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Unsupervised Classification of Landsat-8 Satellite Imagery-Based on ISO Clustering

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ABSTRACT: Remote sensing, specifically satellite imagery, and is gaining prominence in computer science nowadays, in the era of artificial intelligence, in an attempt to deliver more precise information. The satellite images of Earth are gathered, evaluated, and processed for use in civil and military applications with a military aim. Satellite images do have a wide range of services. The areas of study of agriculture, fishery, oceanography, and meteorology include geology, biodiversity, cartography, land use planning, and armed conflict. Transformation is the goal of the categorization of satellite images. Transformation of satellite images into information that can be used rather than having an image of a location. In this paper, a scene of the Landsat-8 satellites with specifications (Path=168 and Row=38) was classified. This scene was classified into four categories (Water, Vegetation, bare land, and Build-up) based on the unsupervised classification method (ISO Clustering). The ISO Clustering method is found in the Arc Map program. The results regarding classification accuracy are a good percentage compared to unsupervised Classification.

Keywords: Clustering, Unsupervised Learning, Satellite Image, Landsat-8 TM

1. INTRODUCTION

In recent times, machine learning (ML), the most advanced domain within artificial intelligence, has been extensively implemented across many applications with remarkable efficacy. Machine learning has facilitated the advancement of various fields, including natural speech processing, pattern recognition, statistical learning, data mining, and computer vision. After the training approaches, machine learning techniques can be categorized as supervised learning [1-7]. A Supportive categorization process involves selecting suitable pixels to symbolize each target class, followed by executing a solitary classification algorithm to allocate those classes to the pixels in the image. The bulk of reported supervised algorithms classify data using maximum likelihood. The process involves selecting suitable pixels to symbolize each target class and executing a solitary classification algorithm to allocate those classes to the pixels in the image. Most published supervised algorithms classify data using maximum likelihood [8]. The two most prevalent methods for pixel-based categorization are Maximum Likelihood Classification and ISO Clustering [9]. Satellite image classification is illustrated in Figure 1

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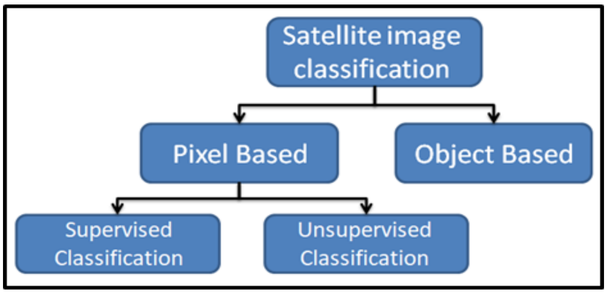

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FIGURE 1. – Satellite Image Classification.

For low to moderate-spatial-resolution data, pixel-based Classification (PBC), a conventional classification technique that uses the aggregate spectral responses of all pixels in a training set for a given class, is regarded as very effective [10]. Pixel-based satellite image classification categorizes individual pixels by comparing their n-dimensional data vectors and the prototype vectors corresponding to each class. Typically, the data vectors comprise the grayscale intensities of individual pixels over many spectrum channels. In order to train the classifier, training data is generally gathered by a field survey, aerial images, geography, and satellite imagery [11, 12]. The purpose of object-based Classification is to address the issue of heterogeneity within the environment.

In contrast to the prior conventional methodology, which treated each pixel individually, this method processes clusters of pixels [10]. Instead of employing pixels as the minimum unit, the system partitions the image into objects and classifies them according to their spectral, spatial, contextual, and linguistic attributes [10, 13]. Two steps comprise the fundamental procedure: Segmentation and Classification. As an initial stage in object-oriented image classification, image segmentation partitions the image into contiguous and homogenous items [28]. Image segmentation techniques have three categories: thresholding/grouping, region, and edge [9, 11, 14].

Classification by maximum likelihood is the most often used supervised technique in the literature [8]. On this principle, supervised Classification is built. The researcher can choose representative sample pixels from an image for particular classes. Subsequently, they can instruct the image processing software to utilize these training sites as benchmarks for classifying the remaining pixels in the image. The researcher employs their expertise to determine which areas to train (sometimes called testing sets or input classes). Pixels are categorized in unsupervised categories based on their attributes. The term for these groups is clusters, and the term for this process is clustering. The user determines the desired number of clusters in this. Acquiring information regarding the Earth's surface using remote sensing does not require physical touch [15]. Remotely sensed data often comprises a multitude of distinct and exceptional spectral, temporal, and polarization attributes; proficiently utilization of these characteristics can enhance the accuracy of categorization [10, 16-21]. Remote sensing is often regarded as the principal method for gathering spatial data. Electromagnetic radiation interacting with objects and the atmosphere is quantified using remote sensing. The direction, intensity, wavelength, and polarization of electromagnetic radiation, in addition to the distance between the sensor and the object, can be deduced from interactions of electromagnetic radiation with the Earth's surface. These measurements have the potential to provide insights into the properties and positional details of the surface materials [19]. Satellite imagery is acquired by using sensors affixed to satellites in orbit around the Earth. The sensors capture visible and near-infrared images of the Earth's surface over various spectral bands. In addition to disaster response, urban planning, and environmental monitoring, these images have many potential uses. Satellite imaging data is accessible via many platforms, including but not limited to Google Earth Engine and Landsat [15, 18].

Multispectral images [10] encompass extensive land cover regions and are intrinsically challenging to handle in this format due to the multitude of elements across the spectrum. Landsat-8, A comprehensive understanding of the attributes of satellite images is crucial in developing an intelligent satellite image analysis system. One of the most widely recognized constellations of remote sensing satellites is Landsat. The initial satellite of this constellation to be deployed in 1972 was Landsat 1. Its two sensors (MSS) were the Return Beam Vidicon (RBV) and the Multispectral Scanner [23]. 185 * 185 km2 remains the ground area covered per scene by Landsat [24, 25], Landsat 5 T.M. Thematic Mapper, Landsat-8 Operational Land Imager (OLI), and Sentinal-2A. Multispectral Instruments supply satellites (sensors) for remote sensing (MSI). The process by which information on things on the Earth's surface is obtained without making direct touch with them is known as remote sensing. Instruments utilized in the course of investigations are sensors [12, 26,27,28].

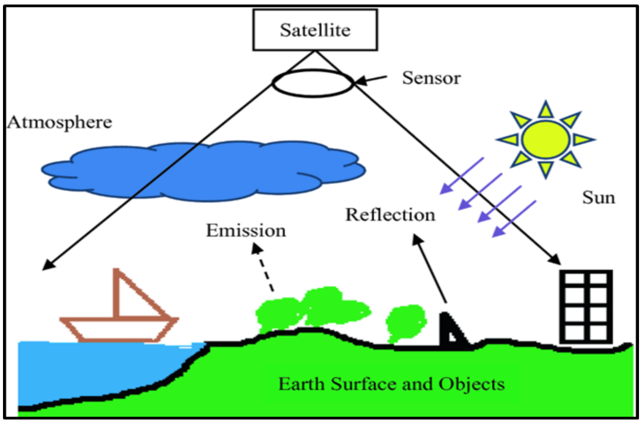

FIGURE 2. – Object reflections and the Earth's surface.

Satellite imaging systems [26] gather and quantify the electromagnetic (EM) radiation emitted or reflected by terrestrial objects. The electromagnetic spectrum comprises visible light, infrared, microwave, and ultraviolet wavelengths. In remote sensing, electromagnetic radiation is the principal carrier of information [29]. The predominant constituents of remote sensing data are electromagnetic waves generated or reflected by the targets. Sensors can detect this data when affixed to space-borne or airborne platforms (e.g., spacecraft, balloons, satellites, and space shuttles) [28]. Figure 3 illustrates electromagnetic (EM) radiation.

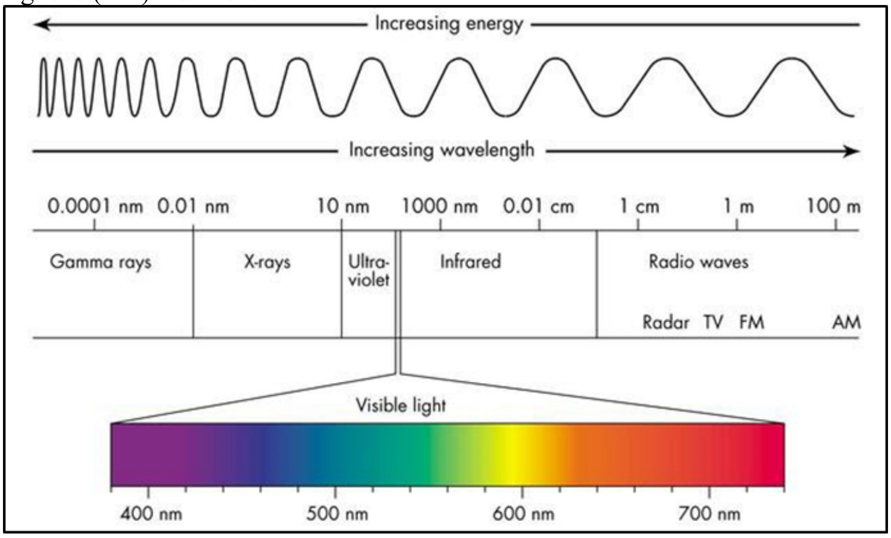

FIGURE 3. – Electromagnetic Radiation.

2. Unsupervised Classification techniques

Unsupervised Classification is implemented in the absence of learned pixels [30]. An unsupervised classification or clustering technique utilizes the closeness of feature points and statistical similarity of feature points to aggregate or group image pixels into a predetermined number of natural clusters in the feature space. The sets are distinguished based on spectral properties, including means, standard deviations, covariance matrices, and correlation matrices. In order to classify newly added pixels to a test image, the cluster to which each pixel in the image belongs must be identified. The analyst then interprets the groups to determine the land cover/use class (water, vegetation, build-up and bare land) as a post-processing step. Using experience, ground truth data, and requirements, the analyst may merge or divide some clusters and assign labels to all groups. Clusters are combined according to statistical and spectral response similarity [26]. Unsupervised learning is so-called because, unlike supervised learning, neither accurate nor teacher-assisted responses are acceptable. Unsupervised learning techniques extract a limited number of features from the input data. When novel data is presented, the model employs the traits it has already learned to identify the data's class. Its primary applications are feature reduction and clustering [1, 20, 31-34]. When provided with an unidentified pixel class training set, an unsupervised classification or clustering algorithm aggregates or groups image pixels into a predetermined number of natural clusters in the feature space. This aggregation is achieved through feature point proximity and statistical similarity. The clusters are distinguished by their spectral properties, including means, standard deviations, covariance, and correlation matrices [37]. By the specifications, ground truth data, and experience, merging or splitting certain clusters and assigning labels to all groups is possible. The cluster merging process is determined by the answers' statistical and spectral similarity [10]. Unsupervised classification techniques are illustrated in Figure 4.

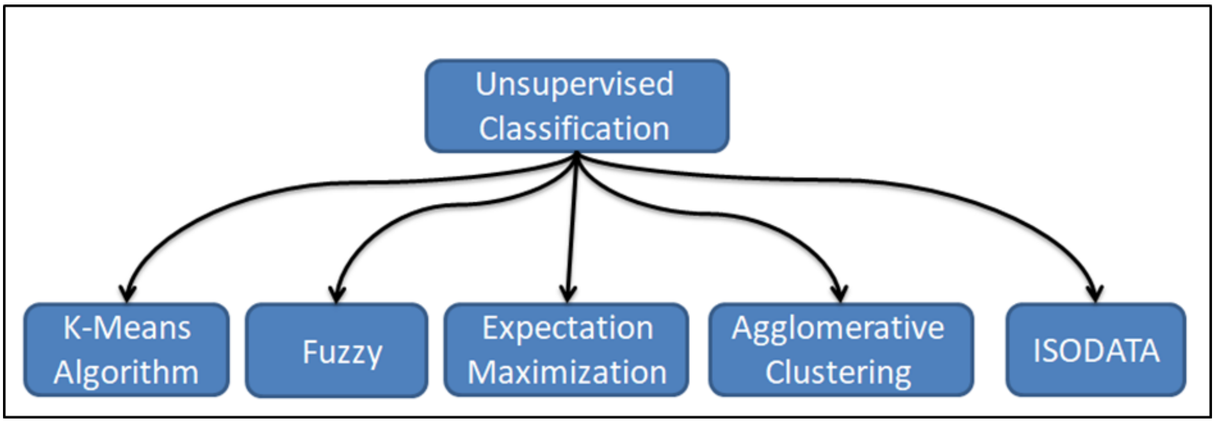

FIGURE 4. – Unsupervised classification techniques.

The k-means algorithm is a straightforward clustering technique in which the Classification of each pixel is determined by its distance from the cluster means. The following is the algorithm: Input: The number N of desired clusters; initial random seeds for each cluster denoted by mi, where I 1…N. Each pixel in the output is categorized into one of N clusters.

[10, 26, 35], Consider an image with a resolution of 24 bits per pixel and the capability to contain up to 16 million colors. Consider a color display with 8 bits per pixel, limited to 256 possible hues. Among the 16 million available colors, we wish to identify the 256 most suitable so that an image rendered with the 256 colors in the palette resembles the original as closely as possible. In this process of color quantization, the resolution is mapped from highest to lowest. The overarching objective is to establish a mapping between a continuous and discrete space; this operation is referred to as vector quantization [36].

Fuzzy: The class of grouping algorithms that employ the fuzzy partition notion is categorized as methods. A diffuse partition is distinguished because each element possesses a certain degree of membership in all the current groups [37]. The fuzzy c-means method is employed in satellite image processing for unsupervised categorization. To determine the optimal number of partitions, an iterative clustering approach minimizes the weighted within-graph sum of the squared error objective function [38].
Expectation maximization: When an equation cannot be solved directly, expectation maximization is an iterative process utilized to find the maximum probability parameters of the statistical model by filling in the missing values in a partition by one at a time [39].
Agglomerative Clustering (AC) denotes a category of greedy, unsupervised learning algorithms that employ bottom-up clustering to construct a hierarchical structure among data points. Modern data science extensively uses A.C. algorithms, including genomics [40]. Furthermore, these algorithms exhibit two notable benefits compared to non-hierarchical or flat clustering techniques: 1) they do not require an initial specification of the number of clusters; and 2) they generate a hierarchy of all samples in the dataset.[41].
Unsupervised Classification (ISO)
We are applying the Maximum Likelihood Classification and ISO Cluster tools on a sequence of input raster bands in order to perform unsupervised Classification. The ISO Cluster Unsupervised Classification program detects clusters in an image automatically and returns an image that has been classed. It utilizes the ISO Cluster application. Water bodies, built-up areas, vegetation (forest/trees), cultivation, and open space are these land use patterns. Determine the area of each polygon by locating the reclassified aster image within the polygon and consulting the Attribute Table provided by the ArcGIS program [10, 42, 43].

3. Related works

Manohar, Pranav [27] 2020, image classification is crucial in image identification, pattern detection, image analysis, and remote sensing. Classification can occasionally be the subject of Analysis. As an illustration, the output of land use classification using remote sensing data is a cartographic representation. Presently, diverse methodologies exist to classify satellite photos, each employed for a specific objective by various researchers.

Jawak, Devliyal [13] 2015, have investigated the fact that the classifier utilized to extract information from satellite images is founded upon two distinct forms of learning—supervised learning and unsupervised learning—and have put forth many classification approaches, including object-oriented Classification, hybrid Classification, and pixel-based Classification (PBC) (OOC). Considering that pixel-based Classification is a classic classification, think that object-oriented Classification surpasses the constraints of pixel-based classification methods.

Schmarje, Santarossa [44] 2021, Unsupervised cluster techniques, which were investigated prior to the advent of deep learning, continue to be extensively implemented. Extensive literature reviews have documented unsupervised and semi-supervised approaches that do not involve deep learning. Only strategies involving deep neural networks will be addressed.

Lemenkova [46] 2021 describes how the ArcGIS Spatial Analyst Tool was utilized to interpret Landsat TM images for categorization, band calculations, and raster data processing. Thus far, Landsat TM imagery has been one of the most extensively utilized satellite-launched projects for Earth observation.

Ouchra and Belangour [10] 2021, the computer science community is increasingly intrigued by remote sensing, particularly satellite photography, as they strive to develop robots capable of environment recognition using satellite picture classification. For military and civil reasons, imaging satellites acquire, analyze, and process photographs of the Earth. Satellite imagery finds extensive utility across various domains, including meteorology, mapping, land use planning, fisheries, agriculture, biodiversity, and warfare.

Zhang and Kerekes [47] 2011, the narrow spectral bands of commercial remote sensing satellites have contributed to the lack of success in fully automated land-cover classification using their pictures. Recent satellite deployment of the eight-band high-resolution WorldView-2 has introduced a fresh opportunity for unsupervised Analysis.

Joumad, Moutaouakkil [48] 2023, and other segmentation approaches have been proposed in several recent publications. Combining the local information provided by super-pixels, the study (Huang et al., 2021) proposed the Chen–Vese model, which is based on the Markov chain and is utilized for unsupervised medical picture segmentation.

Mohammed, Al-Ghrairi [49] 2023, Classification of satellite pictures constitutes a substantial component of the remote sensing discipline. On occasion, the Classification itself may be subject to examination. The end outcome of an investigation, such as identifying the land cover derived from remotely sensed data, is the production of visuals resembling maps.

4. Materials and Methods

4.1 Materials

The study area of interest is connected with the Classification of land use and land cover mapping, which requires satellite image data. The data's resolution was obtained without charge. From the United States Geological Survey (USGS), was 30 meters. The processing of all the data was performed with ArcGIS software. Data is acquired by Landsat-8 TM over six distinct bandwidths. These bandwidths encompass portions of the electromagnetic spectrum's visible, infrared, and thermal infrared regions. Figure 5 includes three images: a map of Iraq, a scene of the study area, and a raster consisting of 1,000,000 pixels for Classification.

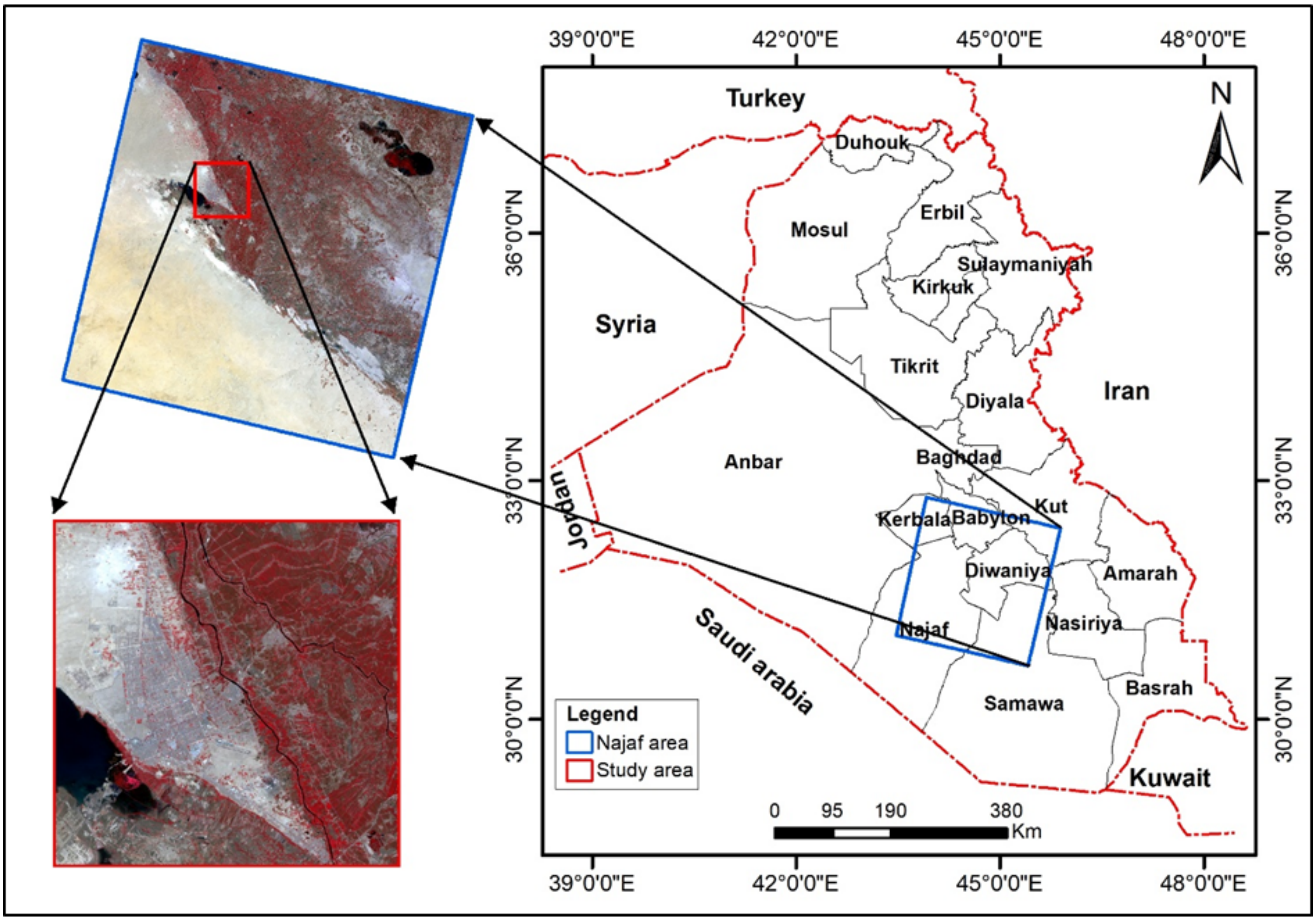

FIGURE 5. – **Study Area.**

4.2 Methods

The following three stages are crucial in thoroughly and precisely comprehending the phenomenon under investigation. To accomplish the research objectives, this context employs three fundamental stages: data preparation, unsupervised Classification, and accuracy evaluation. As indicated in Figure 6, each of these stages and its major function in data analysis will be emphasized.

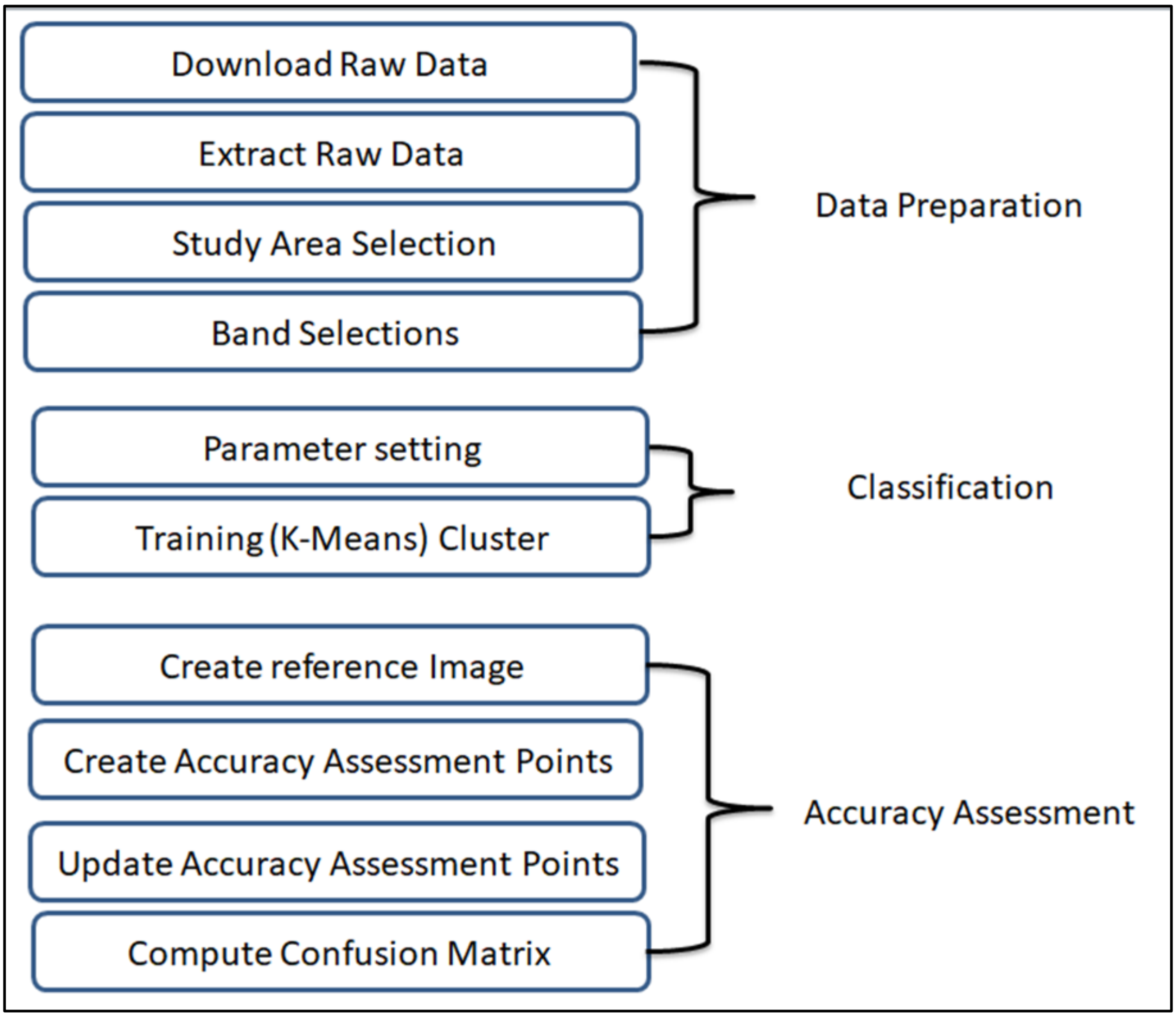

FIGURE 6. – Methodology workflow.

A. Data Preparation Stage

Download Raw Data: Usually, the USGS (United States Geological Survey) platform provides services to researchers or those interested in this field, and its services can be obtained after registering and creating an account on this site through the link https://www.usgs.gov/. Then, you select the area you want to study by selecting Path=168 and Row=38 and selecting the Landsat 8 satellite. The satellite images are downloaded after ensuring that the place you want to study is set.

Extract Raw Data: Opening raw satellite images using the ArcGIS application requires downloading the satellite images and converting them into a format readable by the application. Typically, satellite images are in specific formats such as GeoTIFF, JPEG, and TIF and can be opened and used in ArcGIS.

Study Area Selection: the choice of the study area (the Holy City of Najaf and its surrounding areas), with specific dimensions such as C=1000 and R=1000, depending on the context of our Research, the type of Analysis and the resolution of the available satellite images.

Band Selections: these ranges provide a balance between capturing vital information for diverse applications such as land cover classification (water, vegetation, build-up and bare land) and land cover health assessment and identification. The choice may vary depending on the specific goals of your Analysis and the capabilities of the satellite sensor you are working with.

B. Classification Stage

The ISO algorithm will presently be implemented on the six bands that have been chosen, together with the number of clusters K. The outcomes will then be shown as raster images.

C. Accuracy Assessment Stage

When addressing the ISO method's accuracy evaluation step, we will use three criteria: overall accuracy, kappa, and F1-score. These criteria will be used in three stages: establishing accuracy evaluation points, updating accuracy assessment points, and computing the confusion matrix.

Create reference image: the exported reference image must be available as it provides the required level of detail, clarity and accuracy for its intended purpose, whether for documentation, presentation or Analysis reference. It entails producing a visual representation inside ArcGIS that may be used as a standard or benchmark for comparison or Analysis. Producing this reference image is crucial for several uses, including remote sensing, mapping, and geographical Analysis. In order to precisely measure and assess changes or differences in geographical data, it enables users to set up a baseline or point of reference. In order to produce an extensive and precise reference image, the procedure usually entails picking a particular area or region of interest and gathering the required data, such as aerial imaging, satellite images, or topography data. The quality and dependability of the outcomes may then be improved by using this reference image in various GIS workflows, such as geographic data analysis, map creation, and decision-making procedures.

Create Accuracy Assessment Points: precisely samples point randomly to evaluate accuracy post-classification. Hundreds of randomly selected points are frequently labeled with their classification kinds using reputable sources as references, such as human interpretation of high-resolution images or fieldwork. The reference points are subsequently compared to the categorization outcomes at the precise locations.

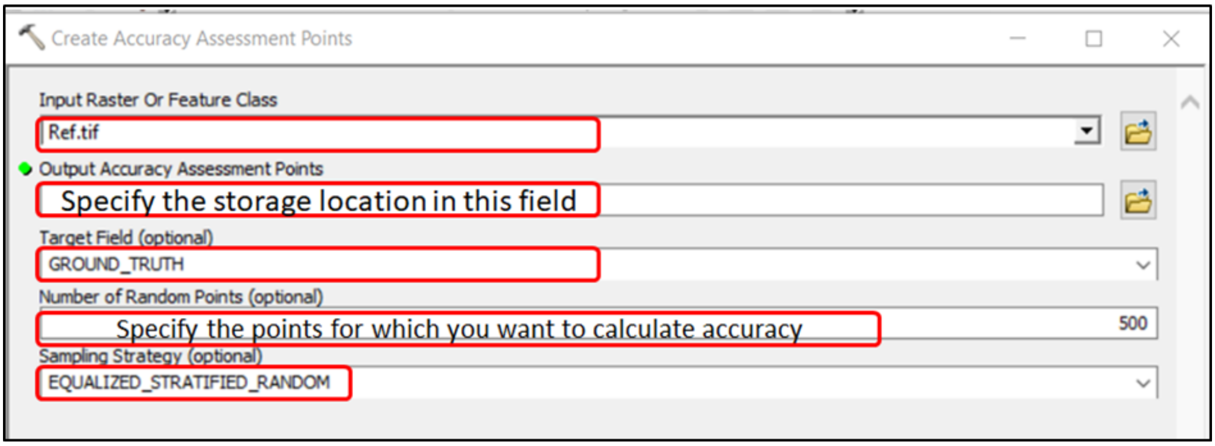

FIGURE 7. – **Create Accuracy Assessment Points Tool.**

Input Raster: This is the dataset of categorized raster's you want to evaluate for correctness. It is the raster file that is produced following the completion of an unsupervised classification process.

Output Accuracy Assessment Point: This option specifies the output feature class for the produced accuracy assessment points. It contains the output file's name and path.

Target Field: The field name in the output feature class where the class I.D.s or names are to be recorded is specified by the target field. This field will have information specifying the class or category of each point when points are created.

Number of Random: You can set the total number of accuracy assessment points created using this option. The precise number of points to be made can be entered. Sampling Strategy: The sampling approach determines the distribution of the accuracy evaluation points throughout the categorized raster. Systematic Arranges points in a way that makes sense for the region, frequently following predetermined patterns or intervals.

Update Accuracy Assessment Points: Modifies the Target attribute table field to enable reference point comparisons with the categorized image. Accuracy assessment evaluates the validity of the categorization model by utilizing known factors.

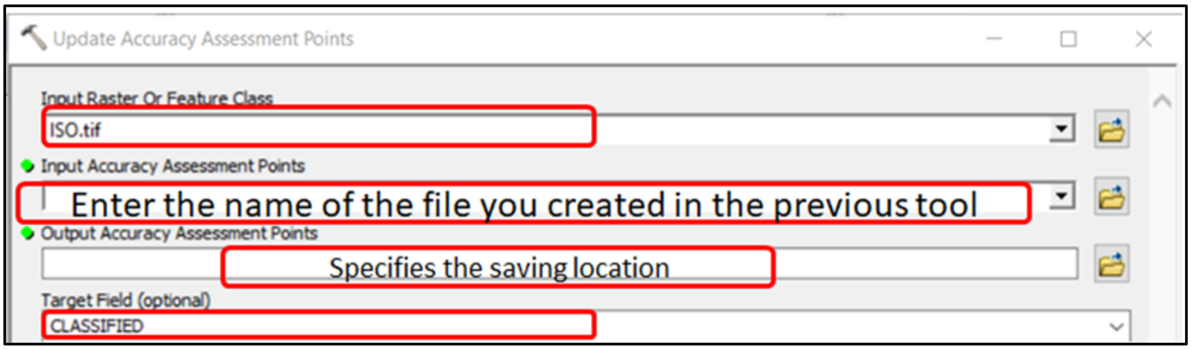

FIGURE 8. – **Update Accuracy Assessment Points Tool.**

Input Raster: This parameter, similar to the "Create Accuracy Assessment Points" tool, relates to the previously evaluated categorized raster dataset that was assessed using accuracy assessment points. The accuracy is being evaluated for the raster dataset.
Input Accuracy Assessment Points: This parameter represents the accuracy assessment points that are now in use, which were previously produced through the use of the "Create Accuracy Assessment Points" tool or a comparable procedure. These are the points that require revision or updating.
Output Updated Accuracy Assessment Points: indicates the name and location of the file or output feature class that will be used to store the updated accuracy evaluation points.
Target Field: The target field in the output file specifies the field name where the class I.D.s or names will be recorded or edited, much to the "Create Accuracy Assessment Points" tool.
Compute Confusion Matrix The confusion matrix is constructed by include mistakes of omission and commission. Subsequently, a kappa index of agreement and an overall accuracy between the reference data and the classified map are derived.

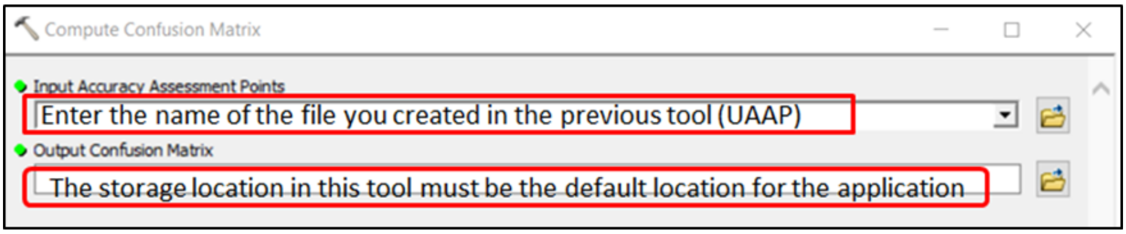

FIGURE 9. – **Compute Confusion Matrix Tool.**

Input Accuracy Assessment Points: The accuracy evaluation points that have been developed or updated to assess the correctness of a categorized raster dataset are referred to by this parameter. These points must contain the ground truth data used to compare the categorization outcomes.
Output Confusion Matrix: specifies the name and location of the output table or file where the confusion matrix will be kept. A table that is frequently used to explain how well a classification model is performing is called a confusion matrix. A summary of the classification accuracy is shown.

5. Results

The study on the subject of ISO technology resulted in many significant results, which were applied to a large number of data in more than one group and shed light on various aspects of the research question. Moreover, the proposed technique was evaluated using the accuracy scale, F1 score, and Kappa and compared with each other, where the results are divided into two types, quantitative and qualitative. The proposed ISO technique is built using an NVidia 2.11 GHZ processor with 12 G.B. of RAM, which the ArcGIS Application provides. Also, the F-score extraction technique is implemented on a Lenovo Laptop with a processor Intel(R) Core (T.M.) i5-10210H CPU @ 1.60GHz, RAM 12.0 GB, and 6 GB NVIDIA UHD Graphics VGA.

5.1 The Qualitative Analysis

The study's qualitative findings indicate that the results are based on a comprehensive analysis and interpretation of the data collected. Overall, the qualitative findings underscore the importance of qualitative research methods in generating in-depth and meaningful results. Figures 9 and 10 shows the maps of reference data and results applied ISO clustering method in ArcGIS. The number of instances of each class in reference and ISO images is detailed in Tables 1 and 2, respectively.

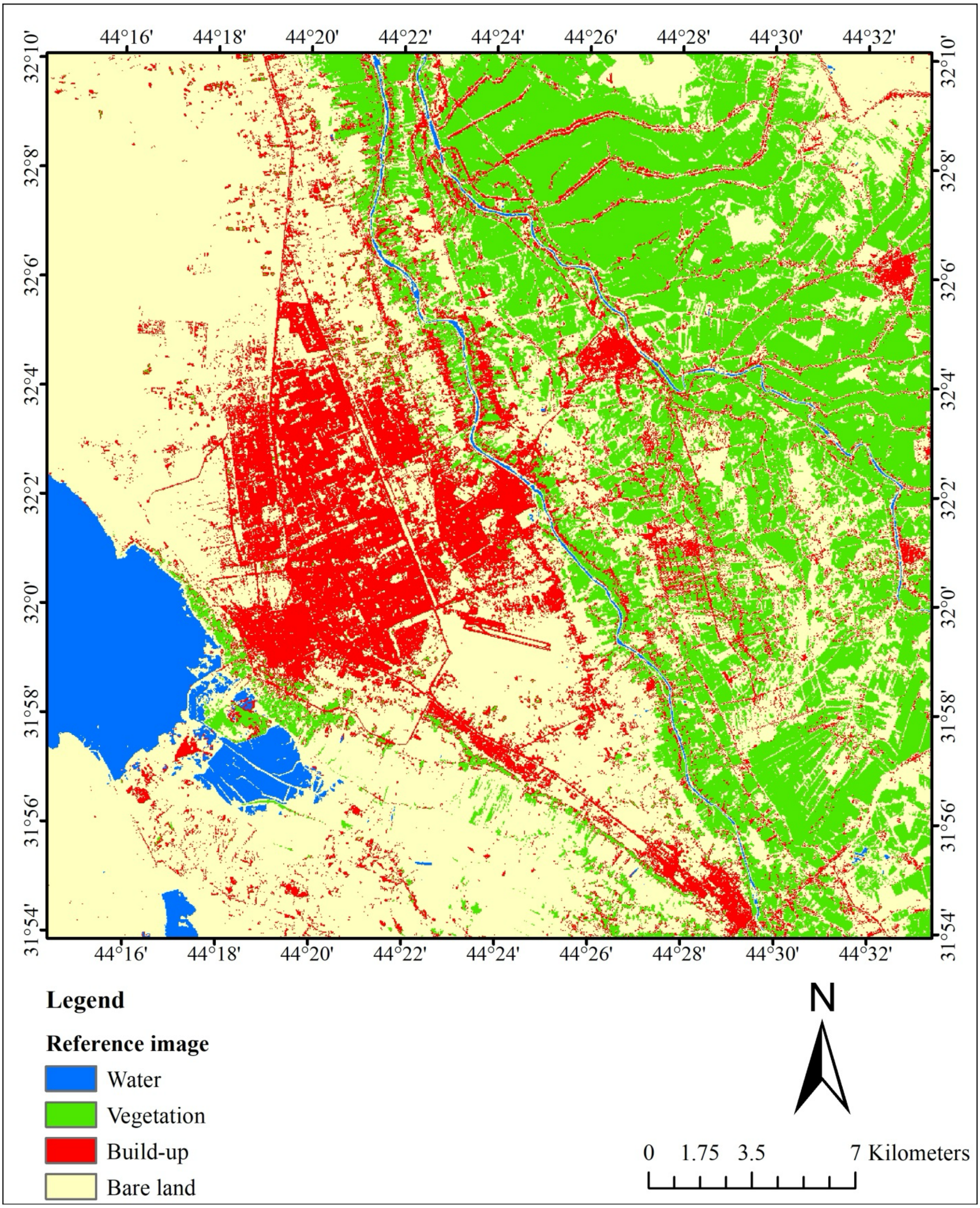

FIGURE 9. – Reference Image.

Table 1. Number of pixels in reference image.

ID	Class Name	Pixel Value
1	Water	54322
2	Vegetation	265095
3	Build-up	157033
4	Bare land	523550

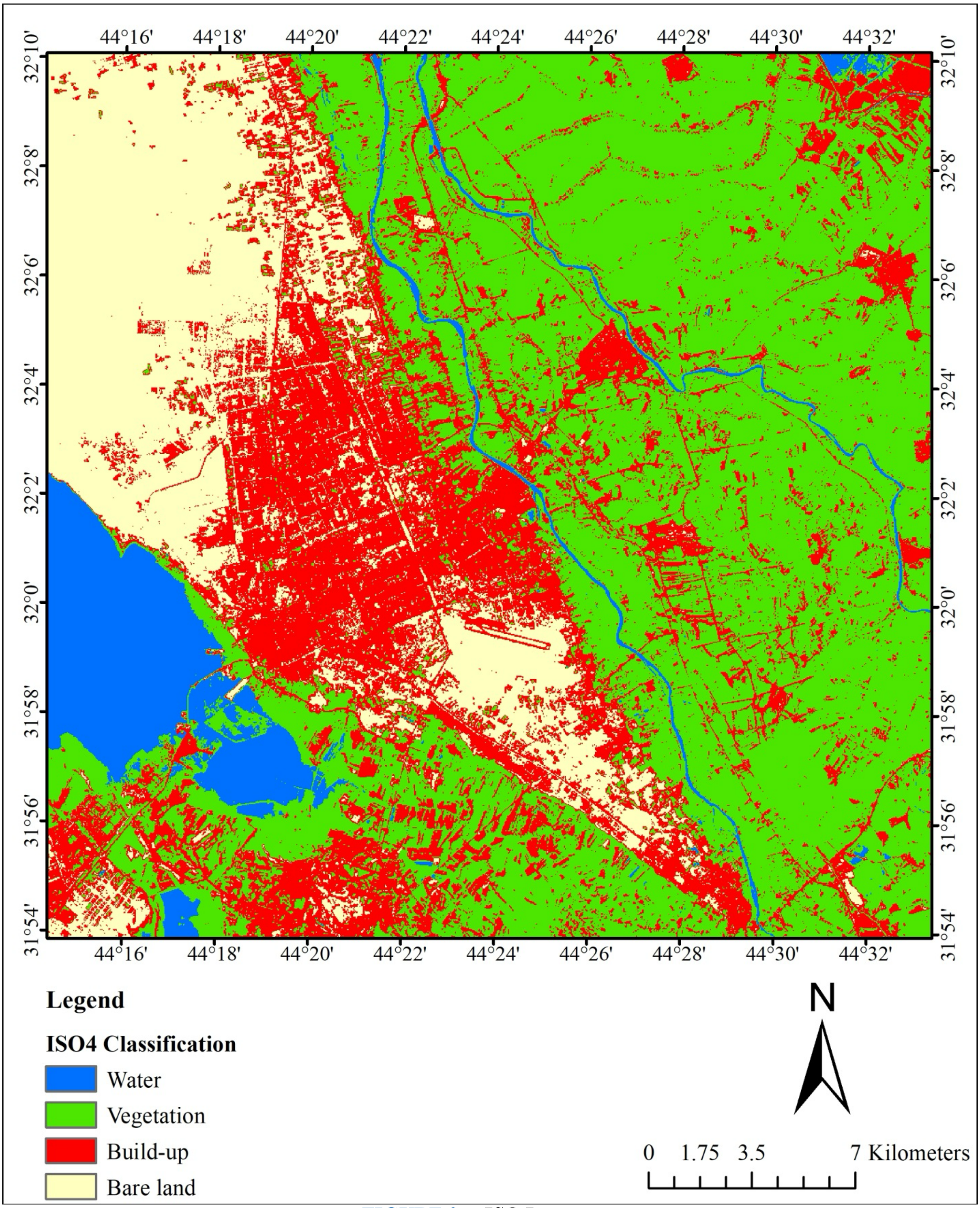

FIGURE 9. – ISO Image.

Table 2. Number of pixels in ISO.

ID	Class Name	Pixel Value
1	Water	67073
2	Vegetation	492742
3	Build-up	256873
4	Bare land	183312

5.2 The quantitative Analysis

Quantitative results: The results we can obtain from the experiment can provide statistical evidence to support the study's results. For each class, the confusion matrix from 1000 to 5000 points distributed equalized is presented in Tables 3 through 7. The correlation between the dispersed points and the accuracy evaluation, kappa, and F1 score is depicted in Table 8.

Table 3. Confusion Matrix with 1000 Random Points.

Class Value	Water	Vegetation	Build-up	Bare-land
Water	250	0	3	4
Vegetation	0	250	40	96
Build-up	0	0	202	67
Bare-land	0	0	5	83

Table 4. Confusion matrix with 2000 Random Points.

Class Value	Water	Vegetation	Build-up	Bare-land
Water	500	0	4	13
Vegetation	0	500	114	161
Build-up	0	0	358	138
Bare-land	0	0	24	188

Table 5. Confusion matrix with 3000 Random Points.

Class Value	Water	Vegetation	Build-up	Bare-land
Water	750	0	5	19
Vegetation	0	750	148	266
Build-up	0	0	565	213
Bare-land	0	0	32	252

Table 6. Confusion matrix with 4000 Random Points.

Class Value	Water	Vegetation	Build-up	Bare-land
Water	1000	0	7	30
Vegetation	0	1000	163	393
Build-up	0	0	796	244
Bare-land	0	0	34	333

Table 7. Confusion Matrix with 5000 Random Points.

Class Value	Water	Vegetation	Build-up	Bare-land
Water	1250	0	9	26
Vegetation	0	1250	252	448
Build-up	0	0	958	332
Bare-land	0	0	31	444

Table 8. Overall Accuracy, Kappa and F-score.

Random Point	Accuracy%	Kappa%	F-score%

1000	**78.500**	**71.333**	**76.048**
2000	77.300	69.733	75.364
3000	**77.233**	**69.644**	**74.873**
4000	78.225	70.967	75.797
5000	78.040	70.720	75.914

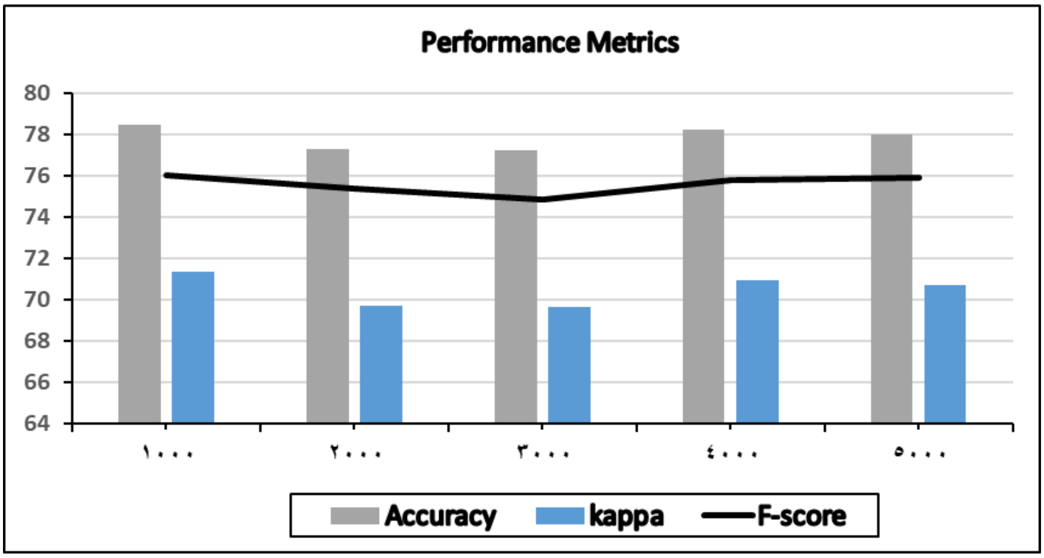

FIGURE 11. – Performance Metrics

The highest possible value that was attained is 78.5, which represents [the highest possible value or result that was measured when the total number of points that were tested was 1000. The value that is the lowest is 77.233, which indicates that the lowest value or outcome that you have observed throughout the total number of points that were checked is 3000.

6. Conclusion

The findings presented here are the outcomes of a thorough and meticulous examination and evaluation of data that was systematically gathered and thoroughly examined. The limitation arises from the substantial volume of remote sensing data, which forms the basis for these classification algorithms, owing to the considerable number of variables captured. Consequently, attaining a high degree of accuracy becomes a challenging endeavor. In addition, the classification problem becomes more complicated because of the medium resolution of distant sensing data, which further hinders non-wave techniques from surpassing the 80 percent accuracy threshold.

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CONFLICTS OF INTEREST

The author declares no conflict of interest.

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