

Snow Cover Estimation from Resourcesat-1 AWiFS – Image Processing With an Automated Approach

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Abstract

Snow and glaciers cover large areas of Himalayas. The resulting runoff from snow and glacier melt provides nearly 30-50% of the total annual water outlay of most of the rivers in north India. There is a need for continuous monitoring of the Himalayan snow cover area at more frequency and over longer period in the context of climate change studies. Normalized Difference Snow index (NDSI) technique which generally used for automated detection of snow cover from remotely sensed data has limitations in the detection of snow under shadow and exclusion of water and gray cloud. A new automated snow cover estimation algorithm has been developed and presented here to overcome the these limitations using the spectral information available in the Red, Near Infrared and SWIR spectral bands of IRS P6 Resourcesat-1 AWiFS sensor. The automated algorithm has been implemented in hierarchical logical steps. Algorithm has been validated by comparing the results obtained with Hall's and Kulkarni's methods and observed that

the new algorithm performs better than other methods in the elimination of noise like glacial water bodies and water bearing dark clouds, while detecting the snow covered pixels in deep mountain shadows. Satisfactory results have been obtained, when used with several temporal images of large image mosaics covering different regions of Himalayas from Kashmir in the west to Arunachal Pradesh in the East covering entire snow belt of Indian region. This has shown the robustness of the algorithm in various locations. Intra annual and inter annual snow cover over Himalayas regions of the India was evaluated and the results were encouraging and are suitable for porting on to a public domain. This algorithm has been evaluated with Landsat ETM and IRS LISS III which has similar spectral bands with different spatial and radiometric resolutions and the algorithm has been found to be working satisfactorily. The algorithm has been found to be useful for regular periodic monitoring of snow cover area and is generic in nature that can be used with various sensor data that has similar spectral bands.

Keywords: Snow cover , Automated algorithm, Remote Sensing.

1. INTRODUCTION

Snow and glaciers cover large areas in Himalayas during winter. The spatial extent of snow undergoes significant change with drop in ambient temperature during winter and snow melt with the commencement of spring. During spring and summer, such a change impacts the stream flow of the rivers originating in the higher Himalayas which are fed by snow and glacial melt run off. Recent study carried out on Himalayan glaciers [1, 2] and National Institute of Natural Resources on the mountain glaciers, Peru [3] reveals that the glaciers are receding rapidly due to the global warming and climate change. Recent reports on climate change due to global warming has predicted rapid change in the snow line and glaciers in Himalayas and its impact on the food production in the South Asian countries. Hence, regular monitoring and mapping of snow cover area is necessary for water resources planning and management in snow fed river basins for the assessment of water resources. The remote sensing technique has been used extensively for snow cover monitoring [4-16] and snow melt run off studies [7] for Himalayan glaciers. Various analysis techniques such as visual, hybrid visual-digital and supervised Maximum Likelihood Classification, have been used to estimate the aerial extent of snow cover.

In the context of global warming and the resulting climate change scenario, there is a need for near real time monitoring of dynamic natural resources like snow cover which involves handling and analysis of large volume satellite data and carry out simulation studies related to climate change or impact of climate change. The availability of large quantity of data from high-resolution space-based sensors along with the existing archives surpassed our ability to extract information from all the data using supervised image analysis techniques. The supervised image information extraction process is complex, time consuming and expensive in nature. This hinders the use of all acquired and accessible data, penalizing large environmental monitoring projects, and might even leave critical phenomena totally undetected.

Presently, earth observation (EO) data are archived and disseminated based on the metadata such as geographical location, date of acquisition and sensor type, which provide no information on the information content of the data. Experts interpret these images to extract information using their domain knowledge and the service provider/user combines them with other legacy information to support decision-making. In this scenario, the offer of data does not match the customer's real need, which is image information. In response to these needs, attempts are being made to develop automatic classifiers [18-20] suitable for the extraction of predefined and specific type of information from the given satellite sensor data with improved throughput in image analysis for better utilization of satellite data by the user. Survey of various classifiers for the analysis of remote sensing data and their comparative analysis showed the knowledge based classifiers provided improved accuracies over others [21].

Two types of automated classifiers are being defined and used for the analysis of remotely sensed data. Walter(1998) has used GIS database of LULC map for the generation of training sample, for automatic classification and updating of GIS database. In this method, the training sample data sets for all the classes are automatically generated using the information available in the GIS database and then the classification is carried as in the supervised classifier. This method assumes that the wrongly captured GIS objects and the number of changes in the real world are substantially less than all the number of GIS objects of the data set. The usefulness of knowledge base, used in these classifiers, is limited to the image data set used for extracting the training samples. The other method is a knowledge-based method [22,23], which relies on invariant / semi invariant feature parameter corresponding to different land use/land cover feature categories and it is most suitable for automatic classification. The spectral reflectance, being the invariant property of objects, has to be used for the extraction of the feature parameters.

Hall et al., [6-7] proposed the use of Normalized Difference Snow Index (NDSI) along with NIR reflectance threshold for snow cover mapping. It has been found that the NDSI based method provide better accuracy in the classification of results compared to the supervised Maximum likelihood classifier, due to the difficulties encountered in defining pixels under shadow that were snow covered without inadvertently mapping non-snow pixels [6]. However, the major difficulty in snow cover monitoring using NDSI based automated technique is elimination of snow under mountain shadow [6-7], inclusion of glacial water bodies ([11]) and gray clouds. These rain bearing clouds occur in the monsoon season. Hence, the combination of digital and visual interpretation techniques has been used for snow cover mapping, which is time consuming. An automated extraction algorithm for the identification of snow cover area using NDSI method has been developed to overcome the above limitations using the information existing in all the four bands of Resourcesat -1 AWiFS sensor. The importance of the usefulness of the Red, NIR, SWIR spectral bands in the elimination of water in the presence of the snow covered pixels under shadow and grey cloud has been brought out. The methodology for the algorithm development, validation of the results on large image mosaics has been reported in this paper

2. METHODOLOGY

Automated image analysis technique for extraction of information from the remote sensing image data must be scene (geographic location) and season independent. The spectral reflectance pattern is the intrinsic property of an object and the objects belonging to a given land Use / land cover class has similar shape, even though it can have variation in the magnitude due the intrinsic variations of the class features because of weathering, wetness etc., and also due to the extrinsic variations due to topography and sun illumination. The discriminating feature parameters that represent the spectral shape such as normalized spectral indices, spectral band ratios and brightness values being used in the classification of the remotely sensed image data. These parameters essentially capture the contrast features present between the feature classes and with-in class feature contrasts. The with-in class feature contrast captures the characteristic feature of the particular class, for example : the large reflectance change between the visible and short wave infrared band for the snow/ice. The between class contrast captures the discriminating features between the given set of object classes. The with-in class contrast features have been used for identification of the feature class, while the between class contrast are used for the elimination of other feature classes in the automated delineation of the specific feature classes such as water, snow, urban areas.

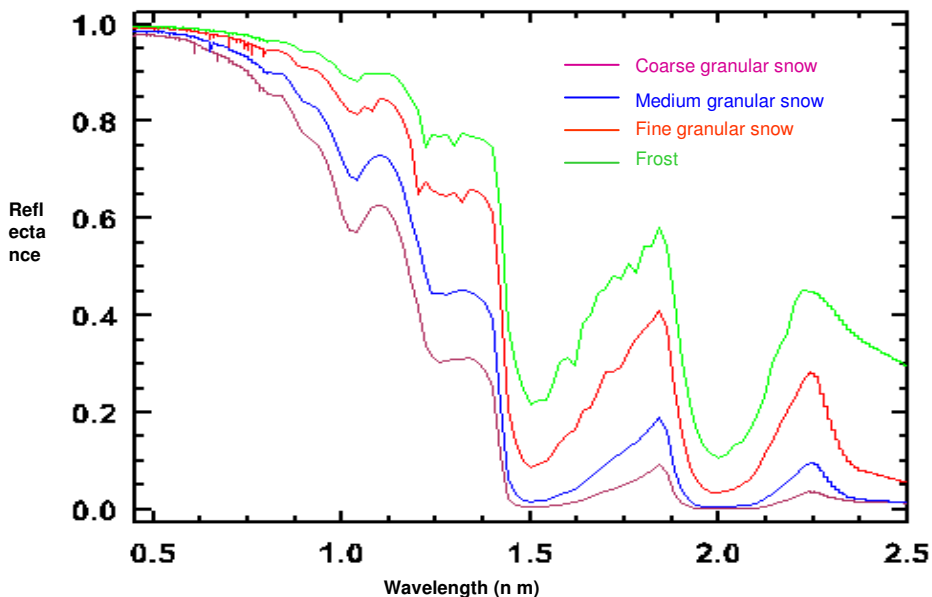
Development of automatic extraction algorithm involves the collection and analysis of spectral information (knowledge base), modeling their relationships, development and implementation of hierarchical logical algorithm, implementation of algorithm on various seasonal datasets, validation of the algorithm by comparison with standard NSDI based methods and hybrid digital visual interpretation techniques. The knowledge based method has been implemented in multi-logic decision equation using spectral spatial and contextual based parameters with suitable threshold levels. The selected parameter either support and reinforce the identification of the particular feature class or eliminate the noise feature classes. It is possible to identify and extract the pixels corresponding to the various feature categories with sufficient number of logical

decisions. A separate logical equations are used for subcategory of the feature classes, to account for the natural variations in the feature classes and also for the variations due to the geo-climatic impact on the spectral response pattern of the feature class. The threshold values used in these logics are flexible as these are used to reinforce the decision taken with multiple logics and is similar to the approach used by human interpreter in analyzing the image data in visual interpretation technique. The logical equations in general contain one or two essential conditions to identify the presence of a particular class and the other conditions are used for the removal of the noisy feature classes that may have similar response in certain geo-climatic conditions.

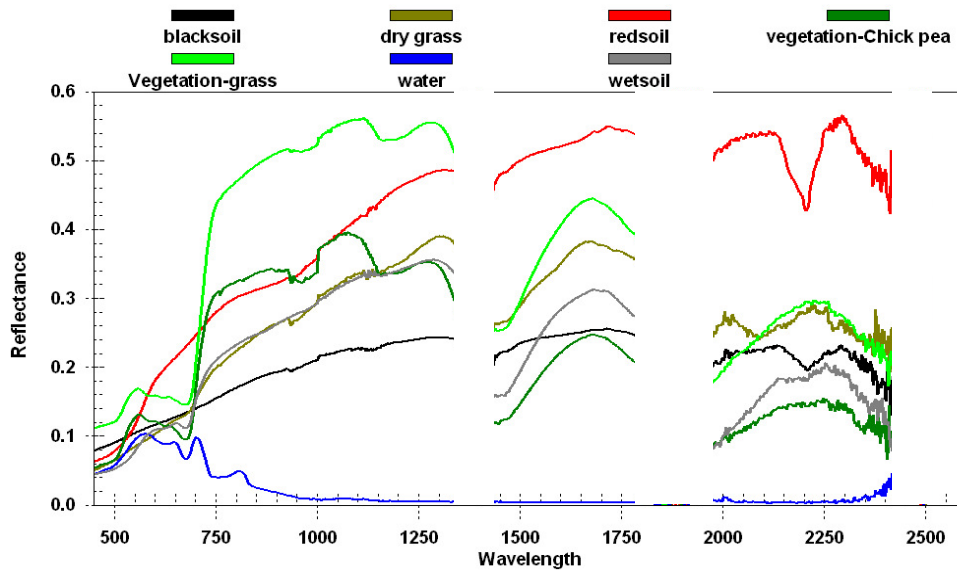
In the case of snow covered pixels / area extraction, spectral information only has to be used and the image information of the area such as texture is not useful due the reason that texture does not represent underground or the presence or absence of the snow cover over the ground. Hence, in snow cover extraction methods, the spectral feature parameters that represent the shape of the reflectance pattern of the snow and discriminating characteristics with respect to the other land cover classes and noise classes like cloud and cloud shadow also has to be used. The normalized difference spectral indices such as NDSI, NIR-SWIR indices and spectral ratios have been computed from the multi spectral image data and for the extraction of the snow covered pixels in the algorithm.

2.1 Analysis of Spectral Reflectance Pattern of Snow

The field measurements of spectral response pattern of different types of snow and ice has been carried out [4, 11] and also in the laboratory at John Hopkins university (spectral library of snow types) and the laboratory measurements is shown in figure 1a.. The spectral reflectance of snow has high values in visible bands and has small value in short-wave infrared band (1550-1750 nm). A comparison of the spectral response pattern of snow/ice cover (figure 1a) and other land cover types (figure. 1b) reveals that (i) snow has higher spectral contrast between the Green and SWIR spectral region compared to others except water ; (ii) snow has relatively higher reflectance in the visible region compared to that of other land types like water, soil, vegetation ; and (iii) Snow has higher reflectance values similar to cloud in visible region, while in the SWIR region it has much lower reflectance and this has been used as discriminating parameter.



(a) Snow / ice



(b) land cover types

FIGURE 1: Spectral reflectance characteristic of (a) snow/ice and (b) different land cover types.

In case of air or space borne measurements, the image DN values representing the satellite radiance is proportional to the ground object and spectral reflectance response pattern has been modified due to scattering and absorption by atmospheric constituents, variations of sun's illumination geometry, and sensor, etc. The conversion of image DN values to Top Of the Atmosphere (TOA) reflectance value [24] has been used to account for illumination of sensor geometry except for the atmospheric effect. Hence, TOA reflectance values for development of the automated snow cover extraction algorithm. The TOA reflectance (pTOA) is computed using the following equation.

$$\rho_{TOA} = \left(\frac{\pi L_{\lambda} d^2}{ESUN \cos(\Theta_s)} \right) \text{-----(1)}$$

- where ρ_{TOA} = TOA reflectance;
- L_{λ} = spectral radiance at sensor aperture ($mW \text{ cm}^{-2} \text{ sr}^{-1} \mu^{-1}$);
- d = Earth-Sun distance (Astronomical Units);
- $ESUN$ = mean solar exo-atmospheric irradiance ($mW \text{ cm}^{-2} \text{ sr}^{-1} \mu^{-1}$);
- Θ_s = solar zenith angle (degrees).

2.2 Normalized Difference Snow Index (NDSI)

Hall et.al [7] proposed the Normalized Difference Snow Index (NDSI) for the detection of pixel having snow and ice cover types based on analysis of the spectral reflectance pattern.

$$NDSI = \frac{\text{Green reflectance} - \text{SWIR reflectance}}{\text{Green reflectance} + \text{SWIR reflectance}} \text{----- (2)}$$

A scatter plot (Figure.2) of NDSI as a function of TOA reflectance in NIR Spectral band for various land use / land cover features indicates that riverine sand/ barren rock, urban and vegetation have negative NDSI values and cloud has value close to 0.2. The NDSI value for

snow/ice has been found to be above 0.4, while water has values in the range of 0.2 to 0.6. The shallow water and mixed pixels of water and soil / sand has lower NDSI values. Sensitivity analysis has been carried out by Kulkarni et al.2006 to know the effect of NDSI threshold on the snow cover area estimation indicated a drop in area of approximately 3% for NDSI threshold of 0.4, beyond which the reduction of snow cover area increases rapidly with higher NDSI threshold and concluded that the NDSI value of 0.4, provides reasonable accuracy for snow cover monitoring. Hall et al [7] has proposed a threshold value of $NDSI > 0.4$ and NIR reflectance > 0.11 for snow cover estimation using TM spectral bands. The same threshold values were also used by Xiato et al [15, 16] with SPOT4 Vegetation (VGT) sensor. The NIR reflectance threshold of 0.11 has been used to eliminate water pixels in the snow cover estimation which lead to exclusion of snow under mountain shadows. Kulkarni et al [11] used a threshold value of $NDSI > 0.4$ to include the snow under shadow and suggested pre-enumerated water body mask for eliminating the water in snow estimation. The spectral reflectance measurements [10,11] has shown that the NDSI is suitable for the detection of the snow cover even under mountain shadow. In view of above, the possibility of using information from other spectral bands to overcome the above limitation has to be studied.

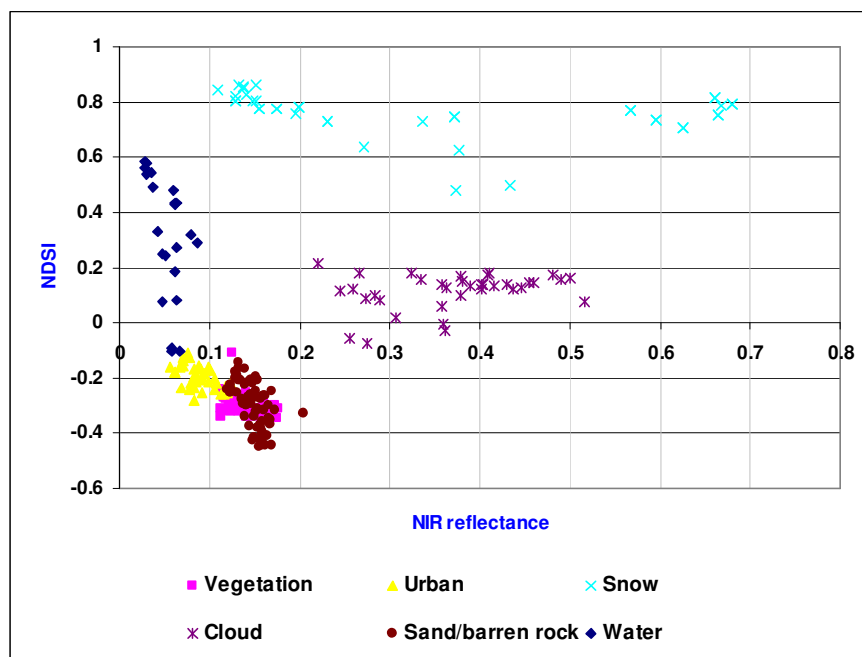


FIGURE 2 : TOA reflectance derived NDSI scatter plot for snow and other land cover types.

2.3. Spectral Reflectance Pattern Analysis and Algorithm Development for Snow Cover Estimation

The snow covered pixels of various levels of illumination (directly illuminated by SUN and those under different levels of shadow cover and at various seasons) were identified by visual observations of the TOA image and their TOA values were extracted. Further, the TOA reflectance values of the noise features such as water and grey cloud pixels were extracted after identifying them visually from different images . Analysis of the spectral reflectance pattern of different snow under different illumination conditions based on visual observations and noise features such as water, grey cloud has been carried out. The scatter plot of NDSI as a function of NIR reflectance for different types of objects including snow under different illumination conditions (that can have NDSI value greater than 0.4) are shown in Figure 3. The NIR reflectance > 0.11 for eliminating water bodies, leads to the exclusion of snow pixels under shadow. If this NIR threshold has been removed, then different method has to be used for the elimination of water pixels for snow cover estimation. Kulkarni et al [11] have suggested the use of water body mask

to remove the water pixels being classified as snow. This may not be suitable for all geographic locations and seasons. To solve the problem of water pixels, a comparative analysis of the spectral characteristics water and snow under shadow has been carried out to identify discriminating features.

2.3.1. Elimination of Water from Snow

The analysis has shown that there exists differences in the spectral reflectance of water (figure.4a), snow under shadow (figure.4b) in the Red–NIR spectral region which can be used for their discrimination. The scatter plot of NDSI as a function of normalized NIR-SWIR difference index (NIR-SWIR / NIR+SWIR) and Red-NIR ratio (Red/NIR) for various types of snow cover and water has been shown in figure 5. It has been observed that a combination of NIR- SWIR index value and Red-NIR ratio can provide the required discrimination of snow from water which has been implemented with suitable threshold along with NDSI in the development of algorithm.

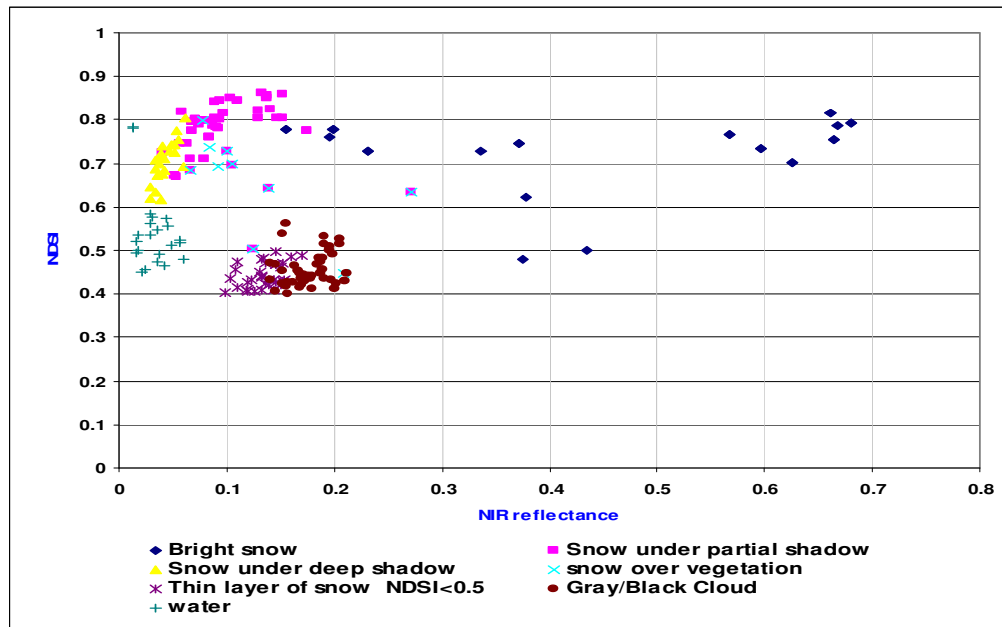
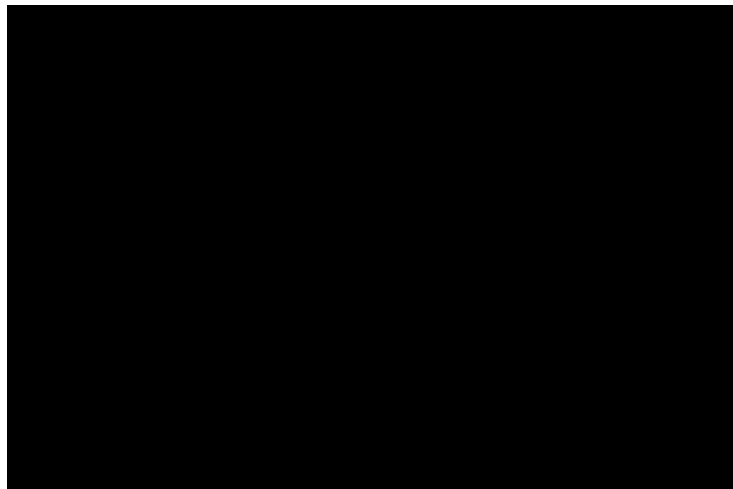
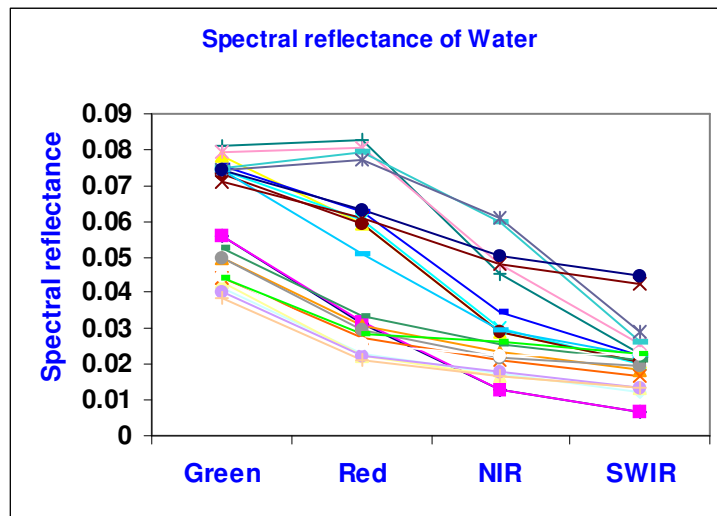


FIGURE 3: Scatter plot of normalized difference snow index (NDSI) as function of NIR reflectance.



a) snow under shadow



(b) water

FIGURE 4: Spectral reflectance pattern of water and snow under shadow.

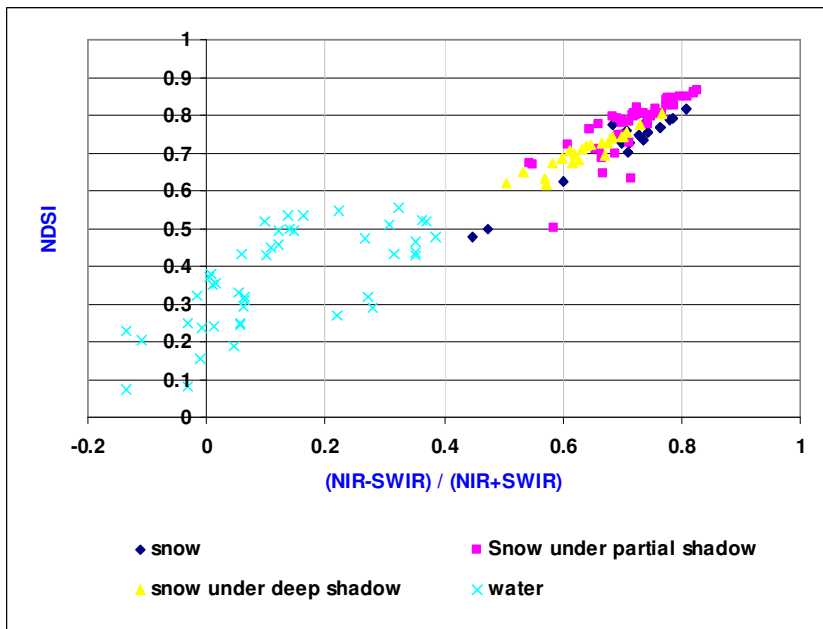


Fig. 5(a)

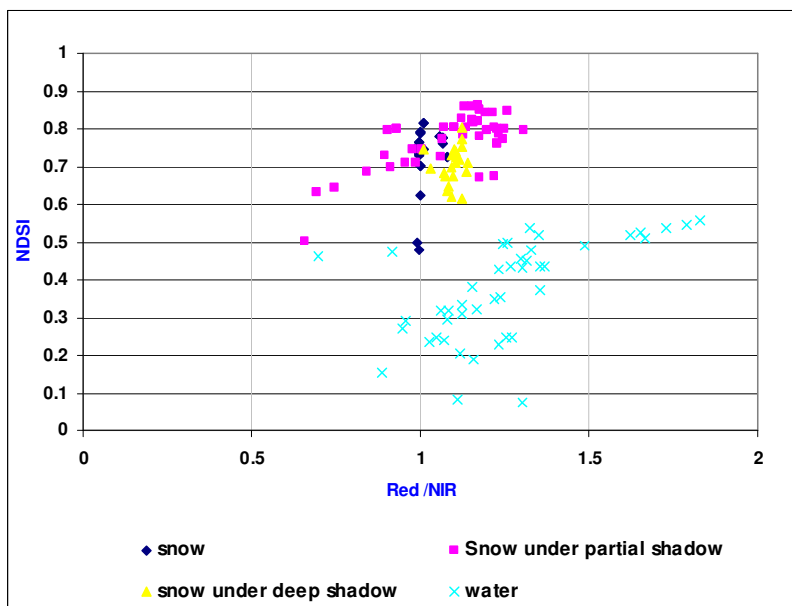
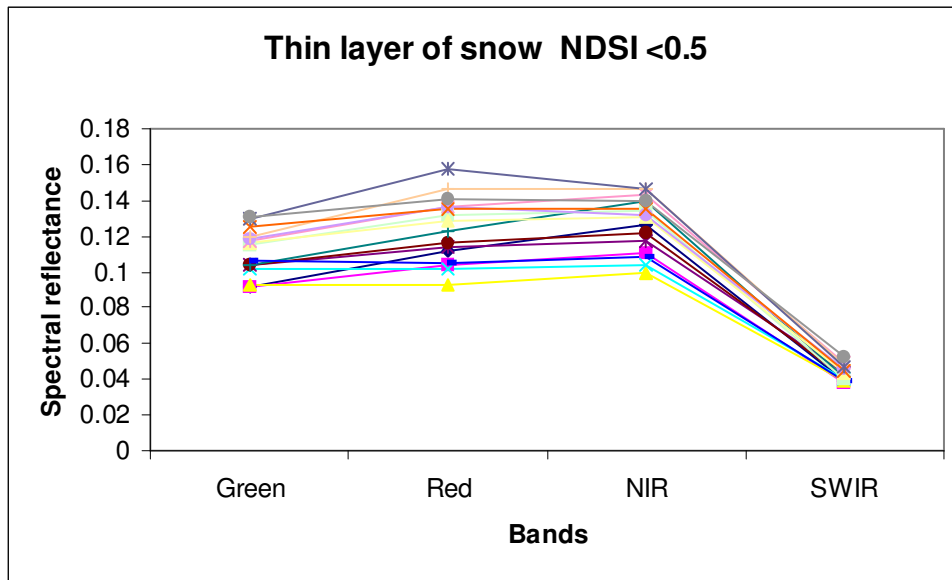


Fig. 5(b)

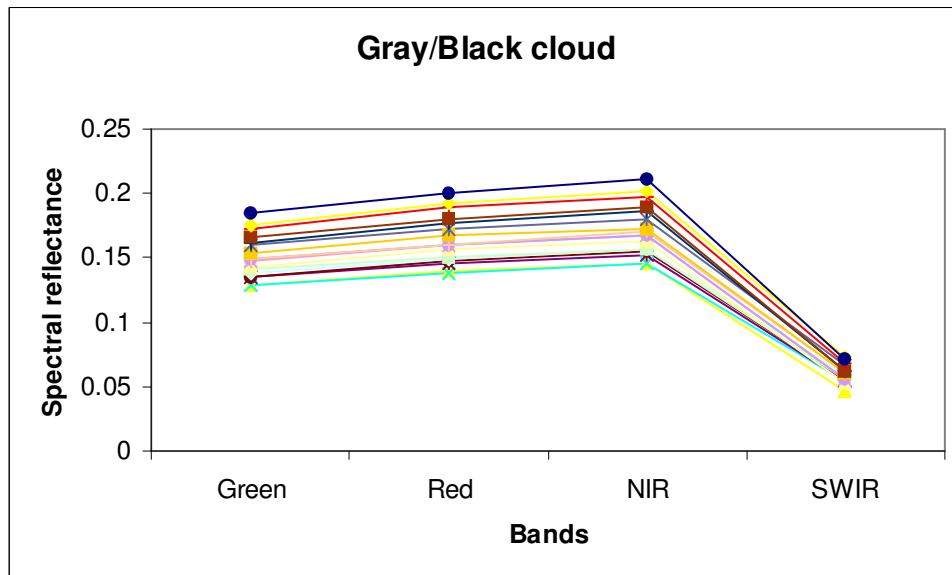
FIGURE 5 : Scatter plot NDSI for snow under mountain shadow and water as function of (a) normalized NIR –SWIR difference Index 9b) Normalized Red-NIR ratio

2.3.1. Elimination of Grey Cloud From Snow

It has been observed from scatter plot (Fig.3) that some of the pixels corresponding to black / grey clouds (water bearing clouds) has NDSI values >0.4 and <0.5 which may be due to the absorption of SWIR radiation by the water molecules present in this type of cloud. Hence, the spectral characteristics of the snow having $NDSI < 0.5$ and those of the gray (water bearing) cloud (Figure 6) has been studied to identify the discriminating characteristics. There exists small difference in the Green reflectance values, total pixel brightness and red-NIR ratio and these were used for the discrimination of the grey water bearing cloud and snow pixels having NDSI values between 0.4 and 0.5.



(a)



(b)

FIGURE 6 : The spectral characteristics of (a) snow having $NDSI < 0.5$; (b) gray (water bearing) cloud.

3. IMPLEMENTATION OF THE ALGORITHM

The automated snow cover extraction algorithm has been implemented in modular, hierarchical approach. The reflectance values for a number of carefully selected sample pixels were extracted from the image data acquired at different time periods and in different locations. Detailed statistical analysis has been carried out to arrive at suitable hierarchical logics and thresholds. At the top level of hierarchy, the candidate pixels for snow has been identified with $NDSI > 0.4$ and this has been implemented as shown below :

```
IF (NDSI>0.4) THEN {check snow logics}
ELSE {non snow pixel}
```

This logical condition eliminates the pixels corresponding to land cover classes such as barren soil, vegetation, urban areas and noise classes like bright cloud, but includes water and few dark cloud covered pixels.

Logics have been implemented for different NDSI ranges for discriminating the snow from those noise features interfere in that NDSI range. For example for $NDSI > 0.6$, noise feature-water has to be eliminated, while in the NDSI range below 0.5 that cloud pixels has to be eliminated in addition to the water. The exact feature parameter identification and the selection of the threshold value (or range) for each of the selected feature parameter has been determined based on statistical analysis of the spectral response. Typical analysis carried out for sub category-snow under shadow for few sample pixels used were given table 1.

A set of parameters viz., the normalized spectral indices, spectral ratios computed for arriving at the threshold values were shown in the table. Similar computations were made for each of sub categories of snow (under different levels of shadow) and the other features that introduce noise in the snow cover estimation such as cloud and water. The selection of the parameter and their threshold were determined by comparing mean, variance, minimum and maximum values of each of the sub category of snow and the mixing noise feature. The implementation of the hierarchical, multi threshold logics for the specific case (NDSI range : 0.5-0.6) has been implemented as given below :

```
IF ( ( NDSI >0.5) AND ( NIR-SWIR index>0.3) ) THEN
{
IF ( (NIR-SWIR index<0.57) AND ( R/NIR>1.15) AND ( Brightness < 0.25) )
THEN { Water}
Else IF (R/NIR < 1.0) THEN { snow }
}
Else IF( (NIR-SWIR index>0.40) AND ( Brightness > 0.375) )
THEN { snow }
}
```

Similar implementation has been carried out for each sub category of snow cover. In all about six such hierarchical set of logics were implemented in the new automated algorithm for snow cover estimation for the identification of snow and elimination of water and cloud pixels and is shown in the flowchart (Figure.7).

TABLE 1: Typical computation table for sub category – snow under shadow with few sample pixel data for the identification of feature parameter and their threshold values for use in hierarchical, multiple logics.

Green	Red	NIR	SWIR	NDSI	R/NIR	NIR-SWIR index	NDVI	sum of reflectance	G/R	G/NIR	R/SWIR	
0.203	0.187	0.175	0.026	0.77	1.07	0.74	-0.03	0.59	1.09	1.16	7.21	
0.203	0.187	0.175	0.026	0.77	1.07	0.74	-0.03	0.59	1.09	1.16	7.21	
0.201	0.188	0.272	0.045	0.63	0.69	0.72	0.18	0.71	1.07	0.74	4.17	
0.199	0.175	0.151	0.015	0.86	1.15	0.82	-0.07	0.54	1.14	1.31	11.72	
0.189	0.167	0.147	0.021	0.8	1.14	0.76	-0.06	0.52	1.13	1.28	8.17	
0.179	0.142	0.129	0.02	0.8	1.10	0.74	-0.05	0.47	1.27	1.39	7.26	
0.179	0.142	0.129	0.02	0.8	1.10	0.74	-0.05	0.47	1.27	1.39	7.26	
0.178	0.162	0.138	0.014	0.85	1.17	0.81	-0.08	0.49	1.10	1.29	11.24	
0.177	0.158	0.141	0.017	0.83	1.12	0.79	-0.06	0.49	1.11	1.25	9.41	
0.175	0.155	0.137	0.013	0.86	1.13	0.82	-0.06	0.48	1.13	1.28	11.56	
0.174	0.155	0.133	0.013	0.86	1.17	0.83	-0.08	0.47	1.12	1.31	12.23	
0.168	0.148	0.129	0.016	0.82	1.15	0.77	-0.07	0.46	1.13	1.30	9.07	
0.158	0.137	0.109	0.013	0.85	1.26	0.78	-0.11	0.42	1.15	1.45	10.43	
0.183	0.162	0.151	0.02	0.8	1.07	0.77	-0.03	0.52	1.13	1.21	8.15	
0.127	0.104	0.139	0.028	0.64	0.75	0.67	0.15	0.40	1.22	0.91	3.76	
0.108	0.095	0.105	0.019	0.7	0.91	0.69	0.05	0.33	1.13	1.03	4.95	
0.098	0.082	0.124	0.032	0.5	0.66	0.58	0.21	0.34	1.20	0.79	2.51	
0.079	0.064	0.052	0.015	0.67	1.22	0.55	-0.10	0.21	1.24	1.51	4.14	
0.078	0.062	0.053	0.015	0.67	1.18	0.55	-0.08	0.21	1.25	1.47	4.05	
0.183	0.162	0.151	0.02	0.76	1.06	0.73	-0.02	0.46	1.16	1.22	7.61	Mean
0.014	0.017	0.039	0.008	0.1	0.18	0.09	0.09	0.12	0.06	0.22	3.04	Std. Dev
0.203	0.188	0.272	0.045	0.86	1.26	0.83	0.21	0.12	1.27	1.51	12.23	Max
0.158	0.137	0.109	0.013	0.5	0.66	0.55	-0.11	0.12	1.07	0.74	2.51	Min

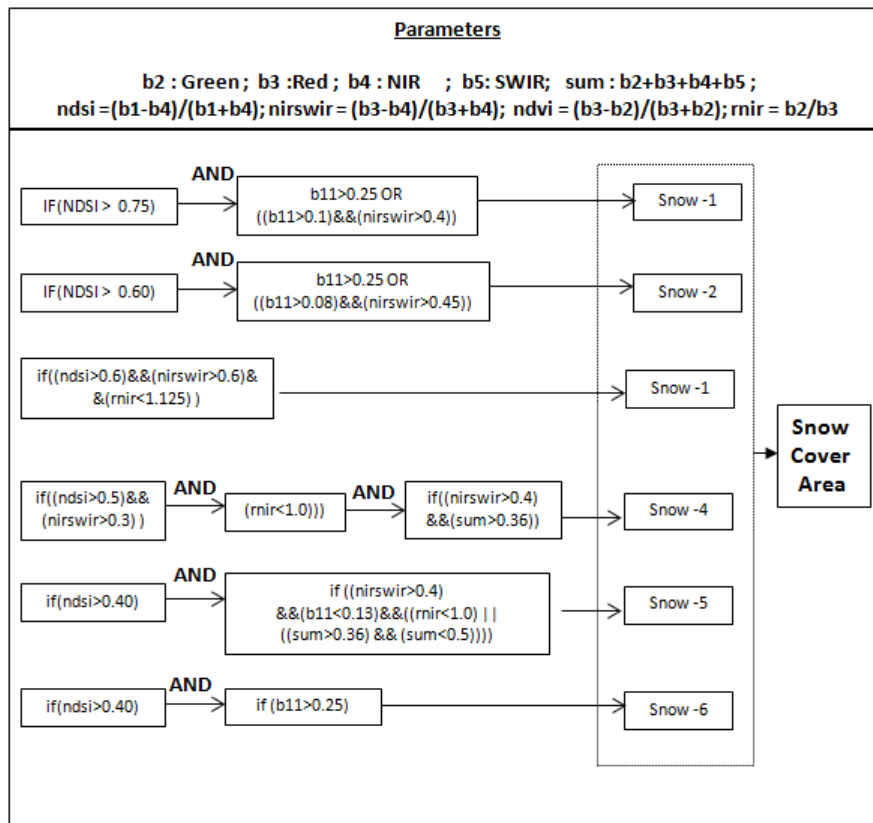


FIGURE 7 : The hierarchical logical equations used for automatic extraction of snow cover

4. VALIDATION OF THE RESULTS

The evaluation of the algorithm and validation of the results has been carried out by comparing the classification accuracy achieved with Hall’s algorithm and Kulkarni algorithm. The evaluation has been carried out using two approaches viz. sample pixel based analysis and the image based analysis. A number of sample pixels of the noise features such as cloud /water and different types of snow has been classified with all the three algorithms in the first approach and the results were shown in Figure. 8.

The new algorithm has been found to be more efficient in the elimination of noise features and is as good as Hall’s algorithm in the elimination of water pixels and has been able to almost eliminate the grey water bearing cloud pixels, which has not been addressed by either of the algorithms. The algorithm has also been found to be very effective in the detection of the snow pixels under shadow. These results has proved that the new snow algorithm is effective in eliminating the noise features in the automated snow cover estimation. A subset of AWiFS image which has noise features has been selected and the snow cover estimation has been

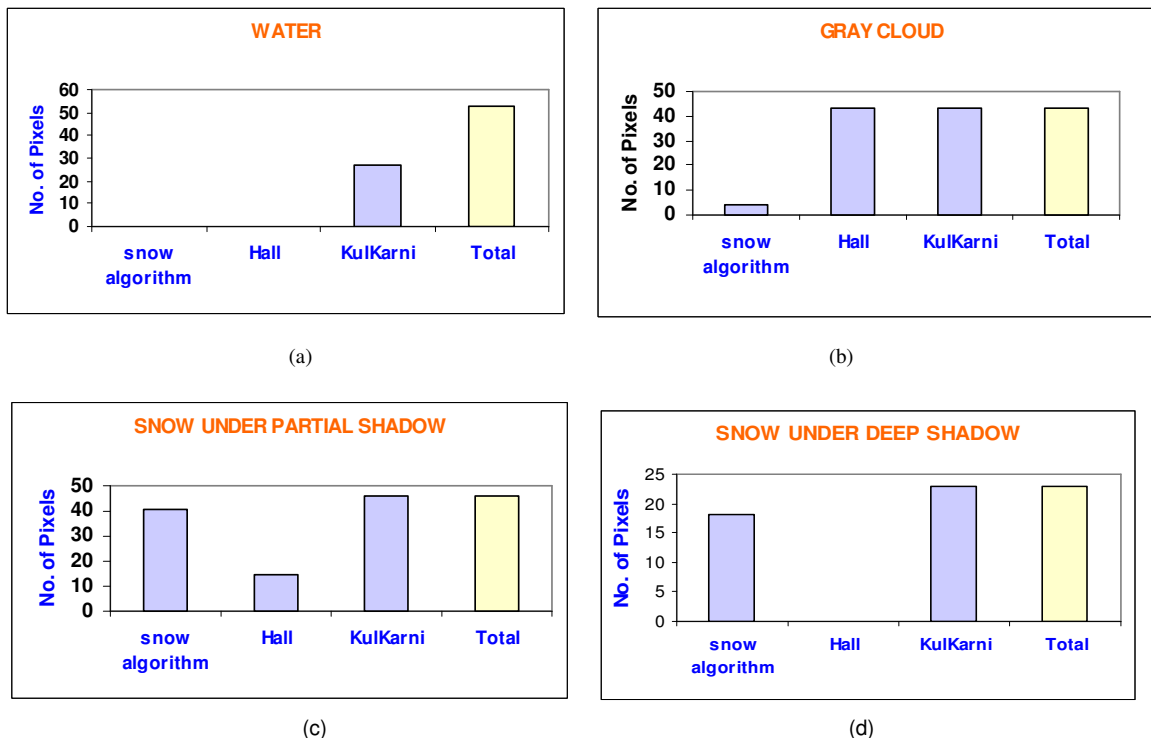


FIGURE 8: Elimination of (a) water (b) grey cloud ; inclusion of (c) snow under partial shadow (d) snow under deep shadow

To evaluate the performance of the algorithm in the exclusion of water bodies, a sub scene of AWiFS image (Fig 10a) has been used and the results obtained with the Hall's algorithm and that of the new algorithm are compared (figure 10b and 10c). The comparison of the results has shown that the new snow algorithm is as effective as that of the Hall's algorithm in the elimination of water pixels. Both the algorithm identifies the frozen water (ice) in a part of the Manasarover lake as snow cover pixels. This is due to the fact that the water in that part of the lake has frozen to form white ice. In this case, the Kulkarni's algorithm has not been considered for comparison as it has been expected to include all the water pixels having $NDSI > 0.4$. carried out using all the three algorithms and the results were evaluated for the improvements achieved with the new snow algorithm. Figure 9a. shows AWiFS image in snow covered mountain area of Himalayas, with a large number of snow cover pixels under mountain shadow. The levels of darkness / illuminations for these pixels vary widely. Most of the snow-covered areas under mountain shadow were eliminated in the snow cover classification results based on Hall's algorithm (figure 9b) due to the NIR reflectance threshold of $NIR > 0.11$. The snow cover estimation with new snow algorithm has included the snow pixels under shadow (Fig 9c) as expected. In case of Kulkarni's algorithm, all the snow cover pixels with $NDSI > 0.4$ will be detected and hence expected to provide results similar to that of new algorithm.

To evaluate the performance of the algorithm in the exclusion of water bodies, a sub scene of AWiFS image (Fig 10a) has been used and the results obtained with the Hall's algorithm and that of the new algorithm are compared (figure 10b and 10c). The comparison of the results has shown that the new snow algorithm is as effective as that of the Hall's algorithm in the elimination of water pixels. Both the algorithm identifies the frozen water (ice) in a part of the Manasarover lake as snow cover pixels. This is due to the fact that the water in that part of the lake has frozen to form white ice. In this case, the Kulkarni's algorithm has not been considered for comparison as it has been expected to include all the water pixels having $NDSI > 0.4$.

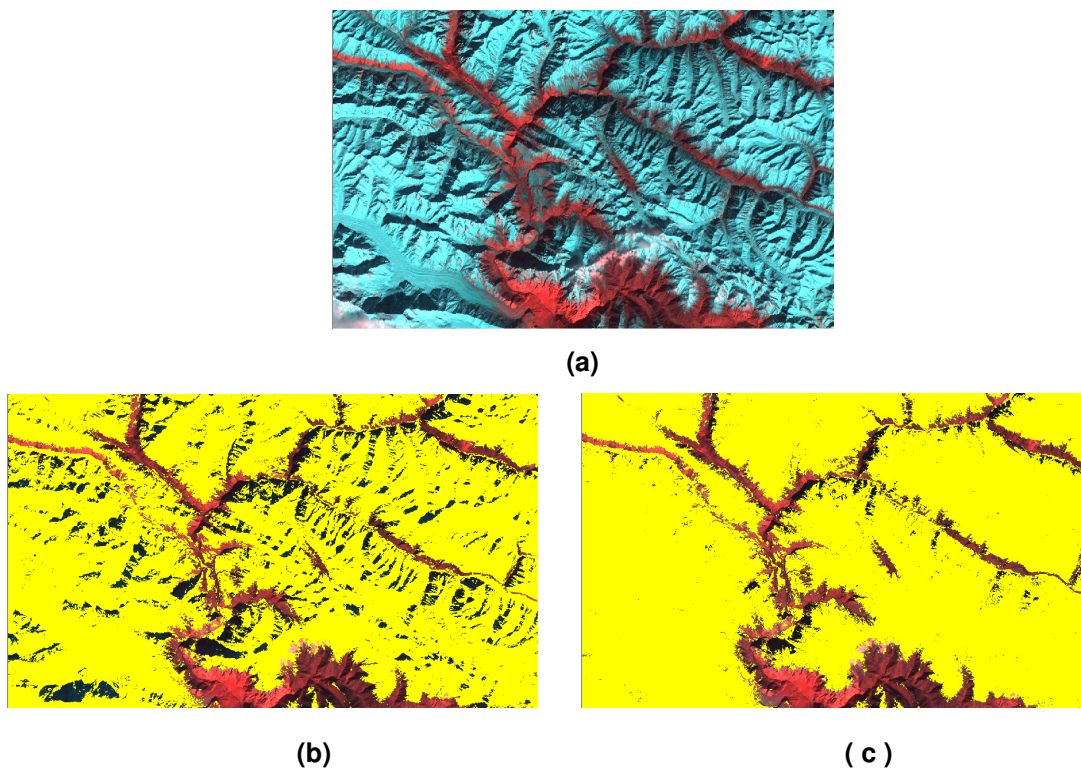


FIGURE 9: Extraction of snow cover under shadow conditions
(a) FCC image (B2, B3, B5) showing the snow cover (cyan); (b) FCC overlaid with snow cover derived with Hall's method (yellow); (c) FCC overlaid with snow cover derived with new snow algorithm (yellow)

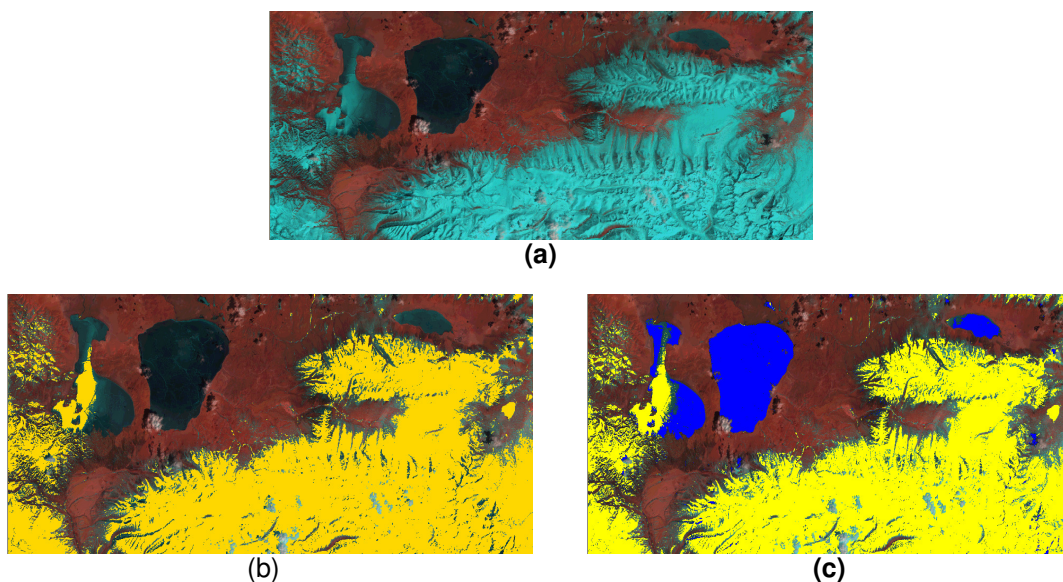
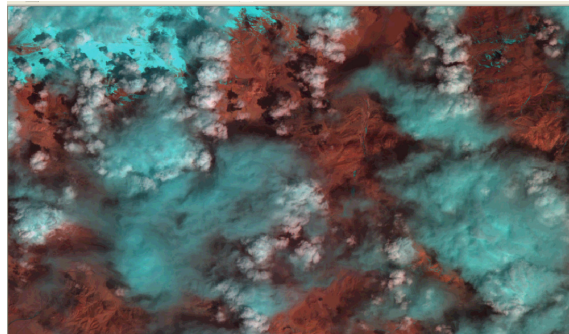
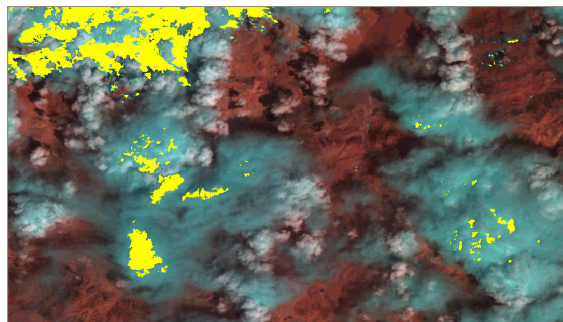


FIGURE 10 : Detection of snow in the presence of water bodies
(a) FCC sub-image(B2,B3,B5) showing the snow cover(cyan) ; (b) FCC overlaid with snow cover derived with Hall's method (yellow); (c) FCC overlaid with snow cover derived with new snow algorithm (yellow: snow ; Blue -Water)

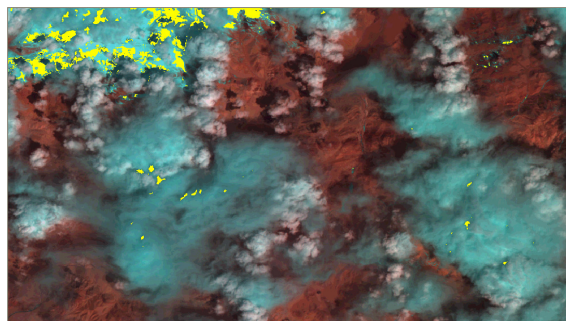
Figure 11a shows the AWiFS image with snow and gray (water bearing) clouds. The classification results obtained with the Kulkarni's algorithm and the new automated snow algorithm has been shown in figure 11b and 11c respectively. A substantial improvement in the reduction of cloud pixel noise has been observed in snow cover estimate by the new algorithm. The results of the Hall's threshold method is expected to be the same as that of Kulkarni's algorithm. This is due to the fact that the only additional condition for the Hall's method is the NIR reflectance has to be more than 0.11 and this condition has been satisfied for almost all the cloud pixels.



(a)



(b)



(c)

FIGURE 11: Elimination of clouds in snow cover extraction

(a) FCC sub-image(B2,B3,B5) showing the snow cover(cyan) ; (b) FCC overlaid with snow cover derived with Kulkarni's method (yellow); (c) FCC overlaid with snow cover derived with new snow algorithm (yellow)

6. RESULTS AND DISCUSSION

The snow cover estimation of the entire Himalayan mountain range covering India, Nepal, Pakistan and China has to be carried out for environmental studies related climate change. This implies that the algorithm for snow cover estimation has to handle larger image mosaic containing many AWiFS images. To validate the algorithm for its ability to handle image mosaics, it was tested with large image (42573 x 26881 pixels) covering Himalayan region of India from the state of Kashmir in the west to Arunachal Pradesh in the east (Figure 12). The algorithm has been found to be working satisfactorily. These results shows the robustness of the algorithm in various locations. Further it has been tested for the various seasons (October, Jan/Feb and April/May) covering the pre-snow fall period, winter and summer seasons.

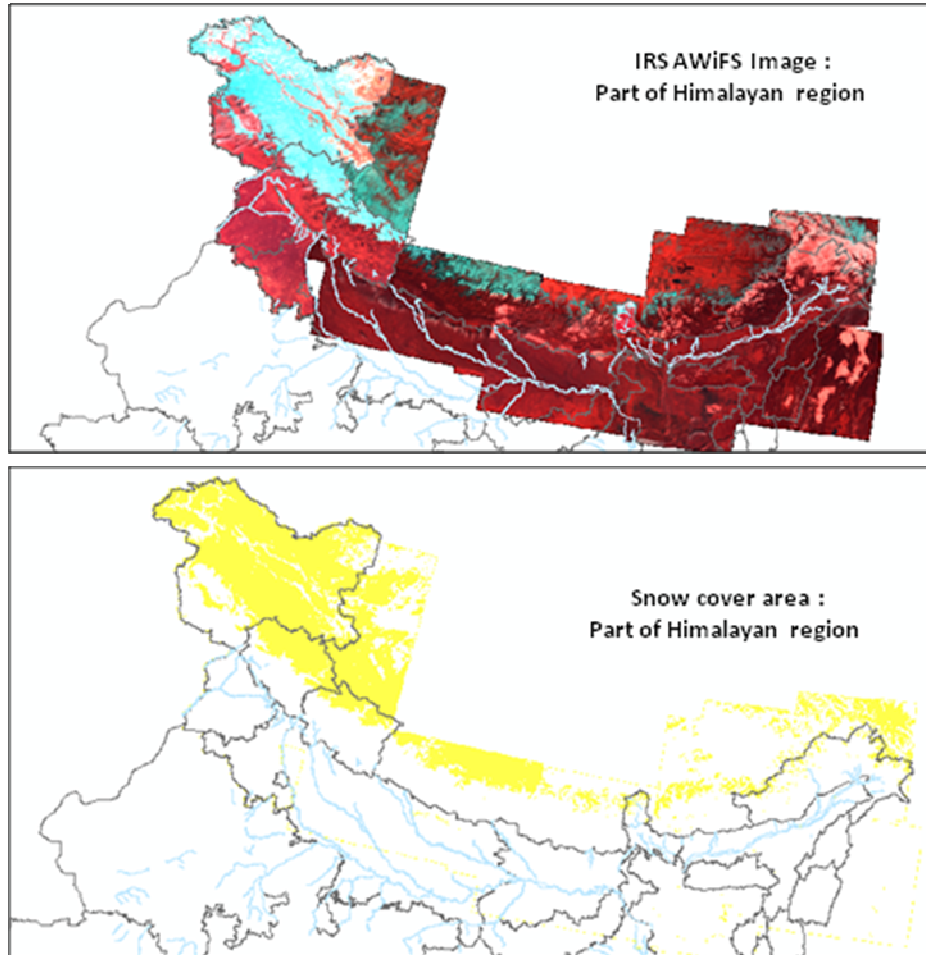
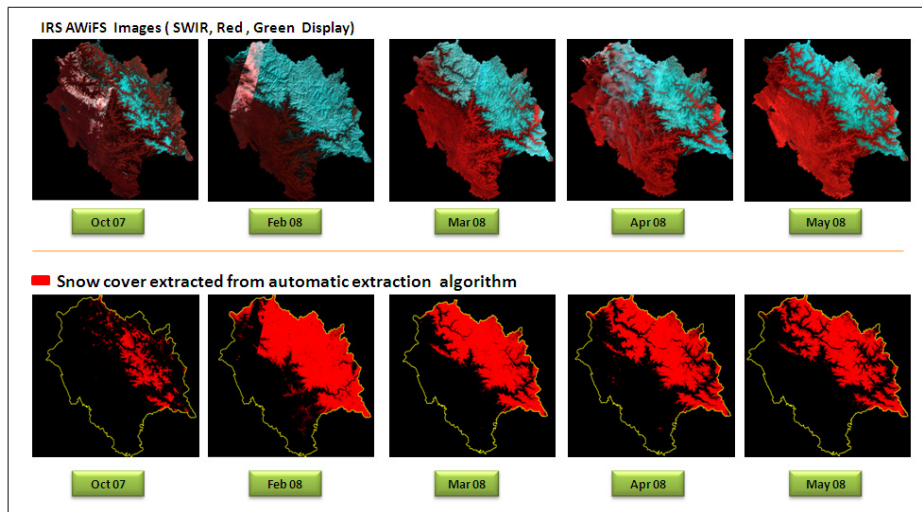
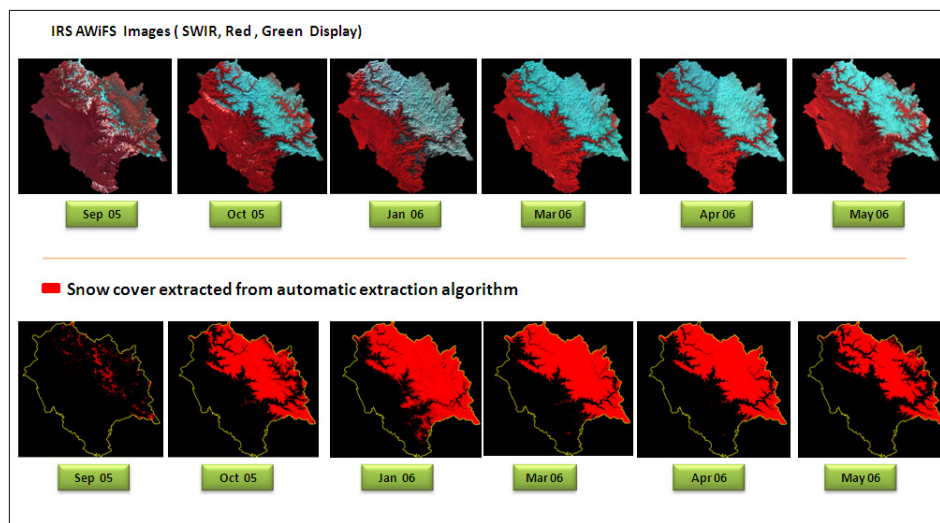


FIGURE 12: snow cover estimation results for AWiFS FCC mosaic (B2,B3 and B5) image scene of Himalayan region

The snow cover estimation for the years 2004-05 to 2007-08 has been evaluated over the Himalayan region of Indian terrain of the hilly mountain area in India and the results were ported into the NRSC web portal Bhoosampada [25]. The intra annual (temporal) change in the snow cover is an important parameter for the estimation of water flow form the snow melt in the rivers and the intra-annual studies are required in the case of environmental studies. Hence, an attempt has been made in the case of AWiFS imagery of Himachal Pradesh State, India for the years 2005-06 and 2007-08 as shown in Figure 13a. and the snow cover area estimates were shown in the Figure 13b. The maximum snow cover area occurs during the Jan-Feb (winter period) due to the snow fall that occurs in the Himachal Pradesh and it gradually reduces in the spring –summer period (March –May) to the extent of approximately 1/3 of the total snow covered area (Figure.14). It shows the minimum extent snow covered occurred in the September – October period before the onset of winter snow fall.



(a) 2007-08



(b) 2005-06

FIGURE 13. Temporal snow cover variation in Himachal Pradesh: (a) 2007-08; (b) 2005-06

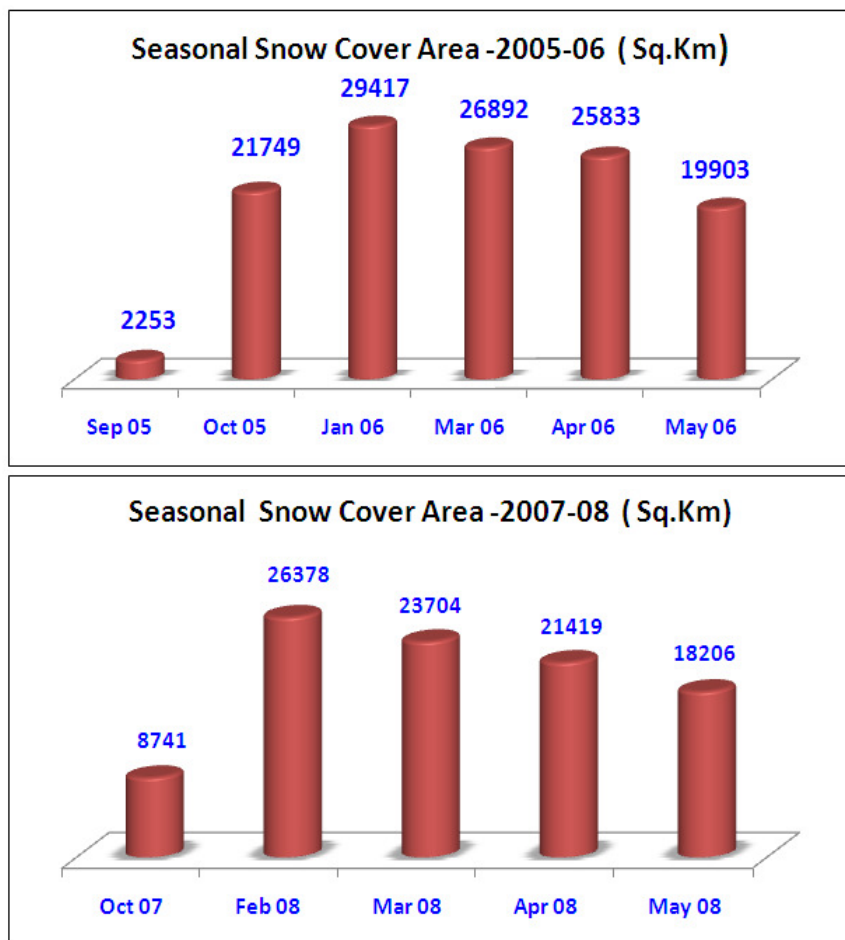
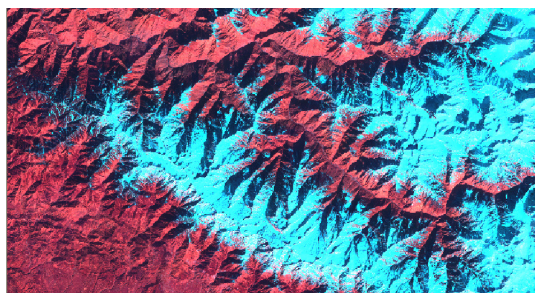


FIGURE 14. Seasonal snow cover area estimates

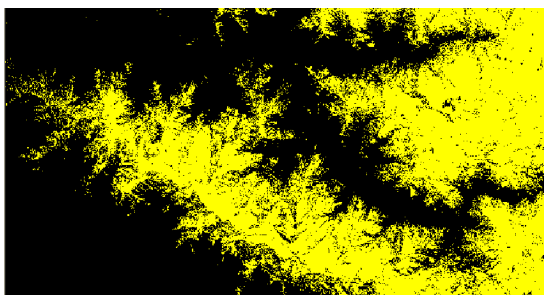
Since, automated snow cover extraction algorithm has been developed essentially based on the spectral contrast features of AWiFS, an attempt has been made to evaluate the same with the data obtained from other sensors having similar spectral bands such as Resourcesat –1 LISS III, LANDSAT ETM. However, it has to be noted that though, the spectral bands are similar, their radiometric resolutions are quite different (Table.2). The algorithm has been evaluated with the data obtained from IRS LISS III, Landsat TM data sets acquired on 02-02-2006, 02-06-2009 respectively were also shown in the Figure.15 and Figure 16. The results shows that the algorithm is suitable for these datasets as well. It has been observed a slight reduction in the snow cover area due to the lower radiometric resolution in ETM and LISS III. Hence, the required minor modifications for spectral thresholds were implemented to obtain the satisfactory result in the case of LISS III as shown in Figure. 15c. Similar exercise would improve the efficiency of the algorithm to enable the national / global application of the algorithm for the other sensors having similar spectral bands. The comparison of results obtained with LANDSAT ETM has shown the improvement achieved with the new algorithm compared to that of the Hall's method, particularly in the case of snow covered pixels in the mountain shadow region.

Satellite/ Sensor	Band width μm	Lmax $\text{W/m}^2\text{-Sr-}$ micron	Lmin $\text{W/m}^2\text{-Sr-}$ micron	DN max	Spatial Resolution m	Radiometric Resolution $(\text{W/m}^2\text{-Sr-micron})/$ Unit DN Value
Resourcesat -1 AWiFS						
B2	0.52 - 0.59	52.34	0	1024	56	0.051113281
B3	0.62 - 0.68	40.75	0	1024	56	0.039794922
B4	0.76 - 0.86	28.425	0	1024	56	0.027758789
B5	1.55 - 1.7	4.645	0	1024	56	0.004536133
Resourcesat -1 LISS III						
B2	0.52 - 0.59	12.064	0	128	23.5	0.094250000
B3	0.62 - 0.68	15.131	0	128	23.5	0.118210938
B4	0.76 - 0.86	15.757	0	128	23.5	0.123105630
B5	1.55 - 1.7	3.397	0	128	23.5	0.026539063
Landsat ETM						
B2	0.52-0.60	30.09	-0.64	256	30	0.120039063
B3	0.63-0.69	23.44	-0.05	256	30	0.096171875
B4	0.76-0.90	24.11	-0.51	256	30	0.096171875
B5	1.55-1.75	3.106	-0.1	256	30	0.012523438

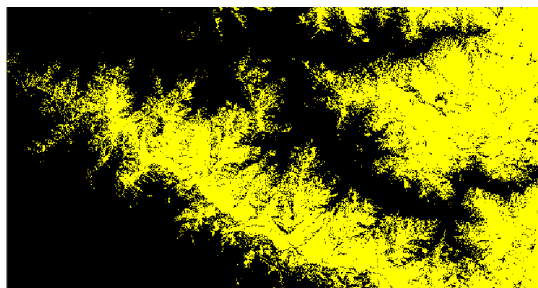
TABLE 2. Comparison of bandwidths in different satellite sensors in Visible & SWIR regions



(a)



(b)



(c)

FIGURE 15 : Algorithm results from IRS LISS III

(a) FCC sub-image(B2,B3,B5) showing the snow cover(cyan) ; (b) Snow cover derived from new automated algorithm for AWiFS ; (c) Snow cover derived from modified algorithm for LISS III

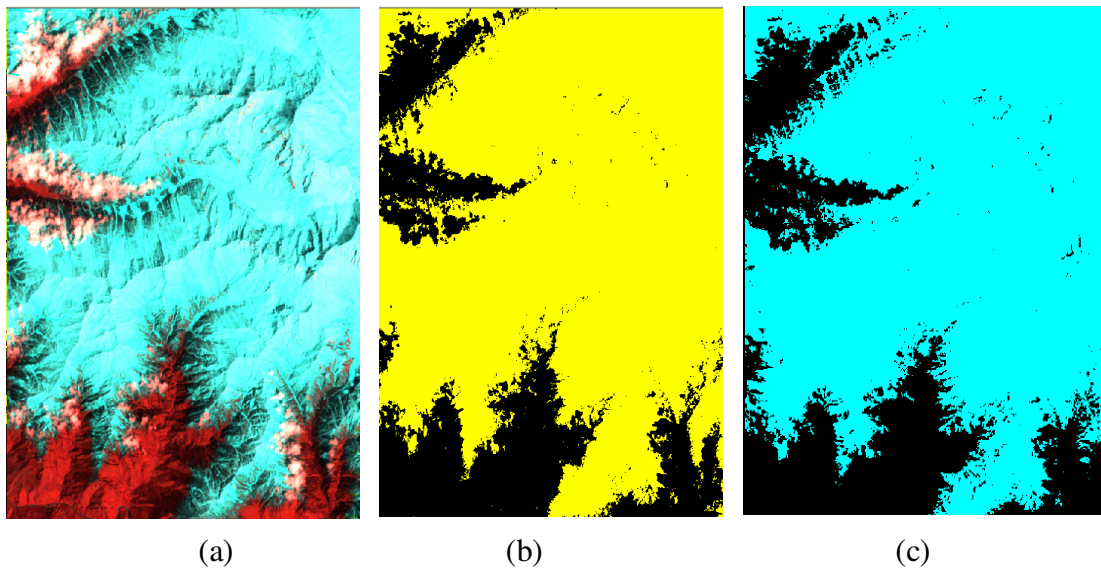


FIGURE 16. Algorithm results from Landsat ETM

- (a) Landsat ETM sub-image(B2,B3,B5) showing the snow cover(cyan) ; (b) Snow cover derived from new automated algorithm ; (c) Snow cover derived from Hall's method

7. CONCLUSION

A new algorithm for the automated extraction of snow cover estimation has been developed and implemented for the Resourcesat-1 AWiFS sensor data. The algorithm has been developed based on the spectral signature of snow and other land cover noise in the spectral region of visible-NIR and SWIR spectral bands. The algorithm combines the best features of both Hall's algorithm and Kulkarni's algorithm overcoming their limitations. The algorithm has been evaluated extensively with large number of image data sets obtained over the Himalayas, bordering India in different seasons and is found to be working satisfactorily. The algorithm has been able to identify snow pixels in the presence of noise features like mountain shadow, water bodies and cloud (both white and water bearing gray cloud types). The algorithm has been found to be suitable for use with other sensor data such as IRS LISS III and Landsat ETM. The automatic snow cover estimation method can be applied for regular periodic monitoring of temporal snow cover change studies for snow melt runoff and estimation of water flow in the rivers originating in Himalaya and climate change. The seasonal snow cover over Himalayas in India over the 4 years (2004-05 to 2007-08) has been extracted from AWiFS data of IRS satellite and they are ported on to NRSC website BHOOSAMPADA (<http://applications.nrsc.gov.in:15001/>).

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