Masters Program in Geospatial Technologies

Unsupervised classification of remote sensing images combining Self-Organizing Maps and segmentation techniques

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Unsupervised classification of remote sensing images combining Self-Organizing Maps and segmentation techniques

by

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Declaration of Authorship

I, Diana Rocío Galindo González, declare that this thesis titled, *'Unsupervised classification of remote sensing images combining Self-Organizing Maps and segmentation techniques'* and the work presented in it are my own. I confirm that:

- The thesis is based on work done by myself.
- This thesis has not previously been submitted for a degree to any other institution.
- Where I have consulted the published work of others, this is always clearly attributed.
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Abstract

This study aimed a procedure of unsupervised classification for remote sensing images based on a combination of Self-Organizing Maps (SOM) and segmentation. The integration is conceived first obtaining clusters of the spectral behavior of the satellite image using Self-Organizing Maps. As visualization technique for the SOM is used the U-matrix. Subsequently is used seeded region growing segmentation technique to obtain a delimitation of the clusters in the data. Finally, from the regions of neurons in the U-matrix are deduced the clusters in the original pixels of the image.

To evaluate the proposed methodology it was considered a subset of a satellite image as use case. The results were measured through accuracy assessment of the case and comparing definition of the obtained clusters against each technique separately. Cramers'V was used to evaluate the association between clustering obtained each method separately and reference data for the specific use case.

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1

Introduction

Classification of remote sensing images is a well-known technique of digital processing to obtain information of the earth's surface covering large areas and using electromagnetic spectrum regions not approachable by the human eye.

As images, remote sensing data sets are composed by pixels, its numbers correspond to representations of the observed object in a determined region of the electromagnetic spectrum. This characterization is given according to the band of the image where the object is represented and depending on the characteristics of the sensor capturing the satellite image.

Classification has as main objective obtain groups of pixels identifying characteristic features or patterns in coverages to assign them into a class. It is mainly divided in two processes supervised and unsupervised depending on the number of parameters and conditions defined for the interpreter in the classification of the image [Chuvieco et al., 2009]. Hybrid classification combines both approaches.

Remote sensing images can be considered multivariate data for the high number of pixels per image and in some cases bands. Commonly algorithms and methods of multivariate statistics and digital processing of conventional images are used to process this kind of information.

Supervised classification is based on having a previous identified pattern of coverages. The classes of the image are previously known in some areas of the image and are used as sample to train an algorithm capable to predict unknown classes in the rest of the image.

Pixel by pixel the image is examined to determine to which predefined classes belongs a pixel. Several analyses using discriminant function, euclidean distances, maximum likelihood algorithm, multilayer perceptron among others are used to predict to which class the pixel should be assigned [Rees, 2013].

On the other hand, unsupervised classification is not based in a previous knowledge about the patterns, instead, aims to establish clusters on the data using similarity measures.

Unsupervised classification of remote sensing images includes processes of clustering or segmentation, identification of coverages, labeling of the clusters with corresponding names of coverages and mapping the final classes [Campbell and Wynn, 2011].

Classification has been approached from two perspectives. As it is described in detail by [Liu and Mason, 2009] classification can be performed using multivariate statistical properties of the pixels or by segmentation based on statistical and spatial relations with neighboring pixels. The first one is known as pixel-based classification and classification aiming segmentation of the image is denominated object-based classification.

The Self-Organizing Maps (SOM) [Kohonen, 2001] is a type of artificial neural network used to pixel clustering aiming at reducing dimensionality of multivariate data. A network of neurons is trained adjusting weights during an iterative process of learning; the final nearest neuron to each element in the input data is selected and named as the "Best Matching Unit" (BMU).

The result is an output layer of neurons connected to the input through codevectors containing weights assigned according to euclidean distances. The SOM method has been applied for remote sensing images [Barsi et al., 2010] and also adapted for spatial data in the method GeoSOM [Bacão, 2005] accounting for the relation of neighborhood in the geographic information context.

As a resource of visualization in the new space of the given data it can be used the Unified Distance Matrix (U-matrix). The U-matrix contains a geometrical approximation of the vector distribution in the Kohonen net [Ultsch and Siemon, 1990], this means a new representation using euclidean distances calculated between the generated winning units. This type of visualization looks also for dissimilarities in distances between neurons to facilitate delimitation of clusters.

From object-based classification, segmentation involves a group of techniques to divide images into regions or objects. For this purpose closeness between pixels characteristics as color or texture is used. It has two approaches: region-based and edge boundary to assign the pixels to one region or another. It has origin in medical sciences research, but the same techniques of segmentation has been implemented to identify clusters and characterize the surface with satellite imagery [Solomon and Breckon, 2011].

Classification is used commonly to transform images to thematic maps. The mapping approach will depend on the characteristics of the satellite data to be used, technical specifications of the final expected map, the characteristics of the geographical area to be mapped and the availability of ancillary data [Caetano, 2011].

This approach includes the definition of the minimum map unit, definition of pixel, sub-pixel or object-oriented and spatial unit of analysis. At the same time it depends on several factors as the spatial resolution of the image, the aimed type of thematic information, the format of the map desired and planned post-processing [Caetano, 2011].

The main objective of this project was to obtain a new approach to cluster a satellite image using Self-organizing maps and segmentation techniques and evaluate its difference with the original methods used separately. To evaluate the method it was necessary implement it.

This study was divided in three phases starting with literature review and reasoning of the integration of the methods then implementation of this reasoning and finally evaluation of the proposed method using a use case. The Figure 1.1 shows the followed methodology.

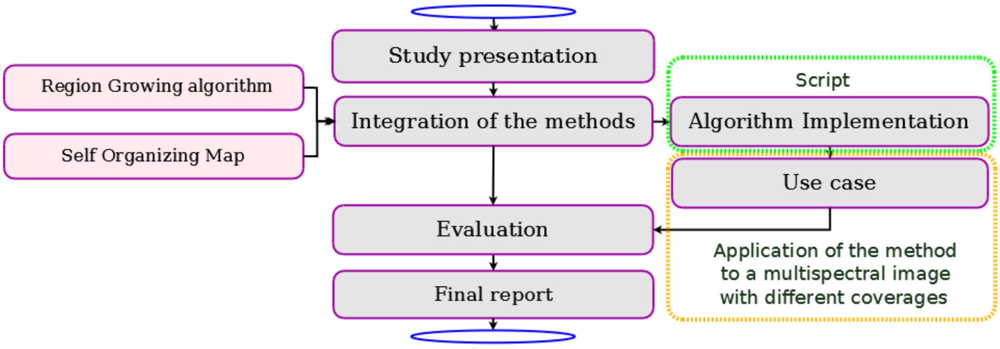


FIGURE 1.1: Study methodology

Combination of different techniques of segmentation including remote sensing images, and in general digital image processing, is a matter of study in recent years. Several attempts such as [Mueller et al., 2004], [Zhang et al., 2005] and [Sarkar et al., 2000] have had successful results defining coverages and features compared with classical methods. Specific implementation of segmentation techniques for remote sensing images are found in different open source projects as SAGA GIS or SPRING GIS and described in [Boehner et al., 2006]and [Bins et al., 1996].

As a general description of the reasoning of integration it can be said that the methodology considers as first approach a clustering of the original pixels using SOM. Over its corresponding U-matrix to apply a seeded region growing segmentation procedure to divide the image in homogeneous regions of coverages. To test the method were used functions and packages of R [R Development Core Team, 2011] and Image J [Abràmoff et al., 2004].

As a way of evaluation of the method it is considered a use case using a subset of a satellite image and its corresponding accuracy assessment. As indicator to establish if the results are significantly different from each method separately it is used Cramer'v statistic comparing obtained result with each technique for the selected use case.

The main aspects to evaluate the results are the definition of the clusters, the overall quality of the unsupervised classification and the estimation of difference in computation time.

2

Background and related work

Satellite images are used to obtain large extension coverages and usually have as a result a thematic map characterizing one or several variables of interest. Different processes of digital processing of images including classification, vegetation indices, transformations are derived from statistical multivariate and artificial intelligence methods. Classification aims to dispose the capabilities of spectral behaviors to analyze and construct patterns explaining and representing the coverages over the earth's surface [Mather and Koch, 2011].

In general, unsupervised classification of remote satellite imagery is based on an aimed number of classes to subsequently assign them one or more labels (depending on the technique). The classification looks for an output with the same spatial structure of the image and according to [Chuvieco et al., 2009]: "The work of the interpreter is more focused on the labeling of the resulting groups than on providing input information to the clustering algorithm.".

For this reason, unsupervised classification just require a number to be performed. The number of clusters considered, including also the level of generalization desired. The labeling process involves a visual analysis including texture, tone, form, arrangement among others [Chuvieco et al., 2009]

[Duda et al., 1995] pointed out reasons to use unsupervised classification which are still valid inside the specific context of remote satellite images. The most representative describes unsupervised classification as an alternative to collection and labeling of patterns in the field which can also provide training areas where there is no previous knowledge of the region.

The main purpose of unsupervised classification is to obtain the division of the natural groups provided by multispectral data nature. It refers to a whole procedure including clustering of pixels or image segmentation, identification of informational categories, labeling and mapping [Campbell and Wynn, 2011].

Unsupervised classification has advantages compared with supervised classification. A detailed knowledge of the studied region to define the possible classes is not required as in supervised classification. However, some previous concept is required to interpret the results produced by the clustering or segmentation process [Campbell and Wynn, 2011]. The human error can be minimized.

In supervised classification the interpreter plays a significant role in the identification and definition of the clusters, in unsupervised classification as the interaction interpreter - clusters is minor or reduced to define the number of desired classes, the probability of human error decreases. Finally, particular classes can be identified as particular clusters. Commonly, in supervised classification small areas with specific behaviors are attached to clusters with similar characteristics while in unsupervised depends on the chosen number of clusters [Campbell and Wynn, 2011].

Some disadvantages include the limitation of unsupervised classification the way to match the clusters in concordance with the intended categories of the interpreter. The result of a clustering relies on spectral homogeneity but, identification of coverages has to be done over the obtained clusters. Generally is required to perform clustering using a higher number of clusters than expected coverages [Campbell and Wynn, 2011].

When the spectral properties change through the time as seasons or years the relationship between the classes and the groups can also change. In other terms, the clustering will be suitable given the same conditions and cannot be used in other images. According to [Richards, 2012], this approach is more time-consuming compared with algorithms for supervised classification.

In general, unsupervised classification is used as exploratory analysis of the satellite image, to establish possible number of classes inside the area, to be used as input for another algorithms and models or to obtain thematic maps. Applications of unsupervised classification in the remote sensing analysis field include mapping, change detection, monitoring and modeling of terrestrial resources [Khorram et al., 2012].

Obtaining Land use and Land cover maps is a common application of unsupervised classification by reason of using classification is possible to cover large area extension or inaccessible places. At the same time, accomplishing this information is possible to establish the changes and monitoring conditions of the earth's surface. Analysis of specific or separated resources as water, forest and agriculture are also monitored using thematic maps.

Social applications are described by [Khorram et al., 2012] including humanitarian operations, peace-keeping and archaeological applications. These include legal estimation of conflict areas, definition of territories and exploration of archaeological sites using spectral information.

Methods of clustering or unsupervised classification of remote sensing images intend pattern recognition. They are based on statistical analysis of the data, segmentation of statistical and spatial relationships. Spatial clustering methods are classified in four categories by [Miller and Han, 2009]: partitioning, hierarchical, density-based and grid-based. A brief summary of each one is presented in the table 2.1.

TABLE 2.1: Summary of clustering algorithms. Source: [Miller and Han, 2009]

Category	Characteristics	Known algorithms
Partitioning	Divide a set of data into a number of non-overlapping clusters. A data item is assigned to a cluster based on a proximity or dissimilarity measure, through iterations the partitioning is improved moving objects from one cluster to other	k-means, maximum likelihood estimation, k-medoids and CLARANS
Hierarchical	Group objects into a tree-like structure, can be agglomerative or divisive according to the hierarchical decomposition considered	Ward's method, linkage, BIRCH, Chameleon, AGMES and DIANA
Density-based	Find arbitrary shaped clusters, are based mostly on distances between objects and growing according to established thresholds examined in neighboring objects	DBSCAN, OPTICS and DENCLUE
Grid-based	Divide the information spaces into a finite number of grid cells and cluster objects based on this structure	STING, WaveCluster and CLIQUE

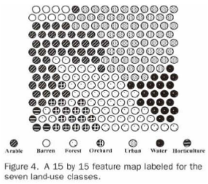
The algorithms commonly implemented are: K-means, ISODATA, Fuzzy K-means and Self-Organizing Maps. Sensitivity to initial arguments is frequently found in algorithms of unsupervised classification. Parametric methods as K-means and ISODATA take into account the model with minor Mean Squared Error (MSE) are chosen. For neural networks or non-parametric methods an estimation able to determine the model to be chosen is the quantization error [Liu and Mason, 2009].

During the last two decades new techniques of digital image processing have been emerging to enhance possibilities in different study fields. Each time more specialized techniques are studied according to the new capabilities of sensors to acquire earth information. The new techniques include improvement of established methods of multivariate statistics and ANN [Benediktsson et al., 1990] and more recently Artificial Immune Systems [Neagoe and Neghina, 2011] [Zhong et al., 2006].

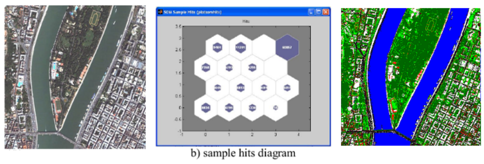
For the objective of this study, along different techniques, SOM has been chosen as the spectral clustering basis for its well performance in results obtained from different authors (See figure 2.1).

[Ji et al., 2000] used SOM to land use classification for Landsat images obtaining satisfactory results and concluding that large-sized maps offered better class separation but, more computation time. Additionally, he found that maps of 25 by 25 units were large enough to describe the data. He experimented different maps using from 25 to 900 units.

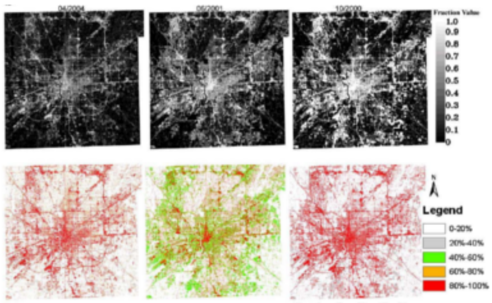
Satisfactory results were also obtained by [Ehsani and Quiel, 2009] and [Barsi et al., 2010] using SOM for unsupervised classification. They used SOM to process Landsat and Quickbird satellite imagery, being these latest resampled to 8-bits images.



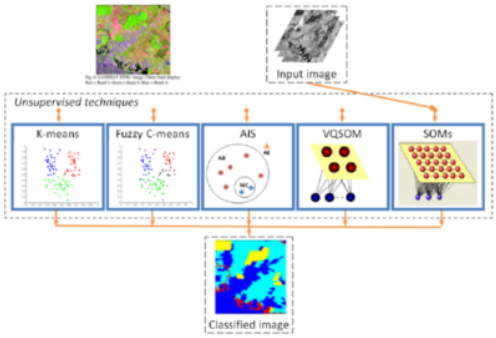
(a) (Ji et al., 2000)



(b) (Barsi et al., 2010)



(c) (Hu et al., 2009)



(d) (Neagoe et al., 2011)

FIGURE 2.1: SOM related work

[Neagoe and Neghina, 2011] proposed a new method called artificial immune system approach and compared different unsupervised classification methods. Among different conclusions, SOM showed a better performance when the total number of spectral bands were used to perform an unsupervised classification.

SOM also has been used in combination with other algorithms. [Hu and Weng, 2009] used SOM and multilayer perceptron to obtain classification of impervious surfaces concluding that the supervised method (multilayer perceptron) had limitations in the definition of the hidden layer and it was more sensitive to initial parameters than SOM.

SOM has been used also with remote satellite images to establish patterns in ocean processes with success incorporating large and complex satellite data sets and complementary types of data [Richardson et al., 2003] (see Figure 2.2). The author indicates the emerging use of neural networks with scatterometer and thermal imagery for oceanography in detailed experiments for improvement of chlorophyll estimation and profiles in the ocean by [Silulwane et al., 2001].

An easy access to its implementation compared with another newer techniques also has been taking into account. An explanation of the use of neural networks including SOM in remote sensing analysis is provided by [Villmann et al., 2003].

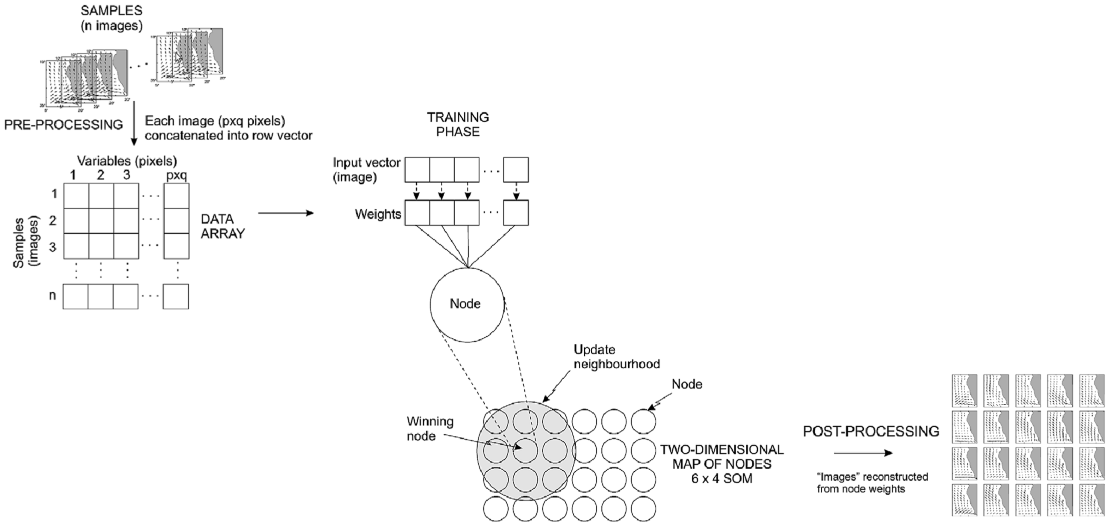


FIGURE 2.2: SOM implementation in satellite imagery. Source: [Richardson et al., 2003]

Concurrently the use of segmentation procedures has been gaining importance in remote satellite imagery processing. In contrast with SOM its procedure is already implemented in different geographic information systems (GIS) as SAGA [Boehner et al., 2006], - SPRING and e-Cognition among others.

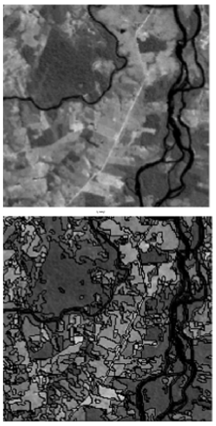
The use of region growing for satellite imagery has used it images with satisfactory results mainly in high resolution satellite imagery as in [Bins et al., 1996], who describes the approach of region growing algorithm specifically for satellite images and used it to assess land use change in the Amazon region.

[Mueller et al., 2004] mixed edge and region-based segmentation approaches of satellite images to extract large man-made objects in high resolution images. First, detecting the edges in the image, then smoothing this result and assigning seeds to obtain final regions from region growing algorithm.

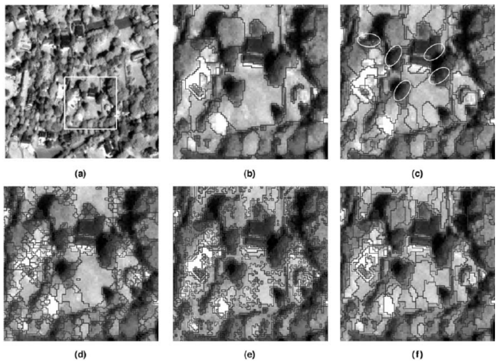
Region growing segmentation has used as complementary technique to evaluate deforestation using Landsat images as describe [Shimabukuro et al., 1998]. This study concludes that this procedure is feasible and adequate specially for scenes of the Amazonia and multitemporal studies.

A comparison of different techniques of segmentation for an IKONOS satellite image can be found in [Carleer et al., 2005]. Results of the related work to segmentation in satellite images can be seen in Figure 2.3.

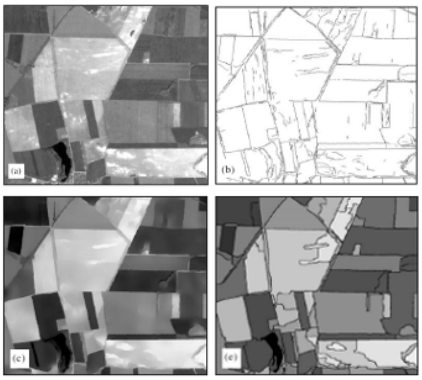
Mixing segmentation techniques and SOM has been explored by [Awad, 2010]. The segmentation method used was T-cluster (Threshold clustering technique) and SOM was



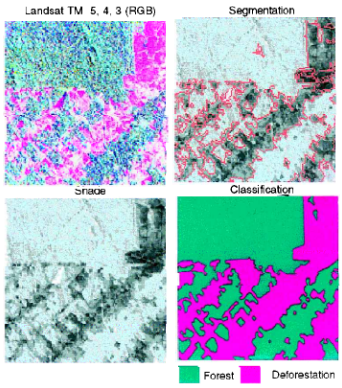
(a) (Bins et al., 1996)



(b) (Carleer et al., 2009)



(c) (Mueller et al., 2004)



(d) (Shimabukuro et al., 2011)

FIGURE 2.3: Region growing segmentation related work

used as unsupervised method. This study concluded that segmentation is an important step for image processing and showed satisfactory results mixing the techniques. The author also referred use of incremental SOM [Nadir Kurnaz et al., 2005] to segment Landsat images with successful results.

3

Methods

3.1 Self-Organizing Maps(SOM)

Self-Organizing maps are a type of artificial neural network based on unsupervised learning aiming to detect relationships within the input data elements. The kohonen's method is composed by one input and one output layer. The input corresponds to the features in the input space and the output layer, also called competitive layer, is composed by units or neurons. According to [Miller and Han, 2009] SOM is a unique method of partitioning clustering method since cluster data and order them in a two-dimensional layout where close clusters are more similar.

The SOM is designed to preserve topological properties of the input space and according to its author [Kohonen, 2001] is an effective tool to reduce dimensionality and visualization of data based on similarity using geometrical relations as euclidean distances (Figure 3.1).

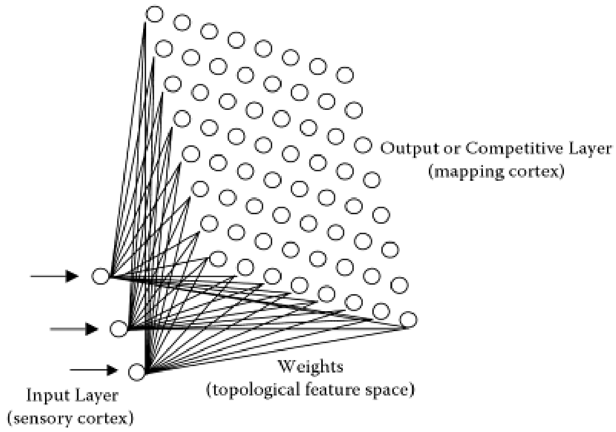


FIGURE 3.1: Example of the topology of a SOM. Source: [Tso and Mather, 2009]

The maps are constructed using the neurons in the output layer. Each neuron has associated a codevector with coordinates to input feature vectors and it is assigned as winning neuron in concordance with the minimum distance to them after the training of the network. The training is done through an iterative process where each neuron in the output layer competes for the opportunity of interaction with the input pattern. A learning rate of the network adjust the capability of displacement of the neuron in each iteration.

A brief explanation about the procedure followed to obtain a self-organizing map is provided by [Tso and Mather, 2009] as follows: Training SOM begins with random initialization of weights w_{ij}. For each input feature vector $x = x_1, x_2, ..., x_k$ where k is the dimension of the input data. The squared distances d_j^2 between an input neuron and each output neuron j are calculated using the Euclidean distance measure (3.1) where x_i^n is the input to neurone i at iteration n.

$$d_j^2 = \sum_{i=1}^{k} (x_i^n - w_i j)^2 \tag{3.1}$$

The selected output neuron is determined from $min\{d_j^2\}, \forall j \in$ output layer. A competitive Hebbian-type learning law adjusts the synaptic weights of neurone j and its neighboring neurons (3.2), where the learning rate α^n (3.3) is a time-decaying function, which means a reduction in its magnitude when the number of iteration increases.

$$w_{ji}^{n+1} = w_{ji}^n + \alpha^n \beta_{j'}(\gamma^n)(x_i^n - w_{ji}^n) \tag{3.2}$$

$$\alpha^n = \alpha_{max} \left(\frac{\alpha_{min}}{\alpha_{max}} \right)^{\frac{n}{n_{max}}} \tag{3.3}$$

With constraints $1 \leq \alpha$ and $\alpha_{min}, \alpha_{max} \leq 0$. $\beta_{j'}(\gamma^n)$ (3.4) corresponds to the neighborhood function and determines a Gaussian neighborhood range centered on the winning neurone j. j' denotes its neighborhood including j itself and γ^n is also a time-decaying function (3.5)

$$\beta_{j'}(\gamma^n) = \exp \frac{-(j - j')^2}{2(\gamma^n)^2} \tag{3.4}$$

$$\gamma^n = \gamma_{max} \left(\frac{\gamma_{min}}{\gamma_{max}} \right)^{\frac{n}{n_{max}}} \tag{3.5}$$

As SOM intends to preserve topological properties, it considers a radius of learning per neuron, this is also defined by the user in concordance with the variance in the input data. A shape of neighborhood can be considered either hexagonal or rectangular. A radius of one in a rectangular shape is equal to include the group of surrounding nine neighbors during the training phase. The fig 3.2 presents the lattice shapes considered for neighborhood.

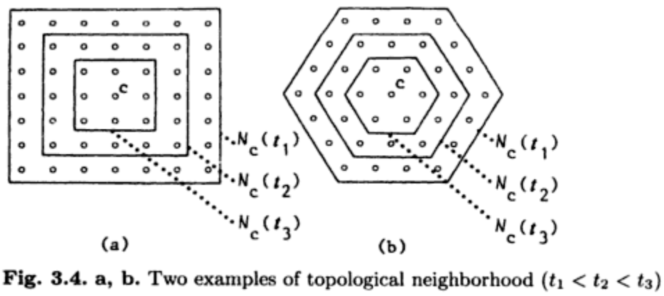


Figure 3.2: Topological neighborhood in SOM. Source: [Kohonen, 2001]

At the end of the learning each neuron in the output layer has associated an adjusted *codevector*. The final codevectors contain the information of the data input belonging to each neuron in the multivariate space [Miller and Han, 2009].

But the kohonen map is not suitable to perform pattern recognition or cluster definition [Ultsch and Siemon, 1990], [Tso and Mather, 2009]. For this purpose one of the methods commonly used is the U-matrix, representing distances between neighboring map units to show clusters, high values of the U-matrix imply high distances meaning a cluster border. It is also possible to visualize the clusters per variable through component planes [Vesanto et al., 1999].

The U-matrix method [Ultsch and Siemon, 1990], is designed to display the neurons in the output layer of the SOM in a new matrix with colors as a representation of distances between them. For a 2D U-matrix, are added cells between to the original arrangement of neurons. These new cells contain the euclidean distances (3.6) among each pair of neurons. Where x_i and y_i of the codevectors obtained from SOM.

$$d = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2} \tag{3.6}$$

Cells of the matrix where several distances should be placed are calculated using the median of the distances taking part in the region. Cells with neurons are calculated with the average (in some cases is also used minimum, maximum or median) of its neighboring cells. The Figure 3.3 describes the calculation of a U-matrix using a kohonen map of four by three neurons.

The particular use of U-matrix for any kind of georeferenced data is described by [Gorricha and Lobo, 2011]. The study concluded that U-matrix can be a powerful tool

1	d(1,2)	2	d(2,3)	3
d(1,4)	m[(1,5),(4,2)]	d(2,5)	M[(2,6),(5,3)]	d(3,6)
4	d(4,5)	5	d(5,6)	6
d(4,7)	m[(4,8),(7,5)]	d(5,8)	m[(5,9),(8,6)]	d(6,9)
7	d(7,8)	8	d(8,9)	9
d(7,10)	m[(7,11),(10,8)]	d(8,11)	m[(8,12),(11,9)]	d(9,12)
10	d(10,11)	11	d(11,12)	12

Where:
d(i,j) Distance between neuron i and neuron j
m[(i,j),(k,i+1)] Median value between d(i,j) and d(k,i+1)
X Mean value of neighboring cells

FIGURE 3.3: Description of calculation of a U-matrix using a 3 x 4 neurons map.

to reduce multidimensionality mainly to 2D space and describing patterns and spatial relationships.

3.2 Segmentation

According to [Solomon and Breckon, 2011], segmentation is the name given to a process to subdivide an image in homogeneous regions or objects demonstrating similarities in properties as color, texture or motion. There are mainly two approaches for segmentation, edge boundary and region-based methods (See Figure 3.4).

In both cases, similarity is closely related with intensity and there is no single correct segmentation, this depends on the regions or objects are intended to identify. In any case, segmentation techniques are part of a broad field of research in image processing and it is common to find combination of methods and approaches, resulting new and hybrid algorithms.

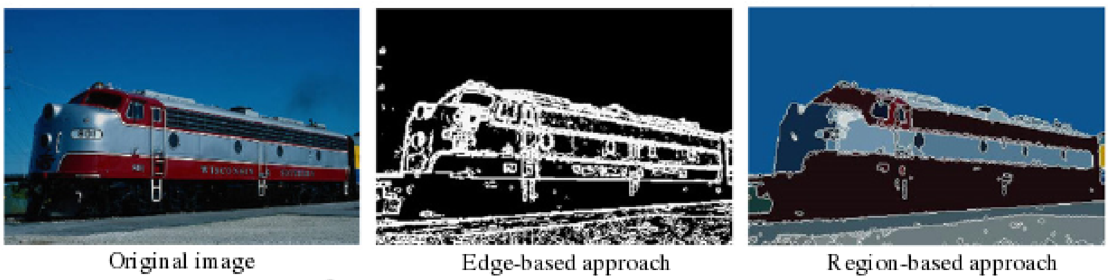


FIGURE 3.4: Example of edge-based and region-based segmentation approaches. Source: [Chung et al., 2010]

Edge detection methods intend to find the boundaries of the objects or regions taking as reference the intensity transition between two objects. The simplest methods of edge detection include Prewitt and Sobel kernels, Laplacian of Gaussian and difference of Gaussian filters and canny edge detector [Solomon and Breckon, 2011].

Region-based methods approach aims to identify in which groups of pixels is divided the image according to a predefined criteria of similarity. Generally, these methods require seeds to initialize iterative processes to evaluate the similarity of the seed with neighboring pixels and establish regions[Solomon and Breckon, 2011]. Region-based algorithms in general can be divided in: merging, splitting, split and merge, pyramid, tree and scale space methods among others.

The region growing algorithm is used as basis for another region-based methods. It relies in the growing of the seed considering its four or eight connected neighbors and merging them in case to satisfy the measurement of similarity. It is translated as a threshold. The growth advance from seeds to regions through iterations until the image is entirely evaluated.

The seeded region growing is considered an appropriate method to fulfill requirements to achieve the mail goal of the project. Its plain and accurate approach supplies the requirements of the segmentation procedure to be used over the generated graphic of a U-matrix. This method was proposed by [Adams and Bischof, 1994].

According to [Wang, 2011] the seeded region growing segmentation is performed examining the neighboring pixels of a set of initial points or seeds $C_1, C_2, C_3, \ldots, C_n$ with their corresponding positions $p_1, p_2, p_3, \ldots, p_n$.

To compute the difference of pixel value of the initial seed point p_i and its neighboring points, if the difference is smaller than the threshold, the neighboring point can be classified into C_i, where $i = 1, 2, \ldots, n$, the boundary and the mean of C_i are recomputed and converted as new seed p_i.

The process iterates until the whole groups of pixels have been assigned to a cluster. The threshold is defined by the user based on intensity, gray level or color values (See figure 3.5).

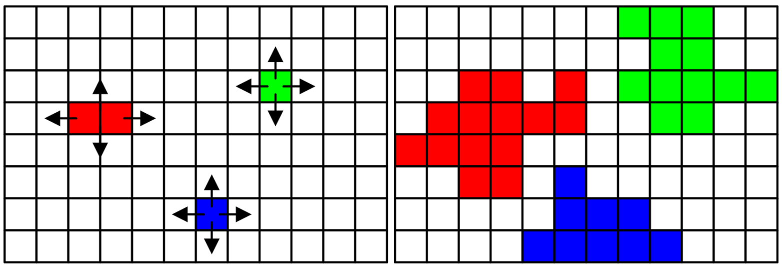


FIGURE 3.5: Seeded region growing. Source: [Vantaram and Saber, 2012]

3.3 Integration of the methods

Given the previous context it is possible to explain that integration of both methods is based on the use of output data from the SOM as input for the segmentation. The integration can be divided in three stages: SOM, segmentation and obtaining final clustering for the image. A flowchart of the integration can be seen in Figure 3.6.

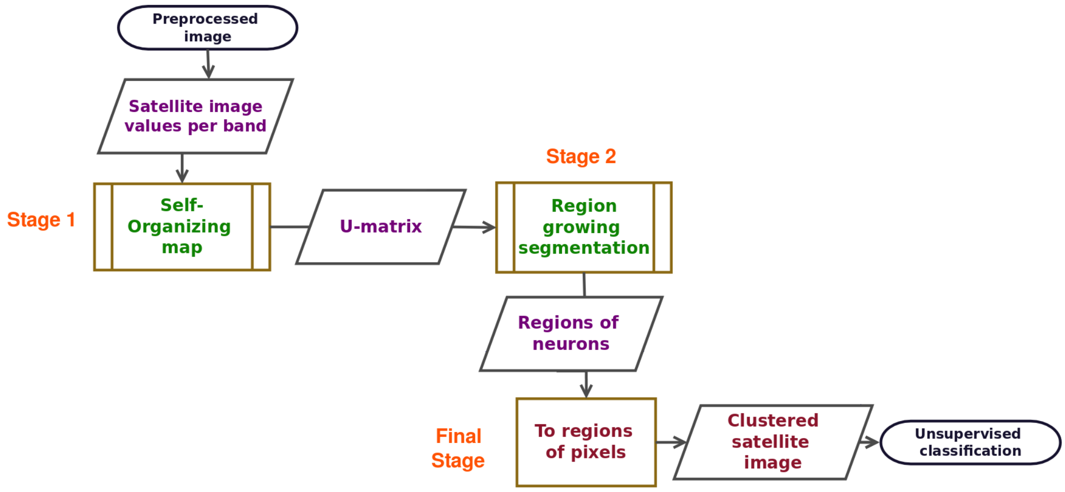


FIGURE 3.6: Flowchart of integration of the methods.

In the first stage, the neural network receives as input data a multispectral satellite image, as a result, it is obtained a U-matrix. This matrix intends to facilitate visualization of clusters. The second stage consists in a region growing segmentation used to support the delimitation of the groups. The final stage is the conversion of the data into satellite image raster space. In the next paragraphs each stage is explained in detail.

The self-organizing map procedure requires different arguments, the first and most important is the data set of information to be mapped. In this case is a set of vectors describing the multispectral satellite image where the individuals are the pixels and the bands are the variables. Remaining arguments are the learning rate, number of iterations, number of neurons and its distribution and the lattice shape of the network.

The number of iterations is the number of times of each input vector is presented to output layer to determine which one is its corresponding winning neuron. The learning rate is distributed in the number of iterations to establish how fast the network learn. In other words, in each iteration the learning rate of the network is adjusted until reach zero.

The number of neurons and its distribution depend on the user's objective. Still there is no rule of thumb in the use of SOM for satellite images, the reviewed literature suggest different arguments for different types of maps.

In the particular case of this project a rectangular shape for the lattice used in the SOM is required. It is assumed for the region growing algorithm when the U-matrix is constructed as an image and the neighborhood is described by rectangular shapes.

As it was explained in the previous chapter, to obtain the U-matrix from the SOM map it is necessary to calculate the distances between the neurons in the output layer and later assign colors to these distances. The rule used by convention is to specify darker colors to indicate short distances between units and lighter colors for longer ones. Once it is done this U-matrix can be treated as a regular image or picture and can be segmented. The first stage is described graphically in the Figure 3.7.

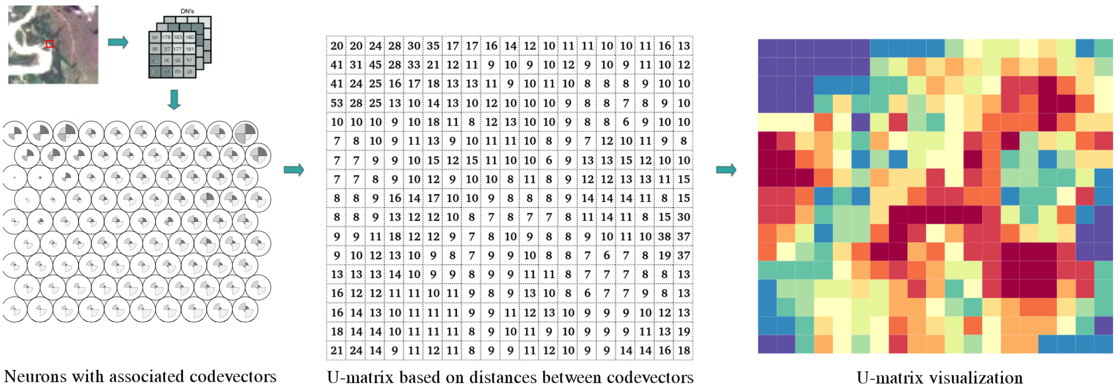


FIGURE 3.7: First stage of integration of the methods

To segment this new image is used the seeded region growing algorithm. This method requires just two arguments, the number of seeds and the threshold which determine if the pixel is part of a region or not. The number of seeds in this context are the final number of clusters desired. The objective of this stage is to obtain the delimitation of the clusters in a single way to identify in this type of visualization (See figure 3.8). These regions group neurons which at the same time are grouping pixels.

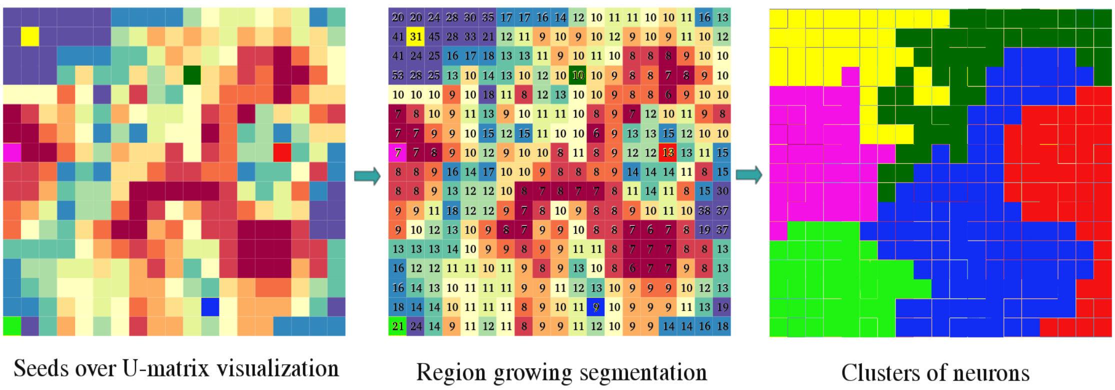


FIGURE 3.8: Second stage of integration of the methods

In the final stage the information obtained from SOM and segmentation over U-matrix is joined to obtain the classification at the level of pixel. From segmented picture of the U-matrix is extracted the region per neuron. At the same time, neurons have been assigned as winning neuron for certain pixels.

Only the cells of the U-matrix with odd position in row and column contain neurons. Having assignment of region per neuron and pixels assigned to a winning neuron, the final regions are joined to the original position of the pixels through the identifier of the neuron.

Once is obtained the corresponding region to the pixel, the array of pixels inherit the characteristics of the original image, including the geographic reference system, to be labeled and displayed as unsupervised classification using the method. The summary of the final stage of the process can be seen in the Figure 3.9

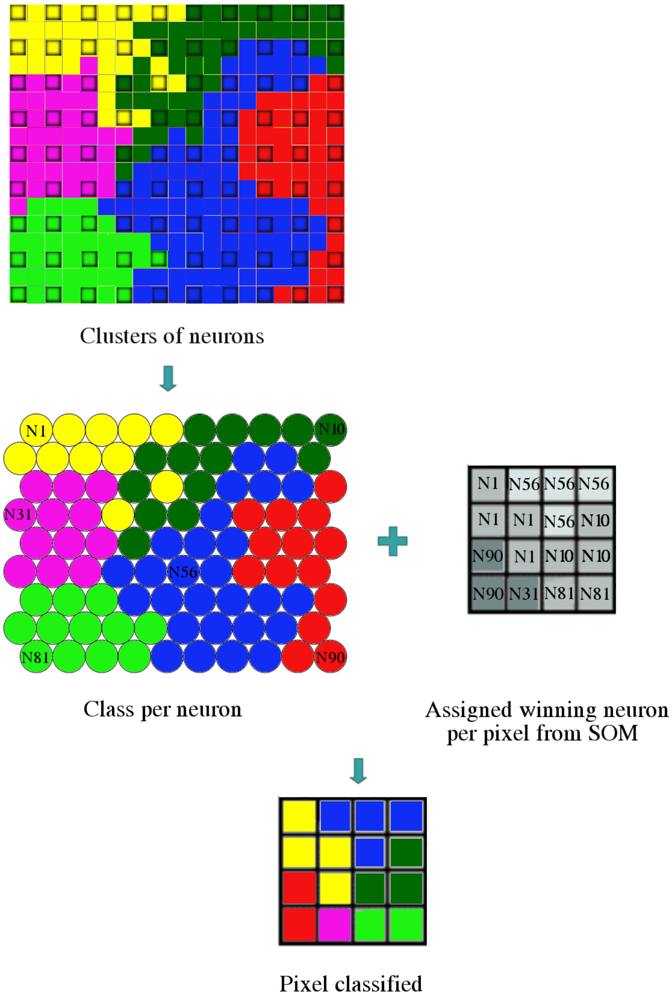


FIGURE 3.9: Last stage of integration of the methods

3.3.1 Implementation

Two main resources were used to implement the algorithm for testing: *R statistical software* [R Development Core Team, 2011] and its packages: *raster*[J., 2012], *kohonen*

[Wehrens and Buydens, 2007a], *lattice* [Sarkar, 2008], *sp* [Pebesma and Bivand, 2005], *rgdal* [Keitt et al., 2012] and *RColorBrewer*[Neuwirth, 2011] and the image processing program *ImageJ* [Abràmoff et al., 2004] and its plugin *ij-Plugins Toolkit*.

The implementation is also divided in three stages as the integration. The SOM function is provided by the package *kohonen* [Wehrens and Buydens, 2007b]. According to its author around the third part of iterations of the function are used as training set and from here on is given the fine-tuning process where a neuron of the output layer is assigned as a BMU.

The U-matrix was not implemented in R software. Therefore, was written a function to compute it. Visualization and exporting of the U-matrix as image are supported with the raster package [J., 2012]. The Figure 3.10 shows an example of the first stage of the implementation and the tools used.

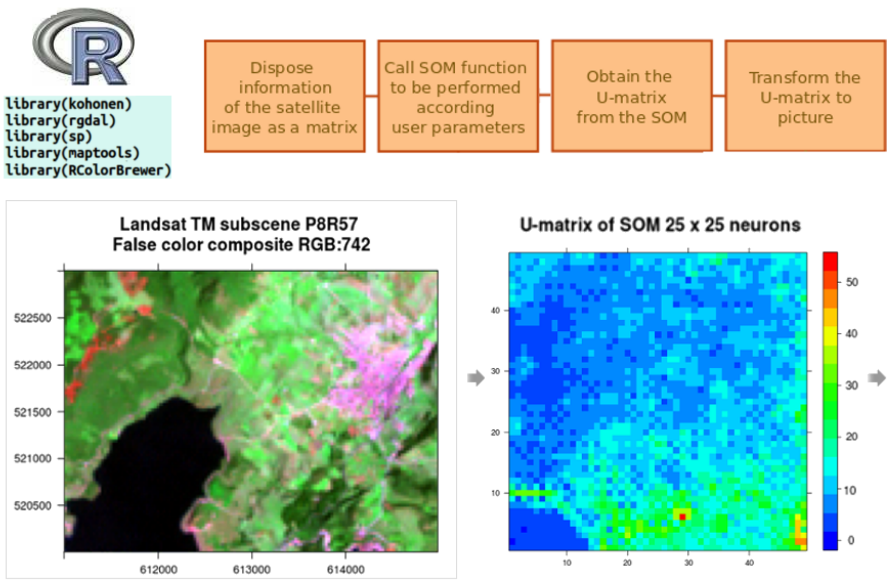


FIGURE 3.10: Example of first stage of the implementation

The segmentation stage is performed using *ImageJ* software. In the software is uploaded the tiff version of the U-matrix generated in *R* to be processed as image. The seeds should be provided and the threshold is calculated by the software. Once obtained the regions are exported as image in tiff format. In the Figure 3.11 can be seen an example of the second stage of the implementation.

Conversion of regionalized U-matrix in clustered satellite image was also implemented in R. This process begins importing the tiff image of regions produced by ImageJ software and reading it in *R* [R Development Core Team, 2011]. The assignment of winning neurons is retrieved from the first stage to be joined to the obtained regions. To accomplish the region per pixel position in the final image is used the ID of neuron as common

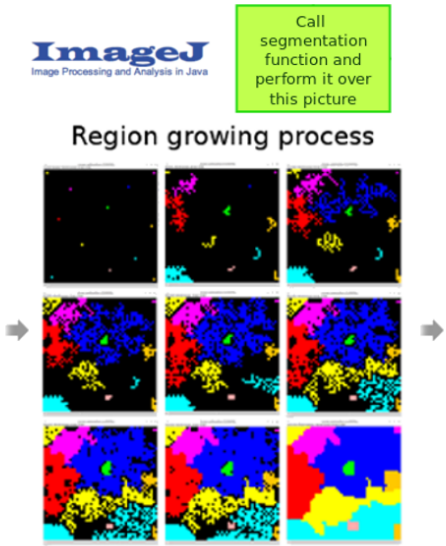


FIGURE 3.11: Example of second stage of implementation

identifier in both datasets. The composition of the final clustering includes inheriting geographic projection from original satellite image. An example of the final stage of the implementation is shown in the Figure 3.12.

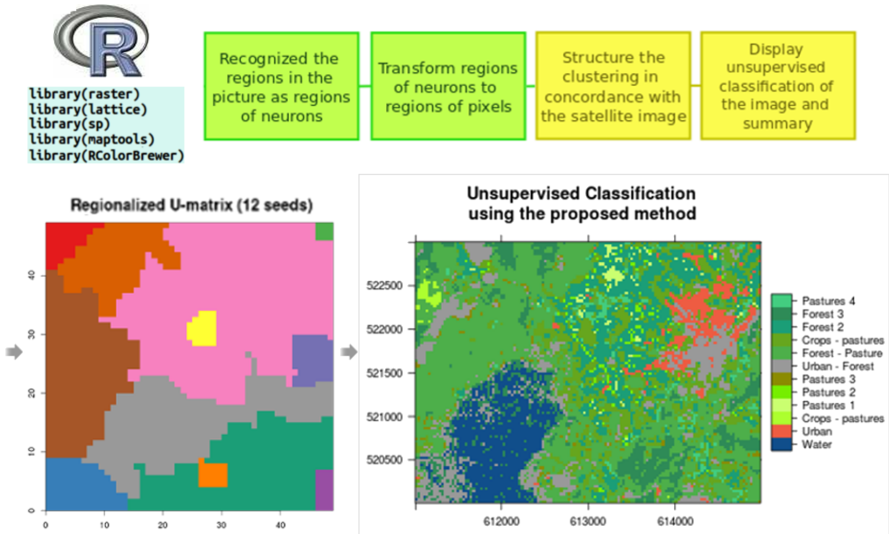


FIGURE 3.12: Example of final stage of the implementation

The complete R script code, using as example a 6-band satellite image, can be checked in Appendix A.

4

Use case

The objective of the use case is to determine what kind of results are obtained using the methodology for a real case. For this project is oriented to obtain the unsupervised classification of a subset of a satellite image using the proposed methodology and its evaluation.

As it was explained in the second chapter the quality depends on the objective of the desired map. The purpose of a map in this context is to obtain a product enabling the possibility of evaluation of the proposed methodology. For this purpose it was used the pixel as minimum map unit and just labeling of the identified classes as postprocessing.

4.1 Description of the data set

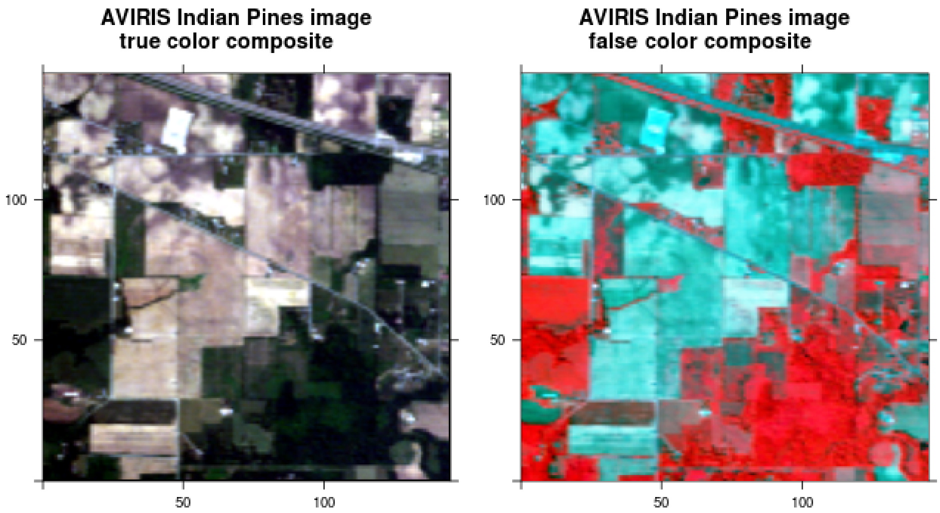
An available remote sensing imagery data set has been selected to use to perform the method. This data set corresponds to a subset of 145 by 145 pixels of a hyperspectral image taken by AVIRIS sensor of Indian Pines in North-western Indiana.

The Figure 4.1 shows an approximately true color composite and a false color composite of the image. The approximately true composite uses the band 27 in red plane, band 17 in green plane and band 7 in blue plane. The false color composite, uses the band 51 in red plane, band 21 in green plane and band 18. It was not found information about the coordinate reference system of the image. There were excluded the bands of noise (000-003, 102-109, 148-164 and 215-220).

The image is characterized by crops, forest and man-made structures as low-density housing, highways and a rail line. It is composed by 224 spectral bands covering wavelengths between 0.4 to 2.5 nanometers.

The image was chosen due to the availability of its reference data set (See figure 4.2). The data set and its corresponding reference data is available to download at the website of the project MultiSpec of the Purdue University [1].

[1]https://engineering.purdue.edu/ biehl/MultiSpec/hyperspectral.html



(a) RGB:27-17-7 (b) RGB:51-21-18

FIGURE 4.1: AVIRIS Indian Pines Image used to test the proposed methodology

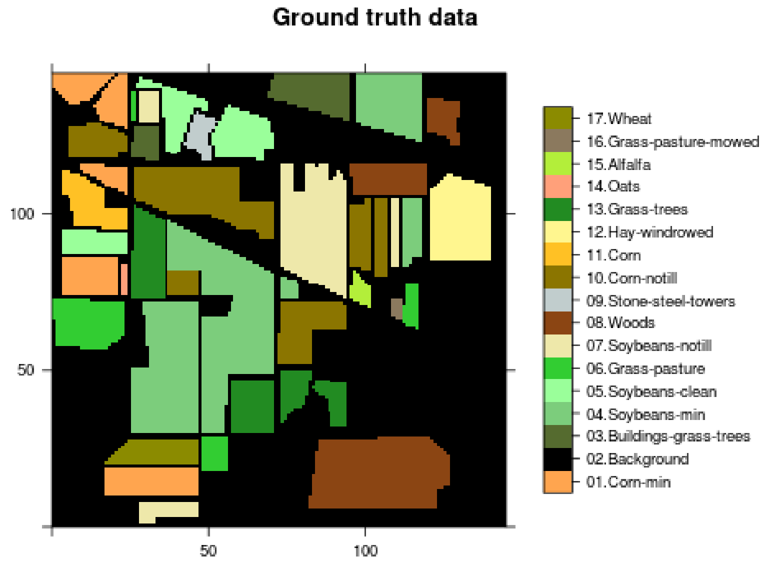


FIGURE 4.2: Reference data of AVIRIS Indian Pines Image

4.2 Obtaining the unsupervised classification

Once determined the data set to be used was executed the methodology using the proposed implementation. There were trained several networks with different dimensions. Initial parameters as learning rate α, radius and iterations were maintained for each training. According to [Kohonen, 2001] changes in their dimensions do not make significant modifications in the results due to the maximum size considered. As was explained in the previous chapter a rectangular shape of the lattice is required.

The initial parameters considered for the networks are listed in the table 4.1, the number of iterations above number of neurons and radius as 2/3 of the maximum distance were chosen based on the found previous work. After the training of the SOM and based on the 2D output layer, the corresponding U-matrices were calculated to visualize distances between neurons. The Figure 4.3 shows the U-matrix visualization obtained for SOM of 10 by 10, 20 by 20, 25 by 25 and 30 by 30 neurons.

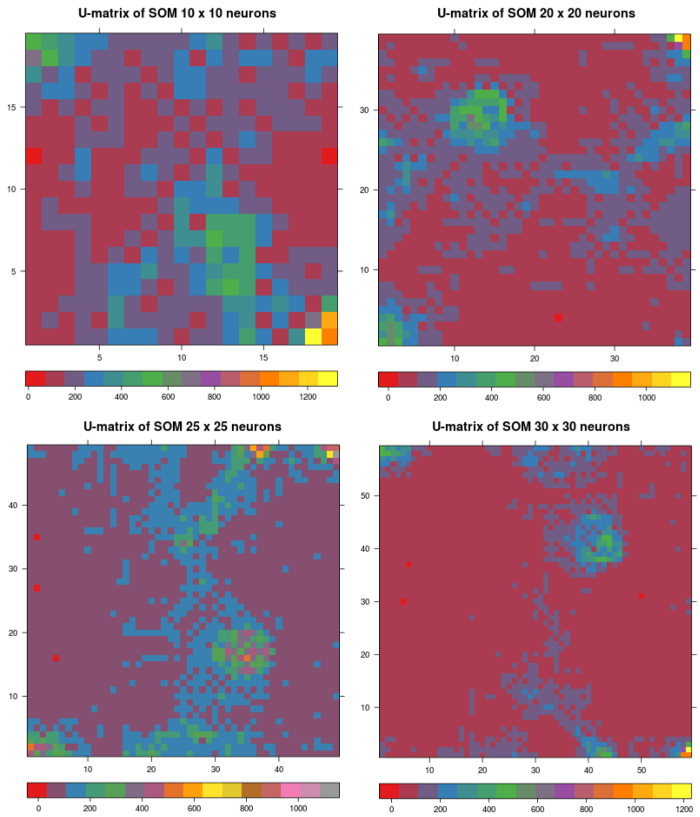


FIGURE 4.3: Calculated U-matrices

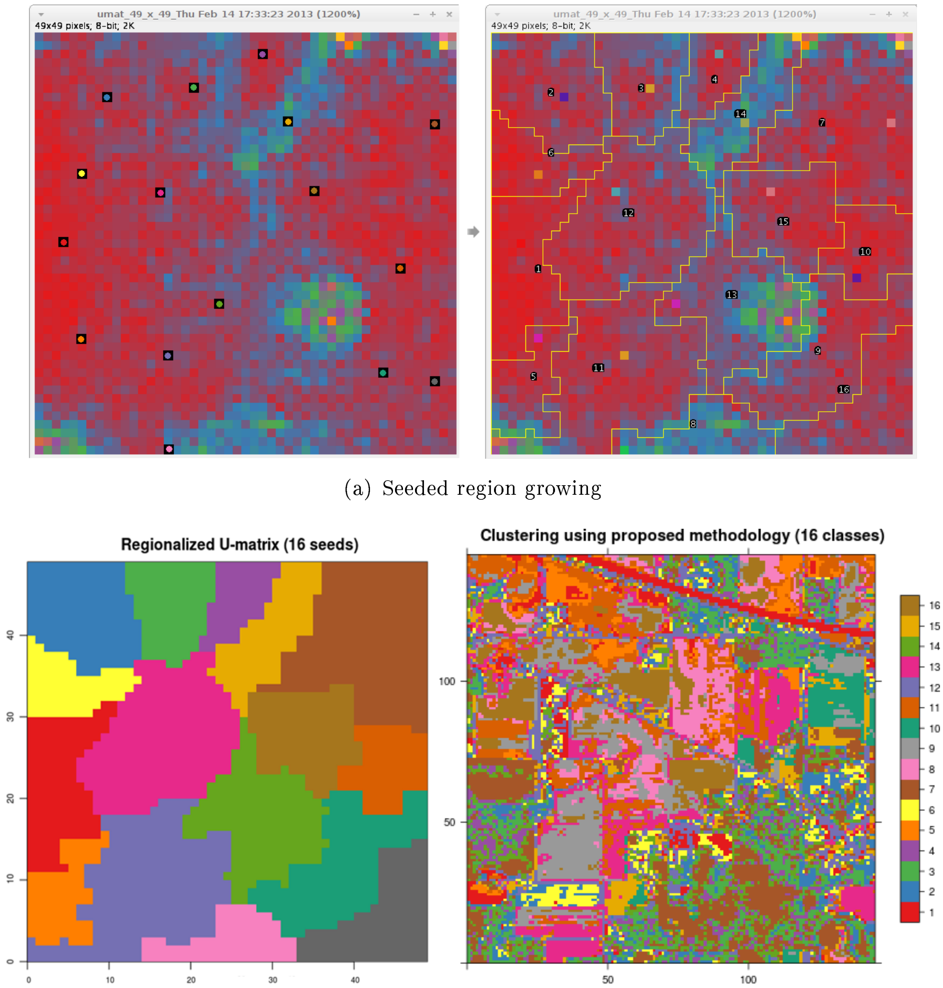
TABLE 4.1: Initial parameters of SOM training

Parameter	Initial value
Learning rate	0.05
Shape	Squared
Radius	76
Epochs	1000

Among the different obtained U-matrices it was selected the one calculated for a SOM of 25 by 25 neurons. This U-matrix showed the best balance between level of detail of the information and calculation time. This means that regions can be identified and the computing time processing is still suitable. The U-matrix with 30 by 30 units offers slightly a higher level of detail but, consumes three times calculation time compared with the one using 25 by 25 units.

The next step indicated in the methodology is to obtain a regionalization of the U-matrix using seeded region growing segmentation. As 16 classes are described in the reference data set the same number of seed were used. Once obtained the seeds, the region growing algorithm is performed. Conversion of regions of neurons in clusters of pixels was done as it was described in the final stage of the implementation.

To summarize, the final clustering selected using the training of a SOM network of 25 by 25 units and a seeded region growing segmentation using 16 seeds with specific locations defined by the user. The Figure 4.4 shows the result of this part of the procedure.



(a) Seeded region growing

(b) Obtained regions

(c) Obtained clustering

FIGURE 4.4: Seeds over U-matrix, obtained regions and clustering for the use case phi

After the clustering, the post-processing given by default to obtain an unsupervised classification includes: assign a name to the clusters identified by the algorithm and filters to smooth the result. Since the objective of the use case is to determine the accuracy of the method no filters were used. The unsupervised classification obtained with the method using the same labels given in reference data set can be seen in the Figure 4.5.

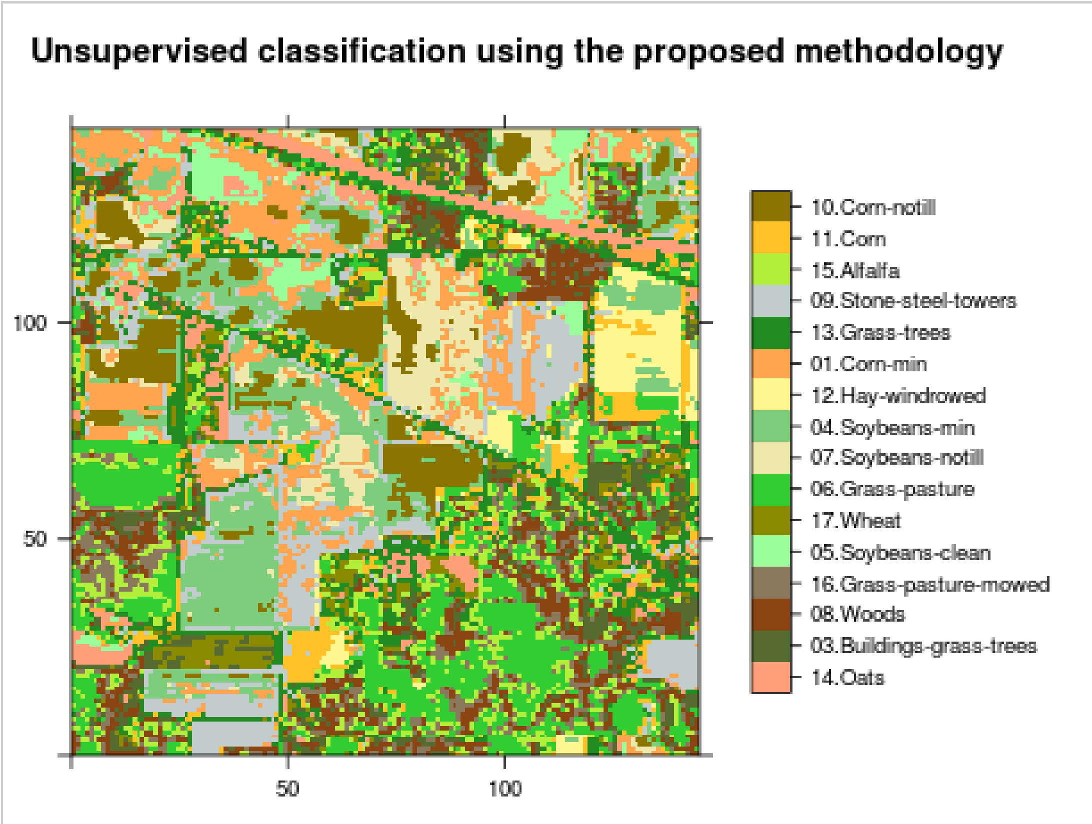


FIGURE 4.5: Unsupervised classification with 16 classes obtained from the proposed methodology

5

Results and discussion

5.1 Results

5.1.1 Accuracy assessment

According to [Congalton and Green, 2008], the purpose of the qualitative accuracy assessment is to identify and measure the map errors. It comprises three phases, the design of the sample, collection of the data per sample and analysis of the results. It is divided in positional and thematic. Positional deals with the distance between a mapped feature and its real location on the surface and thematic checks if the labels in the map are different from the labels in reality.

The purpose of this project approached a thematic accuracy assessment to test the proposed methodology. This means, to evaluate the concordance between the classes obtained from unsupervised classification and those obtained in the field taking a reference data set. As the reference data used for this image was not obtained in this project, only the phase of analysis of results is performed.

The reference data set available contains information in raster model of sixteen coded classes. As it was described in the previous chapter a seventeenth code is included to characterize the background of the image (See figure 4.3). It was converted to a shapefile of points containing the corresponding classes assuming cells of 20 by 20 meters as the original image since there is no additional description for this data set.

Around ten thousand points were obtained excluding the background. Since the main objective of the accuracy assessment in this project is to evaluate the proposed methodology there were used the total of points in the reference data set. The Figure 5.1 shows the arrangement of the reference data set available used for this project.

It was obtained the information from the reference data in points and the information of the unsupervised classification in the same location to be compared. The error matrix was calculated and it is presented in the table 5.2, it is a contingency table to present and compile accuracy statistics [Horning et al., 2010].

TABLE 5.1: Classes in reference data

Code	Class	Code	Class
01	Corn-min	10	Corn-notill
02	Background	11	Corn
03	Buildings-grass-trees	12	Hay-windrowed
04	Soybeans-min	13	Grass-trees
05	Soybeans-clean	14	Oats
06	Grass-pasture	15	Alfalfa
07	Soybeans-notill	16	Grass-pasture-mowed
08	Woods	17	Wheat
09	Stone-steel-towers		

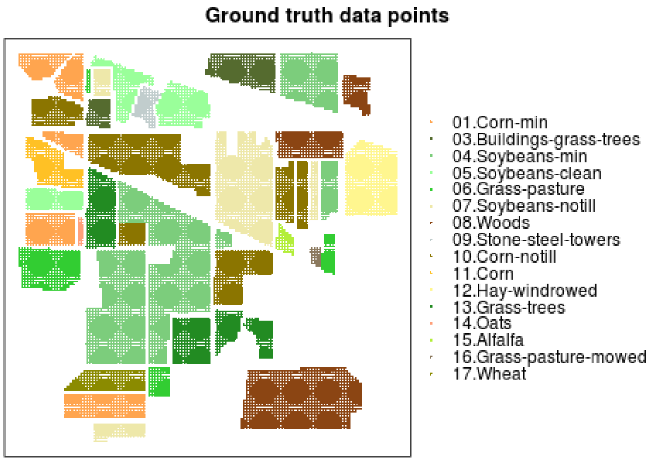


FIGURE 5.1: Points in the reference data set for accuracy assessment

Described as well by [Congalton and Green, 2008] the error matrix shows the number of points assigned to a defined category in one classification relative to the number of points assigned to a particular category in another classification. Generally, rows describe classification obtained from the satellite image and columns information in the reference data, considering the last one correct. They present the error matrix as an effective way to represent map accuracy allowing to estimate errors of exclusion and wrong inclusion of information in the classification.

TABLE 5.2: Error matrix of the obtained map

Unsupervised	Reference Data																
Classification	**01**	**03**	**04**	**05**	**06**	**07**	**08**	**09**	**10**	**11**	**12**	**13**	**14**	**15**	**16**	**17**	**Total**
01	356	1	426	156	0	154	0	81	264	9	0	0	0	0	0	0	1447
03	0	67	2	0	0	0	52	0	0	0	0	10	0	0	0	62	193
04	186	1	891	67	9	5	0	0	279	22	129	0	0	4	13	0	1606
05	45	0	145	88	0	93	0	0	95	13	0	1	0	0	0	0	480
06	0	39	0	0	266	0	482	0	0	0	1	55	0	0	0	0	843
07	13	0	372	12	0	434	0	0	57	0	0	0	0	0	0	0	888
08	0	57	0	0	1	0	322	0	0	0	0	7	0	0	0	0	387
09	137	5	408	50	24	171	0	1	173	50	4	10	0	4	0	1	1038
10	79	0	196	177	0	99	0	11	545	95	0	0	0	0	0	0	1202
11	0	13	2	1	91	0	0	0	4	0	35	25	1	1	9	0	182
12	0	0	1	0	17	6	0	0	1	2	318	0	0	45	4	0	394
13	1	76	16	2	14	3	6	0	4	14	1	220	14	0	0	3	374
14	17	13	8	61	7	3	0	2	12	29	0	173	0	0	0	1	326
15	0	44	0	0	48	0	208	0	0	0	1	82	0	0	0	0	383
16	0	26	0	0	20	0	223	0	0	0	0	4	0	0	0	0	273
17	0	38	1	0	0	0	1	0	0	0	0	160	5	0	0	145	350
Total	834	380	2468	614	497	968	1294	95	1434	234	489	747	20	54	26	212	10366

The accuracy assessment process aims to estimate mainly: Overall accuracy, producer's accuracy, user's accuracy, omission error and commission error. Overall accuracy is the general probability of any pixel to be correctly classified [Horning et al., 2010].

Producer's accuracy is the probability that reference data of a particular class being correctly classified and user's accuracy is the probability of matching between a pixel and its corresponding pair in the reference data. Omission error is the probability of excluding a pixel which should be included inside a class and commission error is the probability of include a pixel in a class when it should be excluded [Horning et al., 2010].

Given the objective of this project it is considered relevant the overall accuracy based on the matrix error (5.2) to evaluate the proposed methodology. Partial accuracy as producer's accuracy and user's accuracy are not considered relevant to the use case aiming to evaluate the method instead specific thematic objectives.

$$\text{Overall accuracy} = \frac{\text{pixels correctly classified}}{\text{Total number of pixels}} \times 100 = \frac{3653}{10366} \times 100 = 35.24\% \tag{5.1}$$

5.1.2 Comparison between the methods

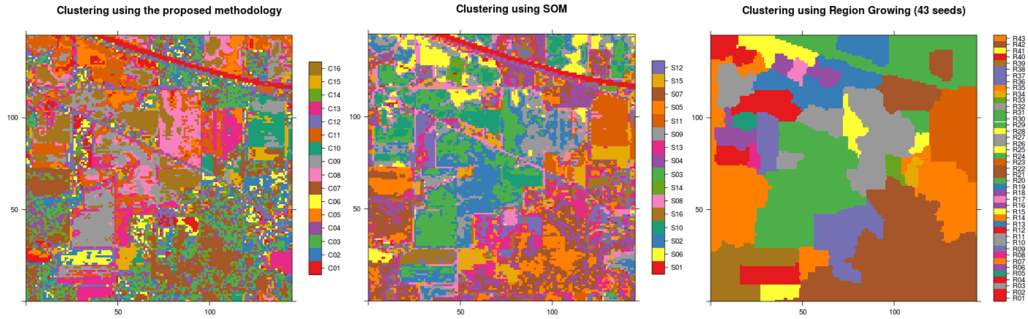
A comparison between the three techniques is made to have a general idea how different the proposed method from each technique separately. This comparison consists in construct the clustering output of use case data using SOM, Region Growing and the combined method independently and establish the association between them.

The Cramer's V is as measure of association between categorical variables which can be applied in this context since classes are nominal variables. Establishing the level of association between the different methods is possible to determine if the proposed one is providing new results from each technique separately.

As each set of clusters obtained with different methods are intended to test correlation it was necessary to calculate SOM and Region growing segmentation separately. For the SOM technique alone was trained a neural network with 16 neurons 1000 iterations and a radius of 18. For this case it was used the hexagonal shape, which is commonly used in SOM and satellite imagery clustering. The winning neuron per pixel was used as identifier of the corresponding cluster.

In the case of Segmentation procedure were allocated 43 seeds according to the number of objects identified in the reference data set.

The Figure 5.2 shows the three clustering approaches for the use case, the proposed methodology in this project in Figure (a), using SOM in (b) and (c) using region growing segmentation.



(a) Proposed methodology (b) SOM (c) Region Growing segmentation

FIGURE 5.2: Clusters obtained using each method separately

The Cramer's V is designed to determine strength of association of two or more categories in multivariate data analysis. It is based on Chi-square test of independence using as well a contingency table of the involved variables, but differs from the first one taking into account dimension of each data set. Cramer's V is calculated as (5.2), where χ^2 is the chi-squared statistic, N number of rows, M number of columns and n total number of elements in the contingency table [Woo, 2005].

$$V = V(X,Y) = \sqrt{\frac{\chi^2}{n\min(M-1, N-1)}} \tag{5.2}$$

Cramer's V equals 0 when there is no relationship between the two variables, and generally has a maximum value of 1. It can be used for any two cross classification tables no matters its dimensions [Greenacre, 2005].

Once obtained the clusters using the three methods contingency tables per pairs are obtained using the whole set of clustered pixels. Later, Cramer's V coefficient are computed for each combination of resulting classes. The procedure was done using the package vcd [Meyer et al., 2006] in R software [R Development Core Team, 2011].

It can be said that pixel-based classification (SOM and combined method) is not comparable with object-based classification (region growing segmentation). The objective of this exercise is to establish if the approach here proposed is related with the segmentation technique taking as an exploratory analysis.

SOM and Combined method

The crossing table for the clustering obtained using SOM and the proposed combined method can be observed in the table 5.3. The Cramer's V obtained is 0.631, which means a medium correlation between the two methods of clustering.

TABLE 5.3: Crossing table between SOM and proposed combined method

Combined method	SOM															
	S01	S02	S03	S04	S05	S06	S07	S08	S09	S10	S11	S12	S13	S14	S15	S16
C01	370	0	0	0	0	204	0	94	0	0	0	256	0	0	0	9
C02	0	0	0	427	0	0	0	0	0	0	0	15	92	0	0	598
C03	0	0	0	1094	0	0	175	0	0	0	0	0	170	0	0	0
C04	0	0	0	4	0	0	816	0	0	0	0	0	108	0	0	0
C05	0	0	0	0	0	576	0	2	54	0	0	0	0	0	0	0
C06	1	0	0	0	0	0	0	0	0	0	0	419	54	0	0	257
C07	0	0	0	0	1350	0	258	0	0	0	4	0	393	0	358	0
C08	0	613	195	0	0	0	0	0	199	0	0	0	0	0	0	0
C09	0	419	1295	0	0	0	0	1	6	35	224	0	0	1	0	0
C10	0	0	0	0	0	0	0	4	0	0	529	0	0	0	95	0
C11	1	532	5	0	0	109	0	88	1043	3	2	0	0	141	0	0
C12	37	0	0	0	0	0	0	507	0	0	5	860	364	1	174	0
C13	0	754	66	0	0	0	0	324	488	0	62	33	0	0	50	0
C14	0	0	0	0	0	0	752	0	0	0	0	14	494	0	30	0
C15	0	0	0	0	0	0	0	93	0	0	116	7	86	0	615	0
C16	0	1	642	0	0	0	0	0	0	751	1	0	0	0	0	0

Combined method and segmentation

The crossing table for the clustering obtained from the combined method and using the region growing segmentation can be observed in the table 5.4. The Cramer's V obtained is 0.39, which means a weak correlation between the two methods of clustering.

TABLE 5.4: Crossing table between segmentation and proposed combined method

Region growing	Combined method															
	R01	R02	R03	R04	R05	R06	R07	R08	R09	R10	R11	R12	R13	R14	R15	R16
R01	3	11	6	0	6	3	0	0	20	0	103	16	9	0	0	0
R02	0	3	0	0	3	4	0	0	24	0	52	6	7	0	2	0
R03	21	0	0	0	12	1	0	50	41	0	37	29	46	2	11	115
R04	14	4	0	0	3	3	4	0	170	2	45	28	60	3	2	92
R05	0	0	0	0	1	2	0	0	16	1	0	3	21	0	3	65
R06	2	0	0	0	5	0	0	17	28	0	42	3	19	0	6	146
R07	3	3	0	0	0	1	4	0	6	29	1	29	19	8	104	0
R08	0	1	0	0	0	6	3	0	5	0	2	42	10	1	4	0
R09	95	4	0	2	1	64	18	0	4	0	5	121	11	32	2	1
R10	0	0	0	0	0	0	4	0	49	1	2	10	9	0	23	203
R11	0	0	0	0	0	0	0	0	30	0	16	9	55	0	1	5
R12	0	0	0	0	7	0	0	1	34	0	97	3	4	0	0	35
R13	71	61	60	17	118	41	31	0	19	12	122	180	52	45	51	1
R14	32	1	0	0	30	3	1	0	0	0	18	25	6	0	0	0
R15	41	2	1	0	128	2	12	2	3	0	127	41	17	4	10	0
R16	29	0	0	0	35	0	0	0	0	0	31	2	1	1	0	0
R17	2	0	0	0	0	0	0	0	0	0	84	0	0	0	0	11
R18	0	0	0	0	0	0	0	1	57	0	20	0	21	0	1	57
R19	14	71	62	30	0	24	32	0	1	1	1	61	8	42	8	0
R20	279	17	15	1	163	11	27	176	135	6	218	132	71	10	44	186
R21	7	22	46	32	0	5	23	0	2	0	1	24	3	20	8	0
R22	7	46	169	56	4	18	64	0	2	21	5	53	8	39	26	0
R23	24	42	5	2	0	20	120	0	152	407	13	95	12	3	169	0
R24	0	0	0	0	29	0	0	0	0	2	12	9	76	0	5	0
R25	0	0	0	2	0	0	4	0	1	5	2	2	58	2	7	0
R26	0	0	0	0	0	0	1	6	1	7	108	1	126	0	3	0
R27	14	0	0	0	47	1	1	358	20	0	233	45	58	0	4	82
R28	0	0	0	0	0	0	0	99	5	0	5	2	4	0	3	94
R29	0	0	0	0	0	0	0	6	12	0	3	1	9	0	1	32
R30	4	3	1	3	3	11	31	262	438	9	362	87	301	7	62	94
R31	2	1	0	0	0	0	0	11	528	0	38	15	144	0	10	27
R32	0	0	0	0	0	0	6	0	13	1	0	1	3	0	6	119
R33	2	3	1	0	0	11	23	0	8	49	0	15	7	2	1	0
R34	0	0	0	1	0	3	12	0	24	8	0	22	1	4	28	0
R35	39	188	68	51	2	91	171	0	3	18	11	216	26	92	89	1
R36	31	35	26	5	0	94	183	0	2	15	2	159	33	103	54	0
R37	26	2	0	0	1	1	1	0	0	0	1	45	6	1	0	0
R38	40	2	0	1	0	31	1	0	0	0	0	14	0	10	0	0
R39	64	139	114	58	20	168	111	0	12	0	7	80	23	85	27	0
R40	0	3	0	0	0	0	0	8	94	0	39	17	147	1	6	14
R41	2	2	6	0	0	1	0	0	0	0	3	27	125	0	7	0
R42	34	347	687	465	3	83	1029	10	11	33	32	187	136	554	79	9
R43	31	119	172	202	11	28	446	0	11	1	24	91	25	219	50	6

Segmentation and SOM

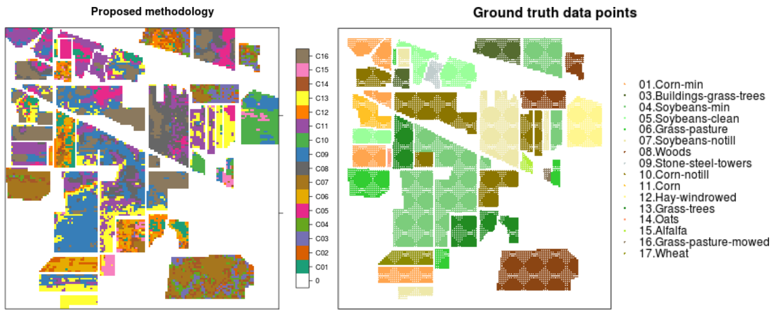
The crossing table for the clustering obtained from segmentation and SOM can be observed in the table 5.5. The Cramer's V obtained is 0.437, a medium correlation between the two methods of clustering.

Table 5.5: Crossing table between SOM and segmentation

Region growing	SOM															
	R01	**R02**	**R03**	**R04**	**R05**	**R06**	**R07**	**R08**	**R09**	**R10**	**R11**	**R12**	**R13**	**R14**	**R15**	**R16**
R01	2	58	5	7	0	8	0	10	63	0	0	13	2	0	0	9
R02	2	50	4	2	0	3	0	6	25	0	0	3	0	0	2	4
R03	11	59	135	0	0	21	0	41	41	28	7	12	2	0	8	0
R04	3	86	169	0	0	8	1	24	42	61	4	22	5	0	0	5
R05	0	9	27	0	0	1	0	9	10	48	3	3	0	0	1	1
R06	0	43	101	0	0	7	0	8	37	63	2	0	0	0	7	0
R07	1	4	2	0	0	0	0	25	1	0	6	11	15	1	139	2
R08	0	8	0	0	0	0	1	10	6	0	1	33	6	0	8	1
R09	3	6	5	0	6	1	5	50	2	1	1	194	76	0	4	6
R10	0	11	51	0	0	0	0	11	1	190	12	4	3	0	18	0
R11	0	63	31	0	0	0	0	15	4	1	0	1	0	0	1	0
R12	0	27	26	0	0	7	0	3	75	42	0	0	0	0	1	0
R13	23	19	4	79	6	161	28	120	90	0	14	117	85	16	76	43
R14	7	1	0	0	0	56	0	23	10	0	0	14	2	0	1	2
R15	4	11	2	0	2	169	0	40	97	1	0	18	19	3	20	4
R16	0	6	0	0	0	64	0	2	22	0	0	2	0	2	1	0
R17	2	0	4	0	0	0	0	1	3	12	0	0	0	75	0	0
R18	0	27	69	0	0	1	0	1	18	40	1	0	0	0	0	0
R19	7	0	0	74	6	0	62	23	0	0	5	59	60	0	11	48
R20	262	170	216	16	1	200	2	65	202	101	29	84	78	21	34	10
R21	7	3	0	51	10	0	51	10	1	0	0	14	18	0	13	15
R22	1	0	0	190	45	5	91	11	9	0	18	47	41	0	41	19
R23	21	0	0	12	3	3	2	44	0	0	566	68	45	11	255	34
R24	0	9	0	0	0	24	0	33	50	0	14	2	0	0	1	0
R25	0	19	0	0	1	0	3	8	32	0	8	1	3	0	8	0
R26	0	106	0	0	0	0	0	11	121	0	11	0	1	0	3	0
R27	1	256	97	0	0	43	0	48	359	33	0	16	1	1	8	0
R28	0	28	174	0	0	0	0	5	1	0	4	0	0	0	0	0
R29	0	10	41	0	0	0	0	2	5	5	1	0	0	0	0	0
R30	2	777	380	0	4	4	0	71	242	21	18	43	26	0	88	2
R31	0	159	528	0	0	4	0	22	25	14	8	3	2	0	11	0
R32	0	4	28	0	0	0	0	4	0	100	3	0	3	0	7	0
R33	1	0	0	0	7	0	0	4	4	0	57	22	8	0	15	4
R34	1	1	1	0	4	0	2	11	0	0	35	12	11	0	24	1
R35	12	0	0	66	80	5	96	66	3	1	16	218	191	3	131	178
R36	1	6	1	7	22	0	9	25	1	0	25	167	293	1	158	26
R37	0	1	1	0	0	1	0	50	1	0	1	16	6	0	5	2
R38	0	0	0	0	0	0	0	0	0	0	0	69	26	0	0	4
R39	14	11	4	120	70	66	164	32	2	0	5	83	44	4	43	246
R40	0	152	80	0	0	0	0	17	35	24	2	5	8	0	4	2
R41	1	57	0	7	0	0	1	32	49	0	3	10	6	0	7	0
R42	13	53	13	703	743	4	1028	64	83	0	55	151	542	4	112	131
R43	7	9	4	191	340	23	455	56	18	3	8	67	133	1	56	65

5.1.3 Comparing reference data with explored methods

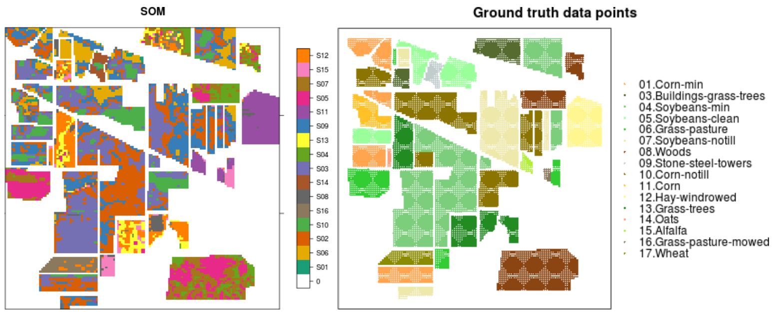
The Cramer's V it was also used to have a comparable estimation of the relationship between the reference data and the results of clustering using the methods. The comparison is made using the reference data excluding the background area and each clustering obtained through the three methods: the combined method here proposed, a self-organizing map and region growing segmentation directly over the image.



(a) Proposed methodology (b) Reference data

FIGURE 5.3: Reference data and corresponding clustering using the combined method

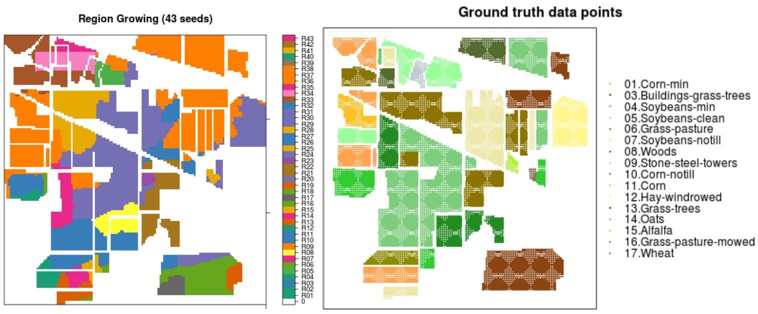
Combined method and reference data: Cramer's V = 0.41 (Figure 5.3). Slight correlation.



(a) SOM (b) Reference data

FIGURE 5.4: Reference data and corresponding clustering using Self-Organizing maps

SOM and reference data: Cramer's V = 0.44 (Figure 5.4). Slight correlation.



(a) Region Growing segmentation (b) Reference data

FIGURE 5.5: Reference data and corresponding clustering using seeded region growing segmentation

Segmentation and reference data: Cramer's V = 1 (Figure 5.5). Strong correlation.

5.2 Discussion

The result for accuracy of the method in this particular case is not completely satisfactory. It presents a modest percentage of overall accuracy 35%, which is considered low. Some factors apart from the methodology itself, as the disposition of the data and coercing the number of clusters to the number of classes in the reference data set, can influence this result.

From the disposition of the data it was found that hyperspectral imagery use particular unsupervised classification methods at times. On the other hand, SOM is conceived to be used in any multivariate data set.

As the reference data is the only source of information of the area the number of clusters should be coerced to the number of classes. This situation can restrict in excess the method.

From the comparison between the methods it can be said in general that three methodologies are related between them moderately. Generally, object-based segmentation and pixel-based clustering are not comparable because of their difference in the approach. Each approach has advantages according to the objective of the unsupervised classification. Obtaining of clusters according to the spectral behavior in the case of pixel-based approach or definition or homogeneous areas in the object-based approach.

Regarding the definition of the objects in the use case image, region growing segmentation directly over the image presented well defined and generalized but separate objects. The relation between this approach and the object-based approaches (SOM and combined method) was slight.

According to the Cramer's V the proposed combined method presents stronger association with the use of Self-Organizing maps. This result was expected since both methods use the same input data and the same algorithm.

According to the literature reviewed SOM is not a good tool of visualization of clusters. The way to establish clusters for Self-Organizing Maps without visualization is the use of the winning neurons. This scenario permits to conclude that in spite of changes in initial parameters, as the shape of the lattice of the neural network and dimensions of the map, the results of the SOM are similar.

Finally, in the comparison of the reference data and the clustering obtained from each method, the SOM and combined method showed a similar level of association with the reference data according to the Cramer's V. A medium association.

The process of seeding directly over the image took more time compared with the used in the combined technique. Nevertheless it showed a better result to cluster the coverages in the use case. It showed the strongest association possible according to the Cramer's V statistic, this association can be also a benefit given by the structure of the shapes in reference data.

6
Conclusions

Conclusions from this project can be drawn at different levels. The first level to be evaluated are the findings during the conception of the methodology and its use. It can be said that the greatest strength of the proposed methodology is related to the identification of number of clusters using the U-matrix as a supporting tool.

Once situated in the space of the U-matrix visualization is easier to find the number of clusters in the image and moreover to identify particular coverages of small proportions inside the data.

The procedure to achieve the final output using the proposed methodology can be too long for an unsupervised method. However, this can be compensated with in another influential way, inside the unsupervised classification context a high initial number of clusters should be considered to subsequently be merged and finally establish the final classes. Using the U-matrix to visualize is easier segregate or join regions closer in spectral characteristics than directly over the image.

Sensitivity in initial parameters is commonly found in unsupervised classification methods. However, during the testing of different parameters for the proposed methodology it was found that slight changes in the initial parameters of the SOM suggest minor or no changes in the final result.

For the specific use case it was found that disposition of the seeds in the borders instead centers or intended regions offer better definition in the clusters of the original data.

Computation time varied drastically depending on the number of bands of the multispectral images. For the hyperspectral image of the use case, the computation time increased notoriously compared with a Landsat image, this can be also given by the software used.

In software not designed for digital image processing of satellite image, the computation time is acceptable treating images as arrays. This is converted into an advantage to test new proposed methodologies for this type of images and not implemented in specialized software yet. The edition based on visual interpretation is constrained in this case.

Regarding the results, the methodology presented a low overall accuracy for this particular use case. As it was explained during the background it should be taking into account that regularly obtaining a thematic map includes more steps and considerations according to the intended map. Although the results obtained from the particular use case, the proposed methodology offers complementary tools for definition in the clusters based on image processing methods instead visual interpretation directly over the image.

By comparing the proposed methodology and each technique separately it was strongly related with SOM as expected. There was a slight association between object-based approaches and seeded region growing segmentation results. Still the result provided by this methodology is not completely overlapping any of the other ones. In other words, the application of the proposed methodology is not replaced with any of the separate techniques.

The obtained results in association with reference data the seeded region growing segmentation showed better association with the reference data than the proposed method and the Self-organizing maps approach. Association of reference data with these two techniques was moderate for both approaches.

Future work goes in the direction of considering different scenarios to test the methodology. Despite the exercise done during this research included just a use case as a way testing, it is concluded that more scenarios can be considered to test the proposed methodology. A deeper testing can include different scenarios as images with different spatial and spectral resolutions to have a better perspective of the scope of this proposal. This also includes the use of any kind of geoinformation.

A

R Script

Next it is presented the R [R Development Core Team, 2011] script generate to implement the proposed methodology. The script uses as an example a multispectral image of 6 bands.

```
rm(list=ls())    # Cleaning the workspace

library(kohonen) # Self-organizing maps package
library(raster)  # To handle images
library(lattice) # To generate required levelplots
library(rgdal)   # To incorporate geospatial elements
library(RColorBrewer) # To use color palettes for outputs
library(sp)       #
library(maptools) #

setwd("/home/dianag/MasterThesis/Implementation") # setting working directory
x = GDAL.open("s1.tif") # Loading subset satellite image
class(x)
img <- getRasterData(x)
str(img) # 100 x 133 columns

sub1 <- as.vector(img[1:133,1:100,1])
sub2 <- as.vector(img[1:133,1:100,2])
sub3 <- as.vector(img[1:133,1:100,3])
sub4 <- as.vector(img[1:133,1:100,4])
sub5 <- as.vector(img[1:133,1:100,5])
sub6 <- as.vector(img[1:133,1:100,6])
tb<-cbind(sub1,sub2,sub3,sub4,sub5,sub6)
head(tb) # verifying initial pixels by band
tail(tb) # verifying last pixels by band

# Self-organizing maps, radius 2/3 of all unit-to-unit distances is by default
somimg <- som(data = tb, grid = somgrid(20,20, "rectangular"),rlen=1000,n.hood="square")
wnpp<-somimg$unit.classif # winning neuron per pixel in input layer
write.table(wnpp, file = "wnpp_somimg20.txt", sep = "\t", dec = ".",
            row.names = TRUE,col.names = TRUE)
codev<-somimg$codes
write.table(codev, file = "codev_somimg20.txt", sep = "\t", dec = ".",
            row.names = TRUE,col.names = TRUE)

# Defining function to obtain U-matrix
umatrix<-function(imgsom){
```

```
attach(imgsom)
n<-grid$xdim ; m<-grid$ydim # number of neurons by row and by column
di<-n*m # Total number of neurons in output layer
wnpp<-imgsom$unit.classif # winning neuron per pixel in input layer
N<-(2*n)-1; M<-(2*m)-1;nu<-(N*M) # setting dimensions of u-matrix
u<-rep(NA,nu); dim(u)<-c(N,M);u # creating empty u-matrix

codev<-somimg$codes # Storing weight vectors
dit<-as.matrix(dist(codev))
# Distances between codevectors for u-matrix calculation
dists<-as.vector(dist(codev))

### U-matrix - Unified distances matrix ###
###########################################

#Calculating cells of u-matrix considering distances between neurons
for(i in 1:N){
    for(j in 1:M){
       if( i%%2 == 0 && j%%2 == 0 ){    # mean distance diagonals
             a=(((i/2)-1)*m)+(j/2)
             b=((j/2)+1)+(m*i/2)
        d=(((i/2)-1)*m)+((j/2)+1)
     f=(j/2)+(m*(i/2))
             g=dit[a,b]
             h=dit[d,f]
             u[i,j]=mean(c(g,h))}
             else if ( i%%2 == 0 && j%%2 == 1 ){  # vertical distances
              a=((i/2)-1)*m + ((j+1)/2)
              b=(m*i/2)+((j+1)/2)
              u[i,j]=dit[a,b]}
        else if( i%%2 == 1 && j%%2 == 0 ){  # horizontal distances
             a=((i-1)/2)*m + (j/2)
            b=((i-1)/2)*m + (j/2)+1
             u[i,j]=dit[a,b]}
}
}
       # Filling empty cells of u-matrix considering mean distances between neurons
for(i in 1:N){
        for(j in 1:M){
        if( i == 1 && (j%%2 == 1 && j > 1 && j < M )){  # Borde superior
             u[i,j]=(u[1,(j-1)]+u[2,(j-1)]+u[2,j]+u[2,(j+1)]+u[1,(j+1)])/5}
        else if( i == N && (j%%2 == 1 && j > 1 && j < M )){  # Borde inferior
            u[i,j]=(u[N,(j-1)]+u[(N-1),(j-1)]+u[(N-1),j]+u[(N-1),(j+1)]+u[N,(j+1)])/5}
        else if( j == 1 && (i%%2 == 1 && i > 1 && i < N )){  # Borde izquierdo
             u[i,j]=(u[(i-1),1]+u[(i-1),2]+u[i,2]+u[(i+1),1]+u[(i-1),2])/5}
        else if( j == M && (i%%2 == 1 && i > 1 && i < N )){  # Borde derecho
             u[i,j]=(u[(i-1),(M-1)]+u[(i-1),M]+u[i,(M-1)]+u[(i+1),(M-1)]+u[(i+1),M])/5}
        else if ( i == 1 && j == 1 ){ # top left
             u[i,j]=(u[1,2]+u[2,2]+u[2,1])/3}
        else if ( i == 1 && j == M ){ # top right
             u[i,j]=(u[1,(M-1)]+u[2,(M-1)]+u[2,M])/3}
        else if ( i == N && j == 1 ){ # bottom left
             u[i,j]=(u[(N-1),1]+u[(N-1),2]+u[N,2])/3}
        else if ( i == N && j == M ){ # bottom right
             u[i,j]=(u[N,(M-1)]+u[(N-1),(M-1)]+u[(N-1),M])/3}
```

```
        else if (i%%2 == 1 && j%%2 == 1 && i != N && i != 1 && j !=M && j !=1){
             u[i,j]= (u[(i-1),(j-1)]+u[(i-1),j]+u[(i-1),(j+1)]+u[i,(j-1)]
             +u[i,(j+1)]+u[(i+1),(j-1)]+u[(i+1),j]+u[(i+1),(j+1)])/8}
}
        }
    return(u)
}
# Defining function to visualize and save U-matrix mantaining dimensions
umpic<-function(u){
        # New color palette for u-matrix
        qual_pal<-colorRampPalette(brewer.pal(6,"Set1"))(255)
x11()
par(mar = rep(0, 4))
image(u, axes = FALSE, col = qual_pal) # displaying u-matrix
name= paste("umat",N,"x",M,date(),sep="_")
dev.copy(png,name, width=N, height=M) # storing it in working directory
dev.off()
}

u= umatrix(somimg)

#output for region growing algorithm
umpic(u)

#output with legend and title
levelplot(u,colorkey=list(space='bottom'), main="U-matrix of SOM 100 x 100 neurons",
          col.regions = qual_pal,regions=TRUE,xlab="",ylab="")

### Next step: Region Growing segmentation over U-matrix ###
### To be performed in ImageJ Package #####################
### as many regions as desired classes ####################

# Import regions in tiff format from ImageJ
regs<-raster("U11.tif")
str(regs)
# displaying u-matrix
image(regs,xlab="",ylab="", col = qual_pal,main="Regionalized U-matrix (11 seeds)" )
regions<-as.matrix(regs)

#vect<-as.factor(regions) # vector of u-matrix cells with corresponding region

# Extracting corresponding class (region) of neurons of output layer
neu<-vector()
for(i in 1:N){
    for(j in 1:M){
        ag = regions[i,j]
        if( i%%2 == 1 && j%%2 == 1 ){
            neu = append(neu,ag)}
}
}
str(neu)

# Creating a dataframe with neuron id and corresponding region
aidis<-seq(1:di)
neufdf<-cbind(as.factor(neu),aidis)
```

```
# neuron_id and corresponding region from region growing
colnames(neufdf) <- c( 'region', 'neuron')
vhgb<-as.data.frame(neufdf)

# Creating a dataframe with winning neuron per pixel id and corresponding region

idpix<-1:nrow(tb)
pixclass<-cbind(wnpp,idpix)
colnames(pixclass) <- c( 'neuron','pixel_id') # pixel_id and winning neuron from som
diga<-as.data.frame(pixclass)

# Using "merge" to join pixels and regions
vig <- merge(diga,vhgb,all.x=TRUE)
rext<-raster("s1.tif") # converting it to raster
plot(rext)
dim(vig)

# Creating the clustered image with geo-parameters
clist<-cbind(vig$pixel_id,vig$region)
colnames(clist) <- c( 'pix_id','region')
olist<-clist[order(clist[,1],clist[,2]), ]
rr<-nrow(img)
cc<-ncol(img)
c_list<-matrix(olist[,2],nrow=cc,byrow=T)
c_img<-raster(c_list,xmn=rext@extent@xmin, xmx=rext@extent@xmax,ymn=rext@extent@ymin,
             ymx=rext@extent@ymax, crs=rext@crs)

pd<-as(c_img,"SpatialPixelsDataFrame")
pd$b1f<-factor(pd$layer)
qcols<-c(brewer.pal(8,"Set1")[1:8],brewer.pal(3,"Dark2")[1:3])

p1<-spplot(pd,zcol=names(pd)[2],col.regions=qcols,colorkey=list(space='right'),
          pretty=TRUE,scales=list(draw=TRUE),main="Unsupervised 11 Classes")
p1

# Exporting the clusters as tiff image
writeRaster(c_img,"11_classes.tif", overwrite=TRUE)
```

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