# Assessment of urban land cover classification using Wishart and Support Vector Machine (SVM) based on different decomposition parameters of fully-polarimetric SAR

LamyaaGamal El-deenTaha
Aviation and Aerial Photography Division, National Authority of Remote Sensing and Space Science, Cairo, Egypt
Email: Lamyaa@narss.sci.eg

(Received: Dec 20, 2016; in final form: Mar 20, 2017)

**Abstract:** Urban land cover mapping is one of the most important remote sensing applications. In this research, various polarimetric SAR parameters derived from fully-polarimetric SAR were explored for urban land cover mapping. The optimization of features is an important step for improving classification accuracy. First, radiometric correction of RADARSAT-2 Single Look Complex (SLC) product data has been performed using PolSARpro5. Two speckle filters (refined Lee and sigma Lee) were selected to be tested in RADARSAT-2 for elimination of noise and smoothing of the SAR images. It was found that sigma Lee filter is better than refined Lee filter with kernel size 5*5. Secondly, geometric correction was performed. The RADARSAT-2 was primarily geometrically corrected using ASF map ready tool in PolSARpro5 software for geocoding. Then second order polynomial based on fifteen well-distributed DGPS points was performed using ENVI 5 software. After that polarimetric decomposition parameters of RADARSAT-2 fully polarimetric SAR image was extracted from polarimetric decomposition techniques like Cloude-Pottier and Yamaguchi 4 components. Preprocessing of RADARSAT-2 data was achieved using PolSARpro5. In the present paper two classification methods, namely, Wishart and Support Vector Machine (SVM), were used for classification based on Cloude-Pottier and Yamaguchi's decompositions and combination of both decompositions. Three processing schemes were proposed based on decomposition parameters and were fed to Wishart and SVM algorithms. A comparison between these three schemes has been carried out and their usefulness in classifying urban land cover type was explored. It was found that SVM is better than Wishart classifier for classification of fully polarimetric synthetic aperture radar data. When applying the classification scheme based on each theorem separately, Yamaguchi's 4 components decomposition gave higher classification accuracy than ''H/A/α' components. The 7 parameter combination gives superior results than applying each theorem separately. Results show that SVM method discriminated each class better than Wishart supervised classification method did, especially for identifying the urban area. In the Wishart supervised classification based on 7parameters, the user's accuracy of the built-up area is very poor (54.73 %). In SVM classification based on 7 parameters, the user's accuracy of the built-up area was much higher (78.03 %).

**Keywords:** Polarimetric SAR; RADARSAT-2; Multi-polarization; full polarimetric; microwave-polarimetric decomposition; polarimetric classification algorithm; quadpol; Wishart supervised classification; SVM

## 1. Introduction

Polarimetric Synthetic Aperture Radar (SAR) is a very important source of information for Earth observation. Polarimetric SAR sensors, in comparison to single channel SAR sensors, have the advantage of a more complete description of objects' scattering behavior (Dabboor, 2011). A substantial amount of research has been carried out showing that fully polarimetric SAR systems are better in discriminating different land covers than single or dual polarimetric SAR data (Mishra and Singh, 2011). It is well known that the classification of different objects, as well as different terrain characteristics, with single channel SAR images can carry a significant amount of error (misclassification) even when operating after multilooking.

One of the main applications of Polarimetric SAR (POLSAR) is the segmentation of different land cover types. However, segmentation of SAR data was always a difficult task due to the presence of speckle noise (Pellizzeri, 2003; Dabboor, 2011). A variety of papers demonstrate how to improve information extraction from SAR images (Sabour et al., 2007).

A precise identification of the borders between built-up and non-built-up areas is particularly interesting for many applications like the study of risks, the study of the population density and the monitoring of urban growth, which is a key issue in many developing countries, where urban growth is an increasing and often uncontrolled phenomenon (Pellizzeri, 2003).

Polarimetric SAR data is available from different sensors for different frequencies like RADARSAT-2, ALOS_PALSAR and TerrSAR-X, RISAT-1 (Moreira et al., 2013). RADARSAT-2 is an active microwave sensor operating at C-band frequencies, to achieve land observations in cloudy conditions. The SAR may transmit and receive waves with vertical and horizontal linear polarization (Sakshaug, 2013; Wiseman et al., 2014). Four different modes are usually considered: HH, horizontally polarized emitted, horizontally polarized received and similarly for HV horizontally polarized emitted, vertically polarized received, VV vertically polarized emitted, vertically polarized received and VH vertically polarized emitted, horizontally polarized received. A fully polarimetric SAR system has all 4 channels HH, HV, VH and VV (Zyl and Kim, 2011).

It is possible to show that the same scene has a different behavior at different polarizations. Therefore, when data of different polarizations about the same scene are available, the information content about the observed region can be increased by fusing the multipolarization information (Dabboor et al., 2011). Recent research work indicates that polarimetric data provide significantly more information than conventional or multi-polarized images, particularly due to the additional phase information. Traditional pixel-based classification methods yield poor results when applied to SAR imagery because of the presence of the speckle and limited spectral information in SAR data (Qi et al., 2010). Therefore, polarimetric classification algorithms evolved. Many classification techniques for PolSAR data have been studied. The classification of PolSAR data itself is not good therefore polarimetric decomposition is made. The input parameters for PolSAR classification are SAR observables obtained by decomposition methods. Many methods for decomposition have been proposed (Qi et al., 2010) and classification methods based on the decomposition results were also used by some researchers.

The research objective is to evaluate two classifications techniques (Wishart and Support Vector Machine (SVM)) based on decomposition parameters or combination of decompositions for urban land cover classification, to assess Ismailia Governorate from RADARSAT 2. The other goal is to find the most favourable subset of polarimetric features derived from the decomposition theorems. The features are evaluated on the basis of an accuracy measure of a classification.

## 2. Study area and data set

The study area is located at Ismailia Governorate with an area of approximately 625km$^2$. Various land cover categories exist in the selected area, e.g., vegetation, urban area, roads, desert, power lines and water (lake). The study area has considered flat terrain.

The following data sources are available for the study area:

- Fully polarimetric data RADARSAT-2 (C band) acquired on 25 Nov 2014 with a 8m spatial resolution–Ismailia was used. The fully polarimetric image was composed by the HH, HV, VH and VV polarizations, each in Single Look Complex (SLC) format, Based on the reciprocity theorem, the VH polarization was not considered since it is equal to the HV polarization.
- Fifteen well-distributed differential ground control points (GPS) and twenty well-distributed differential GPS check points that were observed with accuracy ±10 cm in x, y and z.

Figure 1 depicts RADARSAT 2 image. Table 1 summarizes characteristics of RADARSAT 2 image.

**Table 1: Characterstics of RADARSAT 2 image**

| System parameters | Values |
|---|---|
| Incidence Angle Near Range | 19.6 degree |
| Incidence Angle Far Range | 21.6 degree |
| Swath width | 25 km |
| Range resolution | 11 m |
| Azimuth resolution | 9 m |
| Noise equivalent sigma zero | Better than 30 dB |

## 3. Methodology

### 3.1. Data extraction and importing

The quad-pol data set used is C-band RADARSAT- 2 data. The data set was extracted and imported to PolSAR pro version 5. Scattering matrix was transformed to covariance matrix, the window size selected for covariance matrix generation is 3 x 3 then the covariance matrix was transformed to coherence matrix, the window size selected for coherence matrix generation is 3 x 3.

### 3.2. Speckle filtering

Speckle is a kind of noise usually appears as bright or dark dots in an image (Sakshaug, 2013). Speckle in the radar image is often a problem and should be reduced before the image is used for further quantitative analysis. Many speckle suppression techniques, such as median, Lee-sigma, Gamma-map, local-region and Frost (Lee et al., 1994), can be used to reduce the speckle noise. It is important to identify a suitable filtering method and suitable moving kernel size based on certain criteria. In general, the following factors are used to identify the best filtering method: (1) speckle reduction, (2) edge sharpness preservation, (3) line and point target contrast preservation, (4) retention of texture information, and (5) computational efficiency (Lu et al., 2011). Figure 2 depicts image after filtering with sigma Lee.

In this research refined Lee and sigma Lee filters were applied to the available data. A comparative analysis based on visual interpretation of the filtered images indicated that sigma Lee filter with kernel size 5 x 5 is better than refined Lee filter.

### 3.3 Geometric correction

The RADARSAT-2 was primarily geometrically corrected using ASF map ready tool in PolSARpro5 software for geocoding tool. Then RADARSAT-2 was registered using second order polynomial based on fifteen well-distributed DGPS points observed within 10 cm accuracy and the image was resampled to pixel size of 8 m using the nearest neighbor technique. The resulted RMSE of control points was 0.46 pixel. Rectification was validated using an independent set of twenty well distributed DGPS. The resulted RMSE of check points was 0.49 pixel. This step was performed in ENVI 5. Fig. 3 depicts Pauli RGB.

**Figure 1: RADARSAT 2 image.**

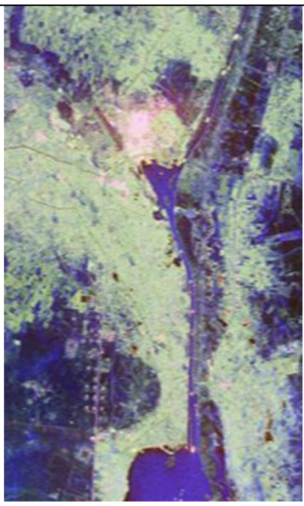

**Figure 2: Image after filtering with sigma Lee.**

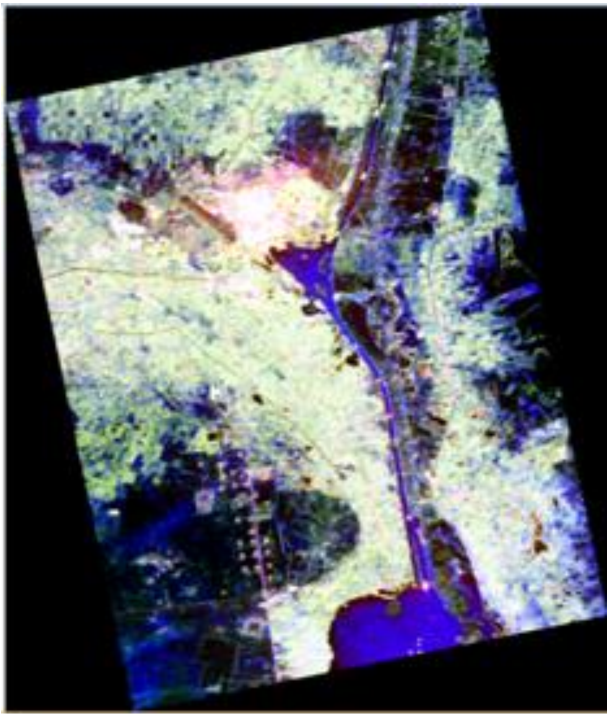

**Figure 3: Pauli RGB ( $|HH-VV|$ as red, $|HV|$ as green and $|HH+VV|$ as blue)**

**3.4. Polarimetric decomposition**

Polarimetric decomposition theorems break polarimetric SAR measurements into components that describe the scattering behaviour of the target (Sakshaug, 2013) to provide a way for interpretation. The objective of target decomposition theory is to express the average scattering mechanism as the sum of independent elements to associate a physical mechanism with each component (Dabboor, 2011; Mishra and Singh 2011).

The polarimetric decomposition theorems project the matrices that describe the backscattering, on to a set of basis matrices and express the backscatter as a linear sum of the basis matrices multiplied with corresponding coefficients (Sakshaug, 2013).

There are many target decomposition techniques available to decompose the data. In this research polarimetric decomposition has been performed by different techniques namely Cloude-Pottier (Entropy – Anisotropy – Mean scattering angle or H-A-α) and Yamaguchi decomposition for understanding polarization-specific scattering behavior of the land use / land cover (LULC) classes. PolSARPro5.0 software was used to implement the H/A/Alpha decomposition, Yamaguchi decomposition and Freeman decomposition. Three processing schemes, namely H/A/α decomposition, Yamaguchi decomposition and a combination of both were attempted.

**3.4.1 Cloude-Pottier (The ‘‘H/A/α’’) polarimetric decomposition:** Cloude-Pottier decomposition is incoherent decomposition method based on the eigen vector / eigen value analysis of the coherency matrix T (Dabboor, 2011). It is also called eigen vector – eigen value based decomposition (Qi et al., 2010). The ‘‘H/A/α’’ decomposition theorem is the basis for the design of the proposed processing scheme for polarimetric SAR images. Entropy (H) is the measure of randomness of scattering. Anisotropy (A) can be defined as the normalized difference between the appearance probabilities of the second and third scattering components (eigen value). From a practical point of view, the anisotropy can be employed as a source of discrimination only when entropy is greater than 0.7 because for lower entropies, the second and third eigen values are highly affected by noise. Consequently, the anisotropy is also very noisy. The parameter α is an indicator of type of scattering and is called scattering mechanism (Mishra and Singh, 2011). Figure 4 depicts polarimetric decomposition main parameters H, A and α.

**3.5 Fully-polarimetric SAR classification**

The choice of the classification algorithm is critical to success and each supervised classification approach has associated pros and cons (McNairn et al., 2009). The Wishart supervised classification and SVM were conducted by using the PolSARPro5.0 software based on the selected polarimetric decomposition parameters and combination of different decomposition parameters. The classification maps resulted from the three schemes of the Wishart supervised classification and SVM were produced as the comparison.

First, a processing scheme that jointly exploits the three parameter (H, α and A) to form a multichannel image in a single classification process was implemented. Secondly, a processing scheme that jointly exploits the Yamaguchi 4 parameter (single, double, volume and helix) to form a multichannel image in a single classification process was implemented. Thirdly, processing scheme that jointly exploits the seven parameters images entropy (H), alpha (α), anisotropy (A) and Yamaguchi (single, double, volume and helix) to form a multichannel image in a single classification process was implemented.

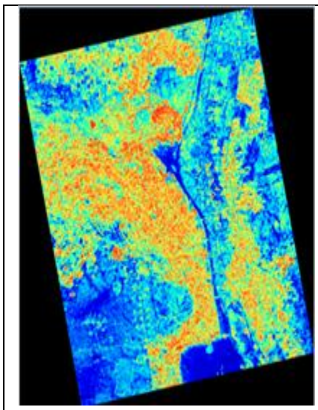

**Figure 4 (a): Entropy**

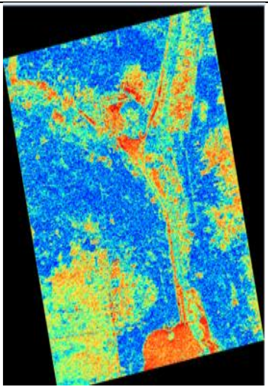

**Figure 4 (b) : Anisotropy**

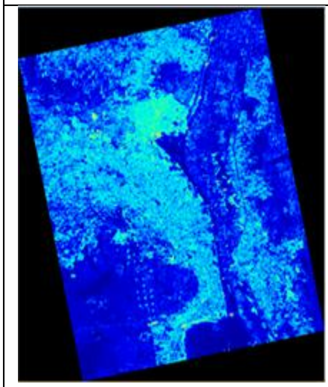

**Figure 4 (c) : Alpha**


**Figure 4: Polarimetric decomposition main parameters: H, A and α.**

Next, both classifiers are trained by using training data (sample data) that extracted from the three processing schemes (30 samples per class) for each scheme). Signatures were evaluated. Meanwhile, a total of 6 classes features (urban, road, desert, water, vegetation, power lines) were extracted for different classifications. Test samples for these classes were collected to generate confusion matrices, Kappa coefficient of agreement, overall accuracy in order to evaluate the classifications. Finally, land cover classification was performed using the Wishart supervised classification and SVM for all three schemes.

The LULC classification results of RADARSAT-2 data based on different decomposition and combination of decompositions were compared for both classifiers. Also an evaluation of the accuracy improvements in the detection of urban features was performed.

**3.5.1 Supervised Wishart classifiers:** The availability of the Wishart classifier in polarimetric tools has led to their widespread use among those performing PolSAR classification. The Wishart algorithm is a maximum-likelihood classifier in which a distance measure is established between each pixel's coherency matrix and the respective cluster means in an iterative process (Atwood et al., 2012), the Wishart classification involved only the T matrix elements especially dedicated to SAR data as it accounts for the Wishart distribution observed due to the presence of speckle noise (Lardeux et al., 2014).

The presented supervised algorithm, is a maximum likelihood classifier based on the complex Wishart distribution for the polarimetric coherency matrix, given by:

$$P(\langle[T]\rangle/[T_m]) = \frac{L^{Lp}\left|\langle[T]\rangle\right|^{L-p} e^{-L\,Tr([T_m]^{-1}\langle[T]\rangle)}}{\pi^{\frac{p(p-1)}{2}}\Gamma(L)\ldots\Gamma(L-p+1)\left|[T_m]\right|^{L}} \quad (1)$$

Each class is characterized by its own coherency matrix $[T_m]$ which is estimated using training samples from the $m^{th}$ class $\omega_m$. According to the Bayes maximum likelihood classification procedure, an averaged coherency matrix $<[T]>$ is assigned to the class $\omega_m$, if :

$$[T]\in[T_m] \quad if \quad d_m([T]) < d_j([T]) \quad \forall j \neq m \quad (2)$$

$$d_m([T]) = L\,Tr([T_m]^{-1}[T]) + L\,ln(|[T_m]|) - ln(P([T_m])) + K \quad (3)$$

This relation shows that if the number of look (L) increases, the a priori probability $P([T_m])$ of the class $\omega_m$ does not play a significant role for the classification. It is generally assumed that without a priori knowledge, the different $P([T_m])$ are equal, in which case the distance measure is not a function of the number of look (L). Usually, to implement the classification, the classified pixel by pixel. These different training sets have to be selected in advance. For each pixel, represented by the averaged coherency matrix $<[T]>$, the distance is computed for each class, and the class associated to the minimum distance is assigned to the pixel. During the procedure, each feature coherency matrix $[T_m]$ is iteratively updated from the initial estimate. The algorithm of this iterative procedure, similar to the k-mean method, is given as follows

1 : Provide an initial $[T_m](0)$ as an initial guess for each class (k=0)
2 : Classify the whole image using the distance measure procedure
3 : Compute $[T_m](k+1)$ for each class using the classified pixels of step 2
4 : Return to step 2, until a termination criterion

defined by the user is met (Pottier et al., 2004).

**3.5.2 Support Vector Machine (SVM) algorithm:** SVM is a modern machine learning method that offers improved generalization performance and can model complex nonlinear boundaries through the use of adapted kernel functions (Li et al., 2011), particularly in the case of extracting feature vectors from fully polarimetric SAR data. Figure 5 illustrates the classification map using SVM utilizing from 7 polarimetric decomposition as features. Table 2 shows the overall accuracy and Kappa coefficient of Wishart and SVM classifiers.

SVM method distinguished each class better than Wishart supervised classification did, especially for identifying the built up area. In the Wishart supervised classification based on 7 parameters, the user's accuracy of the built-up area is very poor (54.73 %). In SVM classification based on 7 parameters, however, the user's accuracy of the built-up area was much higher (78.03 %).

Figure 6 depicts User's accuracy % of Wishart classifier. Figure 7 depicts the Kappa coefficient of Wishart and SVM classifiers.
coherency matrix $[T_m]$ is estimated using pixels within different selected areas of the $m^{th}$ class and data is then

**Table 2: The overall accuracy and Kappa coefficient of Wishart and SVM classifiers**

| Polarimetric features | Wishart overall accuracy (%) | SVM classifier overall accuracy (%) | Kappa coefficient of Wishart | Kappa coefficient of SVM |
|---|---|---|---|---|
| H/A/α decomposition | 66.27 | 89.08 | 0.62 | 0. 89 |
| Yamaguchi's 4 component | 78.53 | 99.08 | 0.79 | 0.95 |

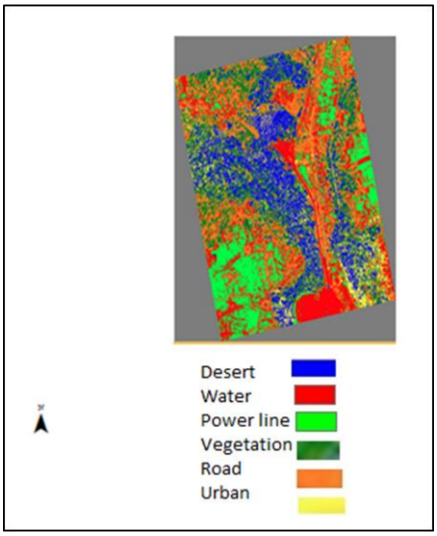


**Figure 5: The classification map using SVM utilizing from 7 polarimetric features.**

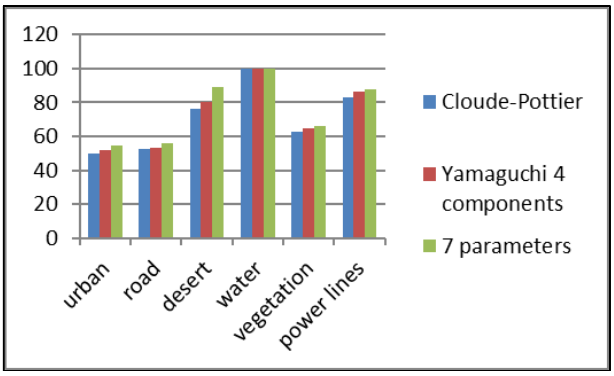


**Figure 6: User's accuracy % of Wishart classifier**

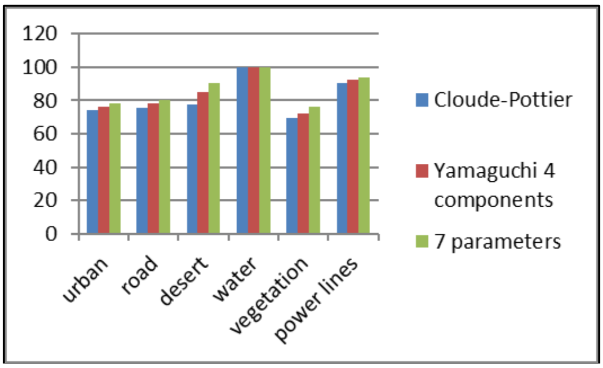


**Figure 7: User's accuracy % of SVM classifier.**

## 4. Results and discussions

The LULC classification results of fully-polarimetric RADARSAT-2 data using Wishart and SVM classifiers based on different decomposition and combination of decompositions were compared. The features are evaluated on the basis of an accuracy measure of a classification. Also an evaluation of the accuracy improvements in the detection of urban features was performed. PolSARPro 5 and ENVI5.1softwares were used for processing of the data sets.

First, sigma Lee and refined Lee filters were applied to the fully-polarimetric RADARSAT -2 image to reduce the noise and enhance the image quality. After speckle reduction SAR was georeferenced to a UTM coordinate system. As the study area presents an almost flat topography, a second order polynomial transformation and nearest neighbour resampling were used to create the output images with 8 m ground resolution. The root mean square error of the polynomial transformation was less than half a pixel. Check points were measured on the geometrically corrected image. The root mean square error of the check points was less than half a pixel.

Total of 7 PolSAR features (parameters) are extracted from the RADARSAT-2 full polarimetric data by the PolSARpro program. The optimization of features is an important step for improving accuracy. Three processing schemes were proposed based on decomposition parameters and were fed to Wishart and SVM algorithms. The classification maps using the three schemes of the Wishart supervised and SVM classifications were produced as the comparison.

By comparing the overall accuracy and kappa index of the Wishart and SVM classifiers, based on Table 2 and from figures 6 and 7, it is clear that different classification accuracies are derived when different PolSAR features are input to the Wishart and SVM classifiers. SVM based approaches for classification of polarimetric synthetic aperture radar data is better than Wishart classifier. One can attribute this to the fact that Wishart algorithm is a maximum-likelihood classifier which mean Wishart algorithm is per pixel classifier (traditional or hard classifier). On the other hand, SVM classifier is a subpixel classifier (soft classifier). The 7-parameters combination gives superior results compared to the other decompositions. Yamaguchi's 4 components is better than H/A/α decomposition. Figure 8 depicts flowchart of urban land cover classification.

In the classification result with the Wishart (approach 1 - H/A/α decomposition), an overall accuracy of 66.27 % percent was achieved. The following compares other approaches with approach 1, so as to determine whether insertion of other information's will improve the classification accuracy. The overall classification accuracy of approach 2, which used the Yamaguchi's 4 components, is 78.53 %, a slight improvement was achieved compared to approach 1. Approach 3 clearly outperforms approach 1. The overall accuracy of 78.99 % was achieved, an improvement of 12.27 %. The combination of 7 parameters improved the classification accuracies of most LULC classes. Approach 3 has the best performance among all the approaches examined.

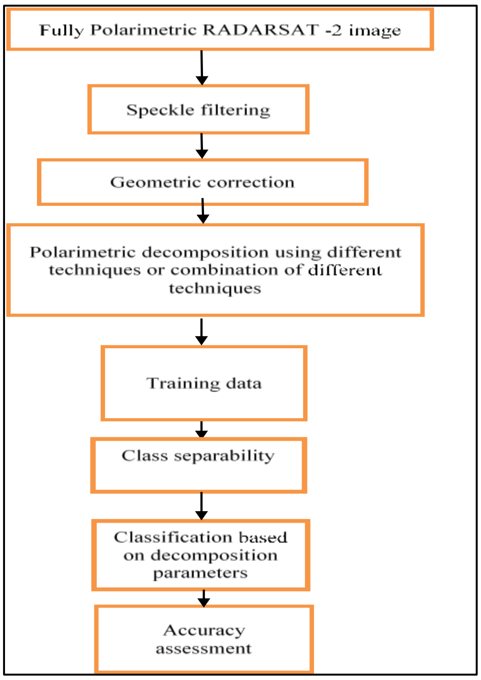


**Figure 8: Flowchart of urban land cover classification**

In the classification result with the SVM (approach 1 - H/A/α decomposition), an overall accuracy of 89.08% percent was achieved. The following compares other approaches with approach 1, so as to determine whether insertion of other information's will improve the classification accuracy. The overall classification accuracy of approach 2, which used the Yamaguchi's 4 components, is 99.08 % percent, an improvement was achieved compared to approach 1. Approach 3 clearly outperforms Approach 1. The overall accuracy of 99.67 % percent was achieved, an improvement of 10.59 %. The combination of 7 parameters improved the classification accuracies of most LULC classes. Approach 3 has the best performance among all the approaches examined.

Based on figures 6 and 7, it is clear that SVM method discriminate each class better than the Wishart supervised classification did, especially for identifying the urban area.

## 5. Conclusion and recommendations

In this study, RADARSAT-2 full PolSAR has been used to extract two decomposition techniques (Cloude-Pottier and Yamaguchi 4 components) and combination of decomposition parameters for urban land cover classification. Experimental results show a better performance of SVM based approaches compared to Wishart based approaches for classification of polarimetric synthetic aperture radar. When applying the decomposition theorems separately, Yamaguchi's 4 component decomposition theorem gave the higher accuracy. The 7-parameters combination gives superior results compared to H/A/α decomposition or Yamaguchi's 4 components.

## ACKNOWLEDGEMENT

The author thanks NARSS for giving the data. The editing and comments of the reviewers is gratefully appreciated.

## REFERENCES

Atwood, D.K., D. Small and R. Gens (2012). Improving PolSAR land cover classification with radiometric correction of the coherency matrix. IEEE Journal of Selced Topics in Applied Earth Observations and Remote Sensing, vol. 5, no. 3, 848 – 856.

Dabboor, M. (2011). New segmentation algorithms for dual and full polarimetric SAR Data. Ph.D. thesis, Department of Geomatics Engineering, Schulich School of Engineering, University of Calgary URL: http://www.geomatics.ucalgary.ca/graduatetheses.

Dabboor, M., V. Karathanassi and A. Braun (2011). Multi-level segmentation methodology for dual-polarized SAR data. International Journal of Applied Earth Observation and Geoinformation 13, 376-385

Han, Y. and Y. Shao (2010). Full polarimetric SAR classification based on Yamaguchi decomposition model and scattering parameters. IEEE International conference on Progress informatics and computing.

Lardeux, C., P. Frison, J.P. Rudant, J.C. Souyris, C. Tison and B. Stoll (2014). Classification of fully polarimetric SAR data for land use cartography. The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences, Volume XL-8, 2014

Lee, J.-S., M.R. Grunesm, E. Pottier and L.F. Famil (2005). Automated terrain classification using polarimetric synthetic aperture radar remote sensing. Remote Sensing NRL Review, 203 – 205.

Li, X., H. Guo, Z. Sun and G. Shen (2011). Urban impervious surfaces estimation from RADARSAT-2 polarimetric data using SVM method. PIERS Online, Vol. 7, No. 7, 671-676.

Lu, D., G. Li, E. Moran, L. Dutra and M. Batistella (2011). A comparison of multisensor integration methods for land cover classification in the Brazilian amazon. GIScience & Remote Sensing, 2011, 48, No. 3, p. 345–370. DOI: 10.2747/1548-1603.48.3.345.

McNairn, H., C. Champagne, J. Shang, D. Holmstrom and G. Reichert (2009). Integration of optical and Synthetic Aperture Radar (SAR) imagery for delivering operational annual crop inventories. ISPRS Journal of Photogrammetry and Remote Sensing 64 (2009) 434_449

Mishra, P. and D. Singh (2011). Land cover classification of PALSAR images by knowledge based decision tree classifier and supervised classifiers based on SAR observables. Progress in Electromagnetics Research B, Vol. 30, 47-70.

Moreira, A., P. Prats-Iraola, M. Younis, G. Krieger, I. Hajnsek and K.P. Papathanassiou (2013). A tutorial on synthetic aperture radar. IEEE Geoscience and remote sensing magazine, March 2013, 6-43.

Pellizzeri, T.M. (2003). Classification of polarimetric SAR images of suburban areas using joint annealed segmentation and ''H/A/a'' polarimetric decomposition. ISPRS Journal of Photogrammetry & Remote Sensing 58 (2003) 55– 70

Pottier, E., J. S. Lee, L. Ferro – Famil (2004). Advanced concepts in polarimetry – Part 2 (Polarimetric Target Classification). Ottawa, Canada, 21-22 October 2004, and published in RTO-EN-SET-081.

Sabour, S.M.T., P. Lohmann and U. Soergel (2007). Monitoring agricultural activities using ASAR ENVISAT data. Proc. 'Envisat Symposium 2007', Montreux, Switzerland 23–27 April 2007 (ESA SP-636, July 2007), 6p.

Sakshaug, S.E. (2013). Evaluation of polarimetric SAR decomposition methods for tropical forest analysis. Master Thesis in Energy, Climate and Environment, University of Tromso, UIT June 2013.

Qi, Z., A.G. Yeh, X. Li and Z. Lin (2010). Land use and land cover classification using RADARSAT-2 polarimetric SAR image. ISPRS TC VII Symposium – 100 Years ISPRS, Vienna, Austria, July 5–7, 2010, IAPRS, Vol. XXXVIII, Part 7A.

Wiseman, G., H. McNairn, S. Homayouni and J. Shang (2014). RADARSAT-2 polarimetric SAR response to crop biomass for agricultural Production monitoring. IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing, Vol. 7, No. 11, November 2014

Zyl, A.V. and Y. Kim (2011). Synthetic aperture radar polarimetry. Wiley Publication.