Biogeography and Plate Tectonics based Optimization for Water Body Extraction in Satellite Images

Lavika Goel[1], Daya Gupta[1], V. K. Panchal[2]
[1]Delhi Technological University, Department of Computer Engineering,
Delhi, India.
goel_lavika@yahoo.co.in, dgupta@dce.ac.in
[2]Defence Terrain & Research Laboratory,
Defense & Research Development Organization, Delhi, India.
vkpans@ieee.org

Abstract. Recent advances in remote sensing have widened the platform for research in science and technology. Undoubtedly the estimation of geo-bio-physical properties of the land cover features like water, urban, vegetation, rocky and barren areas play an important role in environmental, transportation and region planning, natural disaster, industrial and agricultural production. Since the water transport is cheapest, extraction of the water body in hyper spectral images of remote areas for which we don't have enough details of its terrain is inevitable. Till now, natural computation and bio-inspired intelligent techniques like DNA computing, membrane computing, genetic algorithms, neural computing have been used for demonstrating the applications of computational intelligence in the field of remote sensing. However, geo-science has never been used as a nature inspired intelligent technique for developing a computational model. This paper demonstrates the evolution of a new geo-science based approach for satellite image processing using an analogy between plate tectonics and biogeography based optimization. The paper presents biogeography and plate tectonics based optimization (BPBO) as a powerful paradigm for identifying water body area in the satellite image and hence, make a significant contribution towards the development of a new computational intelligence technique in the field of AI. Our major assumption is that it is the entropy which is the driving force leading to the formation of heterogeneous regions called as plates, similar to the convection force in the mantle of the Earth.

Keywords. Remote sensing, plate tectonics, biogeography, entropy.

1 Introduction

Remote sensing [9] refers to the technology of acquiring information about the earth's surface features (land and water) and atmosphere using space-borne platforms. Different land cover features, such as water, soil, vegetation play major role in remote sensing applications. Thus remote sensing data can be put to use in classifying these features. Water body information is very important for urban planning and environment improving. Surveying of water-bodies and delineating its features properly is a very first step for any planning, especially for places like India, where the land-cover is dominated by water-bodies. Watershed is a region (or area) delineated with a well-defined topographic boundary and water outlet. It is a geographic region within which hydrological conditions are such that water becomes concentrated within a particular location, for example, ocean, sea lake, a river, or a reservoir, by which the watershed is drained [10]. Currently, many soft computing techniques like Fuzzy sets, Artificial Neural network, rough set theory, ant colony optimization, particle swarm optimization, membrane computing are being used for feature extraction or image classification. This paper demonstrates the evolution of a new paradigm, a never before concept, for satellite image classification using an analogy between plate tectonics and biogeography [4].

Our motivation is the absence of geo-sciences based approaches as contributory domains to computational intelligence. Fig. 1 shows the division of computational intelligence techniques into techniques based on modelization of human mind and nature inspired intelligent techniques that have been used till date for solving the problem of land cover feature extraction. From the figure, it can be observed that geo-sciences which fall under the category of nature inspired intelligent techniques have never been used for the purpose. Hence, we propose a computational model demonstrating the plate tectonics theory as a geo-sciences based and nature inspired intelligent technique which when integrated with the BBO technique [1] develops an enhanced algorithm for land cover feature extraction (in our application, we target water body in the satellite image).

K. Deep et al. (Eds.): Proceedings of the International Conf. on SocProS 2011, AISC 131, pp. 1–9.
springerlink.com

This paper is an attempt to develop a new AI technique using an analogy between biogeography and plate tectonics as shown in Fig. 2. The paper is organized into five sections; the section following the introduction illustrates the concepts of biogeography and plate tectonics.

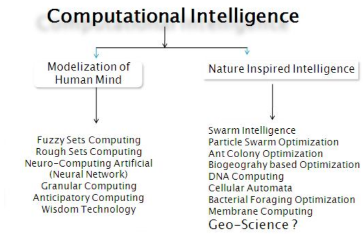

Fig. 1. Taxonomy of computational intelligence techniques for satellite image classification

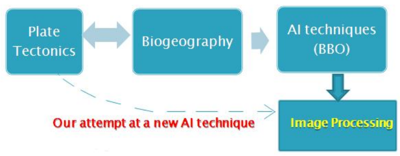

Fig. 2. Our attempt at a new AI technique

The third section describes the proposed biogeography and plate tectonics based optimization technique for land cover feature extraction through the algorithm. The fourth section presents the results and discussion. The last section concludes and summarizes the future work.

2 Basic Concepts of BBO and Plate Tectonics

This section presents the concepts of plate tectonics which can be adaptively applied and integrated with BBO for solving the problem of land cover feature extraction more efficiently [5, 8].

2.1 Biogeography Based Optimization (BBO)

BBO is a population based EA motivated by the migration mechanisms of ecosystems. It is based on the mathematics of biogeography. In BBO, problem solutions are represented as islands, and the sharing of features between solutions is represented as emigration and immigration. The idea of BBO was first presented in December 2008 by D. Simon [1]. It is an example of a natural process that can be modeled to solve general optimization problems. One characteristic of BBO is that the original population is not discarded after each generation; it is rather modified by migration. Also for each generation, BBO uses the fitness of each solution to determine its emigration and immigration rate [1, 3]. In a way, we can say that BBO is an application of biogeography to EAs. In BBO, each individual is considered as a habitat with a HSI [1, 3], which is similar to the fitness of EAs, to measure the individual fitness. Also, an SIV which characterizes the habitability of an island is used. A good solution is analogous to an island with a high HSI, and a poor solution indicates an island with a low HSI. High HSI solutions tend to share their features with low HSI solutions. Low HSI solutions accept a lot of new features from high HSI solutions [1, 3].

2.2 Plate Tectonics

There are two underlying concepts which form the base of the plate tectonics theory, the first being the dynamics of the movement of earth's plates and the second is the crust formation [2, 6]. Fig. 3 shows that the dynamics of movement of earth's plates is synchronous to the clustering of pixels and the resulting crust formation or subduction can be considered as synchronous to the mixed pixels in the image. Hence, the underlying concepts of plate tectonics can be adapted to integrate with the BBO technique for water body extraction in the satellite image.

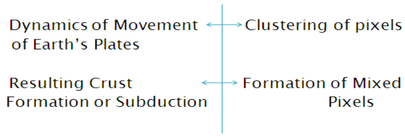

Fig. 3. Adapting Plate tectonics theory for land cover feature extraction

3 Biogeography and Plate Tectonics based Optimization for feature extraction (BPBO)

This section discusses our proposed hypotheses of biogeography and plate tectonics based optimization approach for extracting land cover features from the satellite image, in our case, water body [10]. Alwar area in Rajasthan, illustrated in Fig. 4, is taken as a case study to develop the hypothesis, that may be generalized in future developments. The area is selected as it contains hilly track, water, agriculture land, urban zone, barren lands.

Step I. *Remote Sensing images*, the actual data we have to work on, is reflectance values of solar radiation of the surface objects [9]. This phenomena may be represented through *Texture analysis.*
Step II. Generate heterogeneous regions called *plates* through texture analysis of the region under consideration. We use rough sets theory for texture analysis.
Step III. In the initial state of the *ecosystem* required to initialize our plate tectonics and biogeography based classifier, we consider each of the individual plates obtained through texture analysis as a member of the Universal habitat.
Step IV. From the figure 4, it is reflected that the *surface topography* well represents visible perceptions of the plate concepts. *Surface Topography is an indirect manifestation of the plate tectonic mechanism.* This may be represented nicely through Digital Elevation Model (DEM) or *slope map* or *hill shading.*

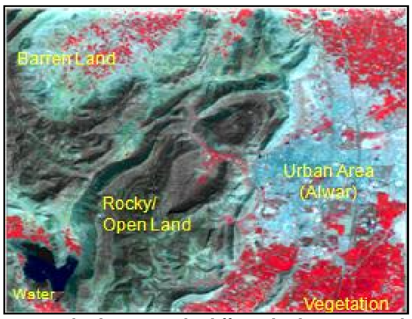

Fig. 4. Surface Topography demarcates the different land use types in the Alwar image.

Step V. Based on this, different areas may be delineated. DEM & Hill Shading of Alwar region are shown below in Fig. 5.
Step VI. Our major assumption is that it is *the entropy which is the driving force of these regions, similar to the convection force in the mantle of the Earth.*

Step VII. Hence, we use the *surface entropy* in the *DEM band* of each of the plates of the Universal habitat to generate the clusters of *similar plates.* For the purpose, we compare the differences in the surface entropies in DEM band of each of the plates in the Universal habitat by migration. *This value is called the plate similarity factor.* Hence, we categorize two plates as similar or homogeneous if their plate similarity factor lies below the *significance level* 'Sf' else they are considered as heterogeneous plates. The significance level marks a threshold for identifying two plates as similar.

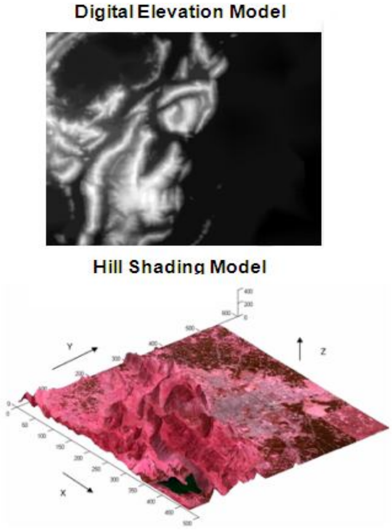

Fig. 5. DEM & Hill Shading of Alwar

Step VIII. *Once we have similar regions or the unsupervised clusters then the next step is to give a class tag to these plates*- For the purpose, the training data set representing *Human Expert's knowledge* is used for supervised classification of these plates. For the purpose, the average entropy in the DEM band for each of the similarity classes 'c' containing the group of similar plates is calculated. Also, the entropy of the training data set in DEM band for each of the land cover features is calculated. Next, we calculate the difference in the average entropy of the similarity class and the entropy of each of the land cover features. Now, the similarity class 'c' is mapped to that feature 'k' with which it has the minimum difference in entropy.

Step IX. *Now, for further refinement of the classification done above* by taking into account the standard threshold 'δ' defined for classifying an input plate into the feature 'k', we classify each of the input plates in the similarity class 'c' by migrating the input plate from the universal habitat to the feature habitat and calculating the *HSI* [1, 3] after migration by finding the difference in the entropy of the input plate and the entropy of the feature habitat. If the HSI calculated is within the threshold 'δ', then, the *input plate in the similarity class 'c' is classified into the feature 'k'* otherwise, the we further split the input plate which remained in the Universal habitat since it could not be classified) through texture analysis.

Step X. *Also, we then initialize a new ecosystem* which follows a similar procedure for a more refined classification of the remaining unclassified plates in the universal habitat.

The above algorithm for biogeography and plate tectonics based feature extraction is summarized in Fig. 6.

```
Algorithm for BPBO_based_Feature_Extraction
{
    while (no. of unclassified plates in 'Hu' ≠ NULL )
     {
        a. Generate individual plates, plates (j) through texture analysis.   /* 'j' ranges from 1 to n */
        b. In the initial state of the ecosystem, consider each of these individual plates as a member of the Universal
           habitat, Hu.
        c. Represent the surface entropy, φ (Ej), through the Digital Elevation Model (DEM).
        d. Calculate the surface entropy in the DEM band of each of the plates of the Universal habitat i.e. ⋃_{j=1}^{n} φ(Ej).
        e. Generate the clusters of similar plates
```

$$\bigcup_{i=1}^{count\ (Sim(j))} plate\ (i)$$

```
           by comparing the plate similarity factor with the significance level 'Sf' for each plate in Hu.
        f. For each similarity class 'c' obtained in step (e), perform supervised classification of the classes using expert
           generated training set by comparing the average entropy of the similarity class 'Avg c' and the entropy of each
           of the land cover features 'φ(Ek)'.
           /* difference obtained is the HSI value */
        g. Proceed for further refinement of the classification in step (f) by comparing the HSI value obtained in step (f)
           with the standard threshold value 'δ' for each plate 'j'.
        h. Initialize a new ecosystem for the classification of the remaining unclassified plates in the universal habitat
           'Hu' .
     }
    /* 'Hu' is empty since no unclassified plates remain in 'Hu'. */
    End of program.
}
```

Fig. 6. Biogeography and Plate Tectonics based Optimization for feature extraction

4 Results and Discussion

This section presents the results obtained after applying the biogeography and plate tectonics based optimization technique for land cover feature extraction on the part of the Alwar image that contains the water body. Table 1 presents the entropies calculated in the DEM band for each plate (equivalence class) obtained through texture analysis on the part of the image from which water body has to be extracted which forms step (a) of the algorithm . The table summarizes the DEM entropies calculated for every iteration; however, we describe the calculations in each iteration in detail next. From the Table 1, it can be observed that eight plates are obtained through texture analysis initially. These plates are then categorized into similar and dissimilar plates based on the entropies calculated in the DEM band with the significance level 'Sf' of -0.05 to +0.05 as shown in Table 2 (step (e) of the algorithm).

Now, we map each of the similarity class to the land cover feature according to step (f) of the algorithm by calculating the difference in the average entropy of the similarity class in DEM band and the entropy of the land cover feature in the DEM band and assigning the similarity class 'c' to the feature with which this difference is the minimum. The above calculations are presented graphically in fig. 8 which shows the feature entropy v/s the plate entropy plotted for each plate in the DEM band. This graph plot presents two graphs one, plotting each input plate entropy in DEM band in each similarity class 'c' and the other, plotting the entropy of the land cover feature in the DEM band with which this difference is the minimum. The above calculations are presented in Table 4. The feature entropies are calculated preliminarily and summarized in Table 3. Next, we proceed with the next step (i.e. step (g) of the algorithm) of further refinement of the classification done above by taking into account the standard threshold 'δ' of -0.05 to +0.05 defined for classifying an input plate into the feature 'k'. For each of the similarity class 'c' , we process each of the input plate 'j' in the similarity class 'c' by calculating the HSI value. The HSI value is calculated by taking the difference of the plate entropy and the corresponding entropy of the feature which mapped to the similarity class to which the plate belongs to. If the HSI value is within 'δ', then we c*lassify the input plate 'j' in the similarity class 'c' into the*

Table 1. DEM Entropies of each plate obtained in each iteration through texture analysis

Iteration (k) / Entropy in DEM band for plate(i)	1	2	3	4	5
1	0.4044	0.4088	0.3833	0.3818	0.3216
2	0.8912	0.4020	0.3989	0.3718	
3	0.5129	0.3601	0.3974	0.4203	
4	0.8893	0.3687	0.3336		
5	0.8874	0.4101	0.4109		
6	0.4100	0.3697	0.3416		
7	0.6491	0.3916	0.3903		
8	0.5452	0.3816	0.3375		
9		0.4008	0.3740		
10		0.8967	0.3393		
11		0.4619	0.3930		
12		0.4668	0.3388		
13		0.9258	0.3433		
14		0.5100	0.3496		
15		0.5029	0.3979		
16		0.9667	0.3409		
17		0.4680	0.3428		
18		0.4692	0.3909		
19		0.9721	0.3382		
20		0.9595	0.3473		
21		0.4785	0.3589		
22		0.9548	0.3388		
23		0.9206	0.3405		
24		0.9593	0.3986		
25		0.9646	0.3810		
26		0.7644	0.3455		
27		0.9181	0.3336		
28		0.9390	0.3784		
29		0.9141	0.3659		
30		0.9127	0.9397		
31		0.9057	0.9304		
32		0.8957	0.9411		
33		0.8962	0.8942		
34		0.9679	0.9000		
35		0.9316	0.9006		
36		0.9387	0.9246		

Table 2. Categorization of plates obtained through texture analysis into similarity classes

Similarity class ‘c’	Plates in ‘c’
1	1,6
2	2,4,5
3	3,8
4	7

Table 3. Feature Entropies in DEM band

Feature Entropy / Band in which the entropy is calculated	**DEM Band**
Vegetation	0.4619
Urban	0.5631
Rocky	0.9316
Water	0.3486
Barren	0.7249

Table 4. Feature categorization step in order to give a class tag to the plates

Similarity class	**Average entropy**	**Feature mapped**
1	0.4072	Water
2	0.8893	Rocky
3	0.5291	Urban
4	0.6491	Barren

Table 5. HSI Calculations and the corresponding classified features for the first iteration

Similarity class ‘c’	**Feature Entropy**	**Plate Entropy**	**HSI**	**Classified Feature**
1	0.3486	0.4044	0.0558	---
		0.4100	0.0614	---
2	0.9316	0.8912	0.0404	Rocky
		0.8893	0.0423	Rocky
		0.8874	0.0442	Rocky
3	0.5631	0.5129	0.0502	---
		0.5452	0.0179	Urban
4	0.7249	0.6491	0.0758	---

Table 6. HSI calculations and feature classifications for iterations II-V

Iteration II

Similarity class ‘c’	Plates in ‘c’	Feature Entropy	Plate Entropy	HSI	Classified feature
1	1-9	0.3486	0.4088	0.0602	---
			0.4020	0.0534	---
			0.3601	0.0115	Water
			0.3687	0.0201	Water
			0.4101	0.0615	---
			0.3697	0.0211	Water
			0.3916	0.0430	Water
			0.3816	0.0330	Water
			0.4008	0.0522	---
2	10,13,16,19, 20,22,23,24, 25,27-36	0.9316	0.8967	0.0349	Rocky
			0.9258	0.0058	Rocky
			0.9667	0.0351	Rocky
			0.9721	0.0405	Rocky
			0.9595	0.0279	Rocky
			0.9548	0.0232	Rocky
			0.9206	0.0110	Rocky
			0.9593	0.0277	Rocky
			0.9646	0.0330	Rocky
			0.9181	0.0135	Rocky
			0.9390	0.0074	Rocky
			0.9141	0.0175	Rocky
			0.9127	0.0189	Rocky
			0.9057	0.0259	Rocky
			0.8957	0.0359	Rocky
			0.8962	0.0354	Rocky
			0.9679	0.0363	Rocky
			0.9316	0.0000	Rocky
			0.9387	0.0071	Rocky
3	11,12,14,15, 17,18,21	0.4619	0.4619	0.0000	Vegetation
			0.4668	0.0049	Vegetation
			0.5100	0.0481	Vegetation
			0.5029	0.0410	Vegetation
			0.4680	0.0061	Vegetation
			0.4692	0.0073	Vegetation
			0.4785	0.0166	Vegetation
4	26	0.7249	0.7644	0.0395	Barren

Iteration III

Similarity class ‘c’	Plates in ‘c’	Feature Entropy	Plate Entropy	HSI	Classified feature
1	1-28	0.3486	0.3833	0.0347	Water
			0.3989	0.0503	---
			0.3974	0.0488	Water
			0.3336	0.0150	Water
			0.4109	0.0623	---
			0.3416	0.0070	Water
			0.3903	0.0417	Water
			0.3375	0.0111	Water
			0.3740	0.0254	Water
			0.3393	0.0093	Water
			0.3930	0.0444	Water
			0.3388	0.0098	Water
			0.3433	0.0053	Water
			0.3496	0.0010	Water
			0.3979	0.0493	Water
			0.3409	0.0077	Water
			0.3428	0.0058	Water
			0.3909	0.0423	Water
			0.3382	0.0104	Water
			0.3473	0.0013	Water
			0.3589	0.0103	Water
			0.3388	0.0098	Water
			0.3405	0.0081	Water
			0.3986	0.0500	Water
			0.3810	0.0324	Water
			0.3455	0.0031	Water
			0.3336	0.0150	Water
			0.3784	0.0298	Water
			0.3659	0.0173	Water
2	29-36	0.9316	0.9397	0.0081	Rocky
			0.9304	0.0012	Rocky
			0.9411	0.0095	Rocky
			0.8942	0.0374	Rocky
			0.9000	0.0316	Rocky
			0.9006	0.0310	Rocky
			0.9246	0.0070	Rocky

Iteration IV

Similarit class ‘c’	Plates ‘c’	Feature Entropy	Plate Entropy	HSI	Classified Feature
1	1,2,3	0.3486	0.3818	0.0332	Water
			0.3718	0.0232	Water
			0.4203	0.0717	---

Iteration V

Similarity class ‘c’	Plates ‘c’	Feature Entropy	Plate Entropy	HSI	Classified Feature
1	1	0.3486	0.3216	0.0270	Water

f*eature 'k' e*lse further split the input plate 'j' through texture analysis and repeat steps above for the input plate 'j' in the next iteration according to step (h) of the algorithm. The above calculations are shown in Table 5. The above HSI calculations and the feature classification can also be deduced graphically by means of the graph shown in Fig. 8.

The blue and the red lines in the graph represent the graph plot of the entropies of the input plates and the feature entropies respectively. The plates for which the entropies do not fall in the threshold interval depicted by green and purple lines for '-δ' and '+δ' respectively in the graph plotted, are the plates which cannot be classified into the corresponding mapped land cover features and hence, are left unclassified (since these may contain mixed pixels [7] and hence, need to be further broken down into smaller plates) and considered for further iterations. Now, we further split the plates which could not be classified and repeat the procedure followed for the first iteration. The calculations for the remaining iterations which lead to the classified image clearly showing the iterative extraction of water body in the Alwar image are shown in Table 6.

The classified image is obtained in Fig. 9 which clearly shows the incremental extraction of water body with each iteration. The yellow color represents rocky area, green color represents vegetation area, black color represents barren area and red color represents the urban area. The white color in the image represents the unclassified pixels of image in the first iteration. It is analogous to those plates that are not absorbed in any feature habitat and are put back to the Universal habitat. These plates represent the unclassified pixels that can be further classified in the next iteration of the algorithm It can be observed that no water body (represented in blue color) is extracted in the first iteration (Fig. 9 (a)) and water pixels remain unclassified (represented in white color). With the increasing iteration (Fig. 9 (b), 9 (c), 9 (d), 9 (e)), water body is clearly extracted at the end of fifth iteration. Fig. 7 shows the final Alwar image after running multiple iterations of Biogeography and plate tectonics based land cover feature extraction algorithm. It can be seen that the water body is extracted clearly and most efficiently along with the other land cover features present in the part of the Alwar image considered for water body extraction.

Fig. 7. Alwar image with the water body clearly extracted at the completion of the BPBO algorithm.

5 Conclusion and future scope

The proposed BPBO algorithm has been applied to a part of the Alwar image in Rajasthan from which water body has to be extracted. The results after running multiple iterations of Biogeography and plate tectonics based land cover feature extraction algorithm on the Alwar image show that the water body is extracted clearly and most efficiently along with the other land cover features present in the part of the Alwar image considered for water body extraction.

The main argument in the paper is finding a novel mechanism of classification of images based on purely geo-sciences process. This may lead to another concept of process randomization, generation of virtual scenario etc. which are important ingredients in battlefield assessment. The paper is an evolution of a new paradigm, a never before concept, the development of a new algorithm based on Plate tectonics Theory for Image Classification (or land cover feature extraction). The proposed biogeography and plate tectonics based optimization algorithm used for the purpose of water body extraction in satellite images in this paper can be generalized in future developments for the extraction of more land cover features from any multi-spectral satellite image. The proposed BPBO algorithm will be a major development in the field of Artificial Intelligence & Image Classification. Also, our BPBO algorithm produces comparable results with the other established AI techniques such as the BBO technique used for water body extraction [8]. The algorithm by integrating with the BBO technique can prove itself to be a better classifier than the simple BBO based land cover feature extractor [8].

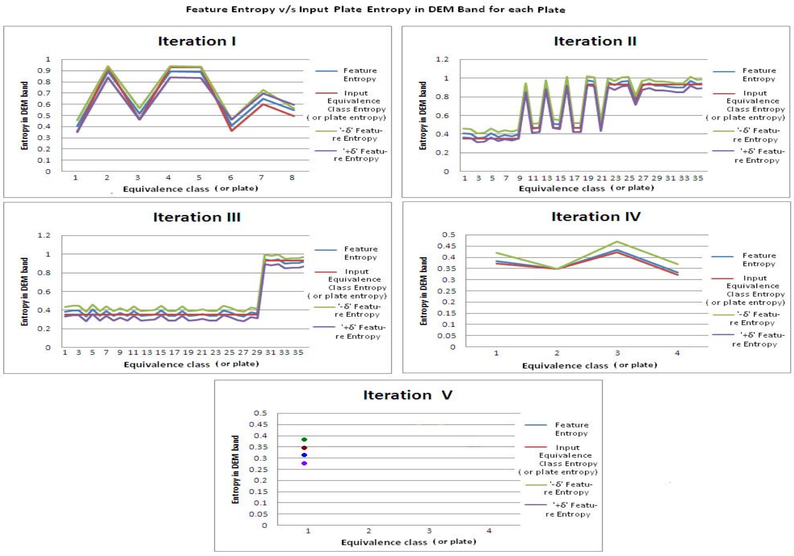

Fig. 8. Feature Entropy v/s Input Plate Entropy in DEM band for each plate

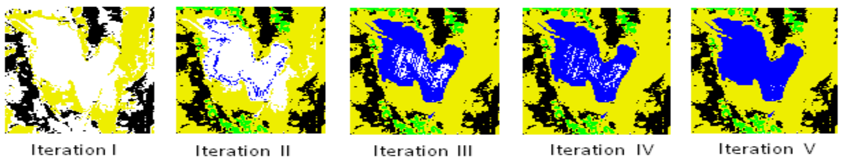

Fig. 9. Water Body extraction (in blue color) from the Alwar image with each iteration. White color portion represents the unclassified image

References

[1] Dan Simon: Biogeography Based Optimization, IEEE Transactions on Evolutionary Computation, 12(6) (2008).

[2] Gornyi, V.I.: The Mantle Convection and the Drift of Euro-Asian Plate (According the Remote Geothermal Method Data), IEEE International Geoscience and Remote Sensing Symposium, IGARSS '02, Vol. 4 (2002).

[3] Haiping Ma: An analysis of the equilibrium of migration models for biogeography-based optimization, Information Sciences 180, 3444–3464 (2010).

[4] J.C. Briggs: Biogeography & Plate Tectonics (1987).

[5] Lavika Goel, V.K. Panchal, Daya Gupta: Embedding Expert knowledge to Hybrid Bio-Inspired Techniques- An Adaptive Strategy Towards Focused Land Cover Feature Extraction, International Journal of Computer Science & Information Security,8(2), 244-253 (2010).

[6] Moresi, L.; Gurnis, M.; Shijie Zhong: Plate tectonics and convection in the earth's mantle: toward a numerical simulation, International Journal of Computing in Science and Engineering, 2(3) (2000).

[7] Nitish Gupta, V.K. Panchal: Swarm Intelligence for mixed pixel resolution, IEEE JURSE, Germany (2011) (accepted).

[8] Panchal, V., Singh, P., Kaur, N., Kundra, H.: Biogeography based satellite image classification, International Journal of Computer Science and Information Security 6 (2), 269–274 (2009).

[9] Ralph W.Kiefer, Thomes M. Lillesand: Principles of Remote Sensing (2006).

[10] Zhaoui, MA Songde: Water Body Extraction from Multi-Source Satellite Images, IGARSS (2003).