Performance Governing Factors of Biogeography Based Land Cover Feature Extraction: An Analytical Study

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Abstract- **In recent years, nature inspired remote sensing image classification has become a global research area for acquiring the geo-spatial information from satellite data. The findings of recent studies are showing strong evidence to the fact that various classifiers perform differently when applied to images having different natural terrain features. This paper is an analytical study and a performance based characterization of the most recent nature inspired image classification technique i.e. Biogeography based Optimization (BBO) that has been used for focused land cover feature extraction [6]. The paper explores the behavior of BBO over different terrain features of a multi-spectral satellite image and establishes the fact that the classification efficiency of BBO for a given land cover feature is proportional to the degree of disorder of the Digital number (DN) values of the pixels comprising that land cover feature when viewed in any of the bands of the multi-spectral satellite image. More precisely, the classification efficiency of BBO on a terrain feature is inversely proportional to the entropy for that feature when viewed in any of the bands of the multi-spectral satellite image. For verification, we calculated the entropies for each of the land cover feature in two bands and found the same results in both the bands, which proves our proposed concept. The dataset on which the proposed concept is demonstrated is the 7-band cartoset satellite image of size 472 × 576 pixels of the Alwar region in Rajasthan. The results indicate that BBO is able to classify the homogeneous regions i.e. the regions with the lower entropy, more efficiently than the regions which show a greater degree of heterogeneity, i.e. higher entropy.**

Keywords- BBO, image classification, entropy, terrain.

I. INTRODUCTION

Classification being the main product of remote sensing image processing extracts useful information from remote sensing data. Classification is one of the key topics for image understanding. Image classification is one of the important approaches for recognizing different terrain features. Several problems could be confronted in conventional classification method. Illustration- More manual intervention may have an impact on the classification and hence can affect the final result; the available information could not be utilized precisely and adequately. As a result numerous other methods have been developed for classification. Currently many soft computing techniques like Fuzzy Sets, Artificial Neural Network (ANN), Rough set theory, Ant Colony Optimization (ACO) [8], Particle Swarm optimization (PSO) [7], Swarm Intelligence (SI) are being used for image classification. Very recently the concept of Biogeography Based Optimization (BBO) has been introduced in this category [1]. Several soft computing techniques have been applied separately or in combination to the process of remotely sensed image classification [2, 3, 4].

In this paper we present an analytical study of the behavior of BBO technique over the natural terrain features by means of a combined tabular representation of the percentage of classification efficiency and the degree of entropy for each land cover feature for each of the bands we take. The main aim in this paper is to classify the image into different terrain features and to compare the classification efficiency of BBO for land cover features of different degrees of entropy in order to establish the proposed concept that the classification efficiency of BBO for a given land cover feature is inversely proportional to the degree of entropy for that feature thereby analyzing the behavior of BBO towards different terrain features [5].

The organization of the paper is as follows: The paper is divided into 4 sections. Section 2 presents a brief description of the dataset and its characteristics which has been used for the demonstration of the proposed concept. Section 3 presents the methodology – the algorithm for the biogeography based land cover feature extraction and the proposed methodology for the performance based characterization of BBO. Section 4 presents the classification results of images of Alwar and its analytical study in order to establish a relation between the classification efficiency of BBO and entropy for a given land cover feature. Section 5 concludes the study undertaken.

II. DATASET

We have used a multi-spectral, multi resolution and multi sensor image of Alwar area in Rajasthan with dimensions 472 X 576 for demonstration of the proposed concept. The satellite image for seven different bands is taken. The Bands are Red, Green, Near Infra-Red (NIR), Middle Infra-Red (MIR), Radarsat-1 (RS1), Radarsat-2 (RS2) and Digital Elevation Model (DEM). The Red, Green, NIR, and MIR band images is taken from LISS (Linear Imaging Self

Scanning Sensor)-III, sensor of Resourcesat an Indian remote sensing satellite. RS1 and RS2 are the images from Canadian satellite Radarsat. Digital elevation model is derived by using images from RS1 and RS2. The 7-Band image satellite image of Alwar area in Rajasthan is shown in figure -1 is taken.

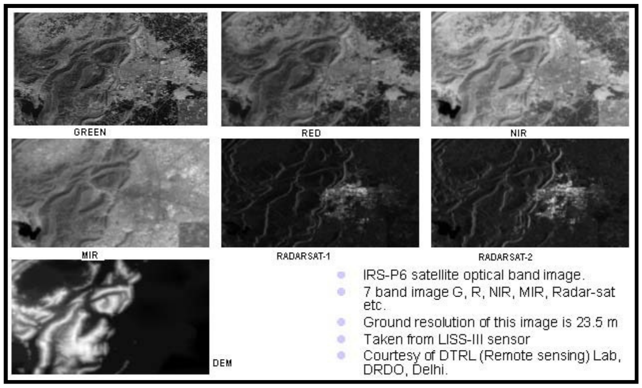

Figure1:7 band images of Alwar

A. Characteristics

Alwar comprises of hills, plains, semi-arid and urban areas. Alwar is geographically situated at Latitude 27° 34' North and Longitude76° 35' East at an elevation of 270 meters above sea level. The city is adorned with expansive stretches of dense deciduous forests that are inhabited by rich flora and fauna. Alwar area can be characterized as a Rocky area. Alwar has a greater proportion of Rocky and Vegetation area whereas a low proportion of water and urban area respectively. Patalganga valley, the study area, between latitudes 30^o 25' - 30^o 29'N and corresponding longitudes 79^o 28' - 79^o 35'E in North-western Himalayan region.

III. PROPOSED FRAMEWORK

The main aim in this paper is to classify the image into different terrain features and to see how precisely BBO classifies the homogeneous and the heterogeneous regions of the specified areas thereby analyzing the behavior of BBO towards different terrain features. Once we obtain the classified image from BBO for the given dataset, we compare the classification efficiency of BBO for land cover features of different degrees of entropy in order to establish the proposed concept that the classification efficiency of BBO for a given land cover feature is inversely proportional to the degree of entropy for that feature. The section I below describe the parameters used in the BBO framework for land cover feature extraction. Section II describes the steps followed for the performance based characterization of BBO for focused land cover feature extraction.

A. Biogeography based Land Cover Feature Extraction

This section presents the algorithm for the biogeography based land cover feature extraction [6] which is referred in later sections.

Input –Multi-spectral Satellite image
Output – Classified image
Classify image in elementary classes using fuzzy c- means and consider them as species of the universal habitat.
Consider each feature as one habitat.
TOTAL NO. OF HABITAT = UNIVERSAL+FEATURE HABITAT
Define HSI, S_{max}, S_{min}, immigration rate and emigration rate.
Calculate HSI for each feature habitat.
Select species from universal habitat and migrate it to one of the other habitat and recalculate HSI.
If recalculated HSI is within threshold then absorb the species to that habitat else.
Check for the other habitats and recalculate the HSI.
If all species in universal habitat are checked then stop else go to step 4.

Figure 2: Algorithm for Biogeography Based Land Cover Feature Extraction

B. Proposed methodology for performance based characterization of BBO for land cover feature extraction

This section presents our proposed methodology for studying the behavior of BBO over different natural terrain features.

(i) Once we obtain the classified image from BBO for the given dataset, we obtain the error matrix which is a representation of the classification accuracy of BBO over different land cover features.

(ii) From the error matrix obtained, we obtain the accuracy measures from the user's and the producer's perspective and generate the tables respectively. These tables help in the clear assessment of the percent classification efficiency of BBO for each of the land cover features.

(iii) From the above tables, we derive a combined table which represents the overall efficiency of BBO for each land cover feature precisely.

(iv) From the table, we observe that BBO displays a wide range of efficiencies in classifying different land cover features.

(v) Next, we analyze why BBO behaves differently for different land cover features. For the purpose, we calculate the entropy of each classified feature in any of the seven bands of the multi-spectral satellite image.

(vi) For the purpose, we copy each of the land cover features classified pixels in an excel sheet and then divide the DN values in the band chosen into 10 intervals for each land cover feature.

(vii) Next, we calculate the no. of pixels of a particular land cover feature falling in each of the 10 ranges obtained above and hence, calculate the entropy of the particular land cover feature by using the following formula-

$$\textbf{Entropy}(\textbf{Ei}) = -\sum_{i=1}^{n} \textbf{Pi} \log (\textbf{Pi})$$

where n is 10 in our case since we divided the DN range corresponding to the band chosen into 10 intervals and

$$\mathbf{Pi= n_i / N}$$

where n_i is the no. of pixels in the i^{th} interval and N is the total no. of pixels classified into that particular land cover feature.

(viii) The above procedure is followed for each land cover feature. The procedure is the same for the second band chosen for verification of the results.

(ix) Construct tables representing the calculation of entropy for each of the land cover features for both the bands chosen.

(x) From the table, we can arrange the land cover features in ascending order of their entropy values in the chosen band. Comparing table obtained in step IX and in step III, we conclude that BBO is able to classify the land cover feature which has the lowest entropy with the maximum efficiency. This means that BBO is able to classify the homogeneous regions more efficiently than the other land cover features. From the tables, it can be observed that the classification efficiency of BBO depends upon the entropy of the land cover feature which is the degree of disorder of the DN values of the pixels comprising the particular land cover feature since the greater is the entropy of the land cover feature, the lesser is the classification efficiency of BBO for that land cover feature.

(xi) Construct another table which is the combined representation of the percentage of classification efficiency and the degree of entropy for each land cover feature in the chosen band arranged in ascending order to reflect the fact that BBO shows a greater degree of classification efficiency on the land cover features with smaller degree of disorder.

(xii) For verification of the results, the entropies are also calculated in another band chosen.

(xiii) Hence, prove the validity of our proposed hypotheses regarding the factors governing the classification efficiency of BBO.

IV. RESULTS AND DISCUSSION

This section presents the classification results of BBO and an analytical study in order to study the effect of entropy or the degree of disorder of the DN values of the pixels comprising a land cover feature with the classification efficiency of BBO on that feature. For the purpose, the case study of 7-band cartoset satellite image of size 472 × 576 pixels of Alwar Region in Rajasthan is taken. Classified image of Alwar has been shown in figure 3 with kappa coefficient .69121 [6]. Now, once we obtain the classified image from BBO for the Alwar region, we obtain the error matrix which is a representation of the classification accuracy of BBO over different land cover features.

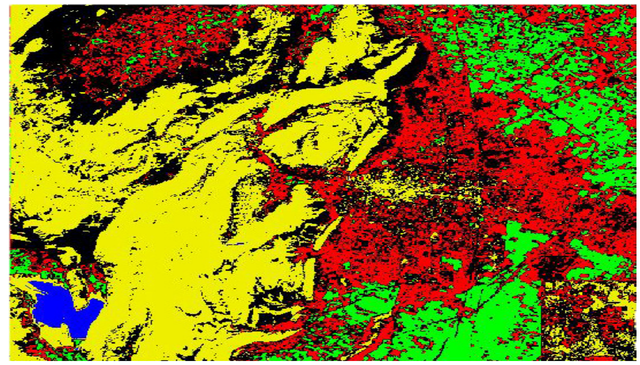

Figure 3: Biogeography Based Classification of Alwar image (with kappa coefficient=.69121)

From the error matrix given in table I, we obtain the accuracy measures from the user's and the producer's perspective and generate the tables II and III. These tables help in the clear assessment of the percent classification efficiency of BBO for each of the land cover features.

TABLE I: ERROR MATRIX FOR THE SATELLITE IMAGE OF ALWAR REGION WHEN BBO IS APPLIED

	Vegetation	Urban	Rocky	Water	Barren	Total
Vegetation	127	1	1	0	0	129
Urban	1	92	0	0	39	129
Rocky	1	15	175	0	3	194
Water	0	0	0	70	0	70
Barren	21	81	26	0	128	256
Total	150	189	202	70	170	781

TABLE II: PRODUCER'S ACCURACY

Feature	Accuracy Calculation	Producer's Accuracy
Vegetation	127/150	84.6%
Urban	92/189	48.6%
Rocky	175/202	86.6%
Water	70/70	100%
Barren	128/170	75.3%

TABLE III: USER'S ACCURACY

Feature	Accuracy Calculation	User's Accuracy
Vegetation	127/129	98.4%
Urban	92/129	71.3%
Rocky	175/194	90.2%
Water	70/70	100%
Barren	128/256	50%

TABLE IV: COMBINED ACCURACY OF BBO FOR EACH LAND COVER FEATURE

Feature	Combined accuracy= (Producer's accuracy × User's accuracy)	Percentage accuracy
Vegetation	84.6 × 98.4	83.2%
Urban	48.6 × 71.3	34.6%
Rocky	86.6 × 90.2	78.1%
Water	100 × 100	100%
Barren	75.3 × 50	37.7%

From the above tables, we derive a combined table (table IV) which represents the overall efficiency of BBO for each land cover feature precisely. From the table IV, we observe that BBO displays a wide range of efficiencies in classifying different land cover features. The table reflects that the highest efficiency is observed on water pixels where BBO displays 100% efficiency, the second highest being the vegetation pixels with 83.2% efficiency, then the rocky (with 78.1% efficiency) and finally the barren (with 37.7% efficiency) and urban features (with 34.6% efficiency) respectively.

Next, we analyze why BBO behaves differently for different land cover features. For the purpose, we calculate the entropy of each classified feature in any of the seven bands of the Alwar image. However, we choose the Radarsat band since this band is the best for viewing the edges of a land cover feature and displays the variations in the reflectance values (DN (Digital Number) ranges) more precisely. Also, in order to verify the results, we calculate the entropy in both the Radarsat bands namely Radarsat-1 and Radarsat-2 bands respectively. For the purpose, we copied each of the land cover features classified pixels in an excel sheet and then divided the DN values in the Radarsat-1 band into 10 intervals for each land cover feature. Next, we calculated the no. of pixels of a particular land cover feature falling in each of the 10 ranges obtained above and hence, calculated the entropy of the particular land cover feature using the formula defined in subsection B of section III.

The above procedure is followed for each land cover feature. The procedure is the same for Radarsat-2 band also. The tables VI and VII below represent the calculation of entropy for each of the land cover features for both the Radarsat-1 and Radarsat-2 bands respectively. The intervals chosen for the entropy calculation in the Radarsat-1 band are 22.9, 25.4, 20.7, 22.1 and 25.5 for vegetation, urban, rocky, water and barren features respectively. For the entropy calculation in the Radarsat-2 band, the intervals chosen are 25.3, 25.5, 24.2, 25.5 and 25.5 for vegetation, urban, rocky, water and barren features respectively. Tables V and VI summarize the entropy of each land cover feature for the RS-1 and RS-2 bands respectively. Figures 4 and 5 are the graphical representations of the entropy in RS-1 band v/s BBO classification efficiency for each of the land cover features.

TABLE V: ENTROPY IN RS-1 BAND V/S BBO CLASSIFICATION EFFICIENCY FOR EACH OF THE LAND COVER FEATURES

Land cover feature	BBO Classification efficiency	Entropy in Radarsat-1 Band
Water	100%	0.0742
Vegetation	83.2%	0.3185
Rocky	78.1%	0.3837
Barren	37.7%	0.3923
Urban	34.6%	0.5004

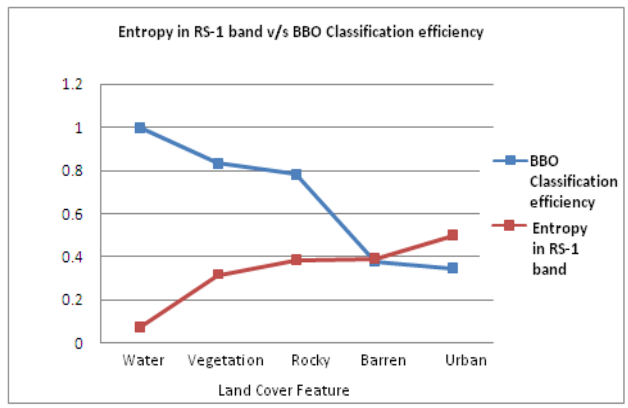

Figure 4: Graphical representation of the entropy in RS-1 band v/s BBO classification efficiency for each of the land cover features.

TABLE VI: ENTROPY IN RS-2 BAND V/S BBO CLASSIFICATION EFFICIENCY FOR EACH OF THE LAND COVER FEATURES.

Land cover feature	BBO Classification efficiency	Entropy in Radarsat-2 Band
Water	100%	0.1052
Vegetation	83.2%	0.3587
Rocky	78.1%	0.4799
Barren	37.7%	0.5162
Urban	34.6%	0.6124

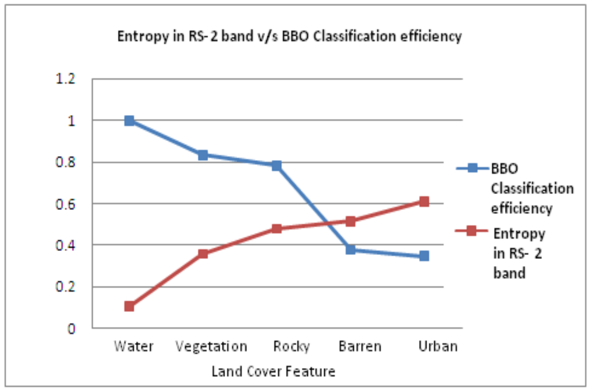

Figure 5: Graphical representation of the entropy in RS-1 band v/s BBO classification efficiency for each of the land cover features.

TABLE VII: ENTROPY CALCULATION IN RADARSAT-1 BAND

	Vegetation (N=36197)		*Urban (N=80653)*		*Rocky (N=87971)*		*Water (N=2544)*		*Barren (N=50347)*	
k	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$
1	14506	0.1591	25738	0.1583	35798	0.1589	2419	0.0208	17030	0.1592
2	20444	0.2993	36937	0.3136	40544	0.3139	90	0.0721	25509	0.3088
3	1058	0.3441	8291	0.4152	8281	0.4105	18	0.0874	4652	0.4044
4	121	0.3524	3371	0.4728	2270	0.4515	7	0.0944	1580	0.4516
5	27	0.3547	2102	0.5141	736	0.4689	2	0.0968	798	0.4801
6	16	0.3562	1254	0.5422	223	0.4755	3	0.1003	388	0.4964
7	9	0.3571	910	0.5642	82	0.4783	0	0.1003	220	0.5067
8	7	0.3578	681	0.5817	24	0.4793	2	0.1027	107	0.5124
9	4	0.3583	569	0.5929	9	0.4797	2	0.1052	41	0.5149
10	4	0.3587	587	0.6124	3	0.4799	0	0.1052	19	0.5162

TABLE VIII: ENTROPY CALCULATION IN RADARSAT-2 BAND

	Vegetation (N=36197)		*Urban (N=80653)*		*Rocky (N=87971)*		*Water (N=2544)*		*Barren (N=50347)*	
k	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$	n_i	$-\sum p_i \log p_i$
1	22517	0.1282	47972	0.1342	59501	0.0970	2461	0.0000	34007	0.1151
2	13174	0.2880	21077	0.2865	21272	0.1149	64	0.0139	11924	0.2633
3	393	0.3093	5531	0.3663	4953	0.2639	8	0.0542	2921	0.3350
4	73	0.3148	2583	0.4142	1606	0.3343	2	0.0620	1008	0.3690
5	25	0.3170	1434	0.4453	496	0.3660	4	0.0645	334	0.3834
6	4	0.3174	798	0.4651	107	0.3787	1	0.0689	92	0.3884
7	5	0.3179	528	0.4794	30	0.3823	1	0.0702	39	0.3909
8	2	0.3182	298	0.4884	4	0.3834	1	0.0716	8	0.3915
9	1	0.3183	238	0.4959	1	0.3836	1	0.0729	6	0.3919
10	2	0.3185	132	0.5004	0	0.3837	0	0.0742	4	0.3923

Table IX presents the BBO classification efficiency in both the RS-1 and the RS-2 bands in a combined form. From the table IX, it can be observed that the entropy of the water feature is the lowest in both the RS-1 and the RS-2 bands. Also, it can be seen that the entropy of the urban region is the highest among all the five land cover features that were classified by BBO in both the RS-1 and the RS-2 bands. From the table IX, we can arrange the land cover features in ascending order of their entropy values in RS-1 band as water, vegetation, rocky, barren and urban features respectively. Also, from table IX, we find that the BBO is able to classify the water feature with the maximum efficiency i.e. 100%. We conclude that BBO is able to classify the land cover feature which has the lowest entropy with the maximum efficiency. This means that BBO is able to classify the homogeneous regions more efficiently than the other land cover features.

From figure 6, it is observed that the classification efficiency of BBO depends upon the entropy of the land cover feature which is the degree of disorder of the DN values of the pixels comprising the particular land cover feature since the greater is the entropy of the land cover feature, the lesser is the classification efficiency of BBO for that land cover feature as is reflected from table IX which is a combined representation of the percentage of classification efficiency and the degree of entropy for each land cover feature in RS-1 band arranged in ascending order to reflect the fact that BBO shows a greater degree of classification efficiency on the land cover features with smaller degree of disorder. For verification, the entropies were also calculated in RS-2 band and the results were found to be the same as is reflected from table IX. Hence, proves the validity of our proposed hypotheses regarding the factors governing the classification efficiency of BBO.

TABLE IX: BBO CLASSIFICATION EFFICIENCY V/S THE ENTROPY IN RS-1 AND RS-2 BANDS FOR EACH OF THE LAND COVER FEATURES.

Land cover feature	BBO Classification efficiency	Entropy in Radarsat-1 Band	Entropy in Radarsat-2 Band
Water	100%	0.3185	0.1052
Vegetation	83.2%	0.5004	0.3587
Rocky	78.1%	0.3837	0.4799
Barren	37.7%	0.0742	0.5162
Urban	34.6%	0.3923	0.6124

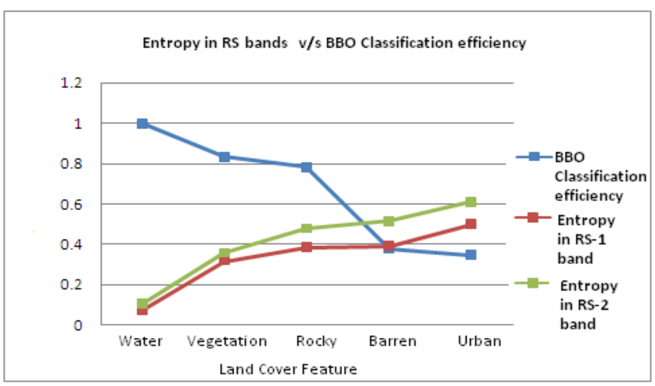

Figure 6: Combined graphical representation of the BBO classification efficiency v/s the entropy in RS-1 and RS-2 bands for each of the land cover features.

V. CONCLUSION AND FUTURE WORK

The paper establishes the fact that the classification efficiency of BBO for a given land cover feature is proportional to the degree of disorder of the Digital number (DN) values of the pixels comprising that land cover feature when viewed in any of the bands of the multi-spectral satellite image. More precisely, the classification efficiency of BBO on a terrain feature is inversely proportional to the entropy for that feature when viewed in any of the bands of the multi-spectral satellite image. The results indicate that BBO is able to classify the homogeneous regions i.e. the regions with the lowest entropy, more efficiently than the regions which show a greater degree of heterogeneity.

For Alwar region, results show that water region is classified most accurately since it is the homogenous region for which the classification efficiency of BBO is the highest i.e. 100% and the classification efficiency decreases as the heterogeneity in the DN values of the pixels comprising the feature increases, hence leading to decreasing classification efficiency of vegetation, rocky, barren and urban features respectively.

References

[1] Dan Simon "Biogeography -Based Optimization", IEEE Transaction on Evolutionary Computation ,12(6), 2008.

[2] Demetrics Stathakis and Anthanassios Vasilakos, "Comparison of computational Intelligence based Classification Techniques for Remotely Sensed optical Image Classification", IEEE Transactions On and Remote Sensing , 44(8), 2006.

[3] Lavika Goel, " Land cover Feature Extraction using Hybrid Swarm Intelligence Techniques-A Remote sensing perspective", ACEEE International Journal on Signal & Image Processing, 1(3), Dec 2010.

[4] Lavika Goel, Daya Gupta and V.K. Panchal, "Embedding Expert Knowledge to Hybrid Bio-Inspired Techniques: An Adaptive Strategy towards Focused Land Cover Feature Extraction", International Journal of Computer Science & Information Security (IJCSIS), 1(2), pp 244-253, 2010.

[5] V.K. Panchal, Samiksha Goel, Divya Bhugra and Vipul Singhania, "Study of the behavior of BBO over natural terrain features", WASET 2011 Spring International Conference, 2011 (accepted).

[6] V.K. Panchal, Samiksha Goel, Mitul Bhatnagar, "Biogeography Based Land Cover Feature Extraction", World Congress on Nature and Biologically Inspired Computing, (NaBIC'09),1588-1591, 2009.

[7] Wang Dong, and Wu Xiang-bin, "Particle Swarm Intelligence Classification Algorithm for Remote Sensing Images" ,IEEE Pacific-Asia Workshop on Computational Intelligence and Industrial Application, 2008.

[8] Xiaoping Liu, Xia Li, Lin Liu, Jinqiang He and Bin Ai, "An Innovative Method to classify Remote-Sensing Images using Ant Colony Optimization", IEEE transaction on geosciences and remote sensing, 46(12), 2008.