



# Comparison of SVM classifier and wish art classifier on L- band alos-palsar-2 data over metropolitan area

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## Abstract

For every country, quantitative assessment of the Land Use and Land Cover (LULC) is essential for proper planning and for proper utilization of the resources nearby. Land cover change is related to global change due to its interaction with climate, ecosystem and from manmade activities. This paper focuses on Land cover classification of L band ALOS PALSAR Dual Pol data over the Metropolitan City Hyderabad. Longer wavelengths have more penetration capability, therefore, L band is opted for this study. The dataset is multilooked five looks in range and one look in azimuth direction, and speckle filtered with refined filter with window kernel size 3x3. In this study, we have compared the classification accuracy with two well know supervised classifiers VIZ Support Vector Machine (SVM) and Wishart Classifier. From this study, the classification accuracy for SVM and Wishart classifiers are almost similar i.e. 91.08% and 91.07%.

**Keywords:** ALOS Palsar-1; Land Use Land Cover; Metropolitan; Support Vector Machine; Wish Art Classifier.

## 1. Introduction

Land Cover classification is the crucial application for remote sensing applications. Generally, Optical remote sensing data is opted for Land Use and Land Cover (LULC) classification and earth observation, but due to its limitations (night acquisition, all weather, cloud penetration), Microwave Remote Sensing came into existence [1]. As microwave remote sensing is active, and transparent to atmosphere image acquisition is possible in all weather conditions and also in night time. The popular wavelengths used for Synthetic Aperture Radar remote sensing are P, L, S, C, X, Ku, Ka. Generally, short SAR wavelengths, such as X-band and C-band cannot penetrate through the canopy and only interact with the top part of the canopy. In contrast, longer wavelengths such as L-band and P-band can penetrate into the vegetation cover and even reach the soil [2]. Therefore, longer wavelengths are mainly used for biomass estimation, LULC classification and soil moisture studies. LULC is essential for urban planning and management, particular in rapidly growing metropolitan cities for utilizing the resources for industrial and residential purposes by maintaining forest and agriculture land ratio, thus by maintaining good balance between land development and environmental protection [3-6].

## 2. SAR datasets and study area

### a) SAR Dataset

Advanced Land Observing Satellite (ALOS) mission was launched on January 24, 2006, using Launch vehicle as H-IIA. Japanese Earth Resource Satellite 1 followed ALOS mission (JERS-1) both were meant for land, atmospheric and marine observations. ALOS has three remote sensing instruments i) (PRISM) Panchromatic Remote-sensing Instrument for Stereo Mapping, (ii) (AVNIR-2) Advanced Visible and Near Infrared Radiometer, (iii) (PALSAR) Phased Array L-band Synthetic Aperture Radar. PALSAR was

jointly developed by JAXA (Japan Aerospace Exploration Agency), JAROS (Japan Resources Observation System Organization) and METI (Ministry of Economy, Trade & Industry). PALSAR is a side-looking sensor with a capability of 8 to 60 incidence angle. PALSAR is operated in four modes, i.e., i) Fine resolution Beam ii) 14 MHz polarimetric iii) ScanSAR VI) Direct Transmission. Data products are supplied in three different formats Level 1.0, Level 1.1, Level 1.5. Level 0 provides raw slant range data; level 1.1 is a Single Look Complex (SLC) slant range processed data, level 1.5 is geocoded and georeferenced data. Alos Palsar-1 (HH-HV) dual-pol dataset was acquired on 23-August-2010, in Ascending orbit direction [7].

### b) Study Area

The study area is located in Southern India with Latitude 17.3850° N, Longitude 78.4867° E. Hyderabad City is the state capital of Telangana, INDIA and it lies on the bank of river Musi in the northern part of Deccan plateau. Presently Hyderabad is the fourth most populous and sixth most populous urban agglomeration in India [8].

**Table.1:** Datasets Used in This Study

S.No	Mission/ Sensor	Date of Acquisition	Resolution (m)	Swath Width (KM)
1	Alos Palsar-1 1270 (MHz) (L-Band)	23-Aug-2010	5x20	40-70
2	Google Earth	----	--	---

## 3. Methodology

### a) Pre-processing

Alos Palsar-1 level 1.1 is imported to PolSarpro. As the level 1.1 has rectangular pixels, therefore it has to be multilooked five looks in range and one looks in azimuth directions. The level 1.1 Single Look Complex (SLC) consists of speckle, so the speckle has to be filtered and to make easy for the analyst for further processing. Boxcar filter with 3x3 window size was opted as speckle filter. Dual-

Pol dataset consists of 2x2 covariance matrix. C2 matrix consists of c11, c12 image, c12 real, and c22. Multilooking is a process of averaging the intensity of Single look complex data in range and azimuth direction and make the resolution cell from rectangle to square shape.

b) Refined Lee Filter

The Minimum Mean Square Error (MMSE) filter cannot remove the speckle near the edges effectively. To overcome this problem refined lee filter uses a nonsquare window to match the direction of the edges. Pixels which are in the non-edge area are used for computation. Refined lee filter follows three processing steps, 1) selection of edge aligned window, 2) Computation of filtering weight (b) from the span image, 3) Filtering each element in the covariance matrix [Y] with the weight (b). The filtered matrix is given by

$$\hat{Y} = \bar{Y} + b(Y - \bar{Y}) \tag{1}$$

Where is the local mean of matrices computed with pixels in the same edge directed window. We have opted a 3x3 window size kernel for speckle filtering.

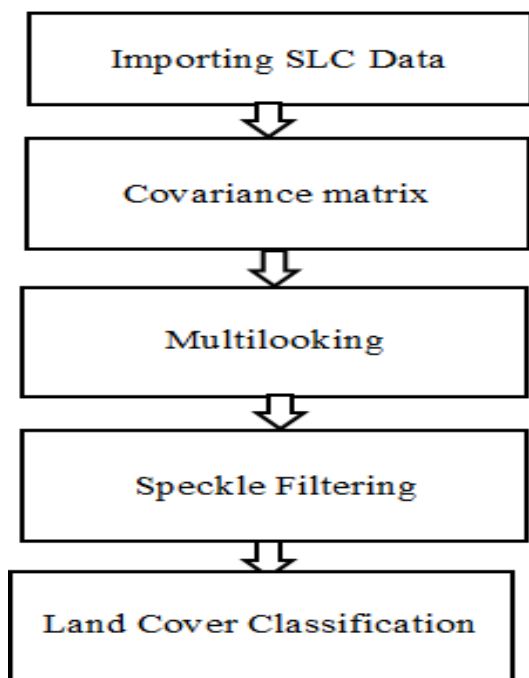


Fig. 1: Flowchart of This Study.

c) Supervised Classification

Wishart Classifier:

In this process, all image pixels are classified into one of the clusters based on their Wishart distance to the center of the cluster [1]. The cluster Centre  $V_m$  for the  $m^{th}$  cluster is the average of covariance matrix of all pixels in the cluster as shown in equation

$$V_m = \frac{1}{N_m} \sum_{i=1}^{N_m} \langle C \rangle_i \tag{2}$$

The Wishart distance measures from covariance matrix C to the cluster center  $V_m$  is defined as the following

$$d(\langle C \rangle, V_m) = \ln |V_m| + Tr(V_m^{-1} \langle C \rangle) \tag{3}$$

Where  $\ln(\cdot)$  is the natural logarithm function, and  $Tr(\cdot)$  Indicate the determinant and the trace of matrix respectively.

Support Vector Machine Classification:

SVM algorithm is a maximum likelihood classifier based on complex Wishart distribution [9]. SVM learning algorithm is a supervised classifier, where the analyst has to know the ground truth of

the given area of interest, based on which training sites will be identified and are applied on the decomposed image. SAR images can be classified in two stages, firstly extraction of appropriate features and secondly labeling the features based on a set of decision rules.

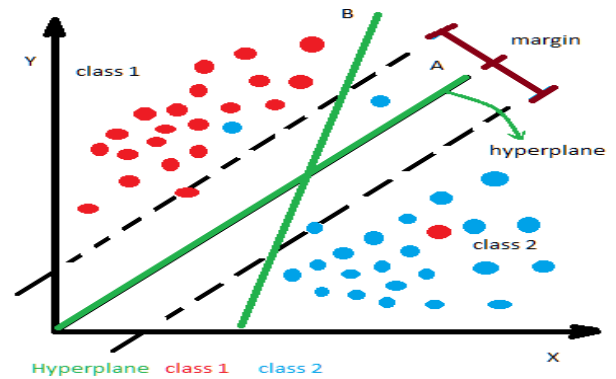


Fig. 2: SVM Classifier.

In this algorithm each data will be plotted in 'd' dimension space with 'N' vectors of the training set, where 'd' is the number of features based on the target types. Later the classifier differentiates in two classes based on the hyperplane as shown in Fig.2. Each sample is described as  $x_i \in R^d$  ( $i=1,2,\dots,N$ ) and the target  $Y_i \in \{-1,+1\}$  is associated with every sample  $x_i$ . The optimum hyperplane is defined by

$$\begin{aligned} f(x_i) &= \omega x_i + b \\ \text{sgn}[f(x_i)] &= Y_i \\ Y_i (\omega x_i + b) &> 0 \end{aligned} \tag{4}$$

The membership decision rule is based on the function  $\text{sgn}[f(x_i)]$ . In finding optimum hyperplane, we have to estimate  $Y_i$ .

$$Y_i (\omega x_i + b) > 0$$

The optimization is performed using Lagrangian formalism

$$f(x) = \sum_{i=1}^N Y_i \alpha_i (xx_i) + b \tag{5}$$

Where  $\alpha_i$  denotes Lagrange multiplier.

SVM classifies the data into different classes by determining the set of support vectors that summarizes a hyperplane. SVM utilizes a linear classifier method for classification. In this approach first, we explicitly define pattern recognition in assigning the class labels to unknown data, with decision rules learned from typical training sets [10]. Later we have to identify the hyperplane which can distinguish the given classes very well. Identifying the best hyperplane can be decided by the distance between the nearest classes on either side to the hyperplane is called margin. If we select the hyperplane with minimum margin, there is the possibility of a mismatch in the classification process. SVM has a robust feature which ignores the outliers and finds the best hyperplane with maximum margin as shown in Fig 2 [11].

## 4. Results

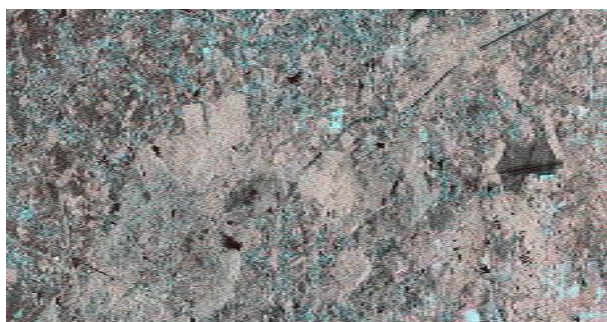
Fig 3(a) is the SLC image of level 1.1 without multilooking, Fig 3(b) is the multilooked image, [5] looks in range and 1 look in azimuth direction. Fig 3(c) is the refined lee filtered image with window size 3x3. Fig 3(a-c), magenta color corresponds to urban class, green color corresponds vegetation class, blue color corresponds crop fields, and black color corresponds to water body. Fig 3(d) is the SVM classified image, where red color corresponds to urban

class, green color corresponds water body class, blue color corresponds crop fields, and yellow color corresponds to forest, and orange color corresponds to bare soil. Fig 3(e) is the Wishart classified image, where red color corresponds to urban class, green color corresponds water body class, blue color corresponds crop fields, and yellow color corresponds to forest, and orange color corresponds to bare soil. From Fig 3(d) and Fig 3(e), the urban class was better classified using SVM classifier.

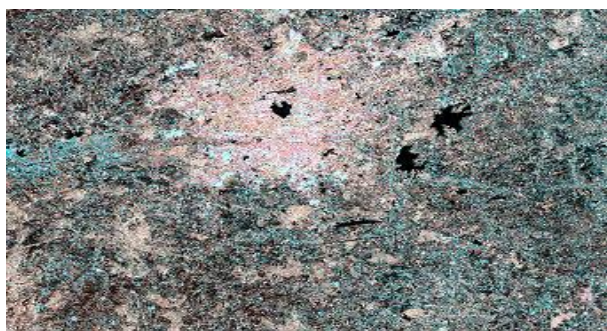
From the Table 2, SVM has classified the urban class 98.37% better than Wishart classifier 96.85%. SVM and Wishart classifiers classified water bodies to 100%. Wishart classifier has classified crop field class to 94.4% better than SVM classifier 92.75%. SVM has classified the forest class to 81.71% better than Wishart classifier 72.21%. Wishart classifier has classified bare soil class to 91.90 % better than SVM classifier 82.61%. On a whole SVM and Wishart supervised classifier, Overall Accuracy were almost similar (91.08% and 91.07%).

**Table 2:** Confusion Matrix for Accuracy Assessment

	U		WB		CF		F		BS	
	W	S	W	S	W	S	W	S	W	S
U	96.8	98.3	0.0	0.0	3.1	0.6	0.0	0.6	0.0	0.2
WB	0.0	0.0	100	100	0.0	0.0	0.0	0.0	0.0	0.0
CF	0.0	0.0	0.0	0.0	94.4	92.7	2.9	0.6	2.6	6.6
F	0.0	0.0	0.0	0.0	0.6	0.0	72.2	81.7	27.1	18.2
BS	0.0	0.2	0.0	0.5	0.4	4.6	7.6	12.0	91.9	82.6
OA	Wishart: 91.076		SVM: 91.088							
U:Urban, W: Water Body, CF: Crop Fields, F: Forest, BS: Bare Soil, OA: Overall Accuracy, W: Wishart Classifier, S: SVM Classifier										



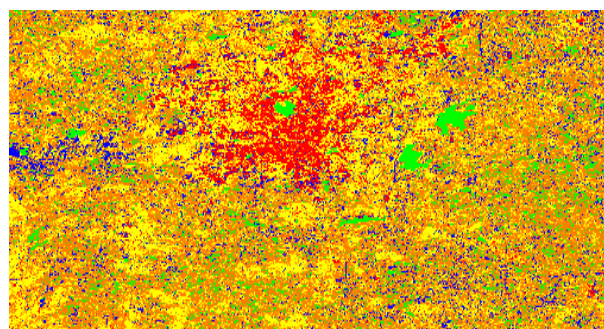
**Fig. 3: A)** SLC.



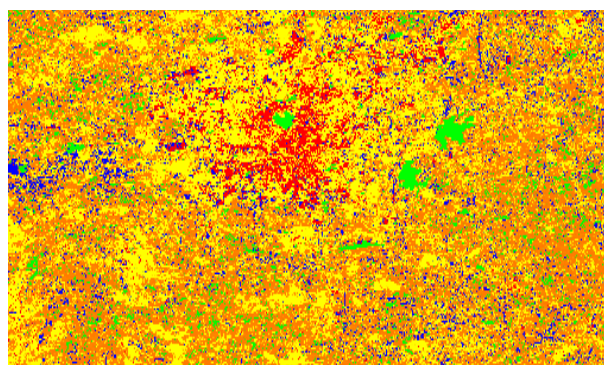
**Fig3: B)** Multilinked.



**Fig. 3: C)** Refined Lee Filtered.



**Fig. 3: D)** SVM Classifier Image.



**Fig. 3: E)** Wish Art Classifier.

## 5. Conclusion

From this study we have explored the performance of L band Alos palsar-1 data using SVM and Wishart classifier on metropolitan areas. In order to know the available natural resources around the city Hyderabad, LULC was performed. As L band has more penetrating capability, the results for SVM and wishart classifier are almost similar. From the Table 2, SVM has classified urban class well when compared to wishart classifier. The (OA) achieved on the data were 91.08% and 91.07% for SVM and Wishart classifier. The preprocessing was carried on POLSARPRO 5.0 version. The classified results were validated using Google Earth images and Ground Truth information.

## References

- [1] Author, "Title of the Paper", *Journal name*, Vol. X, No. X, (200X), pp. XX-XX, available online: <http://xxx>, last visit:28.02.2013
- [2] Author, "Title of the Paper", *Proceedings of the conference name*, Vol. X, No. X, (200X), pp: XX-YY, <http://dx.doi.org/10.1109/MMM.2013.2248651>
- [3] Author, *Title of the Book*, Publisher, (200X), pp:XXX-YYY.
- [4] Cho JH, Chang SA, Kwon HS, Choi YH, KoSH, Moon SD, Yoo SJ, Song KH, Son HS, Kim HS, Lee WC, Cha BY, Son HY & Yoon KH (2006), Long-term effect of the internet-based glucose monitoring system on HbA1c Reduction and glucose stability: a 30-month follow-up study for diabetes management with a ubiquitous medical care system. *Diabetes Care* 29, 2625–2631.
- [5] Fauci AS, Braunwald E, Kasper DL & Hauser SL (2008), Principles of Harrison's Internal Medicine, Vol. 9, 17th edn. *McGraw-Hill*, New York, NY, pp.2275–2304.
- [6] Kim HS & Jeong HS (2007), a nurse short message service by cellular phone in type-2 diabetic patients for six months. *Journal of Clinical Nursing* 16, 1082–1087.
- [7] Lee JR, Kim SA, Yoo JW & Kang YK (2007), The present status of diabetes education and the role recognition as a diabetes educator of nurses in Korea. *Diabetes Research and Clinical Practice* 77, 199–204.
- [8] McMahon GT, Gomes HE, Hohne SH, Hu TM, Levine BA & Conlin PR (2005), Web-based care management in patients with poorly controlled diabetes. *Diabetes Care* 28, 1624–1629.
- [9] Thakurdesai PA, Kole PL & Pareek RP (2004), Evaluation of the quality and contents of diabetes mellitus patient education on Internet. *Patient Education and Counseling* 53, 309–313.