Effect of Pansharpening Methods on the Stability of Bat Algorithm Unsupervised Classification Results

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Abstract

This paper investigates the effect of pansharpening methods on the results of satellite images classified by the Bat Algorithm (BA). Notably, BA is an algorithm using randomized parameters for its initialization and its run, thus giving varying results from one execution to another. Before the classification step, a fusion merging images with different characteristics can be applied to create an improved image to be classified. This new image is used as input to BA and provides more information to interpret. To measure the effect of fusion, experiments are carried out using three techniques: Ratio Component Subtitution (RCS), Local Mean and Variance Matching (LVMV), and the Bayesian pansharpening algorithm (Bayes), to create an input image that combines the panchromatic and multispectral images of the same area. For this research, recent Landsat 8 panchromatic and multispectral images taken over the city of Mostaganem (Algeria) are used to quantify the fusion step impact on the classification. The improvement in the results is confirmed by computing the median and standard deviation of Cohen's kappa and overall accuracy obtained throughout multiple tests. From these results, it can be concluded that a fusion step and precisely the Bayes fusion allow better and more stable results for unsupervised classification problems solved by BA.

Keywords*: Bat Algorithm, Bio-inspired Algorithm, Image Fusion, Remote Sensing, Unsupervised Image Classification, Pansharpening, Ratio-Component Substitution, Local Mean and Variance Matching, Bayesian pansharpening.*

1. Introduction

With the quick progress of remotely sensed image acquisition techniques, the satellite offers more and more images with different characteristics, such as images with different spectral and spatial resolutions [1]. It quickly became interesting to combine data contained in various types of images to refine the analysis and improve the search efficiency for information [2]. The process of combining two or more images to obtain a new, improved, image is called fusion. The development of image fusion methods has become a compelling way to produce images, allowing to reveal new details that are only detectable by using combined information [3]. It has become possible to carry out more in-depth analyses of the environment and therefore to more effectively detect areas that previously were not visible with the use of data from a single sensor [4]. Indeed, the possibility of merging all the data offers significant gains in image analysis, processing, and mapping, and meets various needs such as change detection [5], thematic classification [6], and visual image interpretation [7].

The two essential characteristics of remotely sensed images are spectral and spatial resolutions. Earth observation satellites offer separate multispectral images (MS), which have a high spatial resolution, and panchromatic images (PAN), which have high spectral resolution images. The process of combining PAN and MS images is called pansharpening. The pansharpening step produces an image that has a high spatial and spectral resolution at the same time.

In recent years, there has been an increasing interest in pansharpening. Pansharpening is not only used as a separate process to obtain high definition images, but it is also considered as a preliminary step to improve the results of a more complex process. The impact of pansharpening is highly measured as shown by reviewing the recent literature [3], in which we can deduce that pansharpening can increase classification accuracy [4].

Unsupervised image classification is an increasingly important area in remote sensing. This paper focuses on classification improvement using pansharpaning. Unfortunately, efficient classification results cannot be achieved by using only PAN or MS images alone [8]. The interpretation of the classification results is limited by the missing spectral or spatial information. For this purpose, pansharpening is used to incorporate more information into the classification algorithm.

The results of the classification are not affected only by the amount of provided information, but also by the choice of the classification algorithm. There are many unsupervised classification methods in the literature. Often, bio-inspired algorithms were used to improve the unsupervised classification [9]. These algorithms are inspired by natural phenomena and animal behavior. To apply these, the classification is considered an optimization problem. Their effectiveness has been proven by many papers in the literature [10]. In our study, the bio inspired Bat Algorithm is used. This algorithm is inspired by the behavior of bats hunting their prey [11].

This study aims to analyse the impact of pansharpening on the results given by classification using the bat algorithm. More precisely, the bat algorithm gives results with varying accuracy due to its random nature. By adding a pansharpening step, this aspect can be reduced. A comparison is performed between the results of the classification without any fusion step and the results of the classification with a fusion merging the original MS with the pansharpened images. To this end, three well-known pansharpening algorithms are used: Ratio-Component Substitution algorithm (RCS) [12], Local Mean and Variance Matching (LMVM) [13], and Bayesian pansharpening algorithm (Bayes) [14].

To adequately analyse the stability in Bat classification results, several experiments were performed by applying the aforementioned algorithms to well-known images acquired by the Landsat 8 sensor on the city of Mostaganem (Algeria). Using a known region gives us the advantage of being able to prepare a reliable reference image to evaluate the effectiveness of our classification approach. The evaluation is performed by using Cohen's kappa [15] and the overall accuracy values to determine whether this new approach gives better results or not. The results show that using pansharpening gives higher, but most notably, more stable classification accuracy.

The rest of this paper is organized as follows: section two presents a detailed description of the used pansharpening algorithms, the original bat algorithm, and how it has been adapted for classification. Section three presents the studied area used to test our approach and assesses the experimental results. The last section presents the findings of our work and identifies the problems encountered for further research.

2. Materials and methods

2.1. Pansharpening algorithm

Pansharpening refers to the merging of a high-resolution panchromatic image (PAN) and a low-resolution multispectral image (MS) acquired in the same area. This can be considered as a particular problem of data fusion, for the reason that it aims to merge the spatial details which are uniquely present in PAN with the spectral diversity of MS which is missed in PAN to create a new and unique product [2]. The merged image is not only useful for facilitating visual interpretation, but also for improving the results of classification [16]. In addition, a merged image provides a beautiful color image for image viewing applications [17]. In the following, three pansharpening algorithms used in our study are described: Ratio-Component Substitution algorithm, Local Mean and Variance Matching, and Bayesian pansharpening.

Ratio Component Substitution algorithm

The Ratio Component Substitution (RCS) [12] is an algorithm of the category "component substitution techniques". The basis of this pansharpening category algorithm consists of the spectral transformation of the MS image, and the substitution of one component of the resulting transformed MS with information from the PAN image. Finally, an inverse transformation is applied to obtain the final fused image. The RCS algorithm merges the orthorectified PAN with the MS image. The general principle of this algorithm consists of using of the PAN for multiplication and the filtered PAN image for the normalization of the MS image. For this purpose the lowpass scharpening filter is used. The general RCS fusion equation can be calculated by the equation(1)[12]:

$$y=\frac{MS}{Filtered\,PAN}\,PAN\,E \qquad (1)$$

Where E is the vector of random errors.

Local Mean and Variance Matching

The local mean and variance matching (LMVM) has been designed to reduce the difference between the fused image and the low resolution MS image to preserve the maximum information of the original MS image. The local mean matching filter applies a normalization function at a local scale on the image to match the local mean and variance values of the high resolution PAN image with those of the original low resolution spectral image. The remaining differences correspond to the information coming from the high resolution PAN image. This category of filtering pansharpening has the advantage to increase considerably the correlation between the final fused image and the original image, which reduces the loss of information in the final product. According to [13], the calculation of the fused image based on the LMVM filter is given by the following equation (2):

$$Fused\,image_{i,j}=\frac{\left(PAN_{i,j}-mean\left(PAN\right)_{i,j(w,h)}\times std\left(MS\right)_{i,j(w,h)}\right)}{std\left(PAN\right)_{i,j(w,h)}}+mean\left(MS\right)_{i,j(w,h)} \qquad (2)$$

where:

- *Fused* $image_{i,j}$ is the fused image at the coordinates *i, j*
- $PAN_{i,j}$ is the panchromatic image at the coordinates *i,j*
- $MS_{i,j}$ is the multispectral image at the coordinates *i,j*
- $mean(PAN)_{i,j(w,h)}$ is the mean of the panchromatic image calculated within the window of size (w,h) at coordinates *i,j*.
- $mean(MS)_{i,j(w,h)}$ is the mean of the multispectral image calculated within the window of size (w,h) at coordinates *i,j*.
- $std(PAN)_{i,j(w,h)}$ is the standard deviation of the panchromatic image calculated within the window of size (w,h) at coordinates *i,j*.

- $std(MS)_{i,j(w,h)}$ is the standard deviation of the multispectral image calculated within the window of size (w,h) at coordinates *i,j*.

The amount of preserved information in spectral images depends on the size of the filtering window *(w,h)*. The larger the size is, the more information is incorporated into the final fused image and less MS information is preserved. The choice of the window size must always ensure the maximum possible correlation and the minimal deviation compatible with a constant mean and standard deviation constraint [13].

The Bayesian pansharpening algorithm

The Bayesian pansharpening algorithm (Bayes) is based on the statistical relationships between the MS image and the PAN image without being restricted by the modeling hypotheses. Furthermore, it allows the user to define the weight of the spectral and panchromatic information according to its needs and study areas. The Bayesian pansharpening algorithm is based on the concept that vector Z (the variables of interest) cannot be directly determined. Instead, they are related to the observable variables Y according to an error-like model which is defined in the following equation (3) [14]:

$$Y = g(Z) + E \tag{3}$$

where:

- g(Z) is a set of functional
- E is a vector of random errors that are stochastically independent of Z.

2.2. Unsupervised classification algorithm

The Standard Optimization Bat Algorithm

The Bat Algorithm (BA) is originally designed to resolve a multi-objective optimization problem. It was inspired by the echolocation phenomenon of the microbats [11]. While flying [18], microbats emit high-frequency ultrasound. Then, the echoes are returned to the bat by the different types of prey and obstacles. The bats hear the echoes and analyze them to know the position and the nature of the prey and obstacles. Furthermore, bats are able to find their way and capture their prey even in deep darkness. To solve an optimization problem, the author of BA models the echolocation behavior of bats based on the three following rules:

1. Due to echolocation, bats can obtain detailed information about their environment, such as the distance and the nature of prey and obstacles.
2. Bats move randomly with a velocity v_i at the position x_i with the initial frequency f_{min}, varying wavelength λ, and loudness A_0 to search prey. They can automatically adjust the frequency and the rate $r \in [0,1]$ of their emitted pulses according to the proximity of their target,
3. It is assumed that the loudness varies between the values A_0 and $A_{min,}$ where A_0 is positive and A_{min} is a minimum constant value.

Each bat corresponds to a possible solution to the optimization problem. A new solution is calculated during each iteration of the algorithm, according to equations (4), (5) and (6).

$$f_i = f_{min} + (f_{max} - f_{min})\beta, \tag{4}$$

$$v_i^t = v_i^{(t-1)} + (x_i^t - x_*) f_i, \tag{5}$$

$$x_i^t = x_i^{t-1} + v_t^i, \tag{6}$$

where $\beta \in [0, 1]$ is a random vector calculated from a uniform distribution. For simplicity, the BA's author recommends the following assumptions: f_{min}= 0 and f_{max}= 1.

A bat can be blocked at a specific position and will stop the search for a better solution. To avoid this behavior, a new solution is generated around the best actual solution for each bat using equation (7).

$$x_{new} = x_{old} + \epsilon A^t \tag{7}$$

where ϵ is randomly chosen from values in [-1, 1], and $A^t = \langle A_i^t \rangle$, the average loudness of all the bats at a current iteration.

To switch to the exploitation stage, the loudness A_i and the pulse rate r_i are varied during iterations when necessary. Therefore, as soon as the bat finds its prey, it reduces the pulse emission rate. So, $A_i \in [A_{min}, A_{max}]$ where $A_{min}= 0$ means that the bat has stopped temporarily emitting any sound because it has just found the prey. Under these assumptions, A_i^{t+1} *and* r_i^{t+1} can be calculated as follows:

$$A_i^{t+1} = \alpha A_i^t, \tag{8}$$

$$r_i^{t+1} = r_i^0 \left[1 - \exp\left(-\gamma t\right)\right], \tag{9}$$

Where α and ɣ are constants. For any 0 < α < 1 and ɣ > 0, we have $A_i^t \to 0$, and $r_i^t \to r_i^0$, as $t \to \infty$

For the standard bat algorithm, the simplest case assumes that α = ɣ.

The main steps of a standard bat algorithm are described in Figure 1.

```
Define the objective function: f(x), x=(x1,…,xd)T
Initialize the parameters: population size (N), maximum number of
iterations (nb_iter), α, ɣ, fmin, fmax
Randomly initialize the population of bat: xi,vi and fi
Initialize the pulse rate ri and the loudness Ai
Evaluate the fitness of each bat and initialize x* with the bat
which have the best fitness
set t=0
while (t<nb_iter)
        For each bat do
                Generate new solutions by adjusting frequency,
updating velocities, and location/solutions using equation (8),
(9) and (10)
                if (rand > ri)
                        Generate a new solution surrounding the
selected best solution by using equation (11)
                        Evaluate its fitness
                end if
                if (rand < Ai & f(xi) < f(x*))
                        Accept the new solution
                        Increase ri and reduce Ai
                end if
Evaluate the bats and calculate the current best x*
End while
Display results
```

Figure 1: Original Bat Algorithm

2.3. The proposed unsupervised image classification Bat Algorithm

One aim of our study is to adapt the bat algorithm for remotely sensed image clustering (unsupervised classification). We use the bat algorithm to find the best centers of the groups composing a satellite image. The bat algorithm is simple to implement, and it produces good results for clustering [19]. To use the bat algorithm for image clustering, we consider the following elements:

The objective function

The goal of the bat algorithm is to find the centers of groups with the minimum dispersion from their centers. The mean square-error function [20] is used as an objective function. It is calculated by using the Euclidean distances between each pixel and a group center. The Euclidean distance is calculated as shown in equation (10). The point is affected by the group that gives the lowest value for the objective function.

$$f=\frac{1}{N}\sum_{j=1}^{k}\sum_{i=1}^{N} z_{nk}\left(d\left(p_i, c_j\right)\right) \tag{10}$$

Where, z_{nk} is an indicator variable, such that $z_{nk} = 1$ if the n^{th} pixel p_i belongs to the cluster c_k and $z_{nk} = 1$ otherwise, $d(p_i, c_i)$ represents the distance between pixel p_i and a cluster center c_j. There are different distances that can be used such as Euclidean, Average, and Manhattan distance [21]. In this study, we have chosen the recognized Euclidean distance defined as [22] in equation (11).

$$d\left(P_i - P_j\right)=\sqrt{\sum_{d=1}^{m}\left(p_i^d - p_j^d\right)^2} \tag{11}$$

Where $d(p_i - p_j)$ is the distance between p_i and p_j, and m is the dimension of the data point. In our case, p corresponds to the pixel and m to the number of bands.

The population of bats

In the proposed algorithm, each bat in the population corresponds to a candidate solution and is represented by a vector of dimension $k \times m$ as follows: $x_i = (c_{11}, c_{12}, \ldots, c_{1m}, c_{2m}, c_{22}, \ldots, c_{k1}, c_{k2}, \ldots, c_{km})$, where k is the number of clusters, c_1 represents the first cluster's centroid, and c_k represents the k^{th} cluster centroid.

The principal steps of the bat algorithm for unsupervised image classification are described in Figure (2):

```
Initialization of all parameters of bat algorithm and the
population of bat (assign a random pixel for each bat)
The classification of the image is performed according to the
initial population. We obtain several classified images (each image
corresponds to one bat
Evaluate the fitness value and find the current global best
As long as the number of iterations is not reached do:
        Move each bat by using equations (8), (9) and (10), so we
obtain new position for each bat
        Evaluate the new solution and modify the best solution if
the new solution is better,
        Generate a new local solution surrounding the selected best
solution by using equation (11) and evaluate its fitness
        if (rand > ri)
                Accept the new solution, increase ri, and reduce Ai
if (rand < Ai & f(xi)<f(x*))
                evaluate the bats and find current best bat
(corresponding to the best classification)
Increment the number of iteration
Classify the image with the best bat
```

Figure 2: Unsupervised image classification with Bat Algorithm

3. Results and discussion

To study the importance of using a fusion step before applying bat algorithm classification, the process is carried out using the original multispectral images and the images produced after the fusion. The fusion allows the merging of the panchromatic (PAN) image with the multispectral images using the three methods described in section 2. The images used in this experiment have been obtained by the Landsat 8 satellite. The fusion step is executed through OTB software. The classification step is executed 20 times for each scenario (with and without fusion). Finally, the quality of the classified images is evaluated.

3.1. Study area

To assess the impact of image pansharpening on bat algorithm classification, a high multispectral and panchromatic Landsat imagery of the Algerian city of Mostaganem was used, which was acquired on 2020-02-06. A Landsat 8 image has 11 bands, one of which is panchromatic (PAN). In our experiments, we used the PAN image with a resolution of 15 meters and the three R, G, and B multispectral (MS) images with a resolution of 30 meters. The imagery covers a diversified area of land, particularly challenging for our study. Figure 3 represents a true color (a combination of RGB bands) and panchromatic images of the experimental area. Figure 4 represents the same area once the images have been merged.

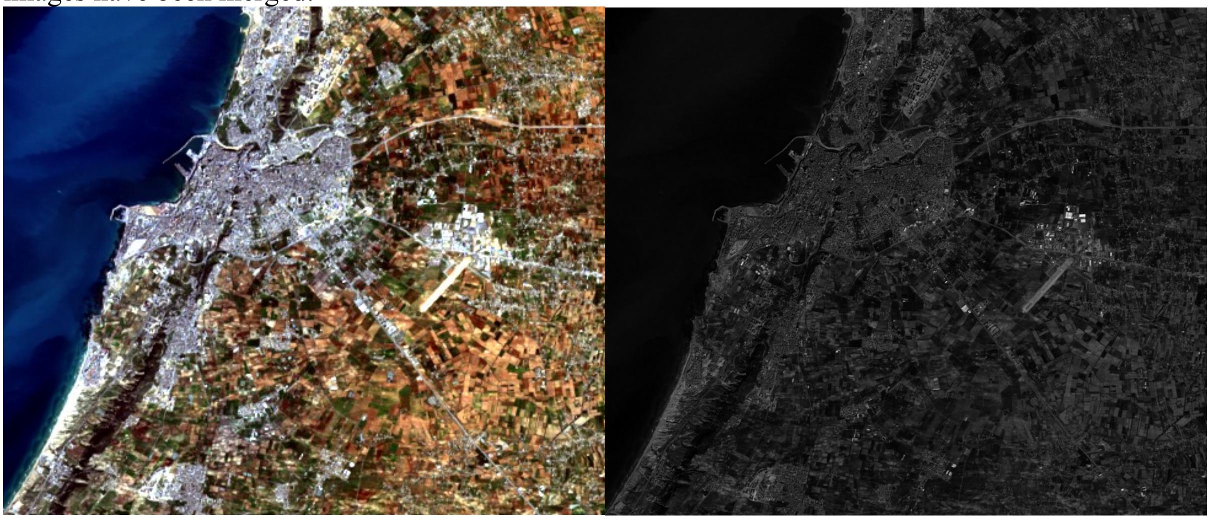


Figure 3: multispectral and panchromatic images of the studied area

Figure 4: Fused images with RCS, LMVM and Bayes respectively

3.2. Bat Algorithm parameters

As described before, the Bat Algorithm (BA) highly depends on several parameters, such as the frequencies or the attenuation. Obviously, these parameters greatly impact the effectiveness of the algorithm. The parameters used for this paper are detailed in Table 1.

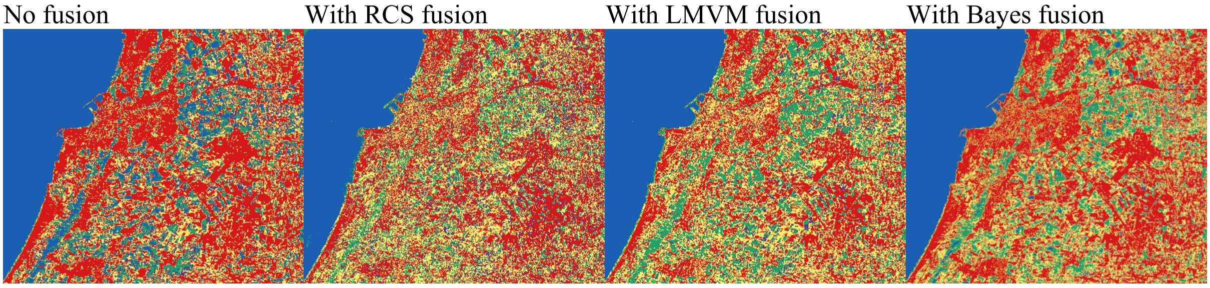
Table 1: Parameters setting in BA algorithm

Parameters	Retained
Population size	20
Number of iterations	30
Minimal frequency (f_{min})	2
Maximal frequency (f_{max})	15
Attenuation coefficient of loudness (α)	0.95
Increasing coefficient of pulse emission (γ)	0.05
Updating solution coefficient (ε)	100
Number of groups	5

3.3. Results

To assess an unsupervised classification approach, comparing a classified image with a ground truth image is still the most used evaluation method. For this, we proceeded in two steps. First, we prepared a reference image by manually classifying the studied area using our knowledge about the region and cartographic information available on Google Maps. Then, a confusion matrix is calculated between the image obtained by the bat algorithm and the reference image. The confusion matrix gives the number of pixels correctly and not correctly classified, and two important metrics can be extracted from this: Cohen's kappa and overall accuracy. Figure 5, shows an example of the output given by BA for this study.

No fusion | With RCS fusion | With LMVM fusion | With Bayes fusion



Kappa= 0,76 | Kappa= 0,8 | Kappa=0,85 | Kappa=0,87

Overall accuracy=0,82 | Overall accuracy=0,84 | Overall accuracy=0,88 | Overall accuracy= 0,9

Figure 5: Classified study area

To evaluate our results, we applied the bat algorithm on the original MS image without fusion and then on the three fused images. This process has been repeated 20 times for each algorithm. Table 2, gives a snippet of the best results, sorted, and obtained using the bat algorithm with the different fusion algorithms. From this table, we can see that the use of Bayes fusion algorithm allows the Bat algorithm to attain higher metrics values than using LMVM, RCS, and without using fusion at all. Furthermore, lower than expected values can also be found. Such values emphasize the random aspect of the algorithm and the eventuality to obtain less accurate results on some runs.

Table 2: Snippet of the best results from Bat algorithm

No Fusion		RCS		LMVM		Bayes	
Kappa	**Overall accuracy**	**Kappa**	**Overall accuracy**	**Kappa**	**Overall accuracy**	**Kappa**	**Overall accuracy**
0,86	0,89	0,80	0,84	0,85	0,88	0,87	0,90
0,81	0,85	0,77	0,82	0,83	0,87	0,87	0,90
0,76	0,81	0,74	0,80	0,80	0,84	0,86	0,89
0,76	0,82	0,75	0,76	0,76	0,81	0,83	0,87
0,68	**0,76**	**0,69**	**0,74**	**0,71**	**0,80**	**0,80**	**0,85**

Table 3 reports a statistical view of the obtained kappa and overall accuracy values of all classified images. The random aspect of bat algorithm used to simulate the movement of the bats is emphasized through these values. Effectively, the median and standard deviation reflects this behavior, notably when using no fusion.

Table 3: Comparison of Kappa and Overall accuracy values

	Kappa				Overall accuracy			
	No fusion	**RCS**	**LMVM**	**Bayes**	**No fusion**	**RCS**	**LMVM**	**Bayes**
Max	0.86	0.80	0.85	0.87	0.90	0.84	0.88	0.90
Min	0.21	0.41	0.45	0.60	0.36	0.55	0.58	0.69
Median	0.62	0.69	0.68	0.72	0.70	0.76	0.76	0.79
Standard deviation	0.18	0.13	0.11	0.08	0.15	0.09	0.08	0.07

Figure 6 offers a clearer representation of the values presented in Table 3. As shown in these results, the standard deviation is lower and the median is higher when using a fusion algorithm. The random aspect of the bat algorithm is still present, allowing the classification to not be blocked in local optimum. Additionally, the drawback of the randomness is greatly reduced compared to the results given when using no fusion. In other words, the use of a fusion algorithm assures a better stability in the output compared to the same process without any fusion. A good accuracy is assured for every run of the algorithm.

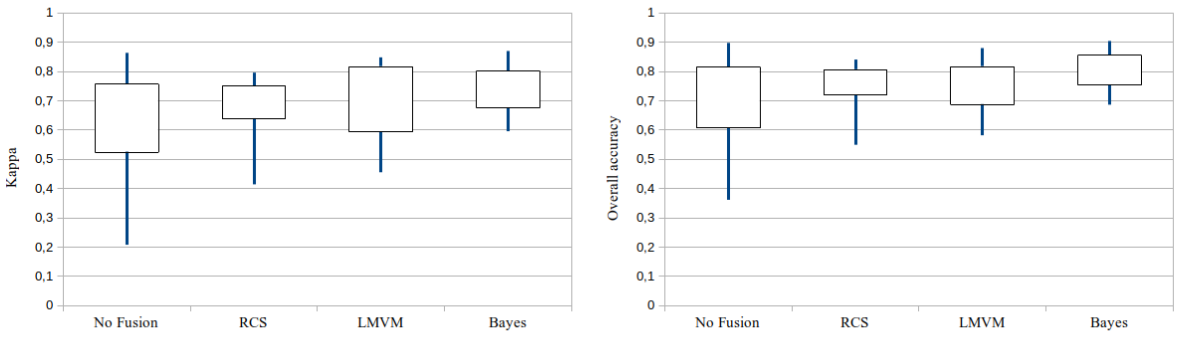


Figure 6: Stability of Bat Algorithm classification over 20 runs

4. Conclusion

The study of this paper consists of investigating the influence of fusion algorithms applied before a classification using the Bat Algorithm (BA). One important aspect of BA is its use of random numbers, meaning that the algorithm can produce not always good results depending on the initial values and the behavior throughout the execution. During this research, we observed the effect on the results of three fusion algorithms: Ratio-Component Substitution algorithm, Local Mean and Variance Matching, and Bayesian pansharpening, compared to the lack of a fusion step. The objective is to reduce the occurrence of less valuable than expected results, hence improving stability and confidence in the algorithm. This experiment has been applied to panchromatic and multispectral Landsat 8 images, and the results are evaluated using two classification quality metrics calculated from the confusion matrix.

The obtained results have shown that the classification gives at least equal or better results when a fusion step is applied. Additionally, by using a fusion step, the results will have a higher minimum accuracy and produce less deviation, giving better confidence in using this algorithm for automated and unsupervised classification. This behavior is confirmed through the kappa and overall accuracy values obtained using a ground truth image.

In conclusion, using a fusion step is essential to produce more stable and better results. Notably, Bayesian pansharpening is the most effective in this scenario.

A future study investigating the use of the Bat Algorithm on supervised classification would be very interesting.

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