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Land Use Classification and Analysis Using Radar Data Mining in Ethiopia

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Abstract Land use classification in tropical areas, is hindered by frequent cloud cover which limits the availability of optical satellite data. Satellite-borne radar is a possible alternative to optical data for land use classification in tropical areas. However, radar data is affected by noise (i.e., speckle) that must be minimized before its use in land classification. Median, Lee-Sigma, and Gamma-MAP de-speckling techniques were applied to Fine Beam, Dual polarization (FBD) PALSAR radar data acquired over central Ethiopia. Each of the de-speckled images were then subjected to supervised classification using Maximum Likelihood, C4.5, Multilayer Perceptron and Stacking techniques. Validation results indicated that de-speckling techniques improved classification accuracy by up to 25%, 20% and 16% using Gamma-MAP, Median and Lee-Sigma respectively. Gamma-MAP de-speckling in combination with the Multilayer perceptron classifier achieved the best overall classification accuracy at 91.2%. This study proved the importance of radar data as an alternative source of information for land use classification in the tropics. Further research should focus on the application of radar data for forest fire detection and crop classification. The use of fully polarized radar data has the potential to further improve the proposed land use classification in tropical countries.
Keywords *PALSAR; Speckle; C4.5; Multilayer Perceptron; Maximum Likelihood; Algorithms*

1. Introduction

Land use changes such as deforestation are recognized as a key component of global change (Patz et al., 2004; Soria-Ruiz et al., 2010). The major driving factors for deforestation are agricultural expansion and urbanization (DeFries et al., 2010). “The global rate of tropical deforestation continues at staggering levels, with nearly 2–3% of forests lost globally each year” (Patz et al., 2004). As a consequence, land use change, land degradation, and poverty are increasingly impacting many countries in Africa. Therefore, it is crucial to accurately assess land use and deforestation. Remote sensing plays a fundamental role in determining land coverage changes in areas where direct in-situ observations are sparse or not available at all. This research focuses on land use classification and analysis using radar data, and different techniques of classification and data processing techniques in Ethiopia.

Radar is an active sensor which sends energy to illuminate the earth surface and to detect the portion of back scattered energy. Radar sensors receive scattered energy from the surface feature and the amount and direction of scattering is affected by the type of material, moisture content, angle of illumination and angle of backscatter retrieval, surface roughness and surface geometry. The presence of noise or speckle in radar images is a source of uncertainty in the retrieved data. Radar sensors produce microwaves and these waves may create dark or light pixels when the wave comes in contact with the target (Noreiga and Fabian, 2000). This is due to the coherent nature of the radar wave (Jenson, 2005), which may create an artificial heterogeneity for a homogeneous region. Speckle affects image classification and interpretation (Nyoungui et al., 2002). Therefore, it is crucial to reduce speckle noise before radar data is used in classification studies (Maghsoudi et al., 2012). Different speckle reduction techniques such as median can be used to preserve image sharpness and detail. De-speckling techniques use a moving window with a size defined by the user. The mean filter is the least effective method of speckle reduction; it is useful only for applications where loss of spatial resolution is not a problem (ERDAS, 1999). The Sigma and Lee filters utilize the statistical distribution of the digital numbers (DN) values within the moving window. According to a study by Capstick and Harries (2001), Lee-Sigma, and Gamma-MAP produced the best results for identifying agricultural crops. Median filter produced the best result in speckle reduction and in detail preservation (Qiu et al., 2004). The three de-speckling techniques evaluated for land use classification in Ethiopia were median, Lee-Sigma, and Gamma-MAP.

After pre-processing, image classification algorithms are commonly applied to compile land cover maps. The most widely adopted parametric classification method is the maximum likelihood algorithm. Supervised maximum likelihood classification (MLC) is the most popular statistical classification algorithm (Emrahoglu et al., 2003) and is usually preferred unless there are particular reasons for believing that data do not follow a Gaussian distribution (Pal and Mather, 2003). Most applications of MLC method assume that each class has an equal probability of occurring in the study area and has a multivariate normal distribution. However, this assumption may not be true for remote sensing images. Therefore, C4.5, Multilayer Perceptron and Stacking classification methods were also included in this study.

C4.5 is a non-parametric classification method. It is an extension of the Iterative Dichotomiser 3 (ID3) algorithm (Chandra and Paul, 2007). C4.5 is a decision tree approach used for classification in which the classification procedure recursively partitions a data set into smaller subdivisions on the basis of a set of tests defined at each branch or node (Friedl and Brodley, 1997). In a decision tree, the hypothesis, rules, and conditions may be considered as the trunk, a limb, and a leaf of a tree, respectively (Jensen, 2005). It is possible to see the stages of classification at each branch. Decision trees yield a set of rules which are easy to interpret and suitable for deriving a physical understanding of the classification process (DeFries and Chan, 2000). In decision tree, a minimum error or entropy is used as a threshold to select each class (Kumar et al., 2010).

Multilayer Perceptron (MLP) is an Artificial Neural Networks (ANN) which can be used for land use classification. The input layer may include images of reflectance, texture, slope, etc. Neural networks use less statistical assumptions than maximum likelihood algorithms and makes no prior assumptions of normal distribution A research study by Yuan et al. (2009), recommends that in complex land use mapping applications, supervised MLP networks may be used to derive detailed and more accurate image classification. The difficulties in conventional classification can be improved using Neural Network (NN) (Kumar et al., 2010). According to Idol et al. (2015), classification algorithms such as NN are important for radar data classification. Therefore, in this study in Ethiopia, MLP was applied to classify land use and compare its classification accuracy results to that of MLC and C4.5 decision tree classifiers. Besides this, MLP and C4.5 were combined using Stacking method to classify the images. Stacking is a method of combining multiple classifiers. The objective of the study is to produce land cover maps using different techniques of image enhancement and classification techniques in central Ethiopia.

2. Study Area and Data Sources

2.1. Study Area

Ethiopia has a total area of 1,127,127 km^2, and it is the third largest country in Africa. Agriculture is the main economic sector and the majority of the population lives in rural areas. Extensive dependence on traditional agriculture has resulted in over-exploitation and natural resources degradation for centuries (Getu and Hurni 2001; Bewket, 2002; Darbyshire et al., 2003). Unsustainable agricultural practices have exposed the country to rapid deforestion, soil erosion, and biodiversity loss, among other issues. A study by Dessie and Kleman (2007) shows that during the past half-century, the total forest cover has decreased from 16% in 1972 to 2.8% in 2000 in the south central rift valley region of Ethiopia. Badege (2001) showed rapid decline of forest cover in the country over the last 100 years, which is due to many factors. A recent study in northern Ethiopia has shown that forest disturbance and excessive utilization of forest products for fuel wood had a significant effects on tree species composition and diversity (Berhane et al., 2015). Inappropriate land management policies, based on poor land use information enhance desertification and loss of agrobiodiversity (Taddese, 2001).

The study area is located in Kombolcha, central Ethiopia. The study area was selected based on the history of land use changes in the region and availability of radar data. The study area has experienced substantial land cover changes since early last century (Tekle and Hedlund, 2000).The agro-ecology of the research area in Amhara regions is “*Weyna Dega*” (midlands) and the temperature ranges from 15^{o}C to 25^{o}C depending on topographic elevation. Weyna Dega is one of the traditional agro-climatic zone in Ethiopia. The main rainy season is from July to September and the average annual rainfall is 866.25 mm (*Desse* station). The major cities in the research study are Kombolcha (11^o 4’N and 39^o 44’E) and Haik. Kombolcha has an estimated total population of 68,766 (CSA, 2005). The administrative *weredas* included in this site are Bati, Desie Zure, Werebabu, Tehuledere, and Kombolcha. The main economic sectors in Kombolcha study area are agriculture, livestock, and industry.

2.2. Data Sources

This study investigated the possibility of retrieving information on land use and land cover from satellite-based radar data. Specifically, this study used data collected by Phased Array type L-band Synthetic Aperture Radar (PALSAR) board of the Advanced Land Observation Satellite (ALOS). ALOS was launched on January 24, 2006 by Japan Aerospace Exploration Agency. PALSAR is an L-band (wavelength of 23.62 cm) active microwave sensor for day and night data collection with spatial resolution of 12.5 m at ground. Fine Beam Dual Polarization (FBD) with HH and HV bands was used. HH is Horizontal, Horizontal Polarization, whereas, HV is Horizontal, Vertical Polarization. The radar image used for this study is PALSAR from 02/06/2008. Figure 1 shows the PALSAR radar image and study area location in Ethiopia.

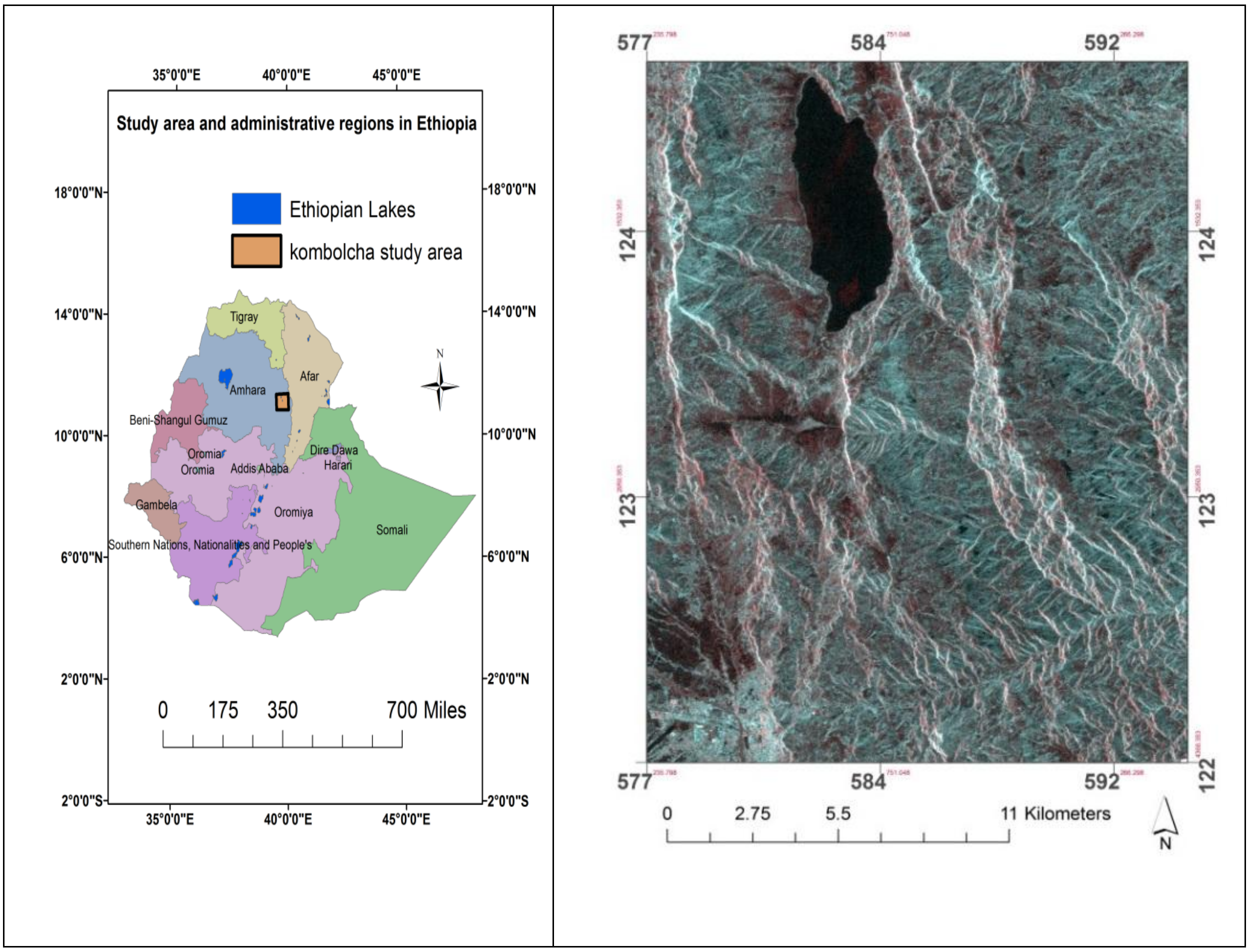


__Figure 1:__ Study area in central Ethiopia and PALSAR data from June 02, 2008 (HH and HV)

3. Methodology

The objective of this study was to analyze the impact of different de-speckling and classification techniques on land use classification. The specific objectives are the following:

A) To determine which de-speckling approach produces the best input radar images for land use classification, and

B) To analyze which combination of de-speckling and supervised classification approaches produces an accurate land cover classification.

The steps of this study include: i) remote sensing image collection, ii) data collection, iii) image enhancement, iv) land use classification, and v) accuracy assessment and analysis.

3.1. Data Processing and Analysis

The original radar data were converted to GeoTIFF data format using Mapready software (2.3) from the Alaska Satellite facility. The data was projected to universal transverse marcetor projection. Then, image enhancement methods were applied in order to observe the impacts of these techniques on land use classification accuracy. All image enhancement techniques were applied using a moving window of different sizes. The window size ranged from 7 ×7 to 27 × 27. Window size determines the number of pixels to be included in each statistical analysis. The image enhancement methods adopted in this study were Median, Lee-Sigma and Gamma-MAP de-speckling filters. Median filter replaces the pixel of interest by the median digital value (DN) with in the window. Lee-Sigma assumes normal distribution and both mean and variance are used to estimate the value of the particular pixel. The formula used to calculate the DN value for the Lee filter is shown in the following set of equations (ERDAS, 1999):-

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

where Mean is the average of the pixels in a moving window. K is defined by the following equation:

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

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

$$Var(x) = \left\{\frac{[Variance\ within\ window] + [Mean\ within\ window]^2}{sigma^2 + 1}\right\} - [Mean\ within\ window]^2 \quad (3)$$

The Maximum A Posteriori (MAP) filter assumes non-Gaussian distribution and it considers statistical and geometrical characteristics of the pixels. Gamma-MAP filter estimates the original pixel DN and maximums the posterior density function (ERDAS, 1999).

$$\hat{I}^3 – I\,\hat{I}^2 – \sigma\,(\hat{I} + – DN) = 0 \quad (4)$$

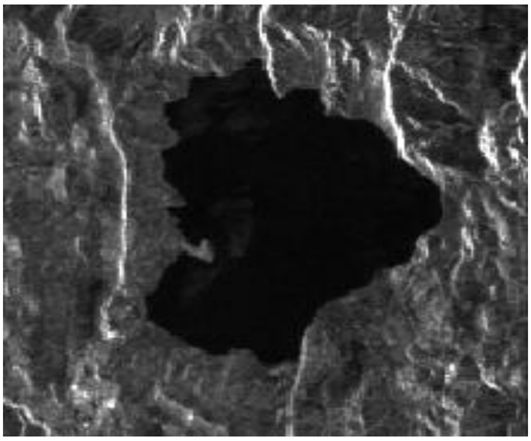
where IÎ is sought value, I is mean value, DN is input value, and σ is original image variance

Figure 2 shows unfiltered and de-speckled radar data images from the Kombolcha study area using those de-speckling techniques. Applying these filters increases the visual separation of the land cover units. Increasing window size increases the separability of land cover units after Median; Lee-Sigma and Gamma-MAP filters are applied.

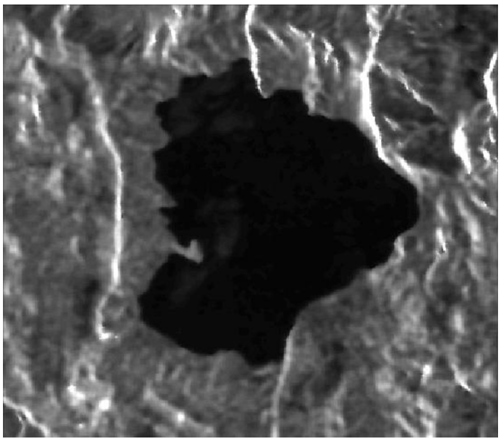
3.2. Land use classification and accuracy assessment

3.2.1. Land use classification

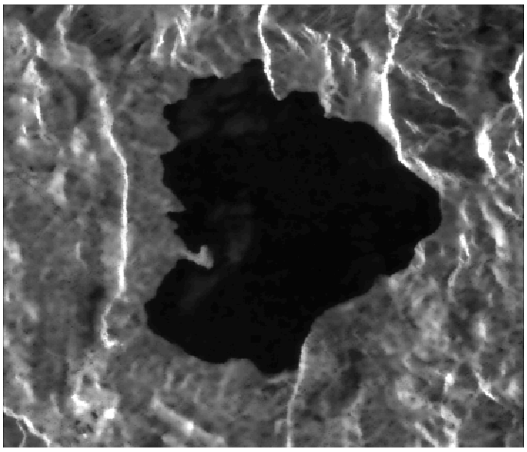
Supervised image classification was used for this study. This classification method requires prior knowledge of the available land covers. Therefore, all primary and secondary data were collected for calibration and validation purposes. The land covers considered were forest, agriculture, water and urban. A representative signature or area of interest identification (AOI) was used to train and calibrate the classification algorithm. The statistical values of these training samples were evaluated using transformed divergence. Four classification algorithms were applied after pre-processing:- Maximum Likelihood (MLC), C4.5 (decision tree), Multilayer Perceptron (MLP) and a combination of classifiers or Stacking. The open source software, WEKA was used for Multilayer Perceptron (MLP), C4.5 decision tree and stacking classification. All training and validation pixels were exported from ERDAS to WEKA for C4.5, Multilayer Perceptron and Stacking classification methods.



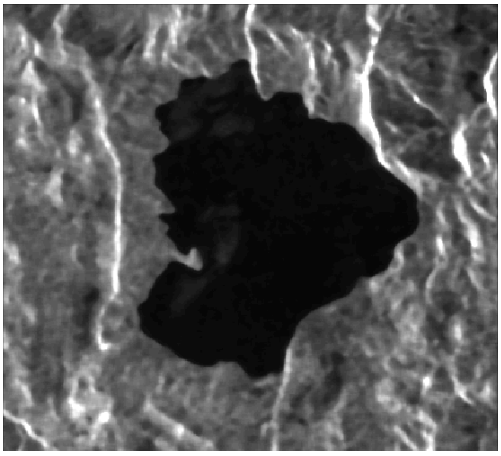
Unfiltered radar data



Gamma-MAP 11X11



Lee-sigma 11X11



Median11X11

Figure 2: *Unfiltered and de-speckled radar images using Gamma, Lee-sigma and Median at 11×11 windows*

The Maximum likelihood classification considers both mean and variability of brightness values in each class and estimates the probability of each pixel to be assigned to the individual class (Campbell, 2002). It is a parametric classifier and that assumes normally distributed data. The equation for the maximum likelihood classifier is as follows:

$$\boldsymbol{D = \ln(ac) - [0.5 \ln(|Covc|)] - [0.5\,(X\text{-}Mc)T\,(Covc\text{-}1)\,(X\text{-}Mc)]} \quad (5)$$

where *D* is weighted distance (likelihood), *c* is a particular class, *X* is the measurement vector of the candidate pixel, *Mc* is the mean vector of the sample of class *c*, *ac* is percent probability that any candidate pixel is a member of class *c* (defaults to 1.0, or is entered from *a priori* knowledge), *Covc* is the covariance matrix of the pixels in the sample of class *c*, |*Covc*| is the determinant of *Covc*, *Covc-1* is the inverse of *Covc*, ln is natural logarithm function, and *T* is transposition function (ERDAS, 1999).

C4.5 is one of the ways to represent decision tree classification. It divides the data step by step using the available bands or criteria to assign to each node (Figure 3). C4.5 removes unnecessary nodes using pruning. Decision tree computes threshold value using nearest neighbor algorithm to assign to each arc (Pinho et al., 2008). C4.5 algorithm uses gain ratio to select the splitting attribute (Chandra and Paul, 2007).

$$Gain\ Ratio\,(S,A) = \frac{Gain\ (S,A)}{SplitInfo\ (S,A)} \tag{6}$$

where SplitInfo (S, A) is the information due to the split of S on the bases of values attribute of A. Gain (S, A) is the information of example set of S on attribute A (Chandra and Paul, 2007). Figure 3 shows how a land cover such as water, urban class is classified at each node or tree.

Multilayer Perceptron is based on Artificial Neural Networks (ANN) and it contains an input layer, one or more hidden layers, and an output layer (Jensen, 2005). The input layer receives such data as image pixels, DEM, and others. The hidden layer or "brain" of the multilayer perceptron calculates and produces an output. The MLP output is analyzed with the known classes provided during training. Multilayer Perceptron makes no prior assumptions of normal distribution. The MLP equation for forward computation is the following.

$$Vj^{(l)} = \sum_{i=0}^{p} Wji^{(l)}\,(n) Yi^{(l-1)}(n) \tag{7}$$

where $Yi^{(l-1)}(n)$ is the function signal for neutron i in the previous layer and $Wji^{(l-1)}(n)$ is the weight of neutron j in the layer l (Kumar et al., 2010)

```
B2 <= 38
|  B1 <= 10: W (2118.0/13.0)
|  B1 > 10
|  |  B2 <= 27
|  |  |  B1 <= 11
|  |  |  |  B2 <= 16: A (160.0/5.0)
|  |  |  |  B2 > 16
|  |  |  |  |  B2 <= 17: A (60.0/19.0)
|  |  |  |  |  B2 > 17
|  |  |  |  |  |  B2 <= 18: W (24.0/5.0)
|  |  |  |  |  |  B2 > 18: A (21.0/5.0)
|  |  |  B1 > 11
|  |  |  |  B1 <= 17: A (6308.0/36.0)
|  |  |  |  B1 > 17
|  |  |  |  |  B1 <= 20: A (406.0/31.0)
|  |  |  |  |  B1 > 20: U (6.0)
|  |  B2 > 27
|  |  |  B1 <= 17
|  |  |  |  B2 <= 29
|  |  |  |  |  B1 <= 13: F (32.0)
|  |  |  |  |  B1 > 13: A (67.0/1.0)
|  |  |  |  B2 > 29: F (1462.0)
```

Figure 3: *Structure of C4.5 decision tree*

Stacking combines multiple classification algorithms using a single data set. According to Breiman (1996), stacked regressions is a method for forming linear combinations of different classifiers. The classifiers are divided into base-level and meta-level classifiers (Chen et al., 2009). After each base-level classifier predicts a probability distribution over the possible class value, meta-level classifier combines the obtained predictions (Todorovsci et al., 2003).

$$Pc(x) = ((Pc(c_1|x),\ Pc(c_2|x), \ldots\ Pc(c_k|x)) \tag{8}$$

where (c_1, c_2… c_k) is a set of possible class values, and $Pc(c_1|x)$ is the probability that x belongs to class c_j.

According to Steele (2000), combining substantially different classifiers are most useful for classification. For this research in Ethiopia, MLP and C4.5 are relatively different and were combined using stacking regression. The impact of such classifier combination was evaluated.

3.2.2. Accuracy assessment

Land use classification errors may result from image processing errors, registration errors and from spectral inseparability between classes. Classification error is the assignment of a pixel belonging to one category to another category during the classification process (Campbell, 2002). A map requires unbiased representation of the land cover in order to be considered as accurate (Foody, 2002). Accuracy assessment plays a fundamental role in making effective decisions based on maps generated from remote sensing data (Plourde and Congalton, 2003). Therefore, ground truth data collected from field using GPS, satellite images and other sources such as land use map were used to analyze the accuracy of each classification. For this study, two polygon validation sites for each land cover were used. A contingency table was used to analyze producer, user and overall accuracy of the digital classification applied. Besides, a Kappa analysis was also included. Kappa analysis is a measure of the difference between the observed agreement between two maps and the agreement that might be attained solely by chance matching of the two maps (Campbell, 2002). Therefore, this research analyzed kappa coefficient of agreement, overall accuracy, producer, and consumer accuracy. According to Congalton (1991), the equation for KHAT statistic which is an estimate of Kappa analysis can be calculated as:

$$\mathrm{KHAT} = \frac{\sum_{i=0}^{r} Xii - \sum_{i=0}^{r}(Xia \cdot Xib)}{N^2 - \sum_{i=0}^{r}(Xia \cdot Xib)} \quad (9)$$

where r is the number of rows in the matrix; Xii is the number of observation in row i and column I; Xia and Xib are the marginal total of row i and column i, respectively; and N is the total number of observation.

4. Results

In total, 12,229 pixels were used to validate the land cover classification accuracy. These pixels include a sample for water (3,316), urban (2,293), forest (3,183) and agriculture (3,437). The following section presents the classification results for Maximum Likelihood, C4.5, Multilayer Perceptron and Stacking (C4.5 and MLP). The results of each classification algorithms were compared to the original radar data. In addition, classification accuracies were compared among the classification algorithms applied.

4.1. Maximum Likelihood Classifier (MLC)

The original radar image without any enhancement methods produced 66% overall classification accuracy using MLC. The maximum overall accuracy achieved using Median de-speckling and Maximum Likelihood classifier is 86.4% (Table 1). In all de-speckling methods, there is no difference in water classification accuracy because the digital value of water is very different compared to the other land covers. Lee-sigma, Gamma-MAP and Median de-speckling techniques improved the overall classification accuracy by about 15%, 18% and 20% respectively using window size 27 × 27. This shows overall accuracy improvement to more than 80% by using de-speckling. Increasing window size beyond 27 ×27 did not increase the overall accuracy result. Lee-sigma produced the lowest percentage increase in overall classification accuracy compared to Median and Gamma-MAP. This may be related to the normal distribution assumption in Lee-sigma. The overall kappa statistic for Median de-speckling at 27 × 27 window size is 0.82. This is almost 30% increase compared to the unfiltered radar (Figure 5). Overall, these de-speckling techniques have improved the separability of these land cover units.

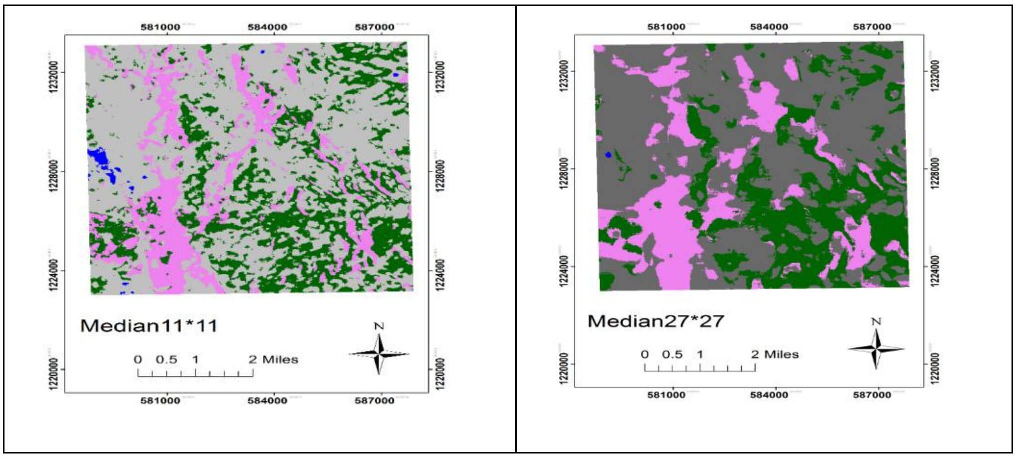
Urban producer accuracy improved by 58% using Median de-speckling at 27 × 27 window size. Gamma-MAP and Lee-sigma at 27 kernel size also improved urban producer accuracy by 53% and 33% respectively. Similarly, Median, Gamma-MAP and Lee-Sigma at 27 × 27 windows improved the producer accuracy for forest by 38%, 36% and 33% respectively. Agriculture's producer accuracy improved by 5% using Lee-Sigma at this window size. Increasing window size beyond 19*19 decreased the accuracy of agriculture when other filters were used. Median de-speckling produced the best urban producer accuracy in all the window sizes used. Lee-sigma produced the lowest urban producer accuracy (49%). However, Lee-sigma achieved the best agriculture producer accuracy in all window sizes. Besides this, Lee-sigma is the best filter to identify the tree cover within urban land use (Figure 4).

These results indicate that classification accuracy is dependent on the de-speckling technique. Median de-speckling produced 100% urban user accuracy beyond 19 × 19 window size.

Overall, all de-speckling techniques improved urban user accuracy to more than 90%. User classification accuracy for agriculture and forest improved by 45% and 17%, respectively when Median filtering was applied. Only forest user accuracy was below 90% when Median de-speckling at a 27 × 27 window size was applied. Such classification accuracy improvement shows the importance of radar data de-speckling techniques for land use mapping. All de-speckling techniques in this study improved both the overall classification and individual land cover accuracies. Smaller window sizes were best for identifying forest patches within the cities (Figure 4). Increasing window size reduced the forest cover within the city.

Table 1: *Land use classification accuracy matrix using Median de-speckled data at 27 × 27 window size*

	Reference data					
	Water	Urban	Forest	Agriculture	Total	User A. (%)
Water	**3316**	0	0	0	3316	100.0
Urban	0	**1728**	0	0	1728	100.0
Forest	0	565	**2893**	808	4266	67.8
Agriculture	0	0	290	**2629**	2919	90.1
Total	3316	2293	3183	3437	12229	
Producer A. (%)	100.0	75.4	90.9	76.5		
					Overall Accuracy	**86.4%**
					Overall Kappa Statistics	**0.8**



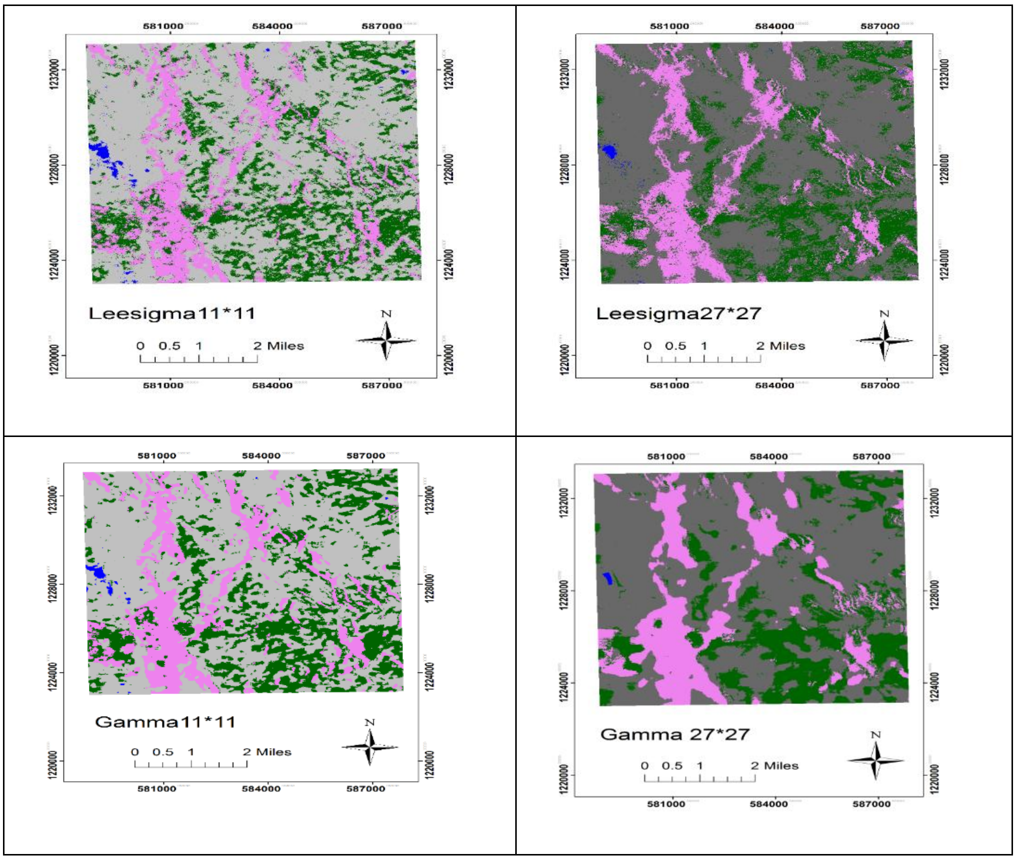


Figure 4: *Land use map using Gamma-MAP, Lee-sigma and Median de-speckling (Urban, pink; Forest, green; Agriculture, grey, and Water, blue)*

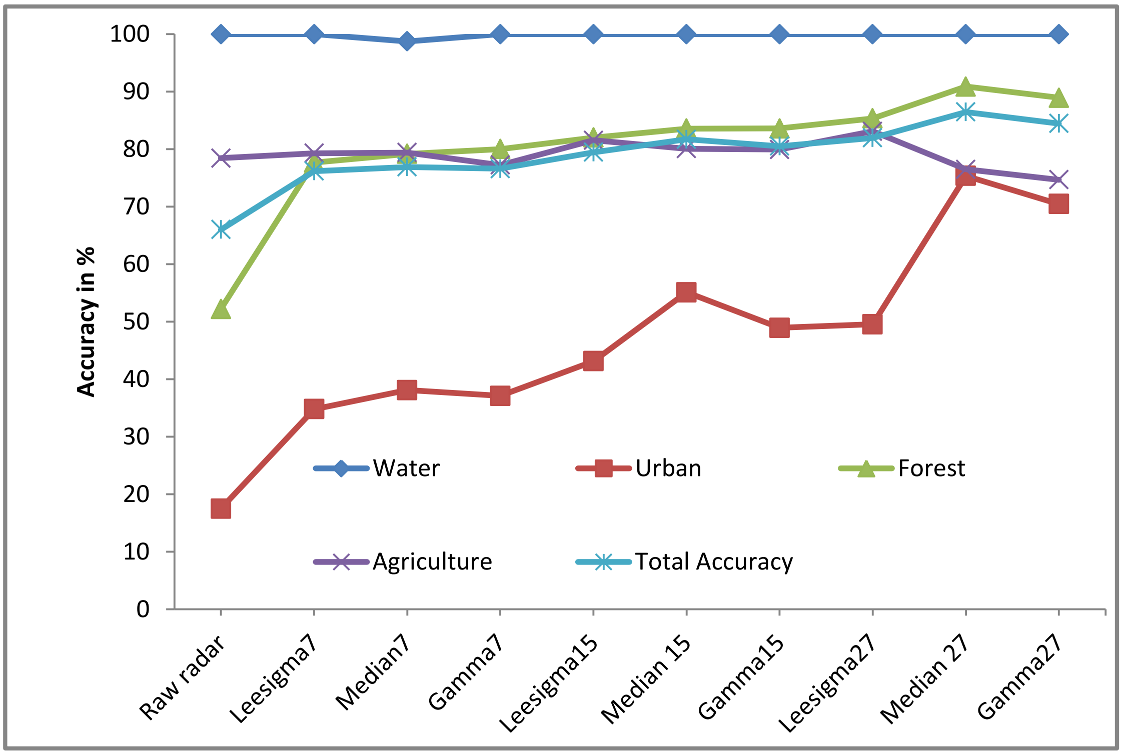


Figure 5: *Original radar and de-speckled image classification accuracy*

4.2. C4.5- Decision tree classifier

The maximum overall land cover classification accuracy achieved using C4.5 classifier and Median de-speckling is 83.3% at a 27 $\times$ 27 window size (Table 2). This is 3% lower than the classification accuracy produced by the MLC classifier. The maximum overall classification accuracy at 27 $\times$ 27 window size using Lee-Sigma and Gamma-MAP is 82.6% and 83.1% respectively. All the de-speckling techniques used in this study produced more or less the same overall accuracy assessments. However, these speckling suppression methods have different user and producer classification accuracy results. Such variability in classification accuracy indicates the importance of trying different classification algorithm.

Gamma-MAP achieved 94.2% urban producer accuracy using decision tree. This was 30% and 20% higher classification accuracy than the accuracy achieved by Lee-Sigma and Median de-speckling respectively. In all window sizes, Lee-sigma achieved the lowest urban producer accuracy. However, the maximum forest producer accuracy (75%) achieved by the C4.5 classifier was accomplished using Lee-Sigma. Median achieved 90.4% agriculture producer classification accuracy. This agriculture's producer accuracy was 7% greater than Lee-sigma and Gamma-MAP's agriculture producer accuracy. Both classification algorithms (C4.5 and MLC) produced similar urban producer accuracy. However, agriculture producer accuracy improved by 14% when C4.5 was applied. On the other hand, forest producer accuracy is 25% lower than the producer accuracy achieved by MLC classifier (Figure 6). In the C4.5 decision tree classifier, more forest pixels were classified as urban and agriculture compared to the MLC classifier.

Median de-speckling at 27 $\times$ 27 window size produced 81.8% urban user accuracy. It was about 11% and 18% higher than the user accuracy result of Lee-Sigma and Gamma-MAP respectively. At this window size, forest has more or less similar user accuracy by all the de-speckling techniques. However, Gamma-MAP produced the highest agriculture user accuracy; and it was 15% and 10% higher than the user accuracies obtained by Median and Lee-Sigma respectively. The maximum urban user accuracy achieved in C4.5 is 18% lower than the accuracy produced by MLC. Forest user accuracy is similar in both classifiers. However, agriculture user accuracy is 10% more in MLC compared to the user accuracy achieved by decision tree. Water user and producer accuracy is the same (100%) in both classifiers at this window size. The maximum kappa coefficient achieved by C4.5 and MLC is 0.78 and 0.82, respectively, when Median at window 27 $\times$ 27 was applied.

4.3. Multilayer Perceptron classifier (MLP)

Multilayer Perceptron produced the highest overall classification accuracy (91.2%) using Gamma-MAP in this study site. In all de-speckled radar data, MLP classifier achieved the best overall classification accuracy. The overall classification accuracy using Median and Lee-sigma was 87.3% and 83.5%, respectively (Table 2). This overall accuracy is greater than the classification accuracy produced by both MLC and C4.5 (Figure 5). MLP also achieved the highest overall classification accuracy at all window sizes. MLP achieved the highest forest producer accuracy (91.9%) using Gamma-MAP (Table 2). Agriculture had the highest producer accuracy in MLP classifier using Lee-sigma filtering. Urban producer accuracy improved by 21% when MLP was applied compared to MLC. However, Multilayer perceptron's urban producer accuracy is 2% lower than C4.5 urban producer accuracy. The overall kappa statistic achieved by MLP is 0.88. This is 5% and 10% improvement compared to MLC and C4.5 classifiers, respectively. Table 2 presents the land use confusion matrices for the best overall classification accuracy achieved using C4.5, MLP and Stacking algorithms.

Table 2: *Classification matrices for de-speckled radar data using C4.5, MLP, and Stacking at 27 × 27 window size*

Methods	Classified Image					Producer A. (%)
	Water	Urban	Forest	Agri	Total	
C4.5 & Median						
Water	**3316**	0	0	0	3316	100.0
Urban	0	**1677**	616	0	2293	73.1
Forest	0	322	**2092**	769	3183	65.7
Agri	0	52	279	**3106**	3437	90.4
Total	3316	2051	2987	3875	12229	
User A.	100	81.8	70.0	80.2		
Overall accuracy and Kappa statistics, 83.3%, 0.78						
MLP & Gamma						
Water	**3316**	0	0	0	3316	100
Urban	0	**2110**	183	0	2293	92
Forest	0	94	**2926**	163	3183	91.9
Agri	0	0	631	**2806**	3437	81.6
Total	3316	2204	3740	2969	12229	
User A.	100	95.7	78.2	94.5		
Overall accuracy and Kappa statistics, 91.20%, 0.88						
Stacking &Gamma						
Water	**3316**	0	0	0	3316	100
Urban	0	**2098**	195	0	2293	91.5
Forest	0	192	**2784**	207	3183	87.5
Agri	0	0	546	**2891**	3437	84.1
Total	3316	2290	3525	3098	12229	
User A.	100	91.6	79	93.3		
Overall accuracy and Kappa statistics, 90.70%, 0.87						

4.4. Stacking (C4.5 and MLP)

Stacking C4.5 and MLP classifiers improved the overall classification accuracy by 2% using Gamma-MAP at 7 × 7 window size. The other combinations did not improve the overall classification in this study site. Combining C4.5 and MLP produced 90.7% overall classification accuracy using Gamma-MAP filtering and this is lower than the overall accuracy achieved using MLP alone. Using this de-speckling and combining the two classifiers, only agriculture's producer accuracy improved, and only by 1%. However, both urban and forest producer accuracies decreased, and this affected the overall classification accuracy. The overall kappa statistic is 0.87 in stacking, which is 1% lower than MLP kappa statistic. The maximum classification accuracies achieved using Median and Lee-sigma are 85.1% and 84.1%, respectively, in Stacking method of classification (Figure 6).

5. Conclusion and Discussion

The main aim of this research was to evaluate and compare the performance of classification and radar data filtering techniques. The original radar data without any filtering process produced less valid overall classification accuracy. Therefore, applying enhancement and filtering processes to remove speckle or noise is essential. All image enhancement techniques used in this study produced some significant classification accuracy improvements compared to the original radar data. However, classification accuracy improvements of these image enhancement techniques depend on the type of classification algorithms applied. In this study, the overall and individual land cover classification has improved by applying different filtering techniques.

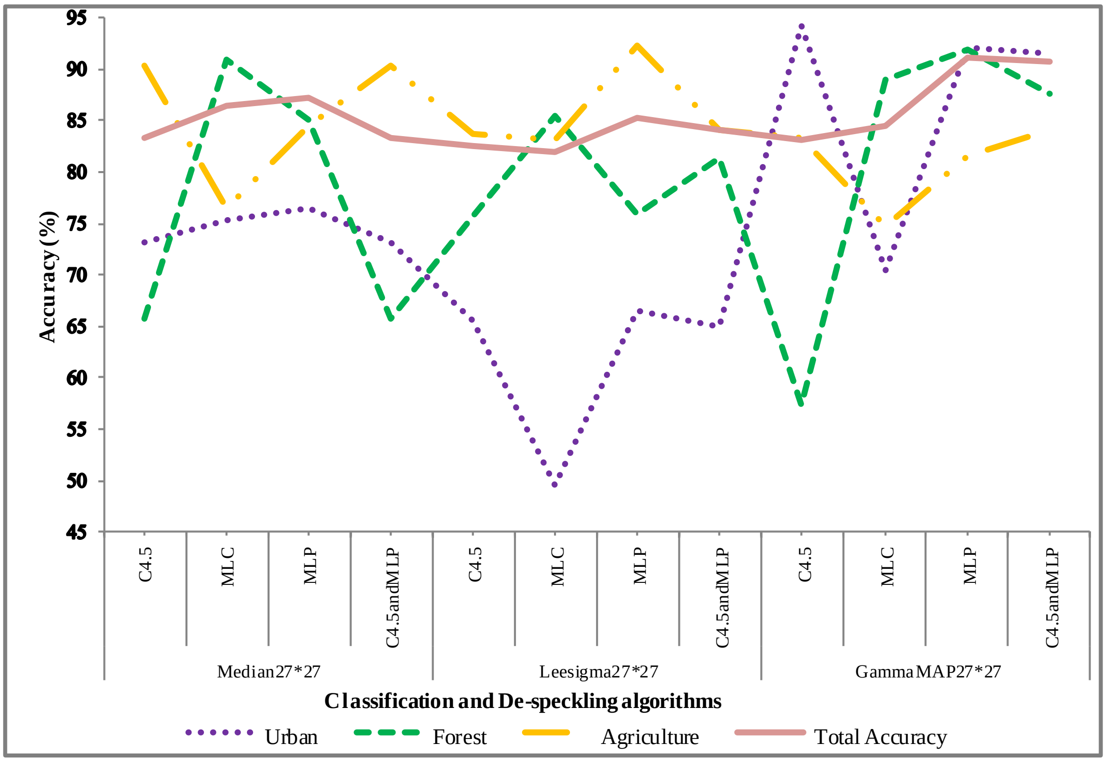


Figure 6: Land use classification accuracy using different speckle filtering and classification algorithms (MLC, C4.5, MLP and stacking)

The highest and the lowest overall classification accuracies in this study were 91.2% and 82.1%, respectively. The highest urban producer accuracy (94%) achieved in Kombolcha was obtained using C4.5 classifier and Gamma-Map de-speckling (Figure 6). However, MLC and Lee-sigma produced the lowest urban producer accuracy (49%) at the 27 × 27 window size. MLP achieved the maximum forest (91%) and agriculture (92%) producer accuracy using Gamma-MAP and Lee-sigma de-speckling respectively. C4.5 and MLC achieved the lowest forest and agriculture producer accuracies, respectively. Overall, the results were dependent on each combination of classifier and filtering techniques applied. The best result in this study was achieved using Gamma-MAP de-speckling and Multilayer perceptron classifier. However, Qiu et al. (2004) found Median filter the best result in speckle reduction.

Enhancement techniques, data source, and classification algorithms have important impacts on the reliability of a given land cover classification map. Therefore, it is very important to apply different combinations of image enhancement techniques and classification algorithms to achieve the best results. Overall, this research study demonstrated that the importance of radar data as an alternative source of remote sensing data for land cover classification and carbon sequestration quantification in Ethiopia and other tropical areas. Past studies have also demonstrated the importance of satellites radars for monitoring and estimating forest change, as well as for flooding detection and quantification and land cover classification (Kuntz and Siegert, 1999; Saatchi et al., 2000; Gaveau et al., 2003). Ethiopia, with inadequately studied physical features, can greatly benefit from the use of radar-based data analysis for its development, land use and environmental plans. The remote sensing data gaps caused by cloud cover and other factors can be filled by radar data in different parts of the world. Further research on the application of radar data for crop classification and forest fire detection may be useful. Besides this, additional research on polarization, post classification filtering, texture, data fusing and other data mining techniques may be important to further analyze radar data applications.

5.1. Comparison among different de-speckling techniques

All the de-speckling techniques used in this research study improved the classification accuracy. Speckle algorithms can produce satisfactory results when used properly (Nyoungui et al., 2002).The overall classification accuracy improvement using Gamma-MAP 27 $\times$ 27 was 25% higher compared to unfiltered radar data (Table 2). The other filtering techniques, Median and Lee-sigma also improved the overall classification by 20% and 17% respectively. In this study area, Lee-sigma de-speckling achieved the lowest overall classification accuracy. Lee-Sigma assumes normal distribution among the land cover units and this may lead to the lower overall classification compared to the other speckle filtering techniques. Overall, increasing window size from 7 $\times$ 7 to 27 $\times$ 27 increased the overall classification accuracy. However, increasing window size beyond 27 did not improve the overall accuracy. This may be due to the fact that de-speckling may also degrade the digital number of each pixel which has an impact on land use classification when increased beyond an ideal size.

The impacts of these speckling techniques on producer and user accuracy of each land cover units were different. The significant effect of de-speckling techniques was on urban producer and use accuracy. The validation results emphasized the importance of image enhancement methods on radar data for better land use classification. Without these image noise filtering techniques, the classification results achieved by the original PALSAR radar data would be less useful for policy decisions. Besides this, the classification accuracy result of each data sources was also dependent on type of filtering applied. Such improvements in the overall classification accuracy showed that PALSAR radar data can provide an enormous potential to study land cover, deforestation, and crop classification in tropical areas where optical data collection is restricted due to cloud cover.

5.2. Comparison among different classification algorithms

This study also analyzed the effectiveness of factoring in the different classification algorithms. The highest classification accuracy achieved by MLC, C4.5, MLP and Stacking were 86.4%, 83.3%, 91.2% and 90.7%, respectively (Table 1 and 2). Such overall classification is good and very important for tropical areas. Where cloud cover limits the availability of optical data, 78% overall accuracy using radar data is very useful (Idol et al., 2015). This study by fur demonstrated above 85% overall classification accuracy. The stacking method also improved the overall classification accuracy by 2% using a smaller window size (7 $\times$ 7). Overall, different machine learning techniques have contributed to varied but improved classification accuracy. The results achieved using different classifiers were, however, comparable. This indicated that other data mining techniques can be effectively used for land use classification in addition to the Maximum Likelihood classifier. Yuan et al. (2009) also recommends supervised MLP. However, Multilayer Perceptron, C4.5 and Stacking methods require more time to prepare and classify the data than Maximum Likelihood classifier (MLC). This study has indicated that the classification accuracy improvements may be dependent on the type of classification and filtering algorithms applied. Overall, Multilayer perceptron achieved the best classification in this study and further research should apply in to other study areas. In conclusion, landscapes are not homogenous, and different combinations of classifiers and pre-processing techniques will achieve the best results.

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