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RESEARCH PAPER

Classification of remote sensed data using Artificial Bee Colony algorithm

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Abstract The present study employs the traditional swarm intelligence technique in the classification of satellite data since the traditional statistical classification technique shows limited success in classifying remote sensing data. The traditional statistical classifiers examine only the spectral variance ignoring the spatial distribution of the pixels corresponding to the land cover classes and correlation between various bands. The Artificial Bee Colony (ABC) algorithm based upon swarm intelligence which is used to characterise spatial variations within imagery as a means of extracting information forms the basis of object recognition and classification in several domains avoiding the issues related to band correlation. The results indicate that ABC algorithm shows an improvement of 5% overall classification accuracy at 6 classes over the traditional Maximum Likelihood Classifier (MLC) and Artificial Neural Network (ANN) and 3% against support vector machine.

1. Introduction

Remote sensing (RS) data with its ability for a synoptic view observe the area of interest over the earth at different resolutions. Extraction of land cover map information from remote sensing images is a very important and challenging task in RS data analysis. Hence, in the above context, accurate image classification results are a pre-requisite. Remote sensing imagery with high resolution data (spatial, spectral, radiometric and temporal) have made analysts to constantly explore the image processing and data mining techniques to exploit their potential in extracting the desired information efficiently from the RS data to improve classification accuracy. Moreover, obtaining satisfactory classification accuracy over urban/semi urban land use/land cover (LU/LC) classes, particularly in high spatial resolution images, is a present day challenge. Because it is intuitive from the simple visual observation that urban/semi urban areas comprise of roof tops made of reinforced concrete slabs, clay tiles, corrugated plastic, fibre and asbestos sheets, parking lots, highways, interior tar roads, vegetation, lawn, garden, tree crowns, water bodies, soil, construction sites, etc. and they show abundant sub-classes within classes (Mondal et al., 2014). Apart from the above, tall trees and buildings casting

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shadows on the adjacent classes, the orientation and geometry of the roof tops, and various man-made structures made of same materials but having different colours stand spectrally distinct even though they belong to the same class (Sylla et al., 2012). Also, the urban landscapes composed of features that are smaller than the spatial resolution of the sensors lead to mixed pixel problem.

Based on the training process, the classifiers are grouped into supervised and unsupervised classifiers; based on their theoretical modelling considering the type of distribution of data the classifiers are also categorised into parametric (statistical) and non-parametric (non-statistical) classifiers (Voisin et al., 2013); soft and hard classifiers examine only the spectral variance ignoring the spatial distribution of the pixels belonging to the classes and other artificial intelligence methods still have limitations because of the complexities of remote sensing classification (Singh et al., 2014). The parametric algorithms evolved so far are parametric in nature and can be summarised as ISODATA, parallelepiped, minimum distance-to-means, Maximum Likelihood Classifier, Bayesian classifier, etc. The limitation of parametric classifiers is that they show limited success on spectrally overlapping features (Voisin et al., 2013). The non-parametric classifiers include decision tree, Artificial Neural Network (ANN), support vector machines, fuzzy and neuro-fuzzy classifiers, etc. (Baraldi and Parmiggiani, 1995; Chen, 1999; Lee et al., 1999). The classification rules generated in the decision tree classifier are easy to understand and the classification process is analogues to human reasoning (Rawat et al., 2013). Moreover, decision tree exhibits higher classification accuracy over MLC but the number of rules generated (tree size) increases with the increase in the training data set and the number of classes (Ashok Kumar, 2011). Further, the practical employability of Artificial Neural Network and support vector machines is not encouraging since both are very slow in training and learning phase and slowly covering optimal solution.

Genetic Algorithm (GA), gives better results for classification of medium resolution images but it is prone to overfitting the training set and derived rule set due to mutation crossover and are difficult to interpret the classes which are spatially homogeneous, i.e., barren land, degraded land etc. (Bandyopadhyay and Maulik, 2002). Particle Swarm Optimisation (PSO), produces higher classification accuracy for coarse resolution image and it identifies the urban area correctly but it fails to update the velocity of each particle when there is a spectral overlapping between two classes such as urban and sand has same reflectance value in LISS III data (Yang and Deb, 2010). Further, the cuckoo search method is capable of searching each proportion of every individual class within a single pixel by un-mixing all available land class information in a pixel and assigning the pixel to multiple classes. But the major drawback of the cuckoo search is that it is very unstable when feature space and training areas are changed (Yang and Deb, 2010). The Ant Colony Optimisation (ACO) method uses a sequential covering algorithm and produces better accuracy compared with traditional statistical methods, ACO has number of advantages. First, ACO algorithm is distribution free, which does not require training data to follow a normal distribution. Second, ACO is a rule induction algorithm, which is more explicit and comprehensible than mathematical equations. Finally, ACO requires minimum understanding of the problem domain. In fact, XOR is a difficult problem in rule induction algorithms. ACO uses sequential covering algorithm to identify each class, so the rules are ordered. This makes it difficult to interpret the rules at the end of the list, due to spectrally homogenous class such as land with/without scrubs, sandy area etc., which makes rule in the list to be dependent on all the previous rules. Finally, this ACO takes a much longer time to discover rules than the non-parametric methods (Liu et al., 2008).

Artificial Bee Colony (ABC), relatively a new member used for classification of data, was proposed by Tereshko, 2000. Intelligent behaviour on the swarm has provided a new technique for classifying the remote sensing data efficiently (Cuevas et al., 2011). Based on the motivation of many nature inspired algorithms, classification of data can be a mimic behaviour of insects for searching best food source, building of optimal nest structure, etc. Waggle dance is one of the mechanisms to share the located food source which indicates a good candidate for developing new intelligent search for distributed computing, local heuristics and knowledge from past experience (Zhang et al., 2010).

It has been demonstrated that Artificial Bee Colony classifier produces satisfactory results in multi-objective environmental/economic dispatch, data clustering and medical image classification (Pan et al., 2010; Sabat et al., 2010; Stathakis and Vasilakos, 2008). However, they have better search of signature classes with better attribute compared to other classification algorithm such as MLC. Banerjee et al. (2012) compared ABC with other algorithms and the study demonstrates that ABC produces better classification accuracy on LISS III data of 23 m resolution data. Also, when compared with the traditional statistical classifiers, ABC requires minimum understanding of the problem domain and does not require complex training data to follow a normal distribution of data. The ABC recruit bees to update itself to cope better with attribute correlation and updating is directly based on performance of classification class from the knowledge of waggle dance (Xu et al., 2010; Dorigo and Stützle, 2005). Therefore, it is ascertained that these types of procedures have a greater potential in improving classification accuracy.

The main objective of this work is to utilise the bee communication and food search method of information exchange to achieve maximum classification accuracy.

Hence, in this work ABC algorithm has been selected for classification of high resolution data as compared to other swarm intelligence techniques due to following reasons.

- Bees are very optimal well defined workers
- Distribute the work load among themselves which does not misclassify the data which is spectrally homogeneous and spectral overlapping.
- The dancing behaviour helps in optimal design.

All the above points are taken care of in the ABC algorithm. Hence, in the RS data classification, the searching element is not known initially. However, just like a random walker like ant, PSO, cuckoo search, etc., the search will be initiated, but at each iteration, the new values derived values help in reaching towards the final classified data without misclassifying the land cover classes. Hence the ABC is one of the promising techniques over other proven classification techniques.

2. Data

2.1. Data products

Table 1 provides the specification of the image data products being used in this study. The multi-spectral data (5.6 m) are of LISS-IV (Linear Imaging and Self Scanning) sensor of IRS P-6 (Indian Remote Sensing Satellite) and panchromatic image (2.5 m) is of IRS P-5 satellites launched and maintained by the Indian Space Research Organisation (ISRO). The satellite data were procured from the National Remote Sensing Centre (NRSC), Hyderabad, and Karnataka State Remote Sensing Agency (KSRAC), Bangalore, India.

2.2. Study area

The study area considered for this work is the Coastal region of Mangalore, Karnataka; its geographical co-ordinates are between 12° 51′ 32″–12° 57′ 44″ N latitude and 74° 51′ 30″–74° 48′ 01″ E longitudes with an elevation of approximately 0.0 m above mean sea level (AMSL). The image dimension of the study area is 1664×2065 pixels in MS data and 2593×4616 pixels in pan-sharpened data. The data comprise forest plantation, crop plantation, urban area, wetlands and water body (Fig. 1). The climate of the study area is relatively mild and humid in winter and dry and hot in summer. The interactions such as extensive agricultural activities, conversion of marshy land to build up land and tourism activities have resulted in a considerable change in the study area. Therefore the above area has been considered as an ideal test-bed site for the study of change detection technique.

2.3. Image registration

The images were geometrically corrected and geo-coded to the UTM with a minimum of 3 GCPs required for registration. To increase accuracy in the ROI, 10 ground control points have been selected and re-sampled with cubic-convolution. The accuracy of image registration was accurate within one pixel with an RMS error of 0.2 pixels.

2.4. Image fusion

Data of higher spatial resolution bring out better discrimination between shapes, features and structures for an accurate identification of land use and land cover classes, whereas finer spectral resolution allows a better discrimination between various classes in spectral space in the remotely sensed data. By fusing the data of higher spatial resolution and multi-spectral data it is possible to derive composite fused data which exhibit the features of both data. The commonly employed data fusion techniques are Intensity-hue-saturation (IHS) transform, Principal component analysis (PCA), Brovey transform (BT), Multiplicative technique (MT), Wavelet transform (WT) and WT + IHS. This study has employed WT + IHS data fusion technique as it exhibits satisfactory results in the evaluation of change detection over coastal land cover classes. The cubic convolution algorithm has been employed for re-sampling of fused data.

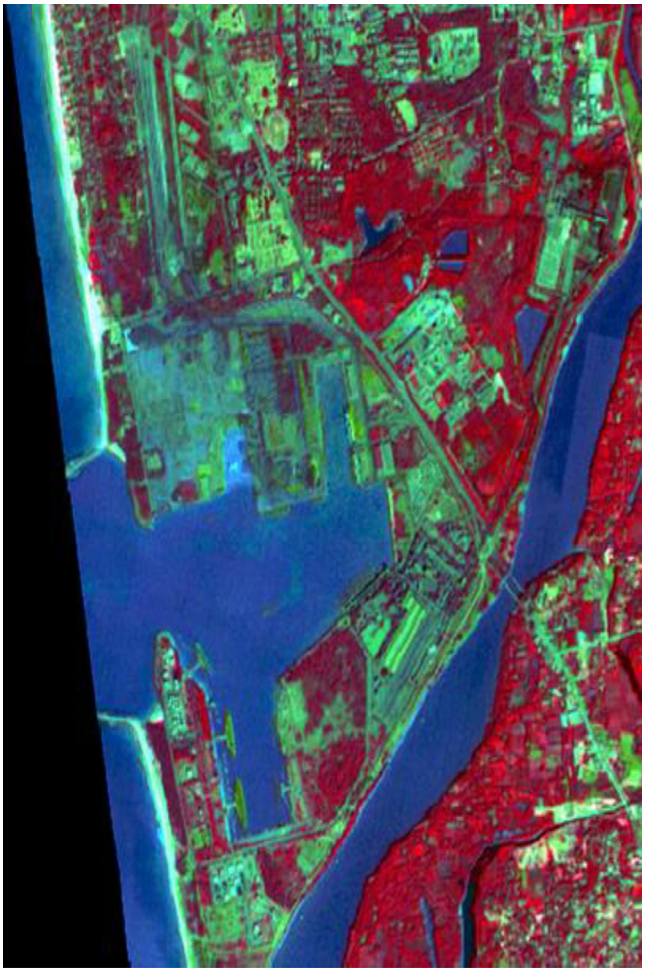

Figure 1 Study area of Mangalore coast.

Table 1 Details of the data products used in our research work.

Sl. No.	Satellite and data type	Date of acquisition	Spectral resolution	Spatial resolution
1.	IRS P-6 (Resourcesat 1) Multi-spectral (2)	26th Dec 2008	Green (0.52–0.59 μm); Red (0.62–0.68 μm); Infrared (0.77–0.86 μm)	5.8 m
2.	IRS P-5 (Cartosat-1) Panchromatic (2)	7th Jan 2008	0.55–0.99 μm	2.5 m

3. Artificial Bee Colony (ABC)

The ABC algorithm is based on bee's behaviour in finding the food source positions without the benefit of visual information (Karaboga and Ozturk, 2011). The information exchange from bees is integrated knowledge about which path to follow and quality of food through a waggle dance. Bees calculate their food source using probabilistic selection and abounding source by sharing their information through eagle dance and food source with less probability of producing new food source in neighbourhood of old source in relation to their profitability.

The ABC has three necessary components: food source, employed bee, scout bee and onlooker bee, and the behaviours are: selection and rejection of the food source.

- *Employed Bee:* The employed bees store the food source information which includes the distance, the direction and share with others according to a certain probability and shares with other bees waiting in the hive, richness and extraction of energy, nectar taste and fitness of the solution.
- *Onlooker Bee:* It takes the information from selected numbers of employed bee and decides the probability of higher nectar amount information of the food source are selected according to profitability of food source.
- *Scout Bee:* If the position of food source is not improved through maximum number of cycles, food source will be removed from the population; employed bee becomes a scout bee and elects a new random food source. Based on the performance of fitness value, if the elected new food source is better than rejected one then scout bee becomes employee bee. This process is repeated until the maximum number of cycles to determine the optimal solution of food source.

The main steps can be described as follows:

(1). Bees are initialised in a colony as $X_i = \{x_i^1, x_i^2, \ldots, x_i^N\}$, where i represents the food source in the colony, n denotes population size. Fitness F_i is calculated for each employed bee x_i which is proportional to the nectar amount of the food source and records maximum nectar amount in the position i.

(2). Employed bees will identify new food position v_i in the neighbourhood of the old one in its memory by

$$v_i = x_i + (x_i - x_k) * \phi k \epsilon \{1, 2, \ldots, N\}, \tag{1}$$

where k is an integer number but it is different from i, ϕ is a random real number in [−1, 1]. Fitness values of x_i is compared with the value of v_i, if v_i is better than x_i, v_i is replaced with x_i, otherwise fitness value of x_i is retained, these types of mechanism are done by greedy selection.

(1). After the search of neighbourhood task completed by employed bees, each onlooker bee chooses a food source depending on the fitness F_i of x_i, the probability value of P_i chosen by onlooker bee is calculated according to Eqs. (2) and (3).

$$P_i = \frac{fit_i}{\sum_{n=1}^{SN} fit_n} \tag{2}$$

$$fit_i = \begin{cases} 1/1 + f_i \\ 1 + abs(f_i) \end{cases} \tag{3}$$

If onlooker bee has selected one food source depending on the probability P_i, modification of P_i is done according to Eq. (1) where fitness strategy is done using roulette selection to check whether there are some abandoned solutions or not in x_i and will be replaced by the food source if it has better nectar amount compared to previous value x_i. If the position of one employed bee cannot be improved through a predetermined number of cycles, the employed bee will become a scout bee and produce a food source randomly according to Eq. (4), a new solution is generated.

$$x_i = \min + (\max - \min) \times \phi \tag{4}$$

3.1. ABC for remote sensing classification

Main component of the proposed ABC algorithm is to select classes by a bee. Selection of classes corresponds to Digital Number (DN) values of images. Bees are represented by pixels of images, Food sources are land cover features, employed bees are simulated by pixels belonging to classified dataset which contains the function values (nectar quality) of the solution, are calculated using euclidean distance (Karaboga and Basturk, 2008).

The following main components in this proposed algorithm are shown in Fig. 2.

- *Initialisation:* Bees select the classes depending on various parameters such as position, pattern, location and association of classes depending on its Digital Number (DN) value. Each employed bee selects the classes on the dataset depending on attributes of dataset. Each class has its lower range of DN values and upper range of DN values for selection of classes within cover percentage.

To evaluate the performance of the data, selection of points from datasets is stored in the UCI datasets for training and signatures are controlled by the size of a colony (land cover classes), by limiting the count of maximum cycle of a bee for a determining the weight of a class and its bound value limitation. In each training period, the classes are divided into K classes. For each time, a single subset of employed bee is used to update the weight of bee to new weight and remaining K subsets are retained with old weight to compare with each new weight for the validation of class.

- *Classification strategy:* Classifications are done based on the upper and lower bound of DN values, which can identify the specific class from different groups. The procedure is defined in Eq. (5) and Eq. (6) as below:

$$\text{Lower bound} = f - k_1 * (F_{\max} - F_{\min}) \tag{5}$$

$$\text{Upper bound} = f + k_2 * (F_{\max} - F_{\min}) \tag{6}$$

Maximum DN values of a class are represented by $F_{\max}$ and $F_{\min}$ is the minimum values. F represents the original DN value of class. k_1 and k_2 are random variables [0 1].

- *Fitness function:* Fitness values are evaluated depending on the land cover class and maximum cycle of an employed bee and scout bee to cover the class depending on their weights.

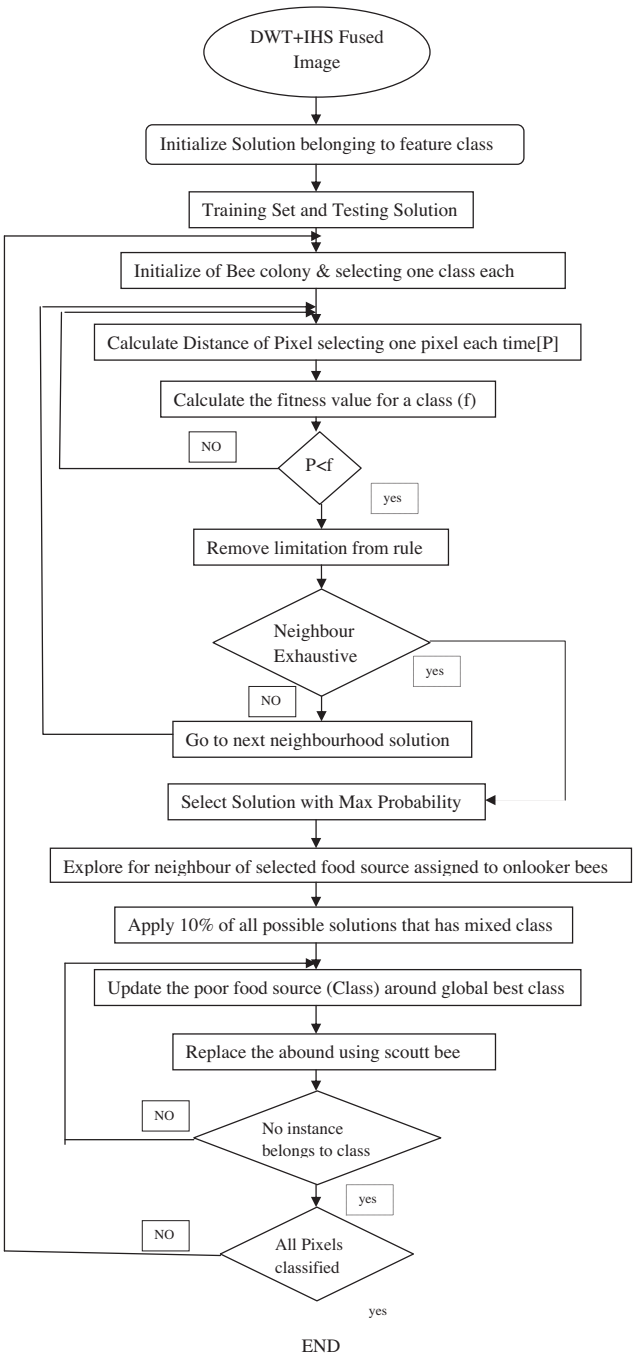

Figure 2 Flow chart for classification using ABC algorithm.

If the class is in between the lower and upper range it predicts the class depending on their evaluated record of employed bee and calculate the fitness and proves this has an predictive record. Its representation is as below:

$$\text{Fitness Value} = T_N/T_N + F_P * T_P/T_P + F_N \tag{7}$$

(I). *True Negative (T_N):* Classes that are not covered by feature and that do not have class in the predictive class.
(II). *True Positive (T_P):* Classes that are in the features and covered by predictive class.
(III). *False Positive (F_P):* Number of bees (pixel) covered by class, but the class is not covered by predictive class.
(IV). *False Negative (F_N):* Number of bees (pixel) not covered by the class, but the class is covered by predictive class.

To avoid overfitting when learning algorithm induces a classifier that classifies all instances in the training set, including the noisy ones, correctly. To avoid this pessimistic pruning approach is used to remove redundant feature limitations, it is repeated till all the classes are evaluated.

- *Search and prediction strategy:* Employed bee starts to search the location of class depending on the DN values and the weights of each class. When an employed bee does not meet the requirement or reach the maximum cycle number it calculates and updates new weight of a class.

$$V_{ij} = X_{ij} \tag{8}$$

where V_{ij} represents the position of the new food source and X_{ij} stands for neighbour of food source, here represented by euclidean distance between food source and particular bee. In addition to these i and K are between 1 and 0, but K is different value from i and j represents the dimension. In our work dimension is equal to the number of class in the dataset.Prediction strategy will determine which class should be predicted when there are mixed classes or when pruned rule is applied when the classes are unknown. Three main steps are as follows.

(a) Calculate the weight for each class and predict new weight for each class which covers the test data record when maximum cycles are not reached for a given class.
(b) Classes are predicted depending on the upper and lower bound weight according to different possible classes.
(c) Select class which has the highest prediction class as the final class.

Prediction is defined as below

$$\text{prediction} = (\alpha * \text{rule fitness value}) + (\beta * \text{rule cover percentage}) \tag{9}$$

where α and β are two weighted parameters, $\alpha \in [0,1]$ and $\beta = (1 - \alpha)$.

$$\text{Cover percentage} = T_P/N \tag{10}$$

- *Selection:* The proposed phases are highlighted. In these phases, 10% of all possible solutions, which have the lowest fitness value, are to be updated. Hence, the proposed phase only updates poor possible solutions. The poor possible solutions are mutated around the g_{best} food source, in this phase. The equation for this phase is:

$$V_{ij} = y_{\text{best}}, j + \varphi_{ij}(X_{pj} - x_{kj}) \tag{11}$$

where V_{ij} is the candidate solution of new food sources, y_{best}, j is the global best food source with j-th dimension, x_{pj} is the p-th food sources of j-th dimension and y_{kj} is the k-th food sources of j-th dimension. p and k are randomly chosen food sources and they are mutually exclusive. Meanwhile the parameter φ_{ij} is a control parameter that represents random numbers within [−1, 1]. As poor possible solutions are mutated

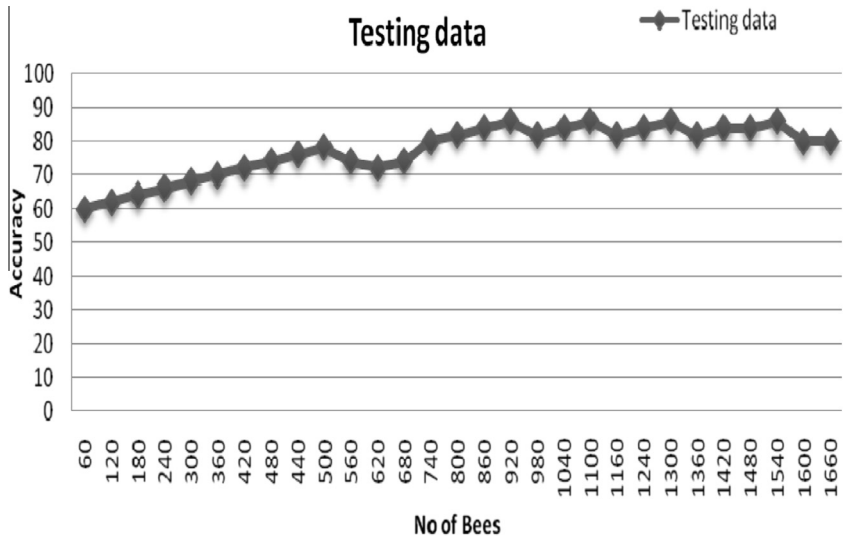

Figure 3 Influence of No. of bees on the performance of classification.

around the g_{best} possible solution, the modified poor possible solutions would be fitter. This way, the number of fit possible solutions increases with increasing generation. Now, there exists a higher probability that a selected possible solution will be mutated with a fit possible solution during employed and onlooker bee phases, as fitness of every possible solution is higher in the proposed algorithm. Hence, the produced candidate solution will be fitter than the existing possible solution.

4. Implementation and results

The image classification and evaluation were performed for six classes using MLC, SVM, ANN and ABC algorithm on panchromatic fused LISS-IV data of 2.5 m spatial resolution. Selection of training samples is directly related to the DN value of class and it is the initial step for Artificial Bee Colony classification. A total of 3090 samples are used to identify the LC classes i.e., 1090 samples as the training data set (Employed bee), and the remaining 2000 samples for validating the classes. The ABC classification was accomplished using the MATLAB software, the supervised classification based on MLC algorithm, Support Vector Machine (SVM), Artificial Neural Network (ANN) and validation were carried out in the *ENVI* RS image processing software. The accuracy of each class is determined by using OCA (Overall classification accuracy), PA (Producer's accuracy) and UA (User's accuracy).

For the implementation of the SVM classifier, we kept constant: the gamma parameter in the kernel function (value: 0.167) the penalty parameter (value: 100) and the pyramid layers (value: 0); and we tested different kernel types (functions): polynomial (1st–6th order), sigmoid and radial basis functions concerning their accuracy results with a 4th order polynomial function (El-Asmar et al. 2013).

For the implementation of the Feed-Forward ANN, we kept constant: the training threshold contribution (value: 0.167), the training rate (value: 0.2), the training momentum (value: 0.9) and the number of training interactions (value: 1000) but we tested different number of hidden layers (one and two) and different activation functions (hyperbolic and logistic). The Feed-Forward, one hidden layered ANN with logistic function.

This Artificial Bee Colony algorithm requires the specification of the following parameters.

(1) *No of bees:* This is the maximum number of bees for a specified class constructed during iteration.
(2) *Minimum number of training samples per class:* This is the minimum number of training samples that each class must cover to help avoiding pruning.
(3) *Maximum number of uncovered training samples in the training set:* The process of calculating the weights for each class until the number of uncovered training samples is smaller than this threshold and updates itself to new weight.
(4) *Maximum number of cycles:* The program stops when the number of iterations is larger than this threshold.

The parameter settings of ABC are as follows: No. of bees = 220 (Employed bees = 60 and Onlookers bee = 160); Minimum training samples = 20, Maximum uncovered training samples = 12; and maximum iterations for onlookers bee = 220. The sensitivity of selecting two parameters such as selection of number of bees and minimum training samples are shown in Fig. 3. Classification result stabilises when number of bees reaches 60 and the relationship changes when maximum number of cycles reaches above 200. Results are compared with MLC, SVM, ANN and ABC through three criteria namely, the same training data (1090 samples) are used for the classification, and the same test data (2000 samples) were used for validation, the overall classification accuracy, and the Kappa coefficient. Total time taken by the ABC is 5 min to complete the identifying of each class by using the training data.

The classification result of the MLC, SVM, ANN and ABC is shown in Fig. 4. The comparison between them shows that ABC algorithm performs better than MLC, SVM and ANN. Area 'A' in Fig. 4 is actually land covered with scrubs, degraded scrubs, fallow land and build up areas, which

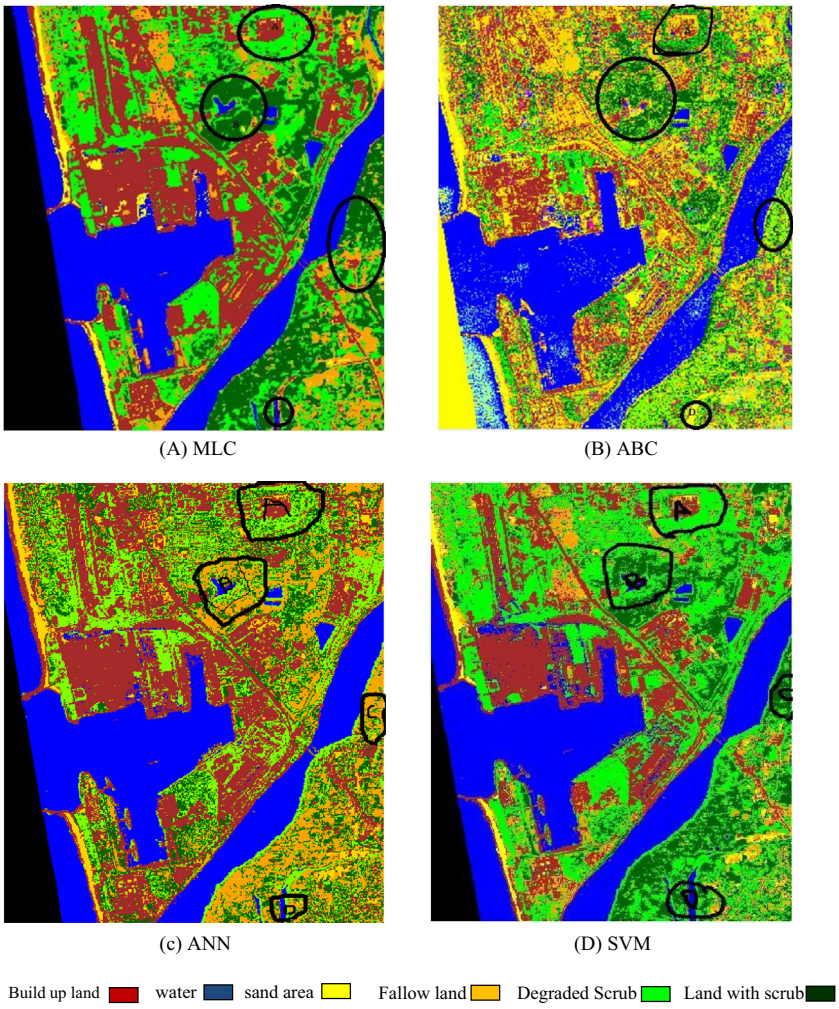

Figure 4 Land cover classification in the area of Mangalore coast: (A) MLC; (B) ABC; (C) ANN; (D) SVM.

MLC and SVM misclassified as degraded scrub whereas ANN correctly classified the degraded scrub area and land area as scrub but it was unable to separate fallow land and urban land. However, ABC classified all the classes correctly in Area A. Further, area B is a mixture of land with scrubs and degraded land. But MLC has misclassified this land area as land with scrubs and ANN as fallow land while SVM and ABC classified the area correctly as land with scrubs and degraded land. Another land cover area 'C' which contains only land with scrub has been classified as degraded land by MLC and SVM, fallow lands by ANN but correctly classified by the proposed technique. However, the one more area under investigation containing water body 'D' has been misclassified as fallow land in the ABC classified image (Fig. 4A–D).

From Table 2, it is intuitive that the highest OCA of 83.03% is obtained in the ABC technique for the training dataset size of 3090 pixels, whereas the OCA in MLC for the same training set size at 6 classes is 77.88%. The SVM and ANN classifiers produced OCA of 80.43% and 78.25%, respectively. Further ABC shows the highest Kappa coefficient of 0.794,

Table 2 Behavioural study of ABC for 6 classes: comparison of classwise accuracy of MLC, SVM, ANN and ABC.

	Producer's accuracy (%)				User's accuracy (%)				Kappa statistics			
Data sets	MLC	SVM	ANN	ABC	MLC	SVM	ANN	ABC	MLC	SVM	ANN	ABC
Build up land	75.94	72.18	77.27	86.79	90.99	93.20	73.91	93.88	0.891	0.572	0.579	0.934
Water	79.49	100	94.44	84.62	81.58	100	100	86.84	0.571	0.746	0.596	0.554
Sand area	81.08	91.11	63.95	89.19	76.92	96.47	67.17	70.21	0.717	0.700	0.594	0.697
Degraded scrub	52.00	73.28	47.62	74.40	89.04	57.14	74.73	79.49	0.756	0.650	0.560	0.896
Fallow land	71.43	70.05	57.68	82.86	60.98	77.51	100	50.00	0.451	0.699	0.588	0.571
Land with scrub	73.60	94.58	41.21	77.60	77.31	87.67	74.07	78.23	0.765	0.685	0.600	0.770
OCA	**77.88**	**80.43**	**78.25**	**83.03**								
Kappa	**0.753**	**0.765**	**0.645**	**0.794**								

and the other techniques stand in the descending order like, SVM (0.765), MLC (0.753) and ANN with the lowest kappa value of 0.645. Taking into consideration the qualitative and quantitative comparisons, it is evident that the Artificial Bee Colony method out performs Support Vector Machine, Maximum Likelihood Classifier and Artificial Neural Network based classifiers and exhibited higher overall classification accuracy.

5. Conclusion

The performance of RS data classification using swarm intelligence can overcome the limitation in constructing proper classifier, when the study area is complex and spectral signature of the classes overlap. This work has presented a new method for classifying RS data using Artificial Bee Colony algorithm. ABC is a multi-agent system with a simple intelligence which can complete the task through cooperation. ABC is based on waggle dance which updates the distance of class values (Nectar amount) and can be represented without using complex equation. As a result, ABC is capable of providing better classification results. This method has been applied in classification of RS images of Mangalore coastal area, India. The comparison of classification results is carried out between the ABC, MLC, SVM and ANN methods. The overall accuracy obtained in the ABC method is 83.03% with a Kappa coefficient of 0.7949. When compared to MLC, SVM and ANN, the ABC method is found to be more effective in the classification of RS data.

However, there is a limitation in using this method in identifying classes. The classes identified by scoot bees have larger number of boxes (classes) in feature space. This is because some of the scout bees become an onlooker's bee if the threshold reaches maximum iteration. In future research classification rule can be applied using XOR condition to identify the classes.

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