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Multi-spectral images classification based on intelligent water drops algorithm

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ABSTRACT

Mosul's city land covers soil, cultivated land, stony, pastoral land, water, and ploughed agricultural land. We have classified multispectral images captured by the sensor (TM) carried on the Landsat satellite. Integrated approach of intelligent water drops (IWDs) algorithm is used to identify natural terrain. In this research, IWDs have been suggested to find the best results for multispectral image classification. The purpose of using an algorithm, give accurate and fast results by comparing the IWD algorithm with the k-mean algorithm. The IWD algorithm is programmed using the MATLAB 2017b software environment to demonstrate the proposed methodology's effectiveness. The proposed integrated concept has been applied to satellite images of Mosul city in Iraq. By comparing the IWD with the k-mean, we found clear time superiority of the IWD algorithm, equal 1.4122 with (k-mean) time equal 18.9475. Furthermore, the water drop algorithm's classification accuracy is 95%, while the k-mean classification accuracy is 83.3%. Based on the analysis and results, we conclude the IWD is a robust promising and approach to detecting remote sensing image changes and multispectral image classification.

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1. INTRODUCTION

A multispectral image is a series of various monochrome images from the sight itself, each captured with different sensors, and each image is consulted as a band. A recognized multi-spectrum image (or multi-band image) is an red, green, and blue (RGB) colour image composed of green, blue, and red images. Each is capture with a sensitive sensor to a different wavelength. Multispectral images are commonly used for distant sensing applications of picture processing. Satellites typically take several images of band frequency in a visible and invisible band. For example, Landsat 5 produces 7 bar images with a wavelength between 450 and 1250 nm.

All standard single-band image processors can be used to process multispectral images of each band individually. Images, rather than a series of monochrome greyscale images, should be considered a single multispectral image. An image with n ranges can then be defined as a point represented by a vector of length n-dimensional space n.

For multispectral image processing, there are special algorithms, and we can differentiate and identify pixels as belonging to a particular area. It is said its intensity at various bands is a character vector that describes its location in the area of the n-dimensional feature. The easiest way to describe a category is to select a lower and upper boundary for each set, thereby creating a three-dimensional "hypercube" in the space of the function. If the pixel vector points to a position within the cube, the pixel can be classified as belonging to that group. The disadvantage of multispectral images is that extra data has to be processed; there is a significant increase in the time needed for computation and memory. However, multispectral images are expected to become very important in many computing areas, as hardware speeds will increase and memory costs will decrease in the future. Classification is undeniably the most important step in processing image data, where algorithms are favoured, particularly where classical deterministic methods are inadequate due to the presence of many heterogeneous parameters and data sets. The use of multimode images in classification is an important step in producing thematic spatial information from satellite imagery data. Over the past two decades, artificial intelligence improvement algorithms used to solve various problems in many disciplines [1].

The multi-spectral image classification subject studied by many researchers and presented papers as follows: A method for building detection from multispectral images and light detection and ranging (LIDAR) data and showing its application in a test position of different building shapes [2]. Dependence of the results of the classification of multispectral forest vegetation images on parameters of wavelet-transform [3]. Obtained the neural network ensemble (NNE) classifier can have better performance, compared with standard classifiers, such as Bayes maximum-likelihood and k-nearest neighbor (K-NN) [4]. Improved classification accuracy of remote sensing images for a k-means algorithm based on the weight coefficient and support vector machine (SVM) hybrid model has applied to the classification of high-resolution remote sensing images [5]. Based on Dempster-Schafer's multispectral imagery theory, they proposed an automated approach to detecting water bodies, combining a specific water characteristic with supervised learning in a spectral range and an unsupervised context [6]. A method has been presented to describe and classify multispectral images that allow the recognition of hardly different object classes. The algorithm is successful in its application to forest vegetation objects [7]. Using multispectral sensors, suggested a novel technique to register images taken and presented a new fusion scheme that fuses the images differently for high and low frequencies [8]. Multispectral image classification based on an Object-Based active learning approach proposed a new (AL) method for selecting object-based samples [9]. Address the trouble of change disclosure in multispectral images by proposing introduced a change disclosure methodology (GBF-CD) based on graphs data fusion [10]. Presented a novel approach for copyright safeguard of multispectral images using particle swarm optimization (PSO) and kernel extreme learning machine (KELM) based watermarking method [11].

When we see rivers in nature, we feel perplexed to see turns and twists along their paths. Must think about why these fluctuations are generated, and are there intelligence or logic behind them? If this is the case, can we build and design an intelligent algorithm that depends on the use of river structures and, as a result of the above, can we adopt it? So, as a result of the above, can we adopt it? The answer to the previous questions is that the intelligent water drop (IWD) algorithm is a step toward modelling some of the procedures that occur in natural rivers and then implementing them in the form of an intelligent algorithm [12].

A quantity of soil during the migration can carry; it one of the essential characteristics of rivers' water flow rate. The soil is transport from the fast parts to the slow portions of the path in the river. Most of the soil is left in the basins of slower rivers. The following characteristics are assumed for the flow of WD in the river [13]:

- A high-speedily WD removes more soil than a low-speed WD.
- WD's speed increases more on a path with low soil than a path with high soil.
- Water chooses a more accessible path with less soil than a path with more soil.

Many researchers have studied water droplet algorithms and presented their studies as; improvement of the IWD algorithm approach for projecting an aerial robot path in complex circumference. Simulation tests show that this suggested method is a practical and feasible method for planning an air robot [14]. The IWD algorithm has examined to get solutions puzzle of the n-queen, travelling salesman problem (TSP), multiple knapsack problem (MKP), in which optimal or near-optimal solutions are acquired [12], [15]. It proposed an IWD optimization algorithm for solving the single unmanned combat aerial vehicle (UCAV) smooth trajectory planning problems in various combating environments. The results found it out more feasible and useful in the single UCAV smooth trajectory designing [16]. It modified the IWD algorithm to be applied for continuous optimization functions; the intelligent water drops-continuous optimization (IWD-CO) was examined with sundry well-known problems [17]. The optimization routing protocol in mobile ad-hoc networks uses the IWD algorithm to decrease the overhead of flooding messages for selecting the regular nodes (RNs) set in the mobile ad hoc network (MANET) environments [18]. Using a modified multi-target extension of the water droplet (WD) algorithm, the proposed WD would minimize each product's time, and the cost of products sold by the Pareto set concept to solve the logistics network problem [19]. The WD algorithm has been used to solve problems of community detection on a set of real-life networks. The suggested algorithm is competitive in a network of nodes in groups of densely connected subgroups, and results verify the model is efficient in finding the quality of the community structure [20]. A search probability map based on an environmental model was presented, and a Unmanned aerial vehicles (UAV) mutual search path optimization problem was formulated. Then, we proposed a solution planning based on an amended WD algorithm [21]. It presented a new Infrastructure for (IaaS) cloud service. The aim has suggested for IWD based workflow scheduling algorithm is to decrease the makespan and achieve higher resource utilization within the given deadline [22]. A new optimization algorithm measures the backscattering restraint sufficiently and reliably from the infinite, finite, and single arrangement of non-linear antennas based on the IWD algorithm. The method's results seemed more accurate and faster than other classics, such as genetic algorithm (GA) and particle swarm [23]. Proposed an optimization model that combines the delivery scheduling and selection of promotional investment strategy for the optimization model of low-carbon logistics routing to achieve value maximization in the business's investment decision-making. The findings indicate that collaborative decisions will increase profits [24].

The water droplet algorithm was contrasted with several researchers' algorithms: the economic load dispatch problem was solved and successfully implemented based on the (IWD) algorithm. The numerical solution indicates that compared to Hopfield, biogeography-based optimization (BBO), PSO, GA, the proposed algorithm converged with promising results [25]. To resolve the maximum clique problem, the algorithm called IWD-Clique was proposed and compared the algorithm with Ant-Clique and Genetic (GENE) algorithms. The comparison results indicated that the IWD-Clique was competitive with these algorithms [26]. A WD algorithm is adapted to solve a distributed type of order scheduling problem. The rejection of received orders late is allowed with a penalty cost and compared IWD with traditional techniques like ant colony optimization (ACO), differential evolution (DE), and GA [27]. Mokhtari [27] studied the IWD algorithm, a nature-inspired for schedule; also, the ACO algorithm's performance for task scheduling was compared with IWD method and shows task scheduling IWD effectively and efficiently appoint tasks. While [28] to task scheduling in a cloud computing suggested to use water drops and compared with many familiar scheduling algorithms, such as PSO, round robin, minimum-minimum (MIN-MIN), catfish particle swarm optimization (C-PSO), first come first service (FCFS), maximum-minimum (MAX-MIN), and minimum completion time (MCT) [13], [28]. The WD-based scheduling algorithm was provided in a cloud computing environment to reduce the mapping of scientific workflows. The results showed that the proposed algorithm in Makespan overcomes the SGA and PSO algorithm [29]. A novel localization algorithm was submitted for WD-based wireless sensor networks. Emulation findings praised the proposed algorithm for higher efficiency than other algorithms, such as optimizing GA, ACO, and particle swarm [30]. Using the IWD algorithm, the proposal of a multi-echelon supply-distribution model optimizes partnerships between different stages. Computational results demonstrated that non-dominated sorting genetic algorithm III (NSGA-III) and non-dominated ranking genetic algorithm (NRGA) outperformed the suggested multi-objective intelligent water drops algorithm (MO-IWD) in terms of diversity and convergence [31].

Some researchers have developed and used the algorithm k-mean and proposed a modification technique in the k-means clustering algorithm [32], [33]. While Vora and Oza conducted a survey on particle swarm optimization and k-mean clustering and compared them [34]. The study aims to use the IWD algorithm to classify the multispectral satellite image dataset and compare the overall accuracy with the conventional image classification method. It proposed a classification scheme of the multispectral image data based on the IWD. In this study, we organized the study as follows: Section two explains the IWD algorithm. In section three, Submit steps for multispectral image classification on IWD. Section four shows the results and discussion. Finally, the present study ends with some conclusions that lay in section five.

2. THE IWD ALGORITHM

The water droplet algorithm is a nature-based algorithm proposed by [15]. It is one of the constructive algorithms that produce a solution from zero as the transmission speed of water droplets on the bottom of a river with less soil leads to an increase in drop velocity [15], [31]. There are two kinds of parameters in the IWD algorithm. One type is considered 'static parameters' and stays constant during the lifetime of the algorithm. Either the other type is the dynamic parameters, which is reinitialized for each algorithm iteration [15]. The IWD algorithm consists of four steps and comprises the following stages: initialization stage, construction stage, reinforcement stage, and termination stage, respectively. The chart of the water drop phases Figure 1 [35].

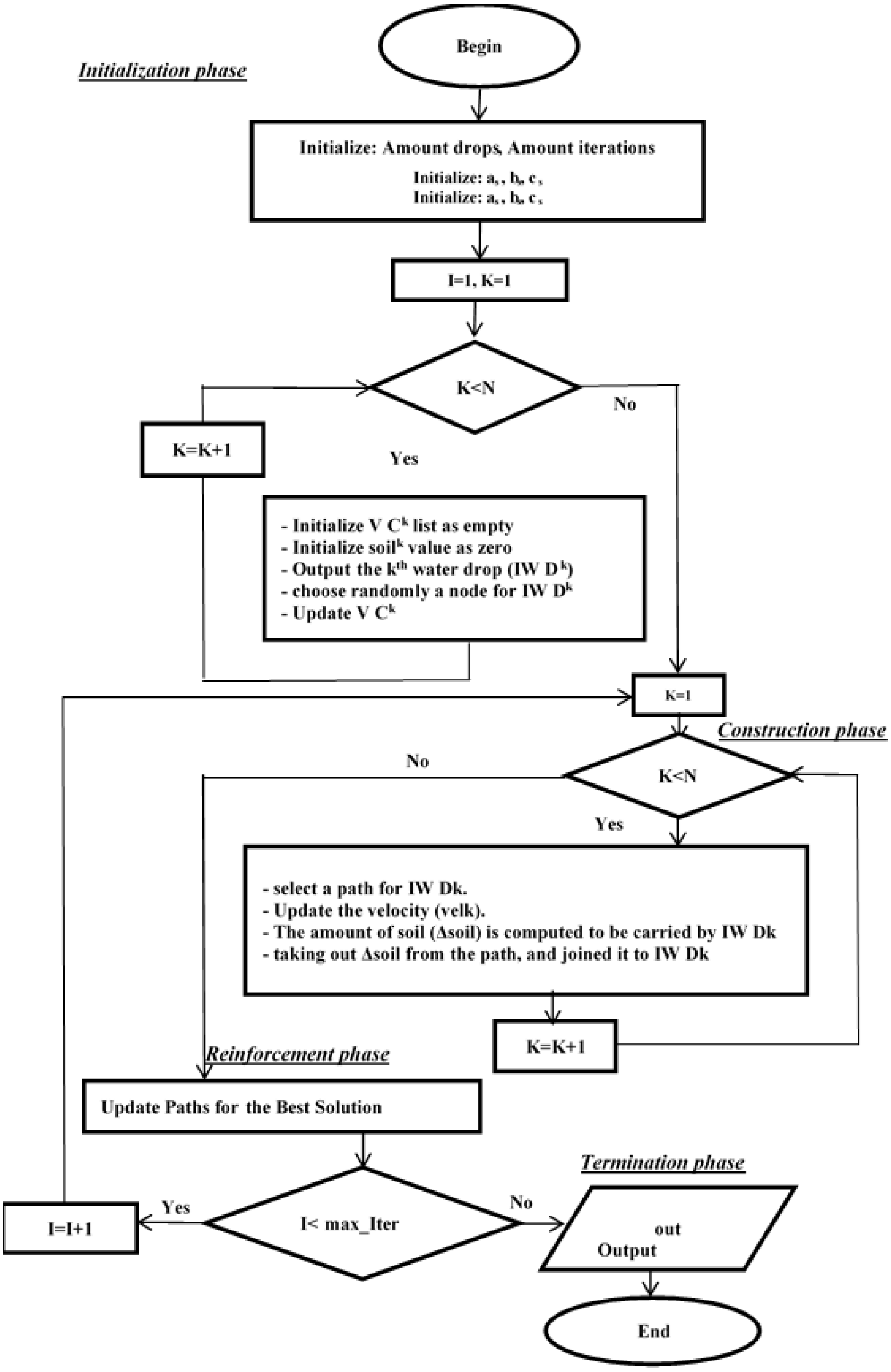

Figure 1. The chart of the water drop phases

3. MULTI-SPECTRAL IMAGES CLASSIFICATION BASED ON IWD

The pseudocode steps of the water drops algorithm:

Step 1 Read the data from remote sensing images and collect them in this code.

Step 2 The classification is chosen according to the nature of the area and visual interpretation, six different including agricultural lands; soil, water, stony, pastoral, cultivated agricultural, and plowed agricultural.

Step 3 Static parameters initialization for soil and velocity updating, a_s=1, b_s=0.01, c_s=1.0; a_v=1, b_v=0.01, c_v=1.0 respectively.

Step 4 Static parameters initialization for updating.
Step 5 Initialize value of alpha, alpha=0.001; Number of clusters: number of iwds = 6.
Step 6 Create an initial random cluster centroid for iwds from
iwd =rand(number of iwds,1)
Step 7 pcs=iwd ; Iteration path= row*col*h.
Step 8 Initialize tamount of soil on the path so that amount of soil = number of iwds.
Step 9 Let us use the following condition:
while (iteration count < iteration path && amount of soil > alpha)
Step 10 We are finding the distance between centroids and image pixels.
Step 11 Distance between centroids and image's pixel.
Step 12 Update cluster centroid.
Step 13 Calculating the amount of soil by using the following equation:
soil = max (abs(iwd-pcs))
In other words, find a maximum absolute difference between current and previous iteration cluster centroids.
Step 14 Iteration count= iteration count+1.
Step 15 Calculating the velocity of t using the following formula:
$Vel_t = [Vel_t; a_v/(b_v+c_v*sum(a_s/(b_s+c_s*mv(:))))]$
Step 16 Repeating steps from 10-15 until satisfy 9.
Step 17 Classify the image and assign it to each category.
Step 18 Output the image (classification result).

4. RESULTS AND DISCUSSIONS

It is essential to include requirements for practical application when conducting any study. One of the most crucial information sources available when performing any data analysis is satellite visuals in multispectral image classification. Each type of these sources in the various applications has characteristics and features. If these entire spectrum beams were used in studies such as land use and land cover classification, it would be more reliable than if each beam was used independently because the variety of the beams provides more spectral information about the land cover. The difference in the spectral beam gives better results. The information from each package separately from the different sensors is a fraction of the earth's factual information [1].

The remote sensing image processing stage is necessary to enhance and interpret information in the images, remove noise, and provide better input for other image processing techniques before moving on to the vegetation loss detection stage. The current research involves studying the sensor's multispectral satellite image (TM) carried on the Landsat satellite for the Mosul region. Seven distinct wavelengths and a distinction resolution of 30 m are used in the multispectral satellite image (except for the TM6 heat beam with a distinctive value of 120m, which excluded in research due to difference in its recognition accuracy for other wavelengths). Using Matlab software, the proposed working algorithm was executed and programmed, and the following images reflect images of the same region with different spectral. For the present study, as shown in Figure 2, six satellite images were selected.

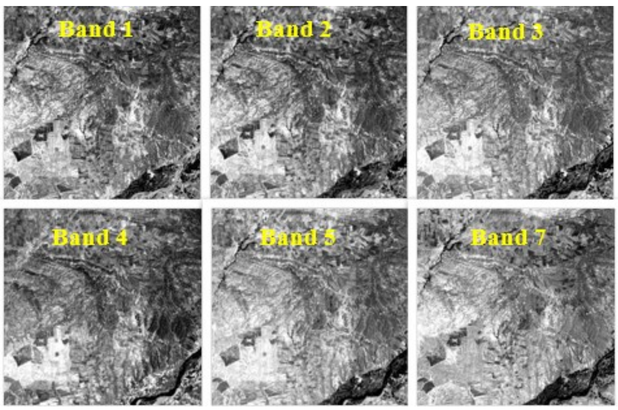

Figure 2. The six image which is taken by the satellite (band1, band2, band3, band4, band5, band7)

The first step, study area, was selected by the software (ArcGIS 10.7) geographic information system (GIS) is one of the workable tools for the use of existing huge information and analysis of data that during previous years has been paid attention by experts. The system of geographic information is a new information bank and, in comparison with an ordinary bank, is intelligence that this tool uses. Development of operational models hydrologic, mainly distributed hydrologic models, requires integration of GIS, remote sensing, and other digital databases for extracting the necessary, model variables, and for visualizing, processing, and analyzing the model results [36], where it was created (shape file), and a part of the city of Mosul was determined to be studied.

The second step is to make an image optimization in MATLAB using the tool (decorrstretch the decorrelation stretch is usually used for three-band images (RGB multispectral composite images or ordinary RGB images), but decorrstretch works on an arbitrary number of bands. The majar purpose of the decorrelation stretch is visual enhancement. Small adjustments to TOL can strongly affect the visual manifestation of the output. Now the most critical stage, which precedes classification by the water drops algorithm, we either rely on field information or maps. We have relied on maps for our study becaussification results depend on the amount of knowledge available to the researcher. After applying the processing steps, which include image reading and enhancement, the false-color composite was formed on the three beams (1,4,7 RGB) sequentially; we get Figure 3, representing the area to be studied.

The step three, Image classification using IWD and k-mean depending on the water drop algorithm, the land cover types can be detected from the remote sensing image using the agglomeration. An interpretation of each class of digital satellite images was made based on this classification, as shown in Figure 4. We compared the results of the classification using the IWD and k-mean methods. We noted that the results of the classification by using the IWD method are more accurate than the results of the k-mean method, as shown by comparing in Figure 4 with Figure 5, where we notice the emergence of regions that were not present in the results of the k-mean method. For example, when comparing class 4 and class 5 in Figure 4 with Figure 5, we found water areas and areas close to the water were clearly distinguished using the IWD method. Unlike the other methods, they are not distinguished.

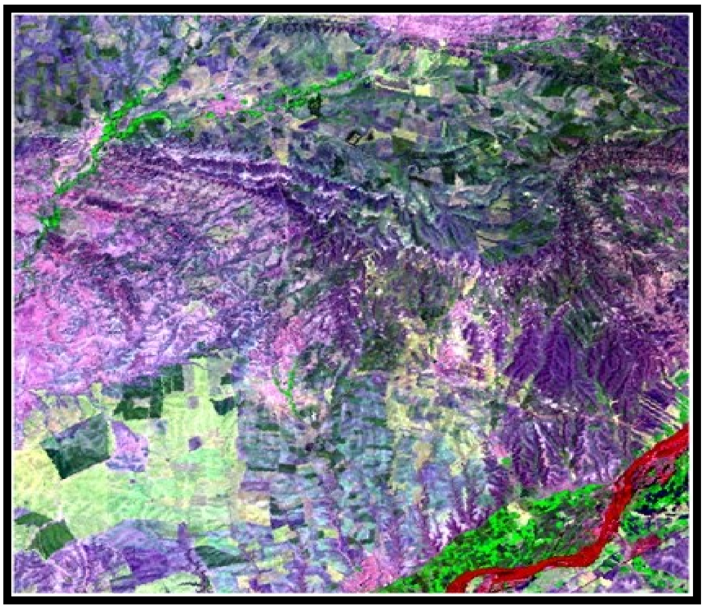

Figure 3. Color image of the study area RGB (band1, band4, band7)

The steps four and five to calculated accuracy and time, the accuracy threshold (1e-4 (default) positive number) is defined as a comma-separated pair consisting of a positive number and a threshold. The algorithm stops when any cluster center moves less than the threshold value in sequential iterations. We find IWD time elapsed is 1.4122, and the k-mean time elapsed is 18.9475. For this reason, the IWD method is better than k-mean because the time elapsed for the IWD method less than the time elapsed for k-mean. We calculate the classification accuracy; the field information of the study area was relied on in addition to the false-color image (RGB). The results presented in Figures 1 and 2 were calculated. The classification accuracy by the IWD method was much better than the k-mean method, as the classification accuracy by the water drop algorithm is 95%, as for the k-mean classification accuracy is 83.3%.

Table 1 shows the results of multispectral image classification using IWD, where consists of six types as following: where the pink color refers to the soil, the blue color represents the cultivated agricultural lands, the turquoise color represents the stone areas, while the green color refers to the pasture lands, the yellow color symbolizes the water and the red color indicates the plowed agricultural land. The following simple flowchart in Figure 6 shows the classification steps for the water drop method and k-mean.

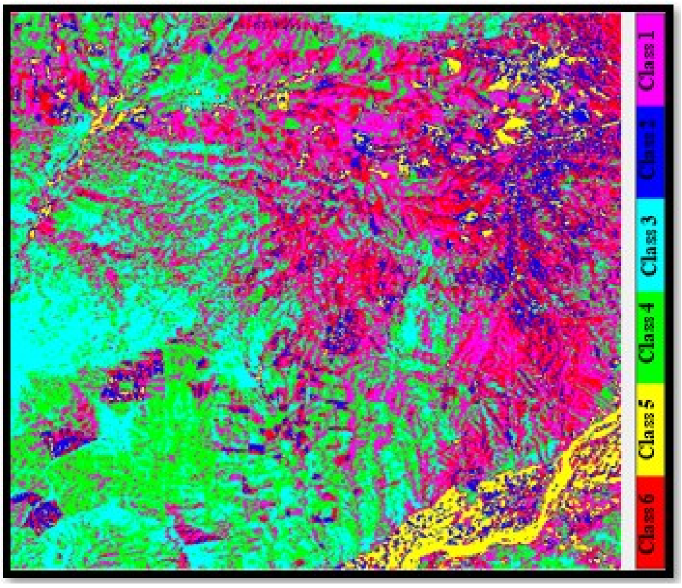

Figure 4. Results of a multispectral image classification using IWD

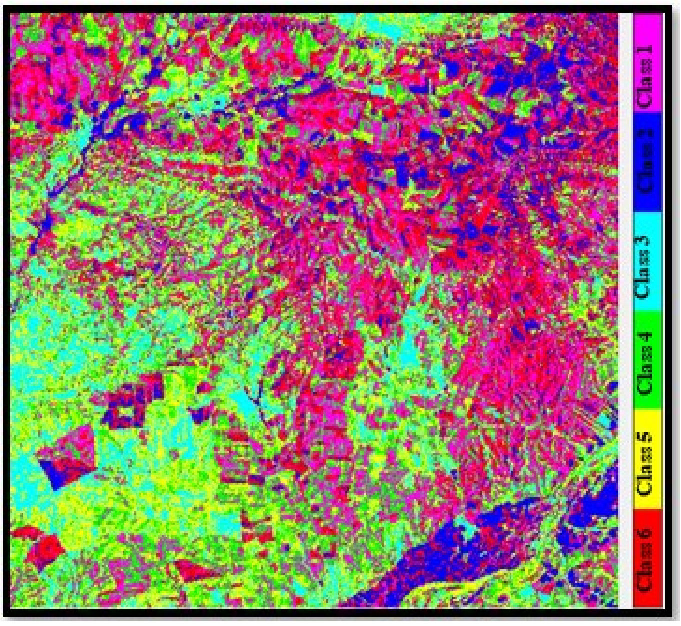

Figure 5. Results of a multispectral image classification using k-mean

Table 1. Results of a multispectral image classification using IWD

Class No.	Colour	Area classification
Class 1	Pink	Soil
Class 2	Blue	Cultivated agricultural lands
Class 3	Turquoise	Stony
Class 4	Green	Pastoral lands
Class 5	Yellow	Water
Class 6	Red	Ploughed agricultural lands

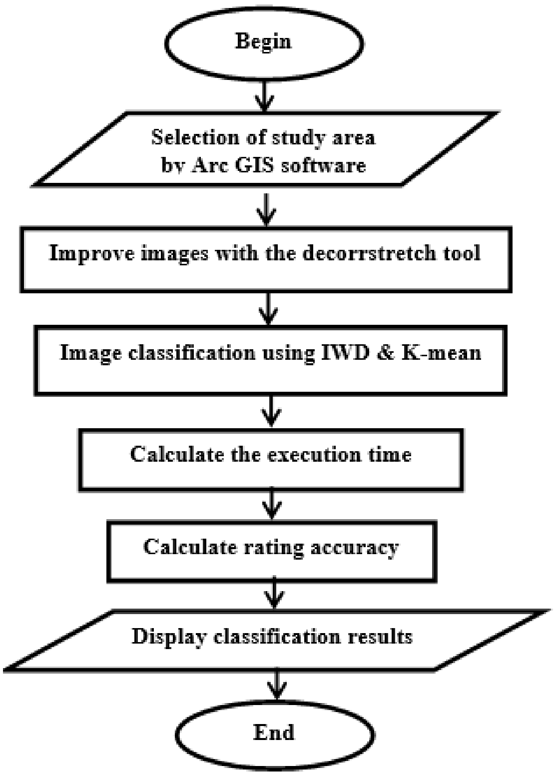

Figure 6. Classification steps for the water drop method and k-mean

5. CONCLUSION

This research is showing the importance of relying on remote sensing data and the images of the Landsat satellite with the sensor TM to detect distinguish and determine the types of land and land cover for the study area and by using Matlab and (Arc GIS) programs to classify the multi-spectral images. The proposed algorithm has proven successful, giving accurate and fast results by comparing the IWD algorithm with the k-mean algorithm. The IWD algorithm's exact time superiority equal to 1.4122 with the k-mean time equal to 18.9475. Furthermore, the water drop algorithm's classification accuracy is 95%, while the k-mean classification accuracy is 83.3%. Proposed algorithms apply in the future for hyperspectral image classification. Hyperspectral image classification also includes details type of specific features of land cover. This feature is mainly useful in identifying the crop in the vegetation area and determining hills.

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