the natural vegetation being comprised of dense and open vegetation is characterized by reasonably lesser magnitude of spectral homogeneity thereby showing reduced PA and UA. The occurrence of the higher UA than PA for the natural vegetation is indicative of the occurrence of the lesser magnitude of misclassification of the other categories as the former. The 100% accuracy of the barren land is attributed to the nature of the surface. The barren land considered in the present study area comprises the uncovered sandy surface appearing in white patches on the standard FCC and bear homogeneous spectral sig-
nature. Therefore, they do not exhibit any spectral mixing with the other categories. Adequate number of training pixels has been extracted in proportion to the areal extent of the barren land in the study area.

### Table 1  Summary of the PA and UA determined from the original images and stacked image of the individual years

| Categories with the number of their training pixels shown inside the bracket | 1996 | 1996 | 2009 | 2009 | 1996-2009 | 1996-2009 |
|---|---|---|---|---|---|---|
| Agriculture (4063) | 98.66 | 100 | 98.68 | 99.92 | 99.21 | 100 |
| Natural vegetation (1011) | 93.66 | 99.83 | 93.16 | 98.82 | 95.56 | 99.87 |
| Barren land (107) | 100 | 100 | 100 | 100 | 100 | 100 |
| Standing water (1023) | 99.8 | 100 | 100 | 100 | 100 | 100 |
| Dense built-up (403) | 96.41 | 97.92 | 95.5 | 99.61 | 97.25 | 99.91 |
| Moderate built-up (290) | 74.34 | 94.83 | 68.93 | 78.65 | 80.67 | 98.43 |
| Low-density built-up (230) | 70.75 | 90.96 | 77.99 | 88.65 | 82.72 | 95.47 |

Among the various impervious categories, the maximum difference between the UA and PA is exhibited by the moderate built-up and low-density built-up categories. Dense built-up category being characterized by the occurrence of homogeneous spectral signature exhibits significantly considerable PA and UA, both being equal or nearly equal to each other in the classified images of the different datasets. The user’s accuracy of the moderate-density built-up and low-density built-up each is found to be higher in the classified images of the original spectral bands as compared to the classified images of the principal components in the respective years and, also, in the classified image of the stacked image of the two years and in the classified image of the principal components of the stacked image. This observation indicates that on the original images, the various categories exhibit lesser magnitude of misclassification with the moderate- and low-density built-up categories, while the magnitude of misclassification increases in the principal components generated from the original bands that could be attributed to the redistribution of the spectral information in the principal components.

### Table 2  Summary of the PA and UA determined from the principal components extracted from the original images and the stacked image of the individual years

| Categories with the number of their training pixels shown inside the bracket | 1996 | 1996 | 2009 | 2009 | 1996-2009 | 1996-2009 |
|---|---|---|---|---|---|---|
| Agriculture (4063) | 99.6 | 99.97 | 99.66 | 99.87 | 99.94 | 100 |
| Natural vegetation (1011) | 97.66 | 98.38 | 98.66 | 98.94 | 99.13 | 99.94 |
| Barren land (107) | 100 | 100 | 100 | 100 | 100 | 100 |
| Standing water (1023) | 99.36 | 100 | 99.8 | 100 | 99.57 | 100 |
| Dense built-up (403) | 97.51 | 98.11 | 96.25 | 98.8 | 98.88 | 99.97 |
| Moderate built-up (290) | 67.57 | 77.2 | 68.93 | 80.11 | 75.68 | 90.83 |
| Low-density built-up (230) | 69.44 | 87.57 | 78.62 | 81.86 | 87.59 | 94.64 |

Comparison of the user’s accuracy of these two impervious categories between 1996 (precapital period) and 2009 (post-capital period) reveals the occurrence of higher UA in the earlier year than in the latter year, both in the classified image of the original bands and in the classified image of the principal components that could be attributed to the significant increase in the spectral heterogeneity of these two categories as a result of the prevalence of the large-scale and scattered urbanization in the postcapital period leading to the misclassification between these categories. Comparison between the user’s accuracy determined from the classification of the images of the individual years and the stacked image of the two years reveals the occurrence of nearly the same UA for the various pervious categories and the dense built-up category, while for the two impervious categories, namely, moderate built-up and low-density built-up, there occurs higher UA in the classified stacked image as compared to the classified image of the individual years. Similar observation also exists for the principal components of the images of the individual years and principal components of the stacked image (Table 2).
These observations signify the potential of the stacked image in providing better spectral information as compared to the images of the individual years due to the aggregation of the spectral information from two different years in the former.

4 Conclusion

From the various types of investigations performed in the present study, the following conclusions are drawn. First, the classification of the stacked image of the two different years corresponding to the precapital and postcapital formation periods provides higher user’s accuracy than the classification of the images of the individual years that is attributed to the aggregation of the spectral information from twice the number of bands from two different years. Second, there is no occurrence of any improvement in the UA of the various pervious and impervious categories in the classified image of the principal components of the original bands as compared to the latter, indicating that the redistribution of the spectral information in the principal components tends to decrease the spectral purity of the training signatures extracted for the various categories thereby leading to the occurrence of increased among-category misclassification.

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