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VEGETATION IDENTIFICATION BY USING PARTICLE SWARM OPTIMIZATION

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ABSTRACT

An image is presented. The required band Landsat 8 (5, 4, 3) and Landsat 7 (4, 3, 2) are considered from the multispectral image for segmentation and identification of vegetation. Two sample images: one from ERDAS format acquired by Landsat 7 'Paris.lan' (band 4, band 3, Band 2) and another image acquired from Landsat 8 (band 5, band 4, band 3) are used in this paper. PSO is used to segment the plane-1(Near infra red spectra) and plane 2(RED spectra). The monochrome of the two segmented images is compared with a monochrome of the images without PSO segmentation.

Keywords: multispectral image; vegetation identification; particle swarm optimization (PSO).

INTRODUCTION

Remote sensing is a process of collecting information on the earth's surface by using satellites from different heights above the earth's surface. Digital cameras that capture multispectral wavelengths are fixed to the satellites. The satellites move along latitude and longitude to cover a specific area repeatedly. The number of times the satellite visit a specific area per day depends on the speed of the satellite.

RELATED WORK

Masroor *et al*., 2013, discussed the traditionally pixel-based and statistics-oriented change detection techniques which focus mainly on the spectral values and ignore the spatial context. A review of object-based change detection techniques is compassed. Also, a study on the spatial data mining techniques in image processing and change detection from remote sensing data is discussed. The significance of the rapid change in the image data volume and multiple sensors and related confrontations on the growth of change detection techniques are highlighted.

Hannes *et al.,* 2016, introduced the importance of annual deforestation information for understanding and alleviating deforestation. An image compositing approach is used to transform 2224 Landsat images in a spatially continuous and cloud free environment. Also, a random forest classifier is used to derive annual deforestation patterns.

Pasher *et al*., 2016, introduced methods for earth observation that can be used to enumerate and keeps track of linear woody features across the environment. In the meanwhile, individual structure can be manually systemized and is concentrated on the enhancement of methods using line intersect sampling for estimating linear woody features as an indicator of environmental assessment in agricultural topography. Curtis et al., 2016, evaluated the significance of topographic correction on trend-based forest change detection conclusions by analyzing the location and an aggregation of changes is classified on an image synthesis with and without a topographic correction. A large amount of change in area is identified when no topographic rectification is correlated to the synthesized image.

Zhao-Liang *et al*., 2013, reviewed the present significance of certain remote sensing algorithms for estimating LST from thermal infrared (TIR) data. A survey on algorithms to gain LST from space-based TIR measurements is accomplished based on the speculated circumstances. Also, an emphasis on TIR data obtained from polar-orbiting satellites is done due to the extensive use, comprehensive relevance and higher spatial resolution in contradiction to geostationary satellites.

O'Loughlin *et al*., 2016, developed the first global 'Bare-Earth' Digital Elevation Model based on the Shuttle Radar Topography Mission for all landmasses between 60N and 54S..

Andrew *et al*., 2016, introduced methods by using a small, unpiloted aerial system to acquire aerial photographs and processing this using structure-from-motion photogrammetry, three-dimensional models were generated. The models describe the vegetation.

Min Feng *et al*., 2016, estimated a mechanism based on per-pixel estimates of percentage tree cover and their associated uncertainty, the dataset currently signifies binary forest cover in nominal 1990, 2000, and 2005 epochs, besides gains and losses due to time.

Mihretab *et al*., 2016, introduced methods for the supervised classification technique to classify and analyze the total forest-cover change in Eritrea.

Mohamed *et al*., 2016 developed a GIS for comparing the appropriate method for main crops based on the needs of the crops and the quality and properties of land.

Yu Zhang *et al.,* 2016, analyzed a study on the configurations and spatial-temporal processes of landscape. The results of the variation partitioning of the landscape indicated complex interrelationships among all of the pairs of driver sets.

Adrien Michez *et al.,* 2016, proposed a technique for an easily reproducible approaches framework using Unmanned Aerial Systems (UAS) imagery.

Gayantha *et al*., 2016, developed extraction of spectrally pure pixels of a given area. using Pixel Purity Index (PPI), identification of the selected end member spectrum using the Modified Gaussian Method (MGM) and mapping of logically identified end members using the Spectral Angle Mapper (SAM) method. Mapping results determine both the capabilities and the limitations of the MGM method of convolution and the SAM method of spectral matching as efficient tools for compositional representation of morphological appearance on the lunar surface.

Inka *et al*., 2016, examined the classification of forest land using airborne laser scanning data.

Trung *et al*., 2016, used Spatial-Temporal Adaptive Algorithm for mapping Reflectance Change. Robinson *et al*., 2016, tested the capability of WV2 imagery. New generation satellite sensors are removing barriers from previously preventing widespread adoption of remote sensing technologies in natural resource management.

METHODOLOGY

Data collection

Multispectral Landsat images are used in this paper.

Sample-1 image

The image taken from Landsat 7 with ERDAS format is presented. It has seven bands. Band 4, 3, 2 are considered for segmentation.

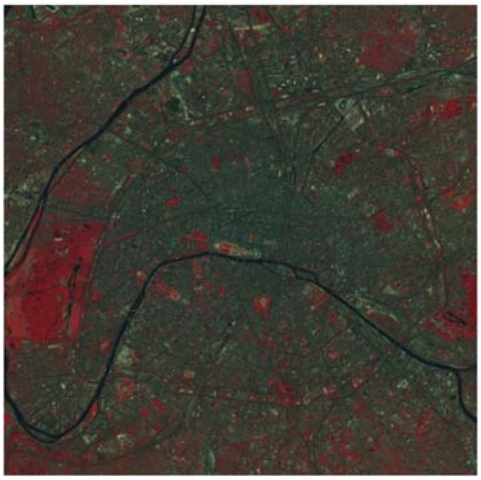


Figure-1. Multispectral composite image (Band 4,3,2) Courtesy: Space Imaging and MathWorks.

Figure-1 shows an RGB image with false colours. Figure-2 shows an enhanced image of the RGB with an increase in the intensity values.

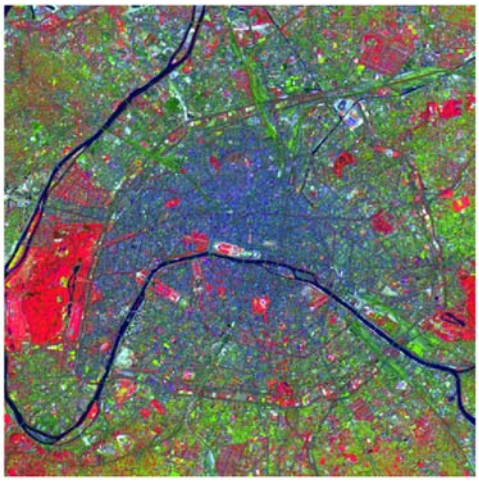


Figure-2. Enhanced image with decorrelation function in Matlab.

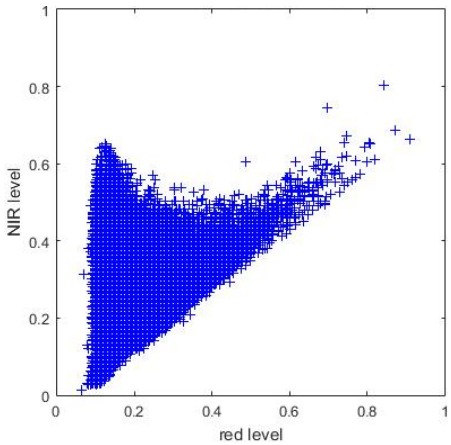


Figure-3. Scatter plot..

Figure-3 presents a scatter plot with RED spectra versus NIR spectra values from the RG planes of Figure-2.

Normalized Difference Vegetation Index (NDVI): It is the most commonly used Vegetation Index, as it enables to eliminate topographic effects and variations in the sun illumination angle, as well as other atmospheric elements such as haze. NDVI images, in contrast to RATIO, have normal distribution given by equation (1).

$$\mathrm{NDVI} = \frac{\mathrm{NIR} - \mathrm{R}}{\mathrm{NIR} + \mathrm{R}} \tag{1}$$

Figure-4 presents the normalized difference vegetation index.

Figure-5 presents an image with threshold =0.4 applied.

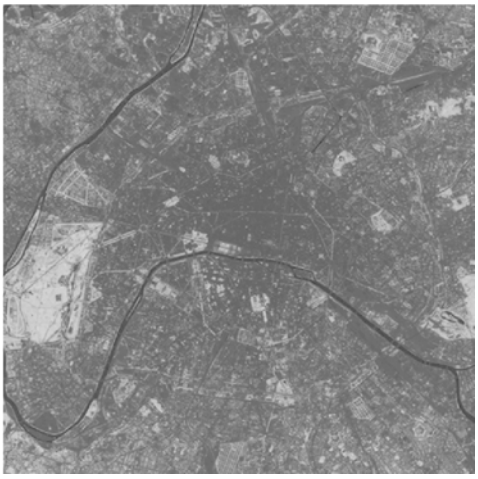


Figure-4. NDVI with gray scale.

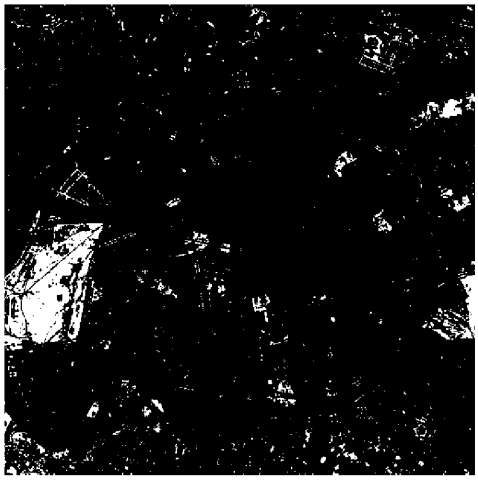
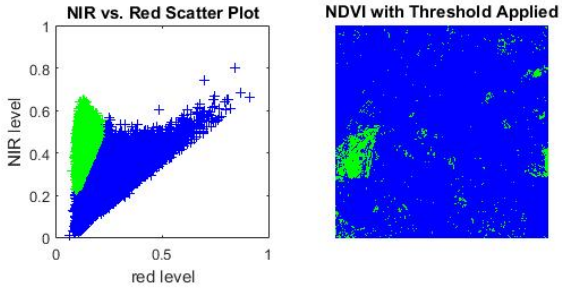


Figure-5. NDVI with threshold=0.4 applied.



(a) (b)

Figure-6. (a)Scatter plot with vegetation and (b)Presence of vegetation (green color).

Figure-6(a) shows the ration of green vegetation with other information (blue). Figure-6(b) presents the distribution of vegetation (green) in the original image (Figure-2)

Sample-2 image

Figure-7 presents Landsat 8 "R G B = 4 3 2" image showing vegetation.

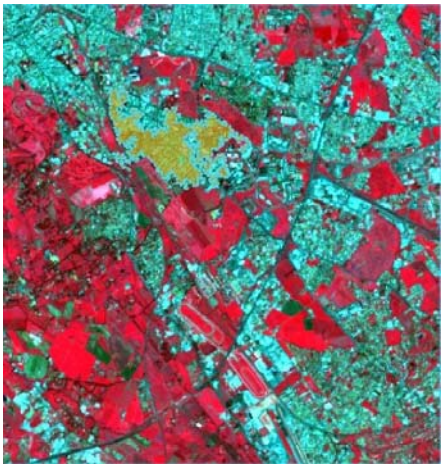


Figure-7. Landsat-8 composite image.

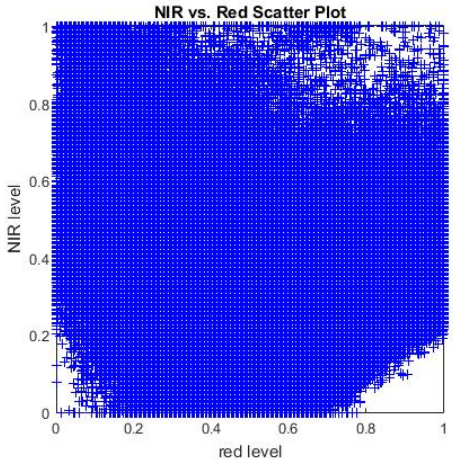


Figure-8. Scatter plot.

Figure-8 presents a scatter plot of RED spectra versus NIR spectra values from the RG planes of Figure-7.

Figure-9 presents the normalized difference vegetation index.

Figure-10 presents an image with threshold =0.4 applied.

Figure-11(a) shows the ration of green vegetation with other information (blue). Figure-11(b) presents the distribution of vegetation (green) in the original image (Figure-7)

Particle swarm optimization

What birds searching for food is described by the particle swarm optimization algorithm. They try to locate food at far away distance. A bird is called particle. A desired target or association value is evaluated by using a target objective function. This helps if the birds have

reached their food. The birds move with specific velocities and directions to reach the food.

The concept of generations is used for searching the location of food. Two best values are used in each generation. Present best value and global best value.

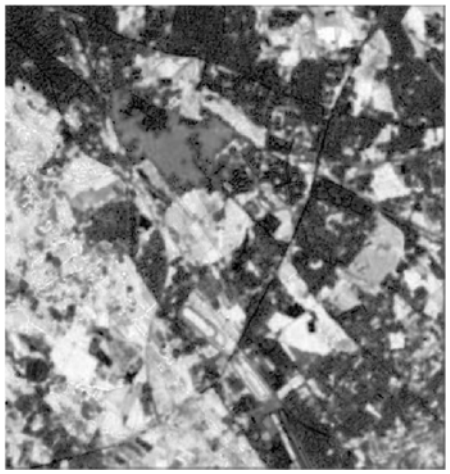


Figure-9. NDVI with gray scale.

Figure-10. NDVI with threshold=0.4 applied.

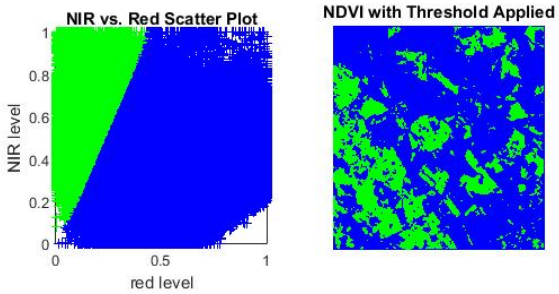


Figure-11. (a)Scatter plot with vegetation and (b)Presence of vegetation (green color).

By using the calculated values, the velocity of the particles and their positions are updated by (2) and (3).

vel[] = vel[] + Fc1 * randnumber * (presentbest[] - current values[]) + Fc2 * randnumber * (globalbest[] - currentvalue[]) (2)
currentvalue[] = currentvalue[] + vel[](3)
vel[] represents the velocity of the particles,
currentvalue[] is the current particle position.
Fc1, Fc2 are learning factors.

PSO parameter control

Based on the population of particles: It can be anything of our choice according to the problem. It can be up to 1000 as well.

Based on the maximum velocity: It indicates velocity changes. Maximum velocity can be any value split into a range from negative to positive.

Based on the knowledge of learning: Fc1 and Fc2 usually can be any value greater than 0.

Based on the program termination: The maximum number of iterations the PSO execute and the minimum error requirement.

Sample-1 image

PSO segmentation of NIR and Red spectral bands

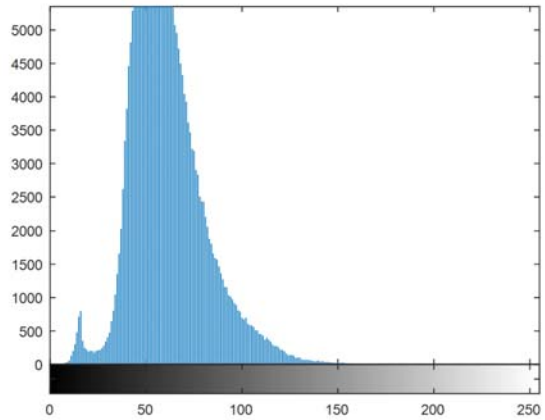


Figure-12. Histogram of NIR Band-4.

Figure-12 presents the histogram of the NIR image. Figure-15 presents a histogram of the RED image. The plots show an inclination towards left-hand side and hence more toward black. The plots show it is not normally distributed.

Figure-13 shows NIR PSO segmented in the grey scale image and Figure-14 shows NIR PSO segmented in a monochrome image.

Figure-16 shows RED PSO segmented in the grey scale image and Figure-17 shows RED PSO segmented in a monochrome image.

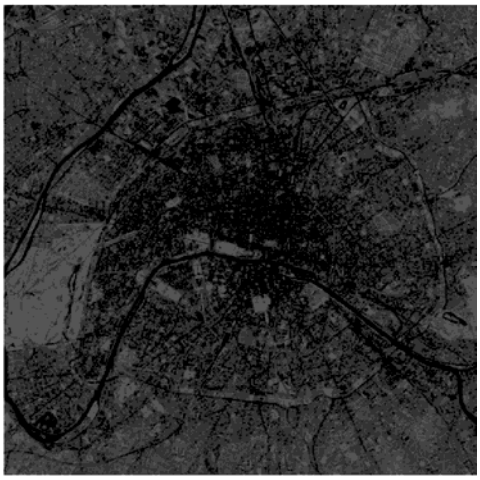


Figure-13. PSO Segmented NIR in gray scale image.

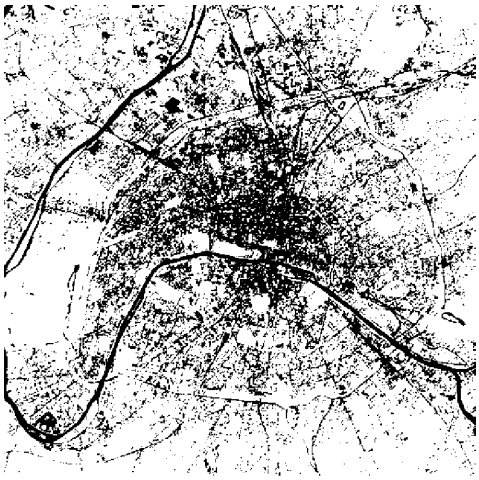


Figure-14. PSO Segmented NIR in monochrome image.

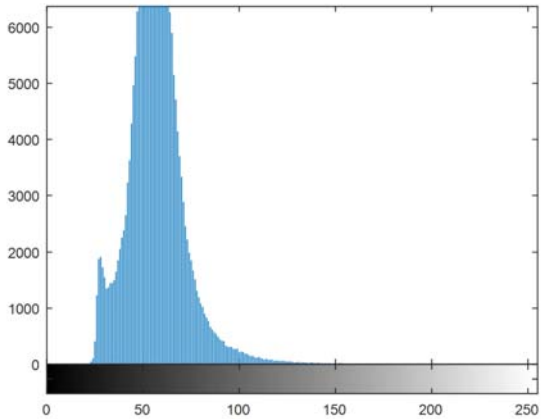


Figure-15. Histogram of RED band-3.

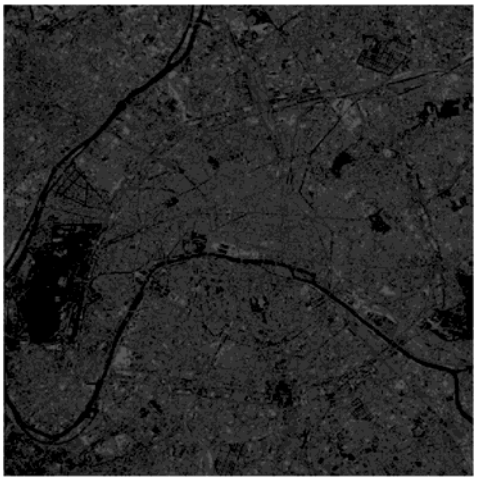


Figure-16. PSO Segmented RED in gray scale image.

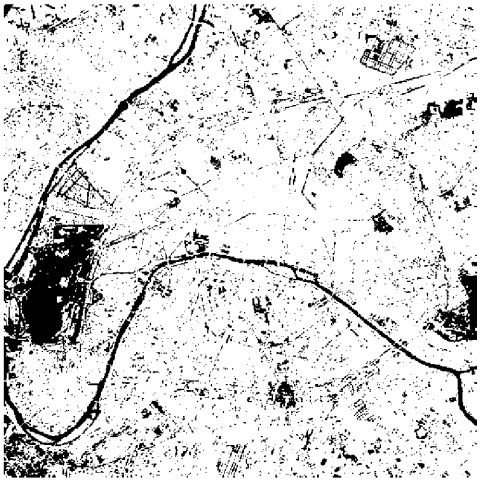


Figure-17. PSO Segmented RED in monochrome image.

Sample-2 image

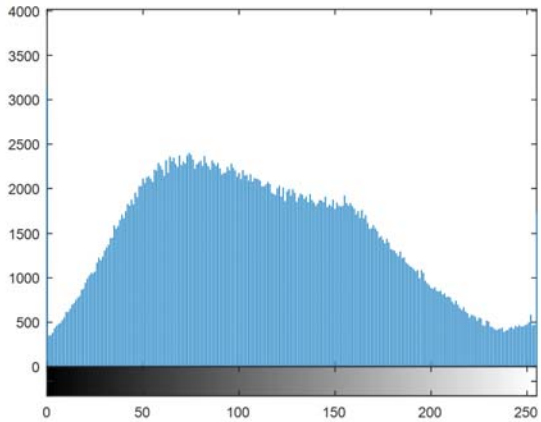


Figure-18. Histogram of NIR band-5.

Figure-18 presents histogram for the NIR image. The histogram is normally distributed. Figure-21 presents

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histogram for the RED image. The histogram is normally distributed.

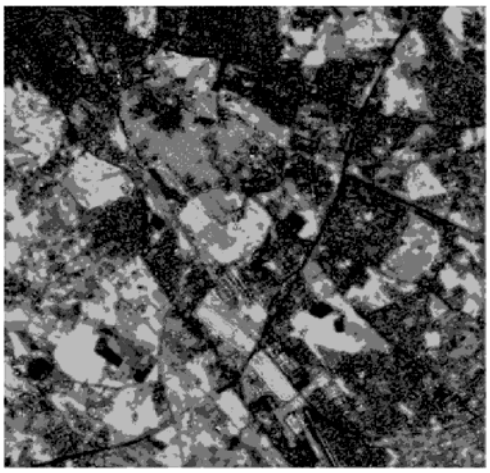

Figure-19. PSO Segmented NIR in gray scale.

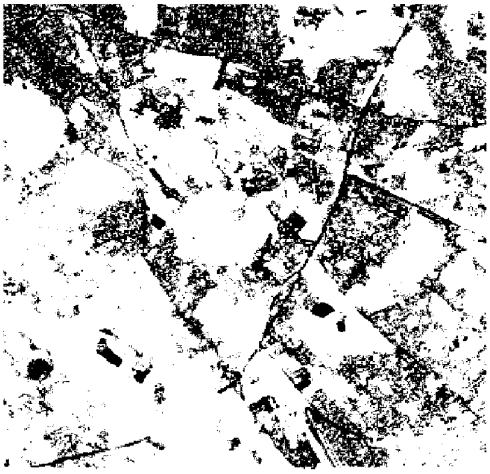

Figure-20. PSO Segmented NIR in monochrome image.

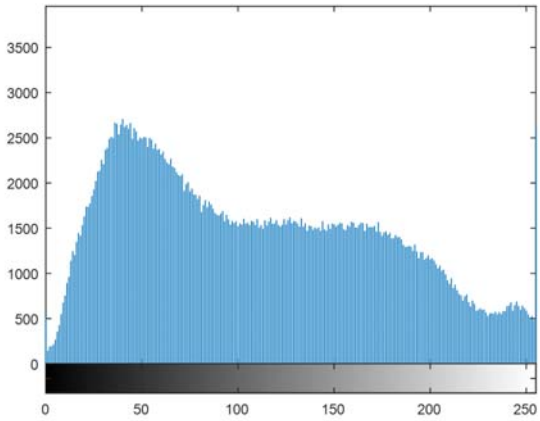

Figure-21. Histogram of RED band-4.

Figure-19 presents the PSO segmented NIR image in gray scale, and Figure-20 presents PSO segmented monochrome of the NIR image.

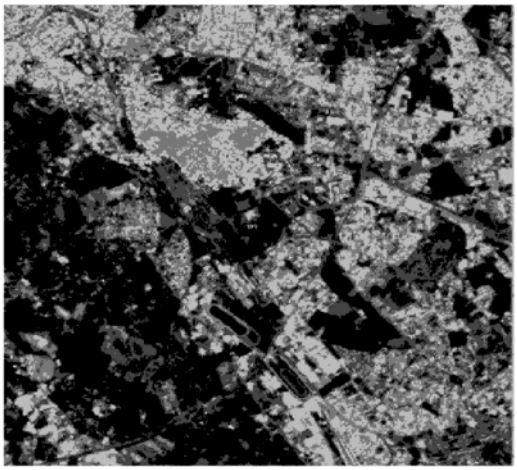

Figure-22. PSO Segmented RED band in gray scale.

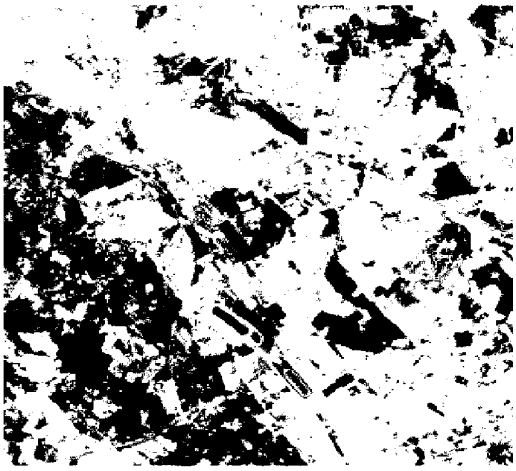

Figure-23. Segmented RED band in monochrome image.

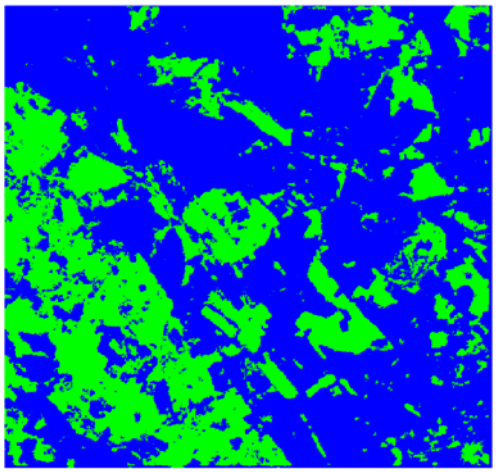

Figure-24. Presence of vegetation (green color).

Figure-22 presents the PSO segmented RED band in gray scale, and Figure-23 presents PSO segmented monochrome of the RED band. Figure-24 presents the distribution of vegetation (green) in the original image (Figure-7).

RESULTS AND DISCUSSIONS

Training the Particle swarm optimization

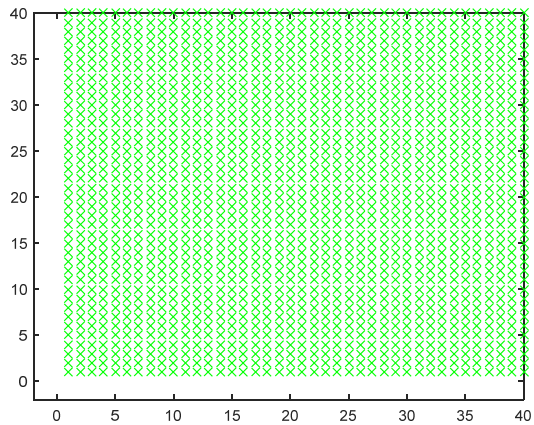

Figure-25. Particles in the initial matrix.

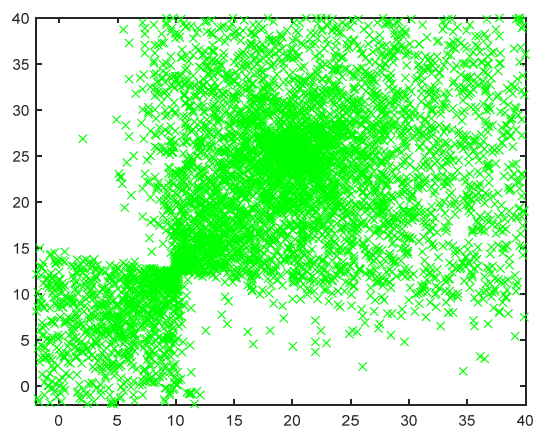

Figure-26. Particles after two iterations.

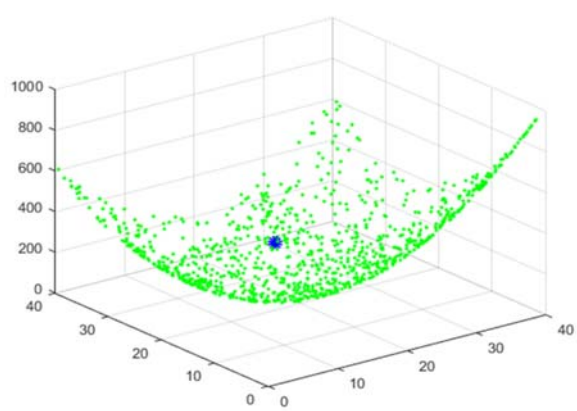

Figure-27. Fitness plot.

Figure-25 presents initial particles positions and Figure-26 presents the movement of particles in two iterations. Figure-27 shows the plot of a function and the path in which the particles moved. This plot shows for two iterations.

Training parameters

N = 150;	population size
N_PAR = level-1;	Number of thresholds
Iterations = 150;	number of iterations
PHI1 = 0.8;	individual weight of particles
PHI2 = 0.8;	other weight of particles
W = 1.2;	inertial factor

vmin=-5;
vmax=5;
globalbestvalueR = -10000;
Find the probability of each intensity values

Receiver operating characteristic curve

ROC curve provides the performance of the algorithms in classification, especially in pattern recognition. Each point in the curve is plotted with false positive rate (FPR) in x-axis versus true positive rate (TPR) in the y-axis. A point in the curve is obtained by considering a minimum of 10 pairs of cover and message images. ROC curve (Figure-9) is drawn using a set of positive and negative outputs.

i. **True positive (TP):** If the image contains vegetation information, and if the algorithm identifies it correctly, then it is truly positive.
ii. **False negative (FN):** If the image contains vegetation information, and if the algorithm says no vegetation, then it is false negative.
iii. **True negative (TN):** If the image does not contain vegetation information, and if the algorithm does not identify it, then it is truly negative.
iv. **False positive (FP):** If the image does not contain vegetation informaiton, and if the algorithm says there is vegetation information, then it is false positive.

$$\text{True positive rate(TPR)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \quad (3)$$

$$\text{False positive rate(FPR)} = \frac{\text{FP}}{\text{FP} + \text{TN}} \quad (4)$$

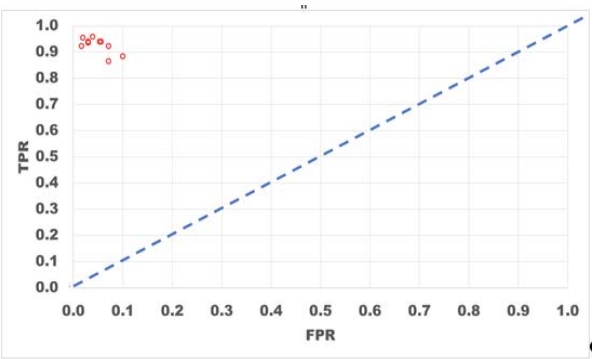

Figure-28. ROC for recovery algorithm.

Figure-28 presents ROC for the performance of PSO algorithm. The points plotted are above diagonal in the ROC plot which is acceptable. The diagonal is drawn from left bottom to the right top of the plot (blue dots). Hence, PSO performance in segmentation of the multispectral image is good.

CONCLUSIONS

Particle swarm optimization algorithm has been implemented in Matlab 2015 for segmentation of Landsat 7 and Landsat 8 images that show land cover vegetation. The segmentation of the PSO is compared with the method of identifying vegetation without PSO segmentation.

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