SPECTRAL RESPONSES OF WATER SUBCLASSES IN C BAND HH POLARIZED DATA

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ABSTRACT

The specific objective of the present study is to identify, compare different water classes using Radarsat-1 SAR. An attempt is made to understand distribution of water classes, estimate parameters of each class and prove statistically the means of different classes statistically significant or not. This type of analysis will help in setting threshold to classify water/non water in SAR and further identify completely submerged areas in post event SAR images.

The study area selected for the present analysis was Kendrapara district of Orissa, India. The study area lies on the Eastern coast of India lying between Latitude $20^{0}21'$ to $20^{0}47'$N and Longitude $86^{0}14'$ to $87^{0}83'$ E). For this analysis, IRS ID LISS III and Radarsat-1 SAR images of October 11, 1999 of study area were procured. The data analysis of IRS 1D LISS III and Radarsat-1 SAR images were performed using PCI Geomatica version 8.2.3 and ERDAS Imagine 8.7.

The overall research methodology is divided mainly into three steps namely, pre processing of IRS 1D LISS III image and Radarsat-1 SAR image, Accurate landcover classification using IRS 1D LISS III imagery and comparison of water backscattering distribution of different water classes.

The IRS 1D LISS III (resolution=23.5m) image of October 11, 1999 of Kendrapara district was geometrically corrected and classified into landcover classes namely water, forest, fallow land, vegetation others and rice using supervised classification technique. The water landcover was further sub classified into three subclasses namely river water, pond water and sea water. It was found that the water area in Kendrapara district was 21.28687 thousand hectares.

The Radarsat-1 satellite image of October 11, 1999 of the study area was geometrically corrected and cleaned for speckle noise. Speckle noise in Radarsat-1 SAR imagery was reduced using enhanced Lee Adaptive filter. The data calibration and Incidence angle correction was performed using standard procedure. Further using model few of pixels of Radar were extracted corresponding to actual water pixels of IRS (these pixels were not close to land -water interface). Using the extracted pixels (now called as water pixels in Radar) normality was tested. It was found that the extracted water pixels backscattering values were normally distributed and parameters of the model were estimated. Further using Analysis of Variance (ANOVA) technique it was found that the water subclasses backscattering values significantly different. The mean of sea water backscattering value was found to be highest among all the other water subclasses. So now to classify water/non water using multi-temporal

Radarsat-1 SAR data it's necessary to just look at sea water distribution and then estimate the parameters and threshold for probabilistic model.

1 INTRODUCTION AND OBJECTIVES

Microwave satellite data availability for all time/seasons is being used in various applications especially in agricultural application, global climate change studies and natural disaster management. In general, water in SAR images has black tone and assumed to be specular reflecting.

Water has the least backscattering values among all other landcovers and the plain water and landcovers completely submerged under water have same backscattering values. This characteristic can be utilized to identify completed submerged area due to floods and cyclones (Shao, Y. *et al.*, 2001). The backscattering values for rice, forest, urban and water are reported using Radarsat-1 SAR imagery. The test site selected was Higashi-Hiroshima city, Japan. The water had least backscattering values and it ranged from –17.0 dB to –15.0 dB (Takeuchi, S. *et al.*, 1998). The rice fields were monitored using Radarsat-1 SAR data and Landsat TM Optical data (Ogawa, S. *et al.*, 1999). The test site was Kantoh plain Tochigi, Japan. The backscattering coefficient range for water bodies like pond and river was –17.0 to –15.0 dB. An attempt was made to compare the Radarsat–1 SAR and Optical sensor data for monitoring of rice plants around Hiroshima (Oguru, Y. *et al.*, 2001). The water backscattering range was found between –24.0 dB to –21.0 dB.

Using deterministic approach, a threshold of -19dB was identified to classify water/non water in the pre event Radarsat-1 SAR image. Using the identified threshold in pre event Radarsat-1 SAR image, completely submerged landcovers in post event images were identified using pre event IRS classified IRS image and post event Radarsat-1 SAR images. The study area selected for this analysis was Kendrapara district of Orissa. This district was affected by severe cyclone which crossed study area on October 30, 1999 (Abhyankar, A. A. *et al.*, 2005). For the same study area and event, evaluation of a single value threshold to classifying water/non water in Radarsat-1 SAR was studied. Pixels of pre event Radarsat-1 SAR were extracted corresponding to the pre event IRS classified water pixels. The plot of backscattering values showed that the water backscattering values exceeded the threshold of -15dB. This paper clearly showed that a single threshold to classify water/non water using Radarsat-1 SAR is not appropriate (Abhyankar, A. A. *et al.*, 2007).

Previous literature only looked at water as a single homogenous entity whereas in the present study we treat water and its subclasses classes heterogeneous. In the present study water is sub classified on the basis of its origin and its composition namely pond, river and sea water. The present study looks at designing representative samples strategy from each subclass and then testing the distribution, estimation of parameters of the model and finally the water threshold. The study will improve threshold setting exercise for submergence analysis in post event SAR images and will reduce the underestimation of submergence results.

2 STUDY AREA AND DATA

The study area selected for the present study was Kendrapara district of Orissa, India. The study area lies on the Eastern coast of India (Latitude $20^{0}21'$ to $20^{0}47'$N and Longitude $86^{0}14'$ to $87^{0}83'$ E). The study area is shown in Figure 1. For this analysis IRS 1D LISS III of

October 11, 1999 was procured from NRSA Hyderabad and the Radarsat-1 SAR image of October 11, 1999 (SNB [ScanSAR Narrow B)] Descending mode) from Radarsat Int., Canada.

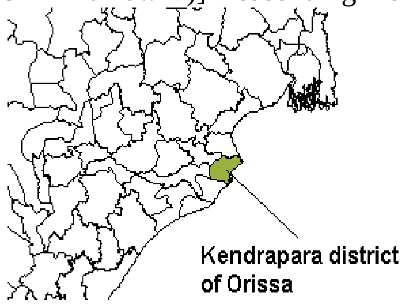

Figure 1. Study Area

3 PREPROCESSING OF IRS AND RADARSAT-1 SAR DATA

The data analysis of IRS 1D LISS III and Radarsat-1 SAR images were performed using PCI Geomatica version 8.2.3 and ERDAS Imagine 8.7. The IRS ID LISS III was initially geometrically corrected. The exact area of Kendrapara district from this geometrically corrected image was extracted using a digitized standard district vector layer. In the present study, for Radarsat-1 SAR imagery, speckle noise was reduced by enhanced Lee Adaptive filter (http://www.pcigeomatics.com/cgi-bin/pcihlp/M_FELEE). The data calibration and incidence angle correction exercise steps were performed (Chakraborty, M. *et al*. 2000). Using this computed incidence angle, the backscattering coefficient σ_{0j} for the *j*th pixel in a scanline is computed as follows:

$$\sigma_{0j} = 10*\log_{10}[(DN_j^2+A_0)/A_j]+10*\log_{10}[\sin(I_j)](\text{in dB}) \qquad (1)$$

Where,
DN_j is the DN; A_j is the scaling gain value;
I_j is the incidence angle at the j^{th} range pixel and
A_0 is the fixed gain offset, usually zero.

Further, the preprocessed image was geometrically corrected using the base map and using the standard Kendrapara district vector layer Kendrapara district was extracted as a separate image. Finally dB values were linearly scaled between 0 to 255 to get DN values.

4 SUPERVISED CLASSIFICATION OF IRS 1D LISS III DATA

Using supervised classification and maximum likelihood technique, Landcover map of Kendrapara district was prepared using IRS data. For supervised classification technique, green, red and near IR bands were considered *i.e.* band 2, band 3 and Band 4 of the IRS 1D satellite. In the present study five landcover classes were identified namely water, forest, fallow land, other vegetation and rice. This georeferenced landuse/landcover map provided the baseline information for the study area. The resultant Landcover map of Kendrapara district and area of each landcover class is given in Figure 2. The area of water, forest, fallow land, other vegetation and rice was found to be 21.286, 9.877, 49.776, 41.295 and 132.786 thousand hectares respectively. Further, all other landcovers other than water were masked and made zero whereas water value was made 1.

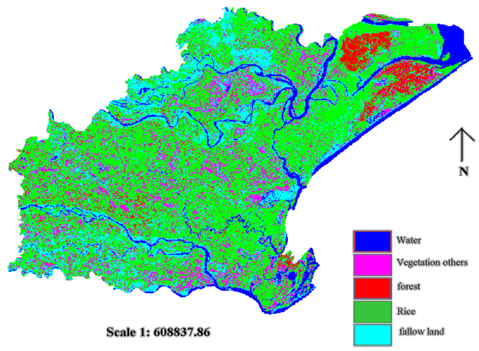

Figure 2 Landcover Map of Kendrapara District of Orissa using Supervised Classification Technique

5 COMPARISON OF SPECTRAL RESPONSES OF WATER SUBCLASSES USING RADARSAT-1 SAR

Three water subclasses were identified namely sea, river water and pond. Few known representative water samples from each of the subclasses from October 11, 1999 Radarsat-1 SAR image was extracted corresponding to IRS water (Precaution was taken to avoid extracting water pixels at the land water interface). Further, these sub classified extracted water pixels of each class were subjected to Analysis of Variance (ANOVA) to test whether the backscattering values of water subclasses are statistically different or not. The independence of cases, normality and homogeneity of variances was assumed before performing ANOVA. Further distribution of each water subclasses was tested and parameters were estimated.

The total river water pixels extracted were 239 whereas pond and sea were 271 and 232 respectively. The descriptive statistics of these three types of water is given in Table 2. It can be seen from Table 2, the mean, standard error, median and mode are highest for the sea water.

Descriptive statistics/water subclass	river	pond	sea
Mean	41.12	63.02	101.654
Standard Error	0.586	1.001	1.07
Median	41.6	61.3	102.5
Mode	35.8	54.1	105.5
Standard Deviation	9.07	16.448	16.31
Sample Variance	82.27	271.865	266.048
Kurtosis	0.334	0.566	-0.583
Skew ness	-0.235	0.481	0.023
Range	57.51	94.6	73.966
Minimum	5.582	24.4	63.7
Maximum	63.1	119	137.666
Sum	9829.123	17080.186	23583.785
count	239	271	232

Table 2. Descriptive statistics of extracted river pond and sea water

These were representative samples for each subclass the minimum sample size was determined by solving for the maximum error of the estimate formula for the population mean (Anderson, D. R. *et al.*, 1999).

6 RESULTS AND DISCUSSION

The extracted river, pond and sea water was subjected to normality test namely K-S test using statistical software SPSS. It was found that the extracted samples of water pixels of each class were normally distributed.

From the river water sample statistics (mean=41.12 and standard deviation 9.07), population parameters of river water were estimated at 95% confidence level (using right tail test and population finite). At 95% confidence level a threshold of DN= 42 or dB= -21.3 was identified to classify water non-water in Radarsat-1 SAR for river water. Similar exercise was performed for pond water and sea water. The threshold to classify water/non water for pond and sea was DN=65 (dB=-19) and DN=105 (dB=-15) respectively.

Next step was to prove the water of three subclasses statistically was different or not. For this ANOVA technique was used. The results are shown in Table 3. It can be seen from Table 3 that p value is less than 0.05 which indicates that water values in these three subclasses statistically different.

Anova: Single Factor						
SUMMARY						
Groups	*Count*	*Sum*	*Average*	*Variance*		
river	239	9829.124	41.12604	82.27546		
pond	271	17080.19	63.02652	271.8659		
sea	232	23583.79	101.6542	266.0482		
ANOVA						
Source of Variation	*SS*	*df*	*MS*	*F*	*P-value*	*F crit*
Between Groups	442074.7167	2	221037.4	1057.653	1.4E-217	3.007909
Within Groups	154442.4753	739	208.9885			
Total	596517.192	741				

Table 3: Result of ANOVA test

The study clearly demonstrates that water backscattering values for different subclasses are statistically different and if complete submergence analysis is to be performed in future due to Cyclone/flood using SAR, it is important to identify water classes and look at sea water first. Then take representative sample, test the normality and set the threshold in pre event image. Calculate water area in the pre event SAR image. Further apply this threshold value in post image SAR images to identify completely submerged areas/landcovers. This work will reduce underestimation of submerged results. The higher mean value for sea water can be attributed to ripples/wave motion of water or dynamics of sea water compared to river and pond.

This tool is rapid and could help policy makers in properly allocate resources/funds and mobilize to the affected people.

7 SHORTCOMING AND FUTURE WORK

The water pixels of IRS and Radar (at the sea threshold) do not match 100%. It was found that only 80% of these pixels have 1:1 correspondence which meant that false positive and false negative errors existed in the present work. Further a program was developed in the present study, attempt was made to determine of the remaining 20% of non matching pixel (*w.r.t* IRS) how many were boundary and non boundary pixels of Radar. It was found that 75% of Radar pixels were boundary pixels *w.r.t* IRS water.

The threshold methodology developed in the present study is statistical and site specific. The other drawback is unavailability of the proper Radar imagery applicability during extreme weather conditions namely, high wind speed or heavy rainfall. It was found that extracted water sample from water subclass not always followed normality. Also it was found that as we increase the sample size, the normality was lost which was against the standard understanding of the researcher. In that case the researcher assumed that the backscattering values of water pixels were normally distributed and then the threshold for water/non water was identified (parameters of models were estimated).

The future work involves submergence analysis using various SAR satellite launch recently, study effect of polarization on water thresholds *etc*.

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