Comparison of land cover image classification methods

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(Received: 3 June, 2011; in final form 25 January, 2012)

Abstract: In remote sensing, many methods have been developed for image classification. In this study, three of the methods namely Maximum Likelihood classification (MLC), Backpropagation Neural Network classification (BPNN), and Sub Pixel classification (SP) are used to classify a Landsat ETM+ image of the Ejisu-Juabeng district of Ghana into seven land cover classes and the results are compared. The seven classes identified were forest, forested wetland, open woodland, water, non-forested wetland, grassland and urban. In the comparison, the top 20 (80%-100% composition) per land cover class from the SP is used against the MLC and BPNN classification. The results show that of the two hard classifications (MLC & BPNN), BPNN gave a better result with an overall accuracy of 92.5 % compared with that of MLC with an accuracy of 78.95%. The SP classification however, gave mixed results although for land cover classes such as forest and forested wetland that are homogeneous in nature, the representations were good. Over all the BPNN classification gave the best representation of the land cover classes in the study area.

Keywords: Land cover classification, Maximum Likelihood classification, Backpropagation Neural Network classification, Subpixel classification

1. Introduction

The availability of up-to-date land use–land cover information is central to much resource management, planning and monitoring programmes (Campbell, 1996; Sellers et al., 1995; Osei, 2003) and maps provide the basis for such information. Recent trends in the mapping industry indicates that the use of satellite images through remote sensing techniques for map production is increasingly becoming the preferred choice to conventional ground survey methods. This is because it is a relatively cheap and quick method of acquiring up-to-date information over a large geographical area compared with conventional ground survey methods of mapping that is labour intensive, time consuming and are done relatively infrequently.

In Ghana, although research work has been conducted by individuals using satellite data over the past decade (Kufogbe, 1999; Braimoh, 2004; Codjoe, 2004; Asubonteng, 2007; Tutu, 2008), most institutions or firms such as Survey Department of Ministry of Land & Forestry, Soil Research Center (CSIR), Forestry Department of Ministry of Land & Forestry, Rudan Engineering Works Ltd., and Grontmij Aerosat Surveys (CTK Aviation) Ltd. employ mainly the use of aerial photographs for their mapping. Centre for Remote Sensing and Geographical Information Service (CERSGIS) however make use of satellite images in their work. In this study, Maximum Likelihood Classification (MLC), Backpropagation Neural Network Classification (BPNN) and Sub-Pixel Classification (SP) are used to classify a Landsat image of the Ejisu-Juabeng district of Ghana. The results from the three classifications were compared to determine which classification method produces the best representation of the land cover classes within the study area.

2. Study Area and Data

A subset from a Landsat ETM+ satellite imagery acquired on 16th February, 2007 (February, Level 1 B with path/row 194/55) was used for this study. On ground, it covers the upper portion of the Ejisu-Juabeng district of Ghana, which is found within Latitude 6° 15' N and 7° 00' N and Longitude 1° 15' W and 1° 45' W (Fig. 1).

The area lies in the moist semi-deciduous forest vegetation zone as categorised by Swaine and Hall (1976). It covers about twenty-three communities including Ejisu, Owne, Kwamo, Akyawkrom, Bonakra, Hwereso, Essienimpong, Kubease and part of the Bobiri Forest Reserve which serves as a tourism, research and conservation center. The off-reserve areas mainly consist of annual crops, cash crops, fallow lands, forest patches and riparian vegetation along rivers and streams and grass in abandoned areas. The level of farming is small scaled and it is scattered.

The image was geometrically corrected to the Traverse Mercator projection with War Office ellipsoid using a 1:50000 scale digital line map (Nangendo et al., 2006) of forest reserves, rivers and roads. A total of 35 ground control points (GCPs) were used and the image transformed using 2nd order polynomial and then resampled to 30m x 30m pixel size using the nearest neighbour resampling method. The resulted RMS error is 0.24 pixels corresponding to a spatial accuracy of about 7.2 m on the ground which is acceptable (Osei and Zhou, 2004; Nangendo et al., 2006; Shalaby et al., 2007).

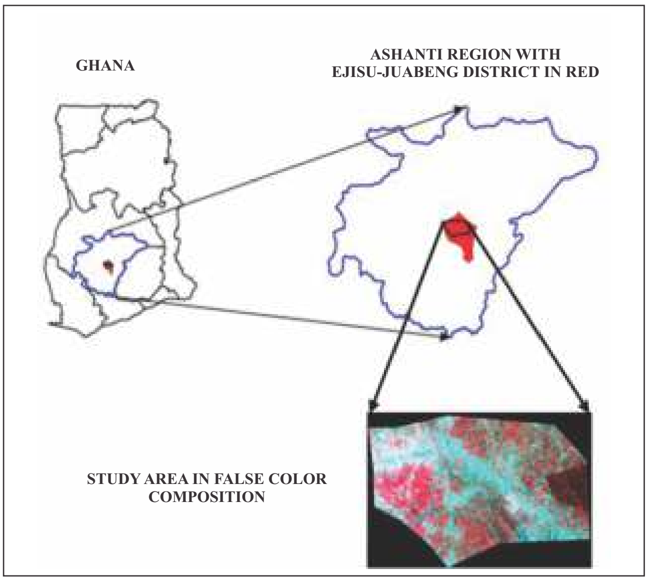


Figure 1: Location Map of Study Area

3.Image Classification

MLC is a hard classification whose decision rule is based on the probability that a pixel belongs to a particular class which assumes that the data (input bands) to be classified follows a normal (Guassian) distribution. It is one of the commonly used supervised classifications (Benediktsson *et al*., 1990).

BPNN is hard classification and one of the many types of artificial neural network. Like all artificial networks, it consists of an input layer, a hidden layer and an output layer. The units in the input layer equal the number of variables used in the classification, while the output produces the network's results that denote the various land cover classes. The hidden layer between the input and the output enables the network to model complex functions (Osei, 2003). The hidden layer is actually made up of a network of weights and bias and it is these that are applied to a set of input to produce an output. Selection of appropriate number of hidden layers and their units is, however, critical for the successful implementation of the neural network (Arora et al., 2000).

SP is a soft classification. With soft classification, the classifier tries to estimate the percentage composition of class members per pixel. Unlike in MLC and BPNN classification where the classification is done by allocating a pixel on a 'one pixel per class' basis and the land-cover classes are mutually exclusive; the allocation of the pixel is not done on 'one pixel per class' basis. Rather, each pixel is expressed as in association with other classes within the neighbourhood of the pixel. The output of a soft classification is a set of images (one per class) that express for each pixel the degree of membership in the class in question.

4.Methodology

Seven land cover classes were used for the classification. Adopting and modifying the classification scheme (level I) developed by Anderson at al. (1976), these seven classes were identified as forest, forested wetland, open woodland, water, non-forested wetland, grassland and urban. Using these land cover classes, the image was classified into three outputs by the MLC, SP and BPNN classifiers. For the BPNN classification, the network design consist of four bands of the image as input, five hidden layers and an output of seven land cover classes. The four bands (band 2, 3, 4 and 5) were so chosen because the area is made up largely vegetation, urban and water and these aided the provision of spectral variability necessary for identification and classification of the land covers. The five hidden layers for the design were chosen after running the classification process many times at increasing numbers of hidden layers comparing the output visually and also in terms of accuracy.

Three hundred and sixty five points were sampled from the field. Eighty of these points were used as training samples and the remaining 285 points for accuracy assessment of MLC. In addition, signature alarms were also simulated to act as additional guide.

In order to assess the performance of the three classification methods used, the number of pixels classified- per land cover class from each classification were compared and are given in table 1. For the SP classification, the top twenty (80% - 100% compositions) were recorded into new images and used in the comparison. The results were used to generate a table of matrix of number of pixels that were classified and the corresponding areas they cover. The matrix was then converted into a column chart.

The softwares used are – ERDAS Imagine 8.7 for MLC and SP classifications; and IDRISI (Kilimanjaro Edition) for the BPNN classification.

4.1. Accuracy Assessment

"Accuracy" measures the agreement between a standard (assumed to be correct) and a classified map. This represents the "correctness" of the classified map. If the final map corresponds closely to the standard, the classified map is thought to be "accurate" (Campbell, 1987).

A total of 285 carefully selected points of the study area are used in the accuracy assessment for the MLC classification. Stratified Random Sampling and Clustering Sampling were the sampling designs employed in the selection of the 285 points. This is because the distribution of the land cover classes is not even but rather localized. Also, the areas covered by the land cover classes differ.

One thousand two hundred and eighty six points of the study area were automatically selected from the image by the IDRSI software and used in the accuracy assessment of the BPNN classification. These were compared with the 285 points recorded from the field and available data sets of the study area and found to be satisfactory. The outcomes of the assessments (error matrices) are as presented in the tables 2 and 3.

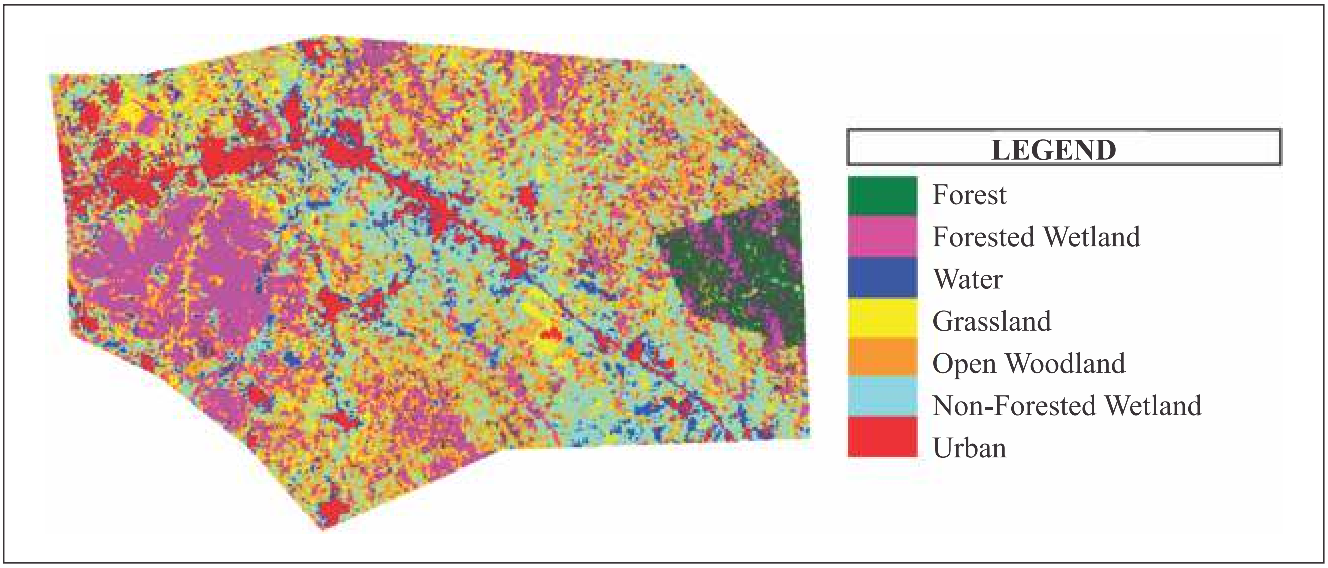


Figure 2: BPNN Classification of Landsat ETM+ 2007

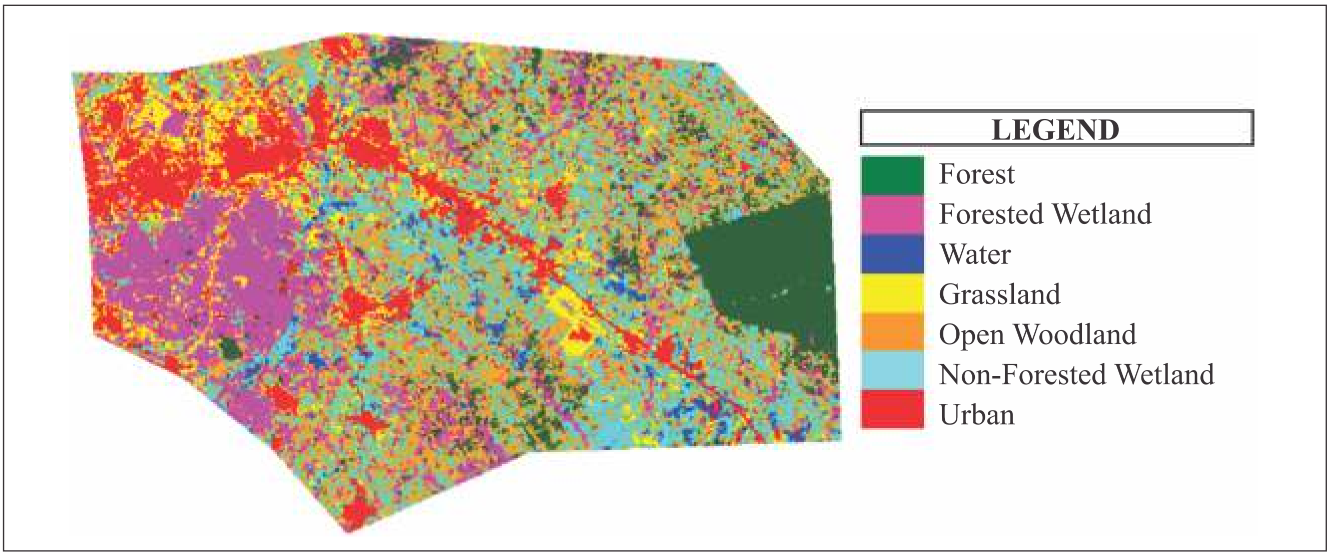


Figure 3: Maximum Likelihood Classification of Landsat ETM+ 2007

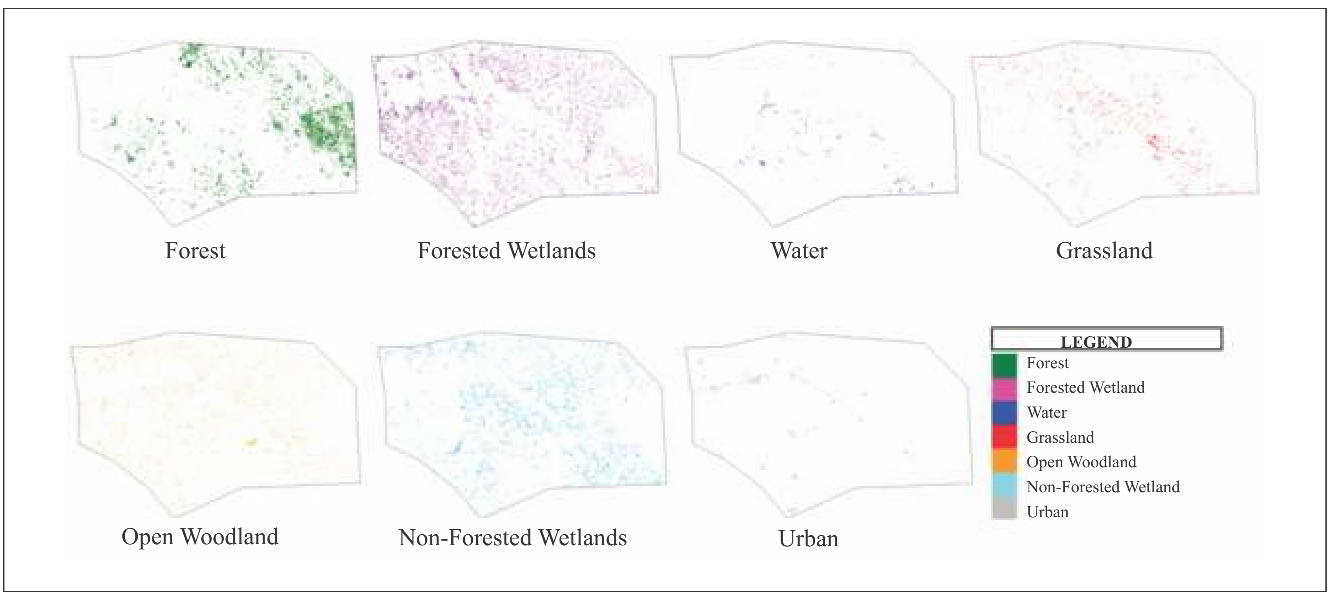


Figure 4: 80%-100% Compositions for the Sub-Pixel Classification of Landsat ETM+ 2007

The usual way of hardening soft classification outputs and comparing with crisp reference data for accuracy assessment, leads to loss of information. Therefore no accuracy assessment was done for the SP classification.

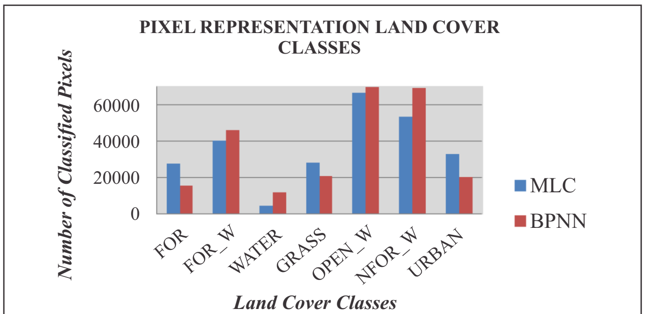
5.Results and Discussion

Classification results of the BPNN, MLC and SP is as shown in fig. 2, fig.3, and fig. 4 above respectively. The display of the SP classification is a set of sevev images (one per land cover class).

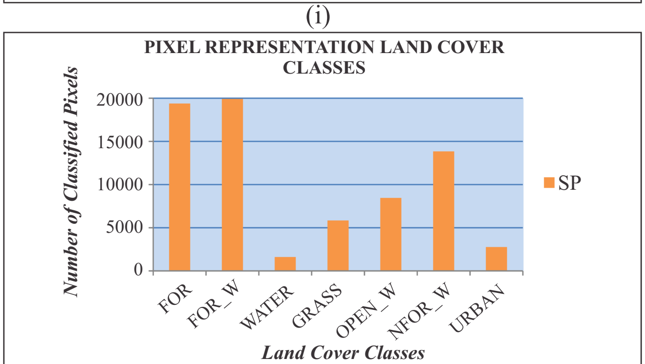
For the comparison of the results, the number of pixels per land cover as classified by each of the three classification used was entered into a matrix and these values converted into a column bar chart. This is shown in Tab. 1 and Fig. 5 respectively. It should be noted that the number of classified pixels by SP classification that is used in the matrix are the 80%-100% compositions.

Table 1:Matrix of Classified Pixel and Corresponding Area

	NUMBER OF PIXELS			AREA (hectares)		
LANDCOVER CLASS	MLC	SP	BPNN	MLC	SP	BPNN
FOR	27468	19357	15604	2472.1	1742.1	1404.4
FOR_W	40282	19911	45649	3625.4	1792.0	4108.4
WATER	4244	1598	11576	382.0	143.8	1041.8
GRASS	27840	5850	20485	2505.6	526.5	1843.7
OPEN_W	66598	8466	69433	5993.8	761.9	6249.0
NFOR_W	53149	13815	69042	4783.4	1243.4	6213.8
URBAN	32581	2762	20373	2932.3	248.6	1833.6



(i)



(ii)

Figure 5: Column Chart of Classified Pixels

A look at the column chart Fig. 5(i and ii) displays indicate that the dominant land covers within the study area are Open woodland and non-forested wetland. This is followed by the forested wetlands class. These results are clearly displayed by the two hard classifiers – MLC and BPNN. However, in all these three classes the BPNN classifier identified more pixels than the MLC classifier. (Refer to the Tab. 1).

Another significant result worth noting is that of the water land cover class. The classified number of pixels from the BPNN classification is about three times that classified under the MLC classification. This is because water is the least dominant land cover class in the study area and for parametric classifiers such as MLC, least class such as water may be under estimated while dominant classes such as open woodland or non-forested may be over estimated (Hagner and Reese, 2007).

A look again at Tab. 1 shows that of the three classifications, the SP classification was the worst. Although the SP classifier performed poorly, it had quite a high representation of pixels for the forest and forested wetland classes. This is likely so because the SP classifier is more suitable for extracting pure material specific, homogeneous in nature or for determining the percentage composition of the material in the pixel. The Forest and Forested wetland portions of the study area are generally homogeneous in nature. With the other classes such as grass or urban where the homogeneity of sampled area was, the performance of the SP classifier was poor. It must be stated that the problem of mixed pixel may have also influenced the outcome of the SP classification.

6.Conclusion

In comparison of the classifications on Landsat ETM+ image, the back propagation neural network method produced a more accurate result than the maximum likelihood method. The overall accuracy in MLC method is 78.95 % and in BPNN method is 92.50%. Also, the thematic map produced from the BPNN classification is more representative of the area of study than that derived from the MLC classification. This ascension was made at after field visits and checks of selected sites within the study area.

Sub-pixel classifiers is not suitable for classification of medium resolution satellite image such as Landsat ETM+ (30m x 30m) due to problems of mixed pixels, the homogeneity of pixels being used as signatures and the distribution of corresponding land cover class within the area of interest. Of all the three methods – MLC, SP, and BPNN; BPNN is the best method for images classification of satellite images, although the design and training of network at the initial stage of the classification is time consuming.

References

Anderson, J. R., E. E. Hardy, J. T. Roach and D. R. E. Witmer (1976). A Land Use and Land Cover Classification System for Use with Remote Sensor Data. Washington, DC. US Geological Survey.

Table 2: Error Matrix of MLC Classification

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
FOR	9	11	8	88.89%	72.73%
FOR_W	46	46	40	86.96%	86.96%
WATER	09	5	5	55.56%	100.00%
GRASS	60	59	45	75.00%	76.27%
OPEN_W	58	46	40	68.97%	86.96%
NFOR_W	54	56	42	77.78%	75.00%
URBAN	49	62	45	91.84%	72.58%
Totals	285	285	225		

Overall Classification Accuracy = 78.95%; Overall Kappa Statistics = 0.7436

Table 3: Error Matrix of BPNN Classification

	FOR	**FOR_W**	**WATER**	**GRASS**	**OPEN_W**	**NFOR_W**	**URBAN**	**Total**
FOR	381	0	0	0	0	0	0	381
FOR_W	45	212	0	0	0	0	0	257
WATER	0	0	74	0	0	8	0	82
GRASS	0	0	0	108	0	0	0	108
OPEN_W	19	6	0	0	58	0	0	83
NFOR_W	3	0	2	14	2	97	0	118
URBAN	0	0	1	0	0	0	256	257
Total	448	218	77	122	60	105	256	1286

Overall Classification Accuracy = 92.50%; Kappa Statistics = 0.9029

Arora, M.K., K.C. Tiwari and B. Mohanty (2000). Effect of Neural Network Variables on Image Classification. Asian Pacific Remote Sensing and GIS Journal, 13, 1-11.

Asubonteng, O.K. (2007). Identification of Land-use/cover Transfer Hotspots in Ejisu-Juaben District, Ghana. International Institute for Geo-information Science and Earth Observation Enschede, Netherlands.

Benediktson, J.A., P. H. Swain and O.K. Esroy (1990). Neural Network Approaches versus Statistical Methods in Classification of Multisource Remote Sensing Data. IEEE Transactions on Geoscience and Remote Sensing, 28(4), 540-552.

Braimoh, A.K. (2004). 'Seasonal Migration and Land Use Change in Ghana', Land Degradation and Development, 15(1), 37-47.

Campbell, B.J. (1987). Introduction to Remote Sensing. New York. The Guilford Press.

Campbell, B.J. (1996). Introduction to Remote Sensing (2nd Edition). Taylor and Francis, London.

Codjoe, S.N.A. (2004). Population and Land Use/Cover Dynamics in the Volta River Basin of Ghana, 1960-2010. Ecology and Development Series, No. 15. Cuvillier Verlag, Gottingen.

Hagner, O. and H. Reese (2007). A Method for Calibrated Maximum Likelihood Classification of Forest Types. Remote Sensing of Environment, 110(4), 438-444.

Kufogbe, S. K. (1999). 'A Remote Sensing Perspective on Land Use and Environmental Change in the Afram Plains of Ghana using Spot-XS Images', in P.W. K. Yankson and M. S. Rasmussen (eds). Remote Sensing and Geographic Information Systems (GIS) in Ghana: Research, Applications and Collaborations, Legon: Media Design, pp. 38-46.

Nangendo, G., A.K. Skidmore and Henk Van Oosten (2006). Mapping East African Tropical Forests and Woodlands – A Comparison of Classifiers. ISPRS Journal of Photogrammetry & Remote Sensing 61 (2007), 393-404

Osei, E.M.Jnr. (2003). Issues in Land Cover with Remote Sensing Data. Journal of Jilin University. 33, 96-104.

Osei, E. M. Jnr and Y. X. Zhou (2004). Land Cover Change Detection in West Jilin Using ETM+ Images. Journal of Geoscientific Research in N. E. Asia, 7(1), 74-84.

Sellers, P. J., B. W. Meeson, F. G. Hall, G. Asrar, R. E. Murphy, R. A. Schiffer, F. P. Bretherton, R.E. Dickinson, R.G. Ellingson, C.B. Field, K.F. Huemmrich, C.O. Justice, J.M. Melack, N.T. Roulet, D.S. Schimel and P.D. Try (1995). Remote Sensing of the Land Surface for Studies of Global Change: Models—Algorithms—Experiments. Remote Sensing of Environment, 51, pp. 3-26.

Shalaby, A. and R. Tateish (2007). Remote Sensing and GIS for Mapping and Monitoring Land Cover and Land-Use Changes in the North-western Coastal Zone of Egypt. Applied Geography, 27, pp. 28-41.

Swaine, M.D. and J.B. Hall (1976). Classification and Ecology of Closed-Canopy Forest in Ghana. The Journal of Ecology, 84(3), 419-428.

Tutu, B.D. (2008). Assessing the Effects of Land-Use/Cover Change on Ecosystem Service in Ejisu-Juaben District, Ghana: The case study of Carbon Sequestration. International Institute for Geo-information Science and Earth Observation Enschede, Netherlands and Kwame Nkrumah University of Science and Technology, Kumasi, Ghana.