

LAND COVER CLASSIFICATION AND ANALYSIS USING RADAR AND LANDSAT DATA IN NORTH CENTRAL ETHIOPIA

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ABSTRACT

Radar and Landsat data were used to classify land cover in north central Ethiopia. Both images were registered and resampled to 12.5 m spatial resolution. Maximum Likelihood Classifier (MLC) and C4.5 algorithm were applied. The original radar data produced low overall classification accuracy (66%). To improve this classification accuracy, de-speckling and texture measures were used for image enhancements. The de-speckling methods used in this study are Median, Lee-Sigma and Gamma-MAP. Lee-sigma, Gamma-MAP and Median de-speckling improved the overall accuracy by 15, 18 and 20% respectively. The maximum overall accuracy achieved in this study by de-speckling method is 86.4% using Median at 27*27. Urban producer accuracy improved by 58% by using Median de-speckling. All de-speckling techniques improved urban user accuracy to more than 90%. In most de-speckling cases, MLC outperformed C4.5 classifier in the overall classification accuracy.

The highest overall accuracies achieved by texture are 88.8 and 90.5% when MLC and C4.5 algorithms at window size 51*51 were used respectively. This shows 22% improvement compared to the original radar data. Urban and forest producer accuracy improved by 58 and 26% respectively at window size 43*43. The overall classification accuracy of Landsat data is 93.7%. Combining Landsat and derived radar data measures improved land cover accuracy by about 5%. This study showed the importance of texture and de-speckling techniques to improve a land cover classification in radar data. Therefore, radar data can be used as an alternative to optical data in the tropics and Ethiopia for land cover classification.

KEYWORDS: Radar, Landsat, Land cover, C4.5 classifier, MLC, Land use

INTRODUCTION

Ethiopia has a total area of 1,127,127 km² landmass and it is the third largest country in Africa. Located between 3.5°N and 15.5°N in the horn of Africa, Ethiopia is a tropical country. Agriculture, the mainstay of economy in Ethiopia is a source of food, raw material, foreign currency and employment. Ethiopia's agriculture is still highly dependent on rainfall, which is erratic and unpredictable. Land use change, deforestation and soil erosion are some of the current environmental problems.

According to different studies, deforestation and land use change in Ethiopia are caused due to agricultural expansion, firewood collection and logging, settlement and urbanization. A study by Gete and Hurni (2001), considered agricultural expansion as the main reason behind deforestation in Ethiopia. One of the main concerns in the land use planning issues in Ethiopia is the lack of accurate data on land use/cover. In different articles, there is variability of research results, and it is very hard to have a sound land cover or forest cover map of the country. The available research results on land use change vary depending on the type of techniques used for the study. If there is no accurate data on the rate of deforestation and land use issues, it will be hard to have an appropriate plan to tackle environmental degradation problems. "Basic information about land use/cover is important to both scientific and decision-making activities" (Haack, 2007). Such information is very limited in Ethiopia and other tropical countries.

Land cover and land use change can be studied by remote sensing techniques. For many years, Landsat data has been used to monitor land cover and deforestation in different part of the world. Optical remote sensing was widely used instrument to classify land-cover. In the tropics and my study area, image classification using optical remote sensing is difficult due to lack of good quality Landsat or other optical data. This is due to the presence of cloud cover. Most of the images are with poor quality and such poor quality data will produce poor land cover

classification results. This problem can be improved by using radar data or active sensors which are available from different sources. These active sensors are not affected by cloud cover and can be a reliable source of data for tropical areas. Recent radar data such as RADARSAT-2 and PALSAR have more than one polarization and can be used for land cover classification

Radar is an active sensor which sends energy to illuminate the earth surface and detect the back scattered portion of energy. Active sensors don't require another energy source like passive sensors. Radar can be used day or night since it is not affected by solar illumination. Radar has the ability to penetrate atmospheric conditions like fog, hail and clouds since they have longer wavelengths. Radar can help to collect data from different geographical areas of the world in the presence of adverse weather conditions (Herold et al., 2005). This data can be used to compliment or replace optical systems to map or monitor deforestation (Almeida et al., 2006). Radar data can be collected from space using RADARSAT, Shuttle Imaging Radar (SIR), the European Space Agency, and ALOS.

Radar sensors receive scattered energy from the surface feature and the amount and direction of scattering is affected due to type of material, moisture content, angle of illumination and receiving, surface roughness and geometry. One of the disadvantages of a space-borne system is the difficulty with the analysis of radar data (Herold et al, 2005). This is due to the issue of a single band and fixed polarization. However, there are good polarized data available from Japanese PALSAR and RADARSAT-2 in recent years. Another problem with radar data is the presence of speckle noise, and this has to be corrected by de-speckling. Speckle filtering algorithms removed speckles effectively in SAR images (Lee, 1981).

After applying different smoothing techniques, radar can be used to classify land cover. A study by Gaveau et al. (2003) used radar data to differentiate categories of forest classes. Radar data can separate forest patches based on the degree of structural disturbance (Saatchi et al., 2001). A similar study by Kuntz and Siegert (1999), shows that the importance of European radar Satellites (ERS-1/2) to analyze forest conversion. A primary forest and deforested areas may have different radar backscatter depending on the time of SAR acquisition (Almeida et al., 2006). This shows such difference in back scattering may help to identify areas of land cover change from forest to other land cover units. Besides this, different research studies indicate the importance of polarization and data fusing to differentiate land cover units. The effectiveness of radar for land cover classification is dependent on the radar wavelength and polarization (Haack and Bechdol, 2000). The same study shows the improvement of classification accuracy by at least 26% by texture measures compared to the original radar data. Another study by Herold et al. (2005), found that 21*21 variance texture achieved 98.1% and 94.46% producer and user forest accuracy in Kenya.

Different algorithms can be used for land cover classification. In land cover classification, Maximum Likelihood Classifier (MLC) is one of the statistical algorithms and is widely accepted as a standard approach (Emrahoglu et. al, 2003). Similarly, expert system and decision tree classifiers are also used to classify land cover. According to Friedl and Brodley(1997), remote sensing classification using decision tree techniques have advantages. There are many decision tree classifiers and among these C4.5 has been used for land use classification. C4.5 algorithm is a hierarchical decision tree builder and can handle continuous and discrete attributes.

In this research study, radar and Landsat data are used to classify land cover and analyze the accuracy results of these classified maps. Texture and de-speckling techniques were used to see the improvements to classification accuracy since the original radar data have poor land cover classification accuracy results due to speckling. Besides this, data fusing techniques were applied to compare land use/cover classification accuracy. Both Maximum Likelihood and C4.5 algorithm were applied for land cover classification in this study area. The overall objective of this study is to classify and analyze land cover classification using different data and classification algorithms.

METHODOLOGY

This study examines land cover classification and analysis using radar and Landsat data. De-speckling and texture measures using different window sizes were applied to the original radar data. ERDAS IMAGINE was used for image registration, enhancement, classification, and accuracy assessments. Maximum likelihood classifier and C4.5 decision tree techniques were used to classify both Landsat and radar data. WEKA, open source software, was used to apply a decision tree for the classification. Digital Numbers (DN) of raster images used for C4.5 classification were converted from Pixels to ASCII for decision tree classification. Image to image registration and resampling were used for both Landsat and radar data to Universal Transvers Mercator (UTM). The resampled cell size of all the images is 12.5 m spatial resolution. The analysis focuses on the impact of radar data enhancement methods on classification accuracy assessments. The de-speckling techniques used in this study are Median, Lee-

Sigma and Gamma-MAP. Equation 1 was used for Lee filter speckle suppression (Lee, 1981). Lee-Sigma assumes normal distribution and both mean and variance are used to estimate the value of the particular pixel. However, Gamma-MAP filter assumes non Gaussian distribution and it considers statistical and geometrical characteristics of the pixels.

$$DN_{out} = [Mean] + K[DN_{in} - Mean] \quad (1)$$

Where :

Mean = average of the pixels in a moving window

$$K = \frac{Var(x)}{[Mean]^2 \sigma^2 + Var(x)}$$

The variance of x [Var (x)] is defined as:

$$Var(x) = \left\{ \frac{[Variance\ within\ window] + [Mean\ within\ window]^2}{sigma^2 + 1} \right\} - [Mean\ within\ window]^2$$

Only variance texture measure using different window sizes were used in this study area. Besides this, data fusing using layer stacking was used for some data combinations. For the accuracy assessment, 12229 pixels used which are different from the training pixels used for the classification. These pixels include samples for water (3316), urban (2293), forest (3183) and agriculture (3437). For each land cover unit, two sites were selected for ground truth validation.

STUDY AREA AND DATA SOURCES

The study area is located in north-central Ethiopia. This research site includes Kombolcha, and Hayk cities in Amhara state. Kombolcha has an estimated total population of 68,766 (CSA, 2005) and it has a latitude and longitude of 11° 4' N and 39° 44' E. This city is located 363 km north of Addis Ababa. The data sources are Thematic Mapper (TM) Landsat data from USGS and PALSAR from Advanced Land observation satellite (ALOS). The spatial resolutions of Landsat and radar data are 30 and 12.5 m respectively. PALSAR radar data used in this study area has HH and HV bands. All Landsat data bands except band 6 were included in this research study.

MAXIMUM LIKELIHOOD CLASSIFICATION RESULTS

Maximum Likelihood classifier (MLC) is one of the commonly used algorithms to classify land cover. This classifier applied to the original radar and Landsat data. De-speckling and texture measures techniques were applied to the radar data, and MLC was used to classify land cover units. ML classifier also used to classify fused data and asses the land cover accuracy results.

Original Radar data

In this research PALSAR radar data with due polarization (HH and HV) was used to classify the images and analyze the accuracy assessments. The original radar image without any enhancement methods produced poor classification accuracy results for each class and overall classification (Table 1). Agriculture has relatively good producer's accuracy (78.4%) as compared to the other land cover units. Urban land cover has 85.9% user classification accuracy. In this original radar data, there is confusion between forest and urban land cover. From the 2293 urban validation pixels, 1165 were classified as forest and this shows the presence of confusion between these two classes. Urban areas have considerable tree cover. Private and public lands such as school have trees and this created a mixed spectral response. Because of this, urban areas have very low producer's accuracy (17.5%). Forest has also confusion with agriculture because there are some trees in agricultural fields. Water has 100 and 93.2% producer and user accuracy respectively, and this shows radar can identify water bodies with good classification accuracy.

Table 1. Original radar data contingency matrix.

Raw radar MLC accuracy matrix	
	Reference data

		Water	Urban	Forest	Agriculture	Total	User Accuracy in %
Classified Data	Water	3316	19	3	222	3560	93.15
	Urban	0	401	63	3	467	85.87
	Forest	0	1165	1662	516	3343	49.72
	Agriculture	0	708	1455	2696	4859	55.48
Total		3316	2293	3183	3437	12229	
Producer Accuracy in %		100.00	17.49	52.21	78.44		
Overall Classification Accuracy							66.03%
Overall Kappa Statistics							0.54

Speckle Filtering

Speckle suppression is a technique used to suppress noise available in radar data. De-speckling normalizes the pixel value caused by any noise. To reduce these speckles, different filters can be applied using different window sizes. There are many de-speckling techniques; in this analysis only three de-speckling methods were used using different kernel size. These are Median, Lee-Sigma and Gamma Map methods of speckle suppression. Different window sizes were used to see the impact of kernel size on accuracy assessments in each de-speckling method used to enhance the radar image. In all de-speckling methods used using different window size, there is no difference in the water's classification accuracy result. Water has unique spectral response or Digital Number (DN) compared to the others and this may contribute to good classification accuracy (100%).

Lee-sigma, Gamma Map and Median de-speckling techniques improved the overall classification accuracy by about 15, 18 and 20% respectively at window size 27. This shows overall accuracy improvement to more than 81% by using de-speckling. Increasing the window size beyond 27 by 27 did not increase the overall accuracy result. The maximum overall accuracy achieved in this study area is 86.4 % when Median at 27 by 27 window size is used. Lee-sigma produced the lowest percentage increase in overall classification accuracy as compared to Median and Gamma-map. The overall kappa statistics for median at 27* 27 window size is 0.82.

Urban producer accuracy improved by 58% by using Median de-speckling at 27*27 kernel size. Gamma Map and Lee-sigma at 27 by 27 kernel size also improved urban producer accuracy by 53 and 33% respectively. Similarly, Median, Gamma Map and Lee-Sigma at 27 by 27 windows improved the producer accuracy of forest by 38, 36 and 33% respectively. Agriculture's producer accuracy improved by only 5% when Lee-Sigma at 27 by 27 window size used. Increasing window size beyond 19 decreased the accuracy of agriculture when Median and Gamma Map techniques used because of the forest and agriculture confusion at larger window size. Median de-speckling results the best urban producer accuracy in all the kernel sizes used. Lee-sigma produced the lowest urban producer accuracy (49%). However, Lee-sigma gives the best agriculture producer accuracy in all window sizes. Overall classification and individual accuracy are dependent on the type of de-speckling techniques used. Figure 1 shows the classification accuracy of each de-speckling at different window sizes. Figure 2 indicated the presence of some misclassification between the land cover units.

Median de-speckling with window size greater than 19 by 19 improved user's accuracy to 100%. Overall, all de-speckling techniques improved urban user's accuracy to more than 90%. Agriculture and forest's user classification accuracy improved by 45 and 17% respectively when Median at 27 window size is applied. Only forest user's accuracy is below 90% when median de-speckling at 27 kernel size is used. Such classification accuracy improvement shows the importance of de-speckling for radar data to be used for the land cover map.

Table 2. Median Speckle 27*27 classification accuracy matrix.

Kombolcha Median Speckle 27 MLC accuracy matrix						
	Reference data					
	Water	Urban	Forest	Agriculture	Total	User Accuracy in %
Water	3316	0	0	0	3316	100.00

Urban	0	1728	0	0	1728	100.00
Forest	0	565	2893	808	4266	67.82
Agriculture	0	0	290	2629	2919	90.07
Total	3316	2293	3183	3437	12229	
Producer Accuracy in %	100.00	75.36	90.89	76.49		
Overall Classification Accuracy						86.40%
Overall Kappa Statistics						0.82

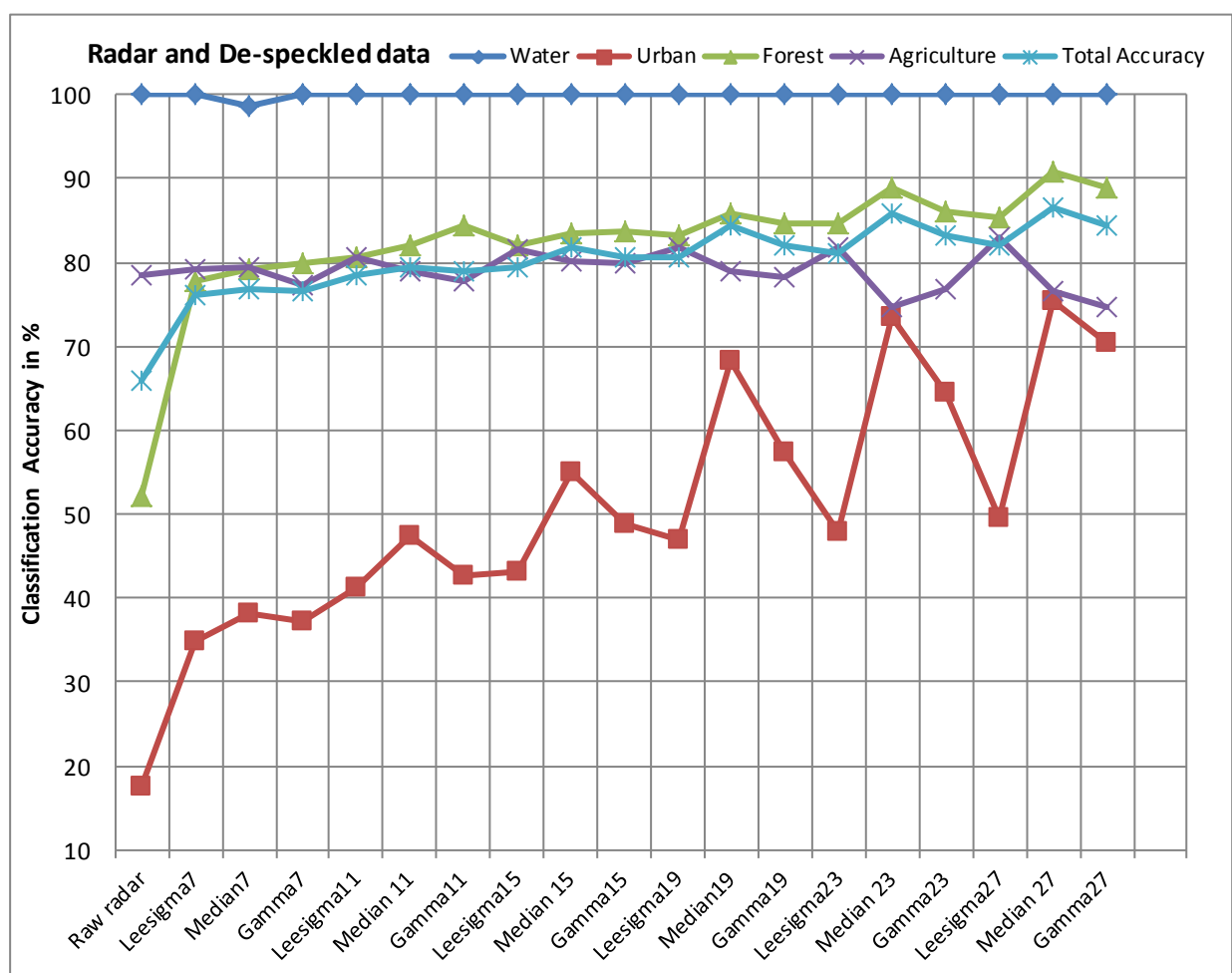


Figure 1. Original radar and de-speckled radar data classification accuracy in percentage.

Texture

Texture enhancement to improve classification accuracy can be done using mean, variance, skewness and kurtosis algorithms. Only variance texture measure is used in this study area to see the impact of this enhancement on the overall classification accuracy and accuracy of each land cover units. Variance measures the variability of Digital Number (DN) and it is helpful to distinguish classes with similar average DN values. The highest overall accuracy result (88.8%) is achieved using window size 51 by 51 in this research site. This shows 22% improvement as compared to the original radar data overall accuracy result. Beyond 51*51 window size, the overall accuracy decreases because of the confusion between urban and forest land cover. The overall kappa statistics at this window size is 0.85 and it is greater than the kappa statistics achieved by de-speckling techniques used in this study area.

The impact of texture on accuracy varies from one land cover to another. Urban and forest producer's accuracy improved by 58 and 26% respectively at window size 43 by 43. Increasing window size increased the accuracy of

agriculture by 21% as compared to the original radar data. For window sizes greater than 50, agriculture's producer accuracy is almost 100%. However, increasing window size beyond 43 increases the confusion between urban, and forest land covers. Because of this, for both land cover units, the maximum producer's accuracy is achieved at this window size. This may be due to the small proportion of forest and urban area as compared to agriculture in the study area. Increasing window size will increase the chance for these two land cover units to be mixed. Water and urban user accuracy improved to 100% after using 15 by 15 and 11 by 11 windows respectively. The maximum user accuracy (78%) of forest is at window size 51, and this is a 28% improvement compared to the original radar data.

Table 3.Texture 51 by 51 accuracy matrix.

Kombolcha Texture 51 MLC accuracy matrix						
	Reference data					User Accuracy in %
	Water	Urban	Forest	Agriculture	Total	
Water	3316	0	0	0	3316	100.00
Urban	0	1622	0	0	1622	100.00
Forest	0	671	2503	22	3196	78.32
Agriculture	0	0	680	3415	4095	83.39
Total	3316	2293	3183	3437	12229	
Producers Accuracy in %	100.00	70.74	78.64	99.36		
Overall Classification Accuracy						88.8%
Overall Kappa Statistics						0.85

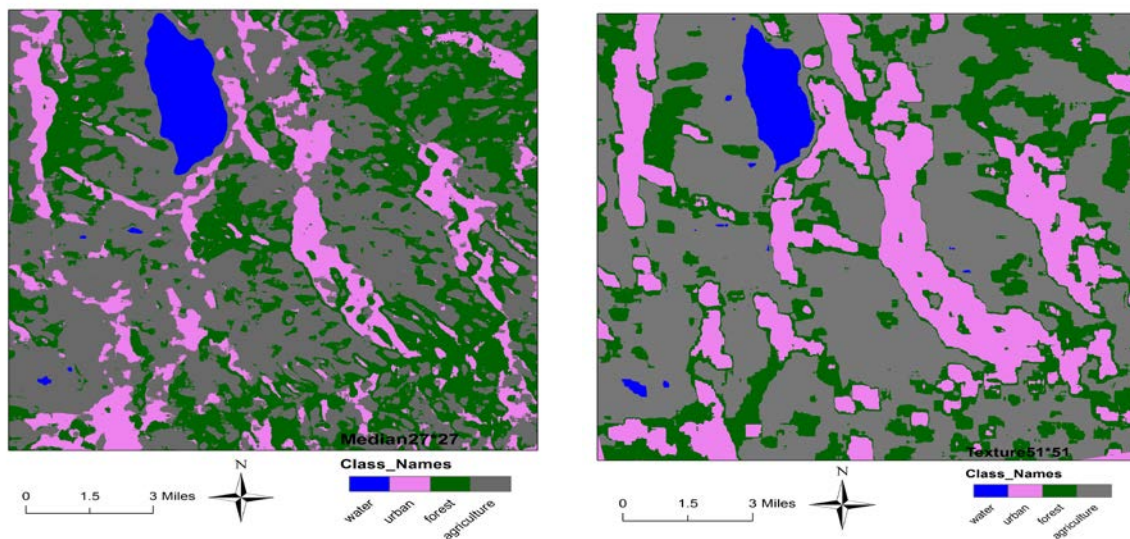


Figure 2. Median 27*27 de-speckled and variance Texture 51*51 classified images.

Landsat

Landsat data is used to compare the classification accuracy with radar and other data used in this study. Landsat data produced 93.7% overall classification accuracy. Agriculture has the lowest producer accuracy because of some confusion with urban pixels. Urban also have the lowest user accuracy due to the addition of agriculture pixels. Water has 100% producer and user accuracy and this shows no confusion with other land cover units. Some forest pixels also classified as urban and agriculture. Landsat data produced 0.92 overall kappa statistics.

Table 4. Landsat Maximum Likelihood classifier accuracy matrix.

Landsat data MLC accuracy matrix						
	Reference data					
	Water	Urban	Forest	Agriculture	Total	User Accuracy in %
Water	3316	0	0	0	3316	100.00
Urban	0	2264	92	483	2839	79.75
Forest	0	0	2980	52	3032	98.28
Agriculture	0	29	111	2902	3042	95.40
Total	3316	2293	3183	3437	12229	
Producers Accuracy in %	100.00	98.74	93.62	84.43		
Overall Classification Accuracy						93.70%
Overall Kappa Statistics						0.92

Data Fusion

Combining two data sources may help to improve land cover classification accuracy. In this site the original radar data is fused with the best texture and de-speckled radar data. In both cases the classification accuracy improvement is very low. This indicates, adding raw radar data to the texture or de-speckled radar data did not improve classification accuracy in this research site. Landsat data fused with a texture at window size 35 by 35 has improved classification accuracy by 5%. Similarly, median 15 by 15 de-speckled radar data has improved accuracy by 3% when it is combined with Landsat data. Adding raw radar data to Landsat data also produced 3% overall classification accuracy improvement.

Agriculture's producer accuracy has improved by 15% when Landsat data is fused with a texture at 35 window size. Similarly, median de-speckling at window size 15 has improved agriculture's producer accuracy by 8% when it is fused with Landsat data. Besides this, urban user's accuracy has improved by 20 and 7% by fusing Landsat data with texture 35 and median 15 respectively. The original radar data fused with Landsat data resulted with 7% improvement in agriculture producer accuracy. Besides this, urban user accuracy also improved by 9% by fusing original radar with Landsat data. Even if the overall classification accuracy improvement is low, fusing has improved agriculture producer and urban user accuracy.

Table 5. Landsat and Texture 35 accuracy matrix.

Landsat and texture 35 MLC accuracy matrix						
	Reference data					
	Water	Urban	Forest	Agriculture	Total	User Accuracy in %
Water	3316	0	0	0	3316	100.00
Urban	0	2269	0	2	2271	99.91
Forest	0	2	3025	18	3045	99.34
Agriculture	0	22	158	3417	3597	95.00
Total	3316	2293	3183	3437	12229	
Producers Accuracy in %	100.00	98.95	95.04	99.42		
Overall Classification Accuracy						98.4%
Overall Kappa Statistics						0.98

C4.5 ALGORITHM CLASSIFICATION RESULTS

C4.5 algorithm was applied to both radar and Landsat data to compare land cover classification accuracy. For this classifier, an open source software WEKA data mining was used and in this software C4.5 is called J48. Both training and test samples were converted from a pixel to weka data format for the classification.

Original radar data

The original radar data produced 67% overall land cover classification accuracy. This is similar to the overall classification accuracy achieved by Maximum Likelihood classifier (MLC). Water has 91.4% user and 100 % producer classification accuracy assessment in C4.5 algorithm. Urban producer accuracy showed about 20% improvement in a decision tree as compared to MLC. However, C4.5 classifier produced 16% lower agriculture's producer accuracy compared to MLC. Similarly, urban user accuracy in C4.5 is 30% lower than user accuracy achieved by MLC. This shows more forest and agriculture pixels are misclassified as urban in C4.5 classifier.

Table 6. Original radar data C4.5 accuracy matrix.

Kombolcha Raw radar C4.5 accuracy matrix						
	Classified data				Total	Producer Accuracy in %
	Water	Urban	Forest	Agriculture		
Water	3316	0	0	0	3316	100.0
Urban	26	891	940	436	2293	38.9
Forest	23	460	1893	807	3183	59.5
Agriculture	264	284	751	2138	3437	62.2
Total	3629	1635	3584	3381	12229	
User Accuracy in %	91.4	54.5	52.8	63.2		
Overall Accuracy					67.4%	
Kappa statistics					0.56	

Speckle Filtering

After de-speckling techniques applied to the original radar data, C4.5 algorithm used to classify the images. The overall land cover classification accuracy achieved in de-speckling is 83.3% when median at 27 window size was applied. This is 3% lower than the accuracy produced by MLC classifier. Both classifiers produced similar urban producer accuracy. However, agriculture producer accuracy improved by 14% when C4.5 was used. On the other hand, forest producer accuracy is 25% lower than the producer accuracy achieved by MLC classifier. In the decision tree classifier, more forest pixels were classified as urban and agriculture.

The maximum urban user accuracy achieved in C4.5 is 81.8%. This is 18% lower than the accuracy produced by MLC. The forest user accuracy is similar in both classifiers. However, agriculture user accuracy is 10% more in MLC as compared to the user accuracy achieved by decision tree. Water user and producer accuracy is the same (100%) in both classifiers.

Table 7. Median 27*27 C4.5 accuracy matrix.

Kombolcha Median27 C4.5 matrix						
	Water	Urban	Forest	Agriculture	Total	Producer Accuracy in %
Water	3316	0	0	0	3316	100.0
Urban	0	1677	616	0	2293	73.1
Forest	0	322	2092	769	3183	65.7
Agriculture	0	52	279	3106	3437	90.4
Total	3316	2051	2987	3875	12229	
User Accuracy in %	100.0	81.8	70.0	80.2		
Overall accuracy					83.3%	
Kappa statistic					0.78	

Texture

Variance texture was applied to the radar images and decision tree algorithm was used to classify and assess the accuracy assessments. The overall land cover accuracy achieved using texture is 90.5% and this is 2% improvement from the MLC classifier. C4.5 classifier also improved urban producer accuracy by 14% as compared to MLC. Forest and agriculture producer accuracy is similar in both classifiers. On the other hand, C4.5 improved forest user accuracy by 7%. Comparing these two classifiers, the significant difference is in the accuracy of individual land cover units. Figure 3 shows the accuracy assessment of each measure when C4.5 and MLC was applied.

Table 8. Texture 51*51 C4.5 accuracy matrix.

Kombolcha Texture 51*51 C4.5 accuracy matrix						
	Classified data				Total	Producers Accuracy in %
	Water	Urban	Forest	Agriculture		
Water	3316	0	0	0	3316	100.0
Urban	0	1938	355	0	2293	84.5
Forest	0	9	2457	717	3183	77.2
Agriculture	20	0	66	3351	3437	97.5
Total	3336	1947	2878	4068	12229	
User Accuracy in %	100.0	99.5	85.4	82.4		
Overall Accuracy					90.5%	
Kappa statistics					0.87	

Landsat

Six bands of Landsat data were used to classify land cover in this study area by C4.5 algorithm. The overall classification accuracy produced by a decision tree is 85.1%, and this total accuracy is 8% lower than MLC classifier. Agriculture and urban has the lowest producer (54%) and user (66.1%) accuracy respectively in C4.5 algorithm. There is confusion among forest, urban and agriculture land covers. Agricultural pixels are misclassified as forest and urban. The forest user accuracy is 12% lower in C4.5 classifier as compared to MLC algorithm.

Table 9. Landsat data C4.5 accuracy matrix.

Kombolcha C4.5 Landsat accuracy matrix						
	Water	Urban	Forest	Agriculture	Total	producers Accuracy in %
Water	3316	0	0	0	3316	100.0
Urban	0	2227	4	62	2293	97.1
Forest	25	13	3013	132	3183	94.7
Agriculture	0	1127	455	1855	3437	54.0
Total	3341	3367	3472	2049	12229	
User Accuracy in %	100.0	66.1	86.8	90.5		
Overall Accuracy					85.1%	
Kappa statistic					0.8	

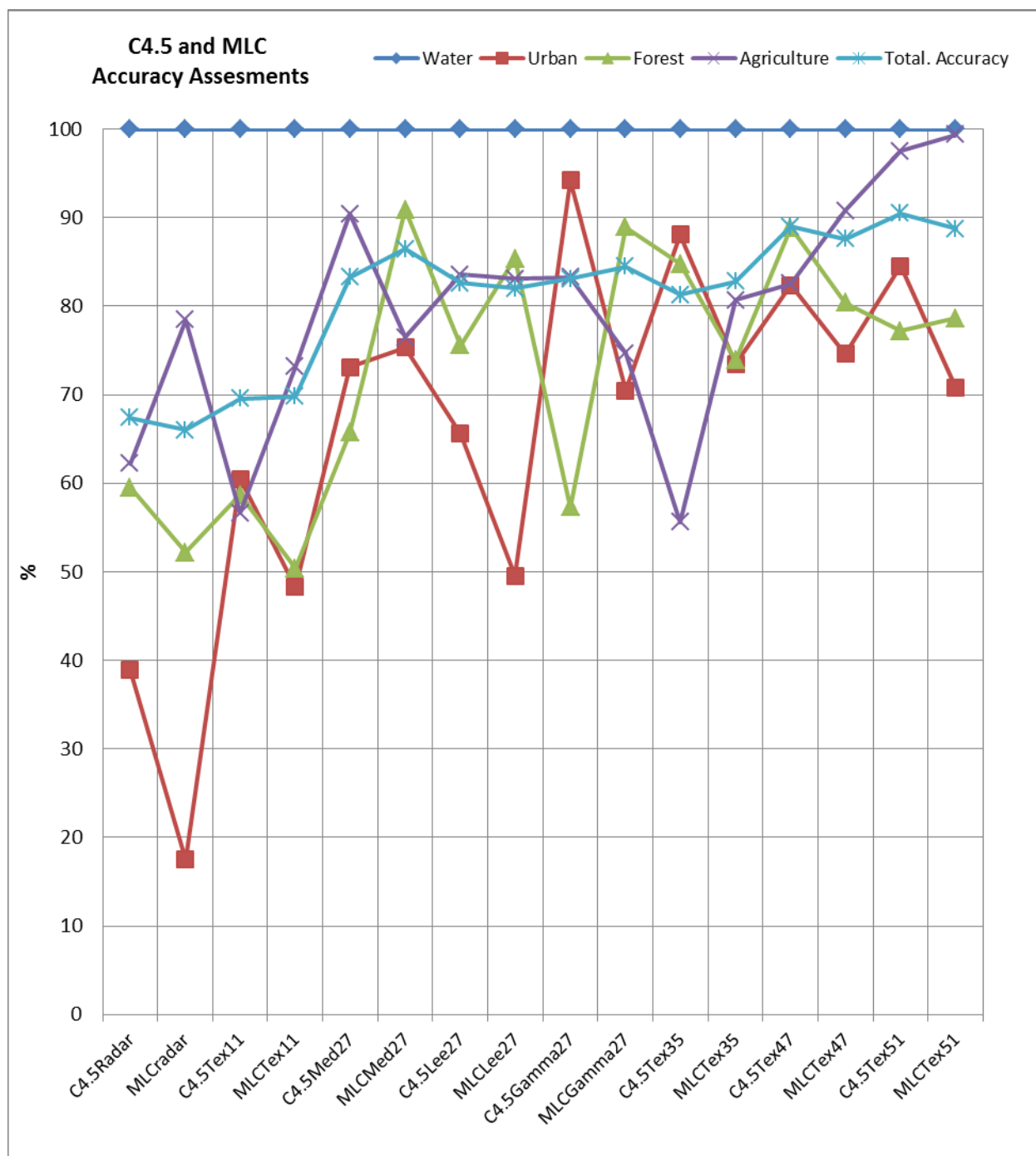


Figure 3. C4.5 and MLC classification accuracy comparison.

CONCLUSION

Land use/cover map is very important for land use planning, and it is very hard to obtain a good land use/cover map in the tropics and Ethiopia. For many years, the only source of remote sensing data was Landsat and other optical data. Those data sources are very limited, and it is hard to find good quality optical remote sensing data for the tropics due to cloud cover. Radar data or active sensors can improve the problems with data shortage in those areas. Nonetheless, the original radar data produced very low overall classification accuracy due to the presence of speckle or noise. The findings of this research study underscored that the importance of de-speckling and texture measures for land cover classification. In most cases, MLC classifier achieved better overall classification accuracy compared to C4.5 when de-speckling was applied.

The best classification accuracy achieved using de-speckling techniques is when median was applied at a window size 27. At this window size, all de-speckling methods used in this study produced more than 81% overall classification accuracy. For urban and forest producer accuracy, median de-speckling techniques gave the best classification accuracy. Agriculture producer accuracy is highest when Lee-sigma speckle suppression was applied. However, Gamma-Map gave the highest agriculture user accuracy. Overall, increasing window size beyond 27 decreases the overall and individual land cover accuracy in de-speckling filtering.

Texture also produced very good land cover classification accuracy 88.8 and 90.5% when MLC and C4.5 classification algorithm were applied respectively. Texture measures produced good accuracy at larger window size as compared to de-speckling. Using a window size above 43 increased the confusion between urban and forest pixels. Data fusing has produced small overall land cover classification accuracy improvements compared to Landsat data alone. However, Agriculture's producer accuracy has improved by 15 and 8% respectively when Landsat data is fused with texture at 35 window sizes and median de-speckling at window size 15. Besides this, urban user's accuracy has improved by 20 and 7% by fusing Landsat data with texture 35 and median 15 respectively. The original radar data fused with Landsat data resulted with 7% improvement in agriculture producer accuracy. Besides this, urban user accuracy also improved by 9% by fusing original radar with Landsat data. Even if the overall classification accuracy improvement is low, fusing has improved agriculture producer and urban user accuracy.

C4.5 algorithm achieved the best urban producer accuracy in most cases as compared to MLC classification. Agriculture's producer accuracy is higher when MLC was used in most de-speckling. On the other hand, C4.5 classifier produced the best agriculture's producer accuracy when texture measure was applied to enhance the image. This shows that the land cover classification results were dependent on the type of classification algorithm and image enhancement methods used.

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