HIERARCHICAL LAND USE AND LAND COVER CLASSIFICATION OF SENTINEL 2-A IMAGES AND ITS USE FOR CORINE SYSTEM

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ABSTRACT

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The aim of this thesis is to investigate the potential of Sentinel-2 satellite for land use and land cover mapping. The commonly known supervised classification algorithms, support vector machines (SVMs) and maximum likelihood classification, are adopted for investigation along with a hierarchical classification model CORINE. The main classes for land cover and mapping are selected as *water*, *vegetation*, *built-up* and *bare-land* in the first level, which is followed by *inland water, marine water, forest/meadow, vegetated agricultural land, barren land and non-vegetated agricultural land* in the second level. The study area for the experiments are selected as the two biggest cities of Turkey, namely Ankara and Izmir, providing sufficient number of classes for comparison purposes. During the utilized methodology, water and vegetation are first extracted by using the normalized difference water and vegetation indexes. Then, sufficient number of pixels are collected from the remaining parts for the first and second level classifications to perform a training and comparison for supervised learning algorithms. The experimental results first indicate that the support vector machines are significantly superior to the maximum likelihood classification with an average of 8 percent accuracy rates. Second, the hierarchical classification is also superior to non-hierarchical classification with the gains between 4 to 10 percent. The overall accuracy rates of the proposed hierarchical methodology are obtained as 85 % and 84 % for the first level classes and 84 % and 72 % for the second level classes, respectively for Izmir and Ankara.

Keywords: Sentinel-2, land use land cover, support vector machine, hierarchical classification, textural features

ÖZ

SENTİNEL-2 GÖRÜNTÜLERİNİN HİYERARŞİK YÖNTEM İLE ARAZİ KULLANIMI VE ARAZİ ÖRTÜSÜ SINFLANDIRILMASININ YAPILMASI VE CORINE SİSTEMİNDE KULLANILMASI

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Bu tezin amacı Sentinel-2 uydusunun arazi kullanımı ve arazi örtüsü haritalaması için potansiyelini araştırmaktır. En çok kullanılan sınıflandırma algoritmaları, destek vektör makineleri (SVM'ler) ve enbüyük olabilirlik algoritması, CORINE hiyerarşik sınıflandırma modeliyle birlikte incelenmek üzere çalışılmıştır. Arazi örtüsü ve haritalama için ana sınıflar, ilk aşamada *su, bitki örtüsü, yapılı alan* ve *çıplak arazi* olarak seçilmiştir. İkinci aşamada bunu, *karasal su, deniz suyu, orman / çayır, bitki örtülü tarım arazisi, kısır topraklar* ve *bitki örtüsüz tarım arazisi* izler. Deneyler için çalışma alanı, karşılaştırma amacıyla yeterli sayıdaki sınıfları sağlayan Türkiye'nin en büyük şehirlerinden ikisi, Ankara ve İzmir seçilmiştir. Kullanılan metodoloji sırasında su ve bitki örtüsü ilk önce normalleştirilmiş fark su indeksi ve normalleştirilmiş fark vejetasyon indeksi kullanılarak çıkartılmıştır. Ardından, öğreticiyle öğrenme algoritmaları için bir eğitim kümesi seçilmiştir. Karşılaştırma yapmak için birinci ve ikinci düzey sınıflandırmalar için kalan parçalardan yeterli sayıda piksel toplanmıştır. Deneysel sonuçlar ilk olarak destek vektör makinelerinin, enbüyük olabilirlik algoritmasından yüzde 8 daha yüksek performans gösterdiğini saptamıştır. İkinci olarak, hiyerarşik sınıflandırma, hiyerarşik olmayan sınıflamadan daha iyi sonuç vermiştir. Bu sonuç yüzde 4 ile 10 arasında değişmiştir. Önerilen hiyerarşik metodolojinin genel doğruluk oranları sırasıyla İzmir ve Ankara için birinci seviye sınıflarında %85 ve %84, ikinci seviye sınıflarında %84 ve %72 olarak elde edilmiştir.

Anahtar kelimeler: Sentinel-2, arazi kullanımı ve arazi örtüsü, destek vektör makinaları (SVM), hiyerarşik sınıflandırma, doku yöntemleri

To my mother and my father

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LIST OF ABBREVIATIONS

LULC	Land Use Land Cover
EO	Earth Observation
UCS	Union of Concerned Scientists
FAO	Food and Agriculture Organization
USGS	United States Geological Survey
CORINE	Coordination of Information on the Environment
ML	Maximum Likelihood
SVM	Support Vector Machine
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
PCT	Principal Component Transform
PCA	Principal Component Analysis
MSI	Multispectral Imager
SNAP	Sentinels Application Platform
ESA	European Space Agency
ROI	Region of Interest
RGB	Red Green Blue

CHAPTER 1

INTRODUCTION

Land use and land cover are frequently used terms in the remote sensing area. Land use defines the purpose of the land without defining the land cover. For example, land use for wildlife habitat for animals can be arranged in forests, seas or barren land. On the other hand, the land cover defines the things (forest, sea, lake, urban area, etc.) on the physical land without defining the land use purpose. For example, forested areas can be used for agriculture, timber production or wildlife habitat but those usages do not concern land cover type. In short, land use is the usage of the land by human beings and land cover is the coverage of the Earth's surface with the natural or artificial structures.

Land use and land cover maps are used for various areas, companies and governmental departments, municipalities and ministries. In today's world, satellite images are one of the fastest ways to see the land use and land cover of a specific area and nearly all countries are working on continuously to having their own satellite. The use of earth observation (EO) for LULC mapping has become widespread due to developments in EO technologies. LULC maps are created by classification of images which are aerial photographs or satellite images in general. At the end of 2016, there are 1459 satellites operating in the Earth's orbit. One of the newest ones is Sentinel-2 (Union of Concerned Scientists, 2017) whose mission objective is described as EO. However, images from the new satellite sensors require new classification algorithms to be developed as each satellite sensor has different spatial and spectral characteristics.

Spatial resolution is one of the most important characteristics of a satellite sensor and can be divided into three groups as a high-resolution sensor (<10m), medium resolution sensor (10-100m) and low-resolution sensor (>100m). Ideal requirements of satellite are defined by the information requirements in the study or experiment. For classical LULC mapping, low-resolution sensors are not being preferred because land cover elements tend to be discrete individual landscape elements. Therefore, low or medium resolution sensors are recommended. Area of region of interest should be taken into account while choosing the suitable spatial resolution (Wulder et al., 2008). Spectral resolution is the second most important characteristics of a satellite sensor. Spectral coverage is determined by the classification classes. Multispectral sensors can be as successful as hyperspectral sensors depending on LULC classes.

EO missions are until now commonly done by LANDSAT, SPOT, IRS, IKONOS, MODIS, NOAA-AVHRR and RADARSAT. The spatial resolutions of these satellites are varying between 1m to 1100m and spectral resolutions are changes from one band (panchromatic) to multispectral. Sentinel 2 is launched as a new satellite in June 2015 to support and complement the missions of existing satellites for EO. It provides a number of different resolutions (10m, 20m and 30m) which is better than LANDSAT in RGB and infrared bands. While its spectral bands are the combination of some of the existing EO satellites (Manakos & Lavender, 2014), it also includes extra spectral bands specially tailored for iron minerals and water vapor. In addition, its public availability and global coverage in every 5 days make its usage more effective and widespread for EO purposes such as climate change, natural hazards and emergency management.

LULC mapping necessitates a definition of classification hierarchy. There are three well-known LULC hierarchies, including the one proposed by the Food and Agriculture Organization of the United Nations (FAO), by the United States Geological Survey (USGS) and the other by the Coordination of Information on the Environment of the European Union (CORINE) (Kleeschulte & Büttner, 2006). While FAO’s hierarchy is mainly based on soil types, USGS’s hierarchy has only two levels, which is not very suitable for a hierarchical classification methodology.

In this thesis, CORINE hierarchy, which is accepted in Europe and Turkey, is adopted for the utilization of hierarchical classification methods with its sufficiently detailed classes for its defined 3-level hierarchy. This hierarchy involves the main classes for land cover and land use ranging from inland water to non-vegetated agricultural land. More specifically, these classes are selected as *water*, *vegetation*, *built-up* and *bare-land* in the first level, which is followed by *inland water*, *marine water*, *forest/meadow*, *vegetated agricultural land*, *barren land* and *non-vegetated agricultural land* in the second level.

The process of LULC mapping first requires the selection of the classification algorithm. Classification algorithms are divided into two, which are referred as unsupervised and supervised classification methods. Among these methods, *Maximum likelihood*, *k-means clustering*, *isodata clustering*, *minimum distance*, *support vector machine* and *decision tree classification* are commonly known techniques used in LULC studies (Richards & Jia, 2006). The details of these algorithms can be found in Chapter 2.

Until now, LULC mapping are performed by using other satellites but the potential of the Sentinel 2 satellite for this purpose with supervised learning algorithms are not explored in detail. This thesis investigates the potential of hierarchical supervised classification methods on Sentinel-2 images for land use and land cover mapping. The detailed objectives of the thesis are stated in the following subsection.

1.1. Objective and Contributions of the Thesis

The main objective of this thesis is to create a LULC map and to test and reveal the capabilities of the newly launched Sentinel-2 sensor for EO. For that purpose, hierarchical supervised classification methods are used and compared. In addition to the spectral information of Sentinel 2 images, textural features are also extracted and integrated to compare the classification accuracies. The contributions of the thesis can be listed as follows:

- One of the main contribution of this thesis is to compare the effectiveness of hierarchical classification system on Sentinel-2 data with one-step non-hierarchical classification system.
- The second contribution is to compare basic supervised classification methods, namely support vector machine and maximum likelihood classification, and to reveal the better methods to be utilized with Sentinel-2 data.
- Third, the integration of textural features to the spectral bands of Sentinel-2 images is performed and the performance of such an integration is revealed in terms of the classification accuracies.
- Fourth, the performance of the proposed hierarchical supervised classification methods for LULC mapping are tested and pointed out for two of the biggest cities of Turkey, namely Ankara and İzmir.
- Last but not least, the utilization of the proposed hierarchical methodology for the classification of basic classes in Corine system is indicated both for the first level classes including *water, vegetation, built-up* and *bare land,* and for the second level classes, including *inland water, marine water, forest/meadow, vegetated agricultural land, barren land* and *non-vegetated agricultural land.*

1.2. Outline of the Thesis

This thesis includes five chapters that cover the corresponding subjects in a systematized way. A brief description of each chapter is as follows. In Chapter 2, past studies about LULC mapping, LULC mapping with Sentinel-2, classification methods used in LULC mapping and accuracy assessment are specified. After that, in Chapter 3, the methodology of the study is presented. In Chapter 4, study areas and practical approach of recommended algorithm and methodology to those areas are given. Finally, in Chapter 5, results of the study for each area, conclusion and recommendations of the study are given.

CHAPTER 2

LITERATURE REVIEW

LULC maps are used for various areas, companies and governmental departments, municipalities and ministries. Satellite images are one of the fastest ways to see the LULC of specific area. The previous researches on LULC mapping is mainly handle the problem in two ways. First approach is, with the same classification algorithm, comparing two or more satellite data. Second, same satellite data is compared with two or more algorithms or methods. In this study second approach is preferred. More specifically, the Sentinel-2 data is first used for comparing Corine's proposed hierarchical levels with non-hierarchical one-step classification method. Secondly the performance of two different classification algorithms are used, namely SVM and ML. Details of mentioned hierarchy and algorithms are given in Chapter 2.

2.1. LULC Hierarchy

LULC mapping has come to the fore more than half century ago. Till then agencies, government and commercial companies started to work LULC maps independently. Without coordination, efforts are duplicated, or data have no value at all. This brings the idea of standardization of classification results. In general, the ideal classification hierarchy cannot be produced since perspectives of classification processes are subjective. Therefore, proposed classification hierarchy should cover and satisfy general classification studies (Anderson, Hardy, Roach, & Witmer, 1976). There are three well-known classification hierarchies that are used internationally. Those are the USGS, FAO and CORINE classification systems.

Hierarchies of USGS, FAO and CORINE can be seen in Figure 1, Figure 2 and Table 1 respectively. USGS and CORINE have common classes in level one but CORINE describes subclasses in more detail in level two and level three. USGS cannot go into details after level two. Both classification hierarchies are simply designed and are easy to understand. On the other hand, FAO defines classes as “vegetated” or “non-vegetated” in the first level. It seems simple but after going into subclasses, even the height of the vegetation is important. Using FAO becomes too complex for a medium resolution satellite. Lastly, non-vegetated areas are not described in detail in FAO. USGS is used in the United States, while FAO and CORINE are generally used in Europe (Giri, 2012) (Anderson et al., 1976) (Manakos & Lavender, 2014). For these reasons, CORINE hierarchy is used in this study.

Level I		Level II	
1	Urban or Built-up Land	11	Residential.
		12	Commercial and Services.
		13	Industrial.
		14	Transportation, Communications, and Utilities.
		15	Industrial and Commercial Complexes.
		16	Mixed Urban or Built-up Land.
		17	Other Urban or Built-up Land.
2	Agricultural Land	21	Cropland and Pasture.
		22	Orchards, Groves, Vineyards, Nurseries, and Ornamental Horticultural Areas.
		23	Confined Feeding Operations.
		24	Other Agricultural Land.
3	Rangeland	31	Herbaceous Rangeland.
		32	Shrub and Brush Rangeland.
		33	Mixed Rangeland.
4	Forest Land	41	Deciduous Forest Land.
		42	Evergreen Forest Land.
		43	Mixed Forest Land.
5	Water	51	Streams and Canals.
		52	Lakes.
		53	Reservoirs.
		54	Bays and Estuaries.
6	Wetland	61	Forested Wetland.
		62	Nonforested Wetland.
7	Barren Land	71	Dry Salt Flats.
		72	Beaches.
		73	Sandy Areas other than Beaches.
		74	Bare Exposed Rock.
		75	Strip Mines. Quarries, and Gravel Pits.
		76	Transitional Areas.
		77	Mixed Barren Land.
8	Tundra	81	Shrub and Brush Tundra.
		82	Herbaceous Tundra.
		83	Bare Ground Tundra.
		84	Wet Tundra.
		85	Mixed Tundra.
9	Perennial Snow or Ice	91	Perennial Snowfields.
		92	Glaciers.

Figure 1: USGS Classification Hierarchy (Anderson et al., 1976)

PRIMARILY VEGETATED						PRIMARILY NON-VEGETATED	
A11 - CULTIVATED & MANAGED LANDS		**A12 - NAT. & SEMI-NAT. TERRESTRIAL VEG.**		**A24 - NAT. & SEMI-NAT. AQUATIC VEG.**		**B15 - ARTIFICIAL SURFACES AND ASS. AREAS**	
I. A. Life Form of the Main Crop	code	I. A Life Form of the Main Strata	Code	I. A. Life Form of the Main Strata	Code	I. A. Surface Aspect	Code
Trees	A1	**Woody**	A1	**Woody**	A1	**Built Up**	A1
Broadleaved	A7	Trees	A3	Trees	A3	Linear	A3
Needleleaved	A8	Shrubs	A4	Shrubs	A4	Roads	A7
Evergreen	A9	**Herbaceous**	A2	**Herbaceous**	A2	Paved	A8
Deciduous	A10	Forbs	A5	Forbs	A5	Unpaved	A9
Shrubs	A2	Graminoids	A6	Rooted	A8	Railways	A10
Broadleaved	A7	**Lichens/ Mosses**	A7	Free Floating	A9	Comm. Lines/Pipelines	A11
Needleleaved	A8	Lichens	A7	Graminoids	A6	Non-Linear	A4
Evergreen	A9	Mosses	A9	**Lichens/Mosses**	A7	Industrial a/o Other	A12
Deciduous	A10	A. Cover		Lichens	A10	High density	A14
Herbaceous	A3	**Closed** (> 70-60%)	A10	Mosses	A11	Medium Density	A15
Graminoids	A4	**Open** (70-60 - 20-10%)	A11	A. Cover		Low Density	A16
Non-Graminoids	A5	(70-60 - 40%)	A12	**Closed** (> 70-60%)	A12	Scattered density	A17
Urban Vegetated Area(s)	A6	(40-20 - 10%)	A13	**Open** (70-60 - 20-10%)	A13	Urban Areas	A13
Parks	A11	**Closed to Open** (100 -15%)	A20	**Closed to Open** (100-15%)	A20	High density	A14
Parkland	A12	(100-40%)	A21	(100-40%)	A21	Medium Density	A15
Lawns	A13	**Sparse** (20-10 - 1%)	A14	(70-60 - 40%)	A12	Low Density	A16
B. Spatial Aspect - Size		(<20-10 - 4%)	A15	(40-20 - 10%)	A15	**Non Built Up**	A2
Large-to Medium-Sized Field(s)	B1	Scattered (4-1%)	A16	**Sparse** (20-10 - 1%)	A16	Waste Dump Deposit	A5
Large-Sized Field(s)	B3	B. Height		(<20-10 - 4%)	A17	Extraction Sites	A6
Medium-Sized Field(s)	B4	**7-2 m** (for Woody)	B1	Scattered (4-1%)	A18	A. Built-Up Object	
Small-Sized Field(s)	B2	**>30-3 m** (for Trees)	B2	B. Height		(scroll list with pre-defined objects)	
B. Spatial Aspect - Distribution		>14 m	B5	**7-2 m** (for Woody)	B1		
Continuous	B5	14-7 m	B6	**>30-3 m** (for Trees)	B2		
Scaterred Clustered	B6	7-3	B7	>14 m	B5	**B16 - BARE AREAS**	
Scattered Isolated	B7	**5-0.3 m**	B3	14-7 m	B6	I. A. Surface aspects	Code
		5-0.5 m	B14	7-3 m	B7	**Consolidated**	A1
II. C. Crop Combination		5-2 m	B8	**5-0.3 m**	B3	Bare Rock a/o Coarse Frgm.	A3
Single Crop	C1	2-0.5 m	B9	5-0.5 m	B14	Bare Rock	A7
Multiple Crop	C2	<0.5 m	B10	5-2 m	B8	Gravel/Stones/Boulders	A8
One Additional Crop	C3						

Figure 2: FAO Classification Hierarchy (Bach et al., 2014)

Table 1: CORINE Land Cover ((Kleeschulte & Büttner, 2006)

Level 1	Level 2	Level 3
1 Artificial surfaces	11 Urban fabric	111 Continuous urban fabric
		112 Discontinuous urban fabric
	12 Industrial, commercial and transport units	121 Industrial or commercial units
		122 Road and rail networks and associated land
		123 Port area
		124 Airports
	13 Mine, dump and construction sites	131 Mineral extraction sites
		132 Dump sites
		133 Construction sites
	14 Artificial, non-agricultural vegetated areas	141 Green urban areas
		142 Sport and leisure facilities
2 Agricultural areas	21 Arable land	211 Non-irrigated arable land
		212 Permanently irrigated land
		213 Rice fields
	22 Permanent crops	221 Vineyards
		222 Fruit trees and berry plantations
		223 Olive groves
	23 Pastures	231 Pastures
	24 Heterogeneous agricultural areas	241 Annual crops associated with permanent crops
		242 Complex cultivation patterns
		243 Land principally occupied by agriculture, with significant areas of natural vegetation
		244 Agro-forestry areas
3 Forest and semi natural areas	31 Forests	311 Broad-leaved forest
		312 Coniferous forest
		313 Mixed forest
	32 Scrub and/or herbaceous vegetation association	321 Natural grasslands
		322 Moors and heathland
		323 Sclerophyllous vegetation
		324 Transitional woodland-shrub
	33 Open spaces with little or no vegetation	331 Beaches, dunes, sands
		332 Bare rocks
		333 Sparsely vegetated areas
		334 Burnt areas
		335 Glaciers and perpetual snow

Table 1 (cont'd)

4 Wetlands	41 Inland wetlands	411 Inland marshes
		412 Peat bogs
	42 Maritime wetlands	421 Salt marshes
		422 Salines
		423 Intertidal flats
5 Water bodies	51 Inland waters	511 Water courses
		512 Water bodies
	52 Marine waters	521 Coastal lagoons
		522 Estuaries
		523 Sea and ocean

2.2. LULC Classification Algorithms

Image classification algorithms are examined in three main categories, namely "unsupervised classification", "semi-supervised classification" and "supervised classification". Each category has its own unique advantages and disadvantages. In this section, brief description of these categories are presented.

2.2.1. Unsupervised Classification Algorithms

Unsupervised classification is based on clustering the image data with analytic procedures without giving any information that can be used before clustering. Information is given before clustering is called "training set", which is used in supervised classification. Unsupervised classification algorithm takes spectral data and divides it into a number of distinct classes or clusters. Then each class or cluster is labeled. At the end of this procedure, a thematic map is created by the algorithm. However, this does not mean that each class represents different ground cover types on the map. With the guidance of the spatial distribution of the labels, merging or dividing of the classes is done by the analyst. Since training the classifier is time-consuming, unsupervised classification is used in need of a quick labeling assignments or for uncomplicated broad land covers such as water (Richards & Jia, 2006).

Unsupervised classification is advantageous since it is time-saving while training the data. It also reduces the analyst bias. On the other hand, spectral classes do not always correspond to land cover classes.

Clustering is the fundamental part of the unsupervised classification. Clustering groups the pixels in an n-dimensional space by their similarity. In this point, the similarity metric is needed. Although many similarity metrics or measures have been proposed, the most commonly used ones are city block (Manhattan or L1) distance and Euclidean (L2) distance. Suppose X_1 and X_2 are the measurement vectors of two pixels. Then, L1 and L2 distances of X_1 and X_2 are given in Equation 1 and Equation 2 respectively.

$$dL_1(x_1, x_2) = \sum_{n=1}^{N} |x_{1n} - x_{2n}| \tag{1}$$

$$\begin{aligned} dL_2(x_1, x_2) &\triangleq \|x_1 - x_2\| \\ &= \{(x_1 - x_2).(x_1 - x_2)\}^{\frac{1}{2}} \\ &= \{(x_1 - x_2)^T (x_1 - x_2)\}^{\frac{1}{2}} \\ &= \left\{\sum_{n=1}^{N} (x_{1n} - x_{2n})^2\right\}^{\frac{1}{2}} \end{aligned} \tag{2}$$

K-means clustering is one of the most commonly used methods in unsupervised LULC applications. User-specified distance metrics and cluster numbers are needed for k-means algorithm. Mean of the pixel vectors are assigned to the arbitrary center of the cluster. In this way, the first set of clusters are generated. Then the pixel vectors are reassigned to the cluster with the closest mean and the means are recalculated. This procedure is repeated until no further movement of pixels is possible between cluster sets or some stop rule is implemented. After clustering is stopped, classes are ready for post-process operations. Each class is checked whether merging or deleting is necessary; and lastly, each one is assigned with labels (Richards & Jia, 2006).

2.2.2. Semi-Supervised Classification

The main theory behind semi-supervised classification, or hybrid classification, is that supervised classification techniques are used for supplementing the results of unsupervised classification.

Clustering is used to determine the spectral clusters as done in the unsupervised classification. But this time, representative subset of data is used for time saving reasons. Statistics of the spectral classes are produced at this point. For reliable classification, feature selection is performed to determine the features (bands) needed. Supervised part is started up to this point; and the entire image is classified with a supervised algorithm. Trained data is the representative subset of the original image (Richards & Jia, 2006).

2.2.3. Supervised Classification Algorithms

Classes are chosen in the first step of supervised classification. While choosing the classes, proposed hierarchy for first and second level classes of LULC should be taken into account. Training data is prepared after the classes are determined. Pure pixels must be taken while creating the test set. With this test set, parameters or constants are generated. If the algorithm needs clear-cut parameters like mean vector or covariance matrix, then it is called "parametric supervised classification". In contrast, if the algorithm works with constants instead of parameters, then it is called "non-parametric supervised classification". At this point, parameters or constants are determined, and the classifier becomes trained. Every pixel is labeled with the trained classifier and a thematic map is produced. These are the general practical steps of supervised classification (Richards & Jia, 2006).

Looking from the remote sensing and image classification point of view, "maximum likelihood" is one of the most used supervised classification algorithms. Most of the LULC maps are created by this method. Let the classes be shown by ω_i, $i=1\ldots M$, where “M” is the number of classes and “x” is a pixel with measurement vector while determining the classes. Conditional probability is given in Equation 3.

$$p(\omega_i|x), i = 1 \dots M \tag{3}$$

The vector x is the brightness value of each band and describes the pixel in spectral space. The probability defined in Equation 3, describes the likelihood of ω_i being the correct class for the pixel x in the spectral domain. If a complete set of (ω_i|x) for each class is known, classification can be done according to the decision rule given by Equation 4, which is called as “maximum posteriori”.

$$x \in \omega_i \ if \ p(\omega_i|x) > \ p(\omega_j|x) \ for \ all \ j \neq i \tag{4}$$

The problem is, maximum posteriori probabilities, p(ω_i|x), are not known; however, p(x|ω_i) is known from the training set of pixels. Bayes’ theorem is used for determining the p(ω_i|x) from p(x|ω_i), equation of which is given in Equation 5.

$$p(\omega_i|x) = p(x|\omega_i)\mathrm{p}(\omega_i)/p(x) \tag{5}$$

By substituting terms, decision rule becomes:

$$x \in \omega_i \ if \ p(x|\omega_i)p(\omega_i) > \ p(x|\omega_j)p(\omega_j) \ for \ all \ j \neq i \tag{6}$$

Then, taking natural logarithm of both sides, decision rule does not change in the basics of mathematic:

$$\mathrm{g}_i(x) = \ln\{p(x|\omega_i)p(\omega_i)\} = \ln p(x|\omega_j) + lnp(\omega_j) \tag{7}$$

Since the natural logarithm is a monotonic function, substituting equation 5 then taking natural logarithm of both sides, decision rule does not change in the basics of mathematic. By substituting terms in Equation 6 with 7 gives the decision rule of the maximum likelihood classification as in Equation 8.

$$x \in \omega_i \; if \; g_i(x) > \omega_j(x) \; for \; all \; j \neq i \tag{8}$$

To develop a maximum likelihood classifier, selection of a particular probability model is required. Most common model is the Gaussian Distribution model, by which the classes of pixels are distributed normally. Normal distribution of classes is not observed in reality, but it is simple, mathematically easy to handle; and its multivariate properties are well-known.

$$p(x|\omega_i) = (2\pi)^{-N/2}|C_i|^{-1/2}\exp\{-1/2(x - m_i)^T {C_i}^{-1}(x - m_i)\} \tag{9}$$

For n-dimensional space, gaussian distribution function is given in Equation 9, where m_i and C_i are the mean vector and covariance matrix of the data in class ω_i, respectively. Substituting Equation 9 into Equation 7. Then, taking the natural logarithm of both sides, decision rule does not change in the basics of mathematic. The discriminant function is obtained as in Equation 10.

$$g_i(x) = -\frac{1}{2}N \ln 2\pi - \frac{1}{2}ln|C_i| - \frac{1}{2}(x - m_i)^T {C_i}^{-1}(x - m_i) \ln p(\omega_i) \tag{10}$$

The first term is removed since it is not class-dependent, and the last term is assumed equal, therefore both terms are omitted. The Gaussian Maximum Likelihood Classifier is given in Equation 11 below:

$$g_i(x) = ln|C_i| - (x - m_i)^T {C_i}^{-1}(x - m_i) \tag{11}$$

This classifier determines the pixels' classes by checking their highest probability of belonging to each class. LULC map is created by labeling each pixel with the gaussian maximum likelihood classifier.

Parallelepiped classifier is another commonly used supervised classification method. In this method, lower and upper brightness values are found for each training set of pixels. Those values define a multi-dimensional box which is called “parallelepiped” and unlabeled pixels are labeled based on the parallelepiped their region is within. It is a very simple and fast supervised algorithm; but its accuracy of classification is not as good as other methods. A simple two-dimensional example diagram is given in Figure 3.

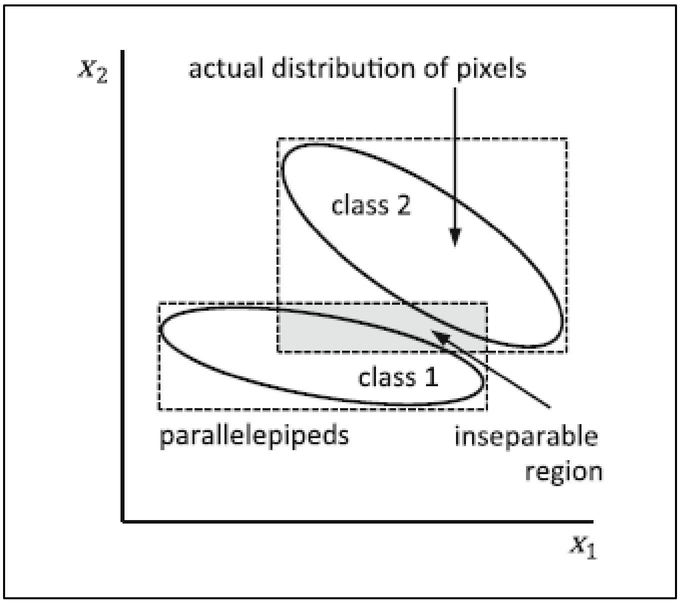


Figure 3: Parallelepiped Classification Example (Richards & Jia, 2006)

The method has some limitations. For instance, there can be gaps between parallelepiped regions or the parallelepipeds can coincide with each other. If there are gaps, classification of some pixels becomes impossible. In case of a coincidence, pixels cannot be separable from each other.

K nearest neighbor (k-NN) is another algorithm that is commonly used in LULC classification. It is simple but also time-consuming. According to the theory behind k-NN, pixels that are close to each other are assumed to be in the same class. A value, denoted by “k”, is selected for the closest neighborhood; and is considered for each pixel. Most crowded class label is given to the unknown pixel.

$$\sum_{i=1}^{M} k_i = k \tag{12}$$

In Equation 12, “M” represents the number of classes and “k_i” is the number of points in k nearest neighborhood. Accordingly, the discriminant function and the decision rule are given in Equation 13 and Equation 14, respectively.

$$g_i(x) = k_i \tag{13}$$

$$x \in \omega_i \; if \; g_i(x) > g_j(x) \; for \; all \; j \neq i \tag{14}$$

Support vector machine (SVM) is the most used supervised classification algorithm. Its success is mentioned before with examples. Before going into details of SVM, some basic concepts should be understood.

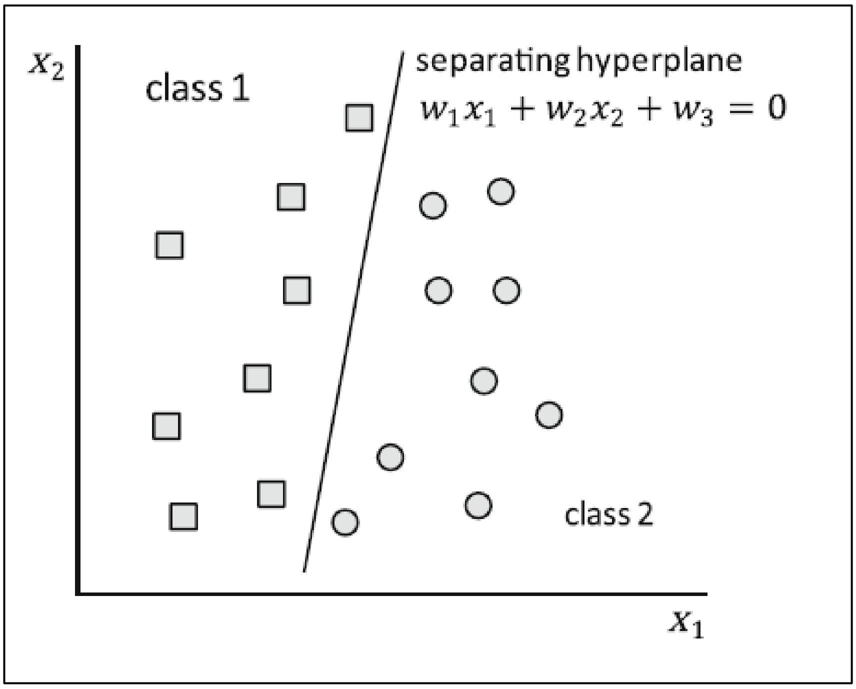


Figure 4: Two-Dimensional Spectral Space with Two Class Example (Richards & Jia, 2006)

An example of two-dimensional spectral space with two classes is given in Figure 4. The line in the example can either be a plane or a hyperplane. Basically, it is a decision surface and it can be expressed as; $w_1x_1+ w_2x_2+ w_3=0$; where x_i are the brightness value coordinates in spectral space and w_i are a set of coefficients, called weights. Number of weight is equal to number of channels in data plus one. In an N band or N channel data, the equation of surface is given in Equation 15 and Equation 16.

$$w_1x_1 + w_2x_2 + \cdots + w_Nx_N + w_{N+1} = 0 \tag{15}$$

Or

$$w^Tx + w_{N+1} \equiv w \cdot x + w_{N+1} = 0 \tag{16}$$

Pixel measurement vector and weight vector are denoted by “x” and “w”, respectively. Position of the separating plane is not known initially but it is found by training set of pixels. There is not a unique solution of the separating plane. In order to test the unknown pixels, x value is replaced by the pixel value. Then, if a pixel is on the left side of the hyperplane, equation becomes negative. If a pixel is on the right side of the plane, equation becomes positive then:

$$x\ \varepsilon\ hyperplane\ if\ w^Tx + w_{N+1} = 0$$
$$x \epsilon\ class\ 1\ if\ w^Tx + w_{N+1} > 0$$
$$x \epsilon\ class\ 2\ if\ w^Tx + w_{N+1} < 0$$

In Figure 5, a basic SVM example is given. It is a two-separable class classification problem in two-dimensional space. It is clearly seen that not all the instances (pixel values of remotely sensed image) are used for creating the hyper plane of SVM. The subset of training pixels that are near the margin are called support vectors, which define the hyper plane of maximum margin. If hyperplane satisfies those support pixels, by definition, distant/remote pixels must also be satisfied (Richards & Jia, 2006) (Manakos & Lavender, 2014).

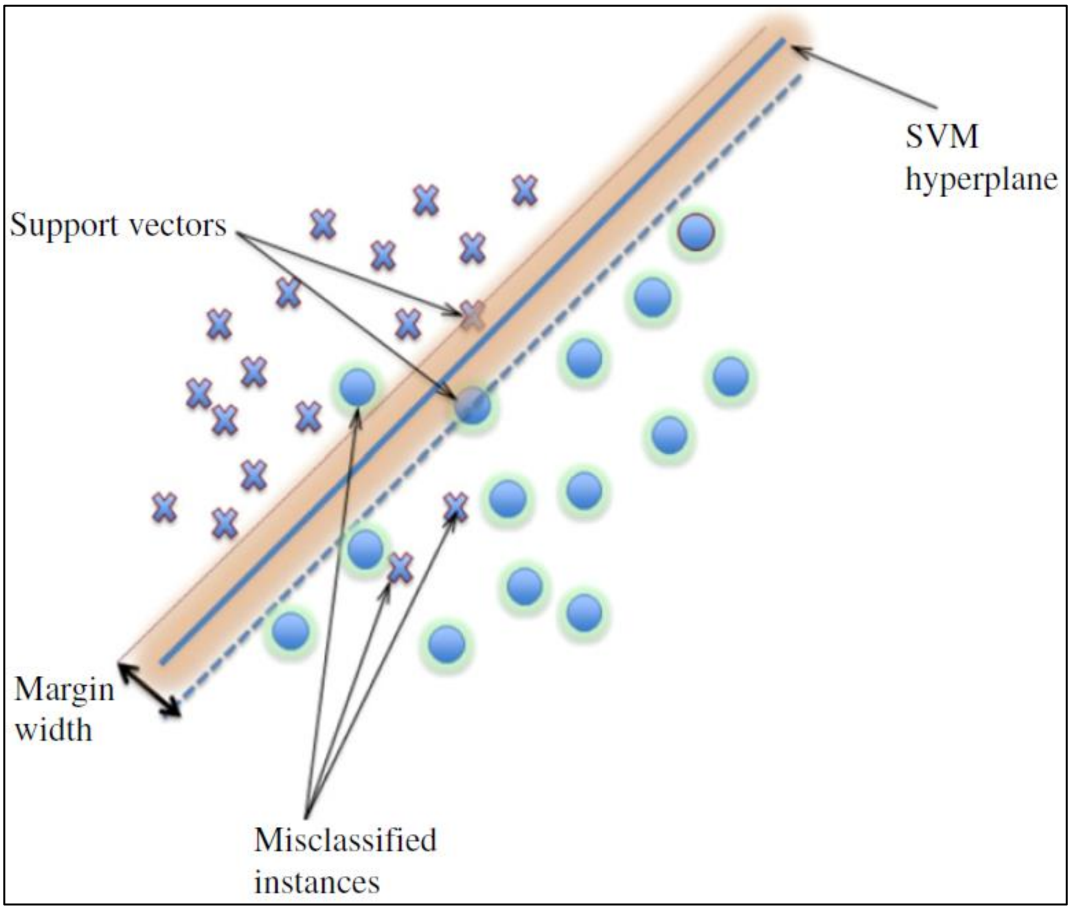


Figure 5: Linear Support Vector Machine Example (Mountrakis, Im, & Ogole, 2011).

Most distinctive property of SVM is its ability to classify with limited quality and/or quantity of training set. Compared to alternative methods like back propagating neural networks, SVM has tantamount accuracy with smaller training data set (Mountrakis et al., 2011).

2.3. Accuracy Assessment

At the very end of the classification, accuracy assessment should be done. To make sure that the objectives of the analysis are achieved, accuracy results should be attached. There are several ways of assessing the accuracy. The most common ones are testing set of pixels, creating error matrix, quantifying error matrix and the kappa coefficient.

Similar to choosing training set of pixels before classification, choosing the set of test pixels is the first step here. The test pixels should be independent from the training pixels and should be randomly distributed. Critical part of randomly distributed pixels can be area-weighted, which means that large classes will be represented by a large number of test pixels while small classes cannot be represented at all. To overcome this problem, stratified random sampling method can be used, which involves dividing image in strata and then choosing random pixels. Strata can be grid cells or any other dividable lines, but the most accurate one is dividing image by each class as a stratum. That way, area bias, which may lead inappropriate accuracy assessments for small classes, will be reduced.

After that the error matrix, also known as confusion matrix or contingency matrix, should be generated. Reference data classes can be represented by rows and thematic map classes can be represented by columns or vice versa. A simple error matrix example is given in Table 2.

Table 2: Simple Error Matrix Example (Richards & Jia, 2006)

		reference data classes			
		A	B	C	sum
thematic map classes	A	35	2	2	39
	B	10	37	3	50
	C	5	1	41	47
	Sum	50	40	46	136

The cells in the table represent where each reference class pixel and map class are common. Ideally, this matrix should be a diagonal matrix, which means every classified pixel should be classified by the classifier in correct class. The column of sums in the example table gives the total number of labelled reference pixels included per class. The row of sums gives the total number of pixels classified by classifier coming from a specific class in the set of random test pixels. Using those cells and sums, commission and omission errors should be calculated. Omission error indicates pixels that cannot be recognized by the classifier while commission error occurs when the classifier misclassifies the pixels. After their calculation, the sums should be converted to percentages. A calculation example is as follows;

For producer's accuracy		For user's accuracy	
A:	35/50=70.0%	A:	35/39=89.7%
B:	37/40=92.5%	B:	37/50=74.0%
C:	41/46=89.1%	C:	41/47=87.2%

And overall accuracy is;

Overall Accuracy = (35+37+41)/136=83.1%

Lastly, kappa coefficient should be calculated to show that accuracy assessment does not depend on chance. More specifically, kappa coefficient is a classifier measurement variable that appears with unbiased results from reference data and classifier output. A calculation example is as follows;

The classifier places:	the reference places:
39/136=0.287 of the pixels in class A	50/136=0.368 of pixels in class A
50/136=0.368 of the pixels in class B	40/136=0.294 of pixels in class B
47/136=0.346 of the pixels in class C	46/136=0.338 of pixels in class C

The probability of placing pixels in class A for both is: 0.287*0.368=0.106
The probability of placing pixels in class B for both is: 0.368*0.294=0.108
The probability of placing pixels in class C for both is: 0.346*0.338=0.117

In total, the probability of placing a pixel in the same class at random is sum of the three probabilities, i.e. 0.106+0.108+0.117=0.331, which is agreement of random chance of a pixel in the same class for one pixel. In contrast, correct classification is equal to overall accuracy, which is 0.831. The equation form of kappa coefficient is given in Equation 17 below:

$$\kappa = \frac{prob.of\ correct\ classification - prob.of\ chance\ agreement}{1 - prob.of\ chance\ agreement} \tag{17}$$

Calculation for the example table is κ= (0.831-0.331)/(1-0.331)=0.747. Meanings of the coefficient values are given in Table 3. In this example, the accuracy assessment can be regarded as "good accuracy assessment" in terms of kappa coefficient ranges (Richards & Jia, 2006).

Table 3: Suggested Ranges for Kappa Coefficient (Richards & Jia, 2006)

Kappa Coefficient	Classification can be regarded as
Below 0.4	Poor
0.41-0.60	Moderate
0.61-0.75	Good
0.76 - 0.80	Excellent
0.81 and above	Almost perfect

2.2. LULC Classification of Sentinel-2 images

There are many fields of study and research fields that utilize remotely sensed data. Landsat, SPOT, IKANOS and MODIS have spectral and/or spatial characteristics and mission objectives similar to those of Sentinel-2. Orbiting around the Earth's surface, these satellites enable studies in various fields like LULC classification, change detection, disaster management and different EO missions. Since Sentinel-2 data has been available only recently, there is not sufficient academic research on some study areas such as LULC classification. The recent research related to the Sentinel-2 include comparing Landsat-8 classification accuracies with Sentinel-2, sub-pixel feature detection evaluation between Landsat-8, SPOT-5 and Sentinel-2 and monitoring and observing biomass suitability of Sentinel-2, which are introduced in this section.

To evaluate newly launched Sentinel-2 image classification accuracies, Landsat-8 images were taken and studied together. For comparison, metropolitan area of Istanbul was chosen as the study area. In addition, two classification algorithms (ML and SVM) were applied to multispectral data to classify eight different land catagories using the same training set of pixels. As a result of this study, classification accuracy of Landsat-8 image was determined as 70.60% with ML and 81.67% with SVM. On the other hand, classification accuracy of Sentinel-2 image was recorded as 76.4 with ML and 84.17% with SVM. In the light of these classification accuracy results, two conclusions were drawn: one, Sentinel-2 performed better than Landsat-8; and two, SVM performed better than ML (Hale, Sertel, & Musaoğlu, 2016).

To measure the qualification of Sentinel-2, sub-pixel feature detection was studied. To compare the Sentinel-2 data, Landsat-8 and SPOT-5 data were also taken for the same regions. The results show that, Landsat-8 failed to detect some small landscape features due to spatial limitations. Likewise, SOPT-5 failed to detect some large landscape features due to spectral limitations. On the other hand, undetected objects were successfully detected by Sentinel-2 (Radoux et al., 2016).

Monitoring biomass is one of the EO missions. Mediterranean seagrasses, namely *Posidonia Ocianica* and *Cymodocea Nodosa* constitute the interest area of biomass studies; and therefore, that of Sentinel-2's. Sensors of Sentinel-2 are not designed for specific biomasses but they can be extracted from NDVI with the Sentinel-2's high spatial and temporal resolution. Results of the study suggest that the costal submarine habitats can be monitored by Sentinel-2 (Traganos & Reinartz, 2017).

CHAPTER 3

RESEARCH METHODOLOGY

Sentinel-2 is a newly launched satellite and a direct LULC classification study has not been done yet. In this study, to test the capabilities of the sensor for LULC map, a methodology is proposed.

Figure 6 shows the proposed hierarchical methodology. First Sentinel-2 data is taken, then for “water” class normalized difference water index (NDWI) is created. Thresholding the NDWI values comes up a conclusion about pixels, “not water” or “water”. “Water” pixels are introduced to a supervised classification algorithm and divided into second level classes, namely “inland water” and “marine water”. On the other hand, for “vegetation” class, normalized difference vegetation index (NDVI) is created with “not water” pixels. After thresholding is applied, second concussion about remaining pixels come to the fore. Those pixels are labeled as “vegetation” and “not vegetation”. For “vegetation” class, pixels are introduced to a supervised classification algorithm. This algorithm separates the pixels into two classes, namely “forest/meadow” and “vegetated agricultural land”. On the other side, “not vegetated” pixels are introduced to a supervised classification algorithm. Output of this algorithm is two new first level classes namely, “built up” and “bare land”. “Built up” pixels are same as in first and second level classification of this study. Lastly, “bare land” pixels are introduced to a supervised classification algorithm. Last classes of second level is determined with outputs of this algorithm namely, “barren land” and “non-vegetated agricultural land”.

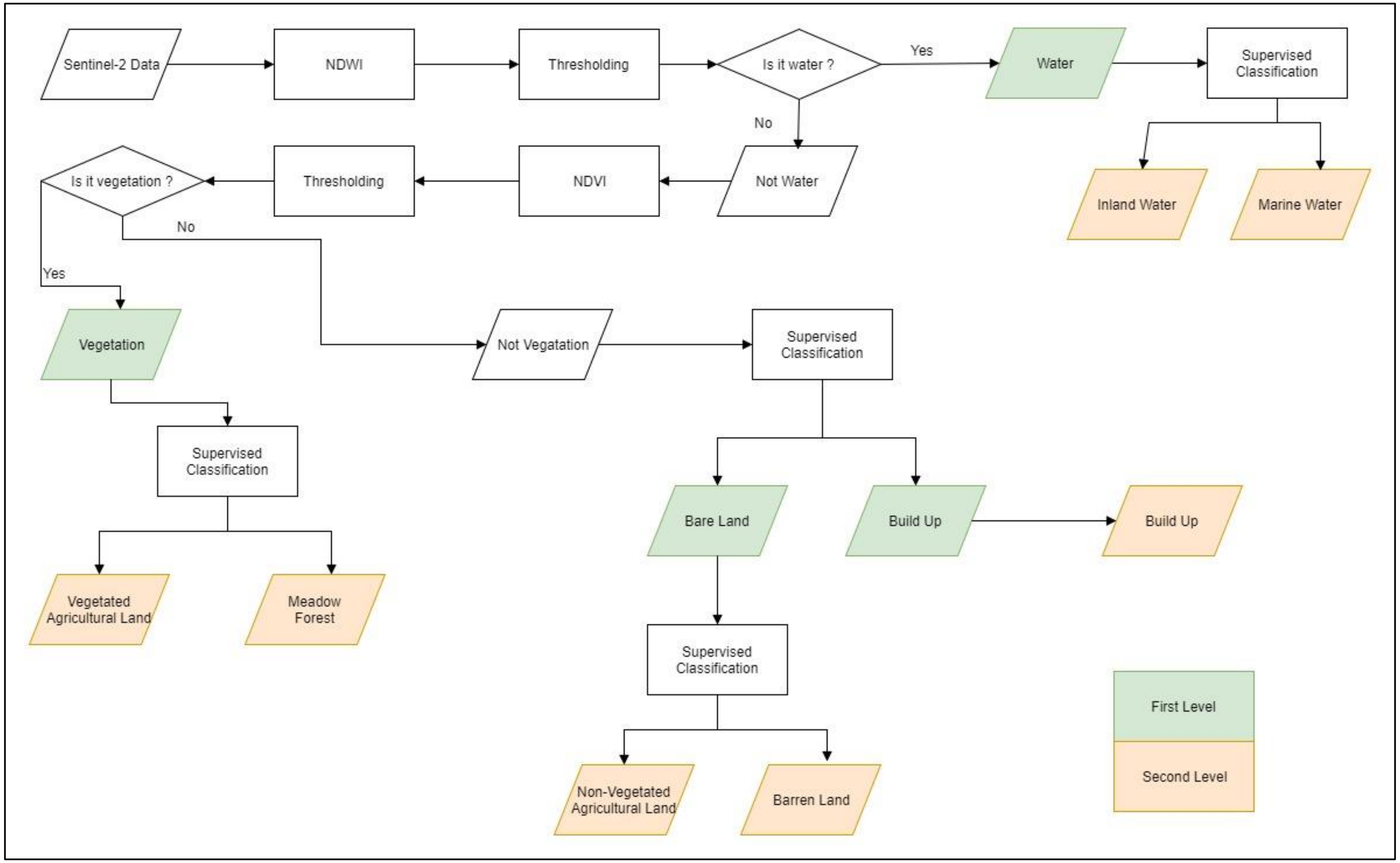


Figure 6: Classification Details of Study

Classes labeld from indexing and first supervised classification is called first level classes and labeled as, water, vegetation, built up and bare land.and represented with turquase, green, purple and dark brown respectively. First level classes are divided into more detailed second level classes with supervised classification method and labeled as inland water, marine water, forest/meadow, built up, barren land and non-vegetated agricultural land and represented with light blue, dark blue, dark green, light green, purple, brown and orange respectively.

Corine hierarcical levels and classes are contained by the classes of this study, level 1 and level 2. Color coding of each class is mentiond above is visulized and given in detally in Table 4.

In this thesis, 2^{nd} level classes are the last step of methodology. Those 2^{nd} level classes are contains Corine’s hierarcical classes. Inland water class contains Corine’s 41 and 51 and corresponding 3^{rd} level, marine water class contains Corine’s 42 and 52 and corresponding 3^{rd} level classes, forest/meadow class contains Corine’s 141, 142, 221, 222, 223, 231, 311, 312, 313, 321, 322, 323 and 324, vegetated agricultural lands contains Corine’s 241, 242, 243 and 244, built up class contains Corine’s 2^{nd} level 11, 12 and 13 and corresponding 3^{rd} level classes, barren land class contains Corine’s 331, 332, 333, 334 and 335, non-vegetated agricultural land class class contains Corine’s 211, 212 and 213. This methodology is specify only 2^{nd} level of Corine hierarchy. Further implementations for this methodology can further specify all 3^{rd} level of Corine hierarcy.

Table 4: Adopted Corine Hierarchy of the Study

Level 1	Level 2	Level 3
1 Artificial surfaces	11 Urban fabric	111 Continuous urban fabric
		112 Discontinuous urban fabric
	12 Industrial, commercial and transport units	121 Industrial or commercial units
		122 Road and rail networks and associated land
		123 Port area
		124 Airports
	13 Mine, dump and construction sites	131 Mineral extraction sites
		132 Dump sites
		133 Construction sites
	14 Artificial, non-agricultural vegetated areas	141 Green urban areas
		142 Sport and leisure facilities
2 Agricultural areas	21 Arable land	211 Non-irrigated arable land
		212 Permanently irrigated land
		213 Rice fields
	22 Permanent crops	221 Vineyards
		222 Fruit trees and berry plantations
		223 Olive groves
	23 Pastures	231 Pastures
	24 Heterogeneous agricultural areas	241 Annual crops associated with permanent crops
		242 Complex cultivation patterns
		243 Land principally occupied by agriculture, with significant areas of natural vegetation
		244 Agro-forestry areas
3 Forest and semi natural areas	31 Forests	311 Broad-leaved forest
		312 Coniferous forest
		313 Mixed forest
	32 Scrub and/or herbaceous vegetation association	321 Natural grasslands
		322 Moors and heathland
		323 Sclerophyllous vegetation
		324 Transitional woodland-shrub
	33 Open spaces with little or no vegetation	331 Beaches, dunes, sands
		332 Bare rocks
		333 Sparsely vegetated areas
		334 Burnt areas
		335 Glaciers and perpetual snow

Table 4 (cont'd):

4 Wetlands	41 Inland wetlands	411 Inland marshes
		412 Peat bogs
	42 Maritime wetlands	421 Salt marshes
		422 Salines
		423 Intertidal flats
5 Water bodies	51 Inland waters	511 Water courses
		512 Water bodies
	52 Marine waters	521 Coastal lagoons
		522 Estuaries
		523 Sea and ocean

Up until now, methodolgy is straight forward. After those analysis and labeling are done, efects of textural features are studied. Textural features are created and classified with same hierarchical order.

In Figure 7, extraction of textural features are given. To see the classification accuracy with only textural bands, those extracted bands are introduced in to the methodology before supervised classification algorithm part by their own. More detally, instead of giving the Sentinel-2 13 band data, extracted textural features inserted to the algorithm and, classification and labeling are done same way

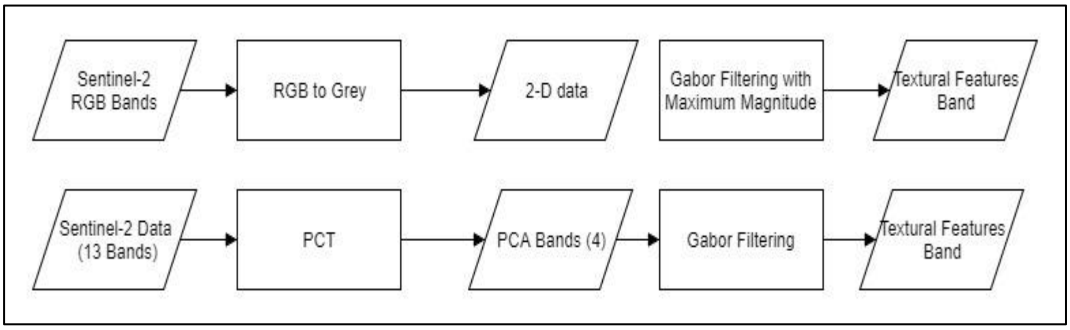


Figure 7: Extraction of Textural Features

Moreover, to see the effects of those textural features, all textural bands are merged with Sentinel-2 bands. Then methodology is repeated again. Instead of using only 13 band data, new 18 band data is introduced to supervised classification algorithm.

3.1. Data Collection

In general, mission objective of Sentinel-2 is EO. Sentinel-2 operation seeks to supply data for risk management, land use and land cover mapping, change detection, natural hazards, water management and so on. Scientists have designed Sentinel-2 to accolade Landsat and SPOT missions and increase the availability of data for users. Sentinel-2 gives a global coverage every five day. It is equipped with a multispectral imager (MSI) with 13 bands (Drusch et al., 2012).

Sentinel-2 has two satellites working together, namely "Sentinel-2A" and "Sentinel-2B". Both satellites are sun-synchronous, and their projected lifecycle is 7.25 years Swath width is 290km and MSI spatial resolution varies between 10m, 20m and 60m for different bands. Band configuration is given in Table 5 (ESA Sentinel-2 Team, 2010).

In data collection phase, ESA Sentinel Online website is used where all Sentinel data are provided free of charge to users. After logging into the website, drawing the region of interest on the world map gives all the available data for that region. By using the advance search tool, cloud percentage and other properties of data can be filtered. In this study, <1% cloud covered data is downloaded and used.

Table 5: Sentinel 2 Band Configuration(ESA Sentinel-2 Team, 2010).

Sentinel-2 Bands	**Central Wavelength (µm)**	**Resolution (m)**	**Bandwidth (nm)**
Band 1 – Coastal aerosol	0.443	60	20
Band 2 – Blue	0.49	10	65
Band 3 – Green	0.56	10	35
Band 4 – Red	0.665	10	30
Band 5 – Vegetation Red Edge	0.705	20	15
Band 6 – Vegetation Red Edge	0.74	20	15
Band 7 – Vegetation Red Edge	0.783	20	20
Band 8 – NIR	0.842	10	115
Band 8A – Narrow NIR	0.865	20	20
Band 9 – Water vapor	0.945	60	20
Band 10 – SWIR – Cirrus	1.375	60	20
Band 11 – SWIR	1.61	20	90
Band 12 – SWIR	2.19	20	180

The study area for the experiments are selected as the two biggest cities of Turkey. Ankara and Izmir, providing sufficient number of classes for evaluation ranging from inland water to non-vegetated agricultural lands. Because Sentinel-2 data is newly available, some of the available data are distorted, therefore both cities data is used from different date of capture. Data of Ankara and İzmir is captured on 27 April 2017 and 02 June 2017 respectively.

Date of acquisition can effect the classes such as some trees are not come into leaf therefore, some areas are classified as bare land instead of forest. Similarly, agricultural areas can have classified as non-vegetated agricultural land with respect to seed type in that area.

3.2. Preprocessing

Since radiometric, geometric and atmospherically corrected data is available, intensive preprocessing operations are not needed. Popular remote sensing software like ENVI, ArcMap, Erdas, OTB and MATLAB cannot read downloaded raw data. Therefore, Sentinel Application Platform (SNAP) is used for opening the image. Sentinel-2 bands have different resolutions from 10m to 30m which is given in Table 5. To export the data in a Tagged Image Format (TIF) format, all remote sensing software can read, resampling the data in same resolution is needed. After resampling the data to 10m resolution, data is ready for classification processes and introduced to software called ENVI.

3.1. First Level Classification

The first classification level of this study consisted of four main classes which are water, vegetation, bare land and built up. For classification of the first level, there were three pre-steps. The first step was creating normalized difference water index (NDWI), the second was creating normalized difference vegetation index (NDVI) and the third was masking the image with these indices. After these steps, SVM was hired for classification.

NDWI and NDVI are introduced in detail in Section 3.1.1. After creating NDWI and NDVI, histograms of indices are created. From those histograms, vegetation and water extraction is done by thresholding.

Thresholding with index base methods like NDWI and NDVI are given good results while classifying the image into binary image. Same as NDWI thresholding gives out water or not water output, NDVI thresholding gives vegetation or not vegetation output. There are different thresholding methods which optimizes the output. Thresholding without any method also gives out a successful output but it is relative to the expert who assign the threshold value. Even though, there can be small changes about the area, water and vegetation can be extracted by visually thresholding the histograms (El-Gammal, Ali, & Abaou Samra R.M., 2014) (Yang, Zhao, Qin, Zhao, & Liang, 2017) (Richards & Jia, 2006). In this study, thresholding is done without any optimization method.

These extracted features are used for masking the image. After masking the image one by one with the extracted features, a 3 new raw data are created. One has only water pixels with the original value and the rest of the pixels are zero, another one has only vegetation pixels with their original value and the remaining pixels have zero value; and the last one has only built up and bare land pixels with their original value and rest of the pixels have zero value.

With these three new raw data, SVM is used for separating the built up and bare land classes. After SVM classification is done, four classes are obtained separately in three data. Classification results are merged with each other and first level classification is finished.

To try to increase the classification accuracy, textural features is introduced to the data. In this study, some textural feature extractions are applied and used in classification. Details about textural feature extraction are given in Section 3.1.2. For this study, gabor filtering for textural extraction is applied. Textural features are extracted from five different data combinations which are; RGB image to gray image, first principal component, second principal component, third principal component and fourth principal component. A short introduction to principal components is given in Section 3.1.2.

These features are introduced like a new band of a data. Classification steps are applied to the textural features extracted from original data too to see if textural features are successful alone for classification and LULC map generation.

After applying these steps to textural features, original data and textural features are merged together. In the original data, there are 13 bands, while in the merged data, there are 18 bands since 5 different textural bands are created. All classification steps are again applied to the new 18 band data.

In Figure 8, different combinations of proposed methodology are given. In first part, only Sentinel-2 data is used. In second part, only extracted textural features are used. Last part combination of two data is used for classification. From that combination, capabilities of Sentinel-2 data, classification based on textural features and effects of textural features in accuracy of classification is observed.

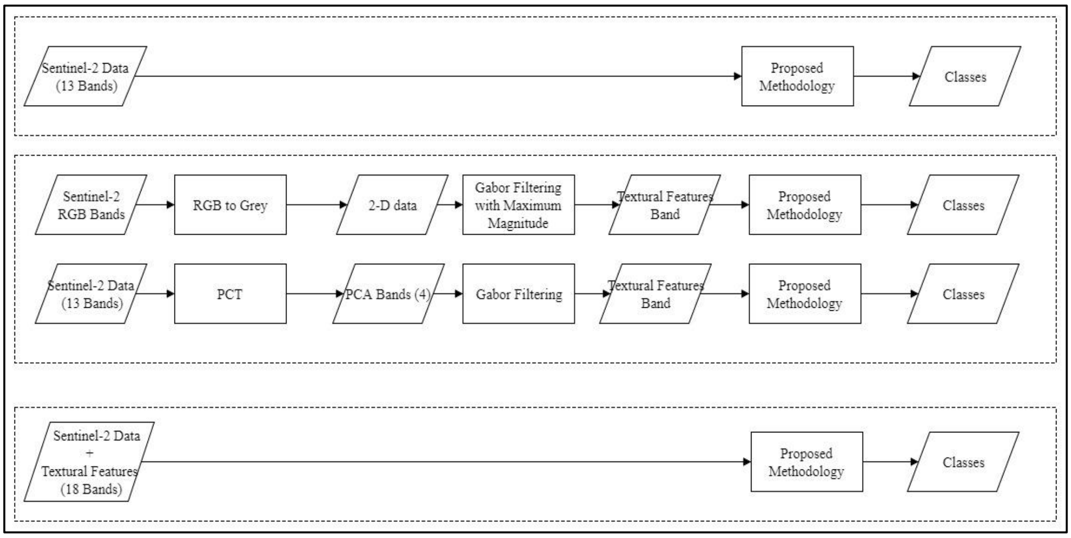


Figure 8: Different Combinations of Proposed Methodology

3.1.1. Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI)

Vegetation indices can be used as measures of vegetation activity. Although there are different vegetation measure techniques; normalized difference vegetation index (NDVI) is relatively more reputable in monitoring agriculture and green land cover from the remote sensing point of view. NDVI thresholding can be a good identification of vegetation. Furthermore, vegetation can be extracted from NDVI (El-Gammal et al., 2014). NDVI formula is given in Equation (18).

$$NDVI = \frac{Near\ Infrared\ band\ pixel\ value - Red\ band\ pixel\ value}{Near\ Infrared\ band\ pixel\ value + Red\ band\ pixel\ value} \tag{18}$$

Index type of computation with two or more multispectral bands like NDVI and normalized difference water index (NDWI) has become popular for boosting water features and suppressed other objects. Then some thresholding should be done for extracting water. Since thresholds are objective, overfitting or underfitting may occur. NDWI formula is given in Equation (19) (Qiao et al., 2012).

$$NDWI = \frac{Green\ band\ pixel\ value - Near\ Infrared\ band\ pixel\ value}{Green\ band\ pixel\ value + Near\ Infrared\ ban\ pixel\ value} \tag{19}$$

3.1.2. Extraction of Textural Features

Textural analysis leads to unusual potentials to characterize the structural heterogeneity of classes. The texture of a remotely sensed data is linked to the spatial distribution of the intensity values in the image. Some textural feature examples can be listed as contrast, uniformity, regularity and rugosity. By using different textural feature extraction methods, reasonable amounts of textural information can be obtained (Ruiz & Recio, 2004).

While studying land use and land cover mapping or object detection, textural features are the most widely used features for remote sensing purposes. The critical part in textural classification is the representation of features. They reflect a pattern, beyond color-related features in the spatial domain. By that sense, they can separate similar or close-colored patterns from class-specific patterns.

Some examples of textural feature extraction methods are Gray Level Co-Occurrence Matrix (GLCM), Gabor filters, Histogram of Oriented Gradients (HOG), Local Binary Pattern (LBP), Local Edge Pattern (LEP) and Edge Orientation (Bayram, Ulya; Can, Gülcan; Düzgün, Şebnem; Yalabık, 2011).

In this study, gabor filtering is used for textural extraction. These filters mimic the human visual system based on multichannel filtering. The human visual system separates an image into several filtered images in the retina. Each filtered image has intensity, orientation and other information (Ruiz & Recio, 2004).

Gabor feature is not a textural feature but it serves as a tool for showing the image texture. Gabor filters are linear filters that represent the edges in the filtered image. Filtering an image is a directional operation; therefore, filtering should be done in multiple directions instead of one direction. Some feature examples are mean, energy, entropy and standard deviation (Bayram, Ulya; Can, Gülcan; Düzgün, Şebnem; Yalabık, 2011).

While Gabor filtering is however applied on 2D images, in the case of remotely sensed multispectral data, the information is not in two-dimensional form but in three dimensions, with the extra spectral axis. Therefore, as an initial stage, this multi dimension data should be reduced to 2D to utilize Gabor filters.

In this thesis, principal component analysis is utilized for this purpose. First of all, in a remotely sensed data, the number of different axes is equal to the number of bands of the image. However, in most cases, the information in different bands are inter-correlated with each other. Principal component analysis is a transformation on the remotely sensed data to decorrelate the spectral information at each band (Abdi & Williams, 2010). With such an analysis, the significant part of the spectral information is extracted and expressed as a set of new orthogonal variables called “principal components”. In this thesis, these principal components, which represent the statistically significant part of the remotely sensed data is utilized in the experiments.

The extraction of textural features using Gabor filters along with PCA in this thesis is presented in Figure 9. The extraction involves the following main stages:

- First, PCA transform is applied to the Sentinel 2-A images and the first principal component is selected for textural feature extraction.
- The first principal component is passed through Gabor filter banks with different orientations and wavelengths.
- The resulting Gabor filter responses are smoothed with a Gaussian filter.
- The smoothed responses are all concatenated into a multi-dimensional cube and then normalized to a zero mean and unit variance.
- Finally, the PCA is applied to the cube of filter responses and the first principal component is selected as the textural feature.

In the implementation of the mentioned procedure, the orientation of the Gabor filters is selected as (0, 45, 90, 135). The wavelengths are selected as ($2\sqrt{2}$, $4\sqrt{2}$, $8\sqrt{2}$, …). The last wavelength is selected as the number in this order, which is smaller than the maximum of the width (row number) and height (column number) of the image. It should be noted that the 2nd, 3rd and 4th principal components as well as the gray level image obtained from the RGB image of the scene are also utilized in this procedure for comparison purposes.

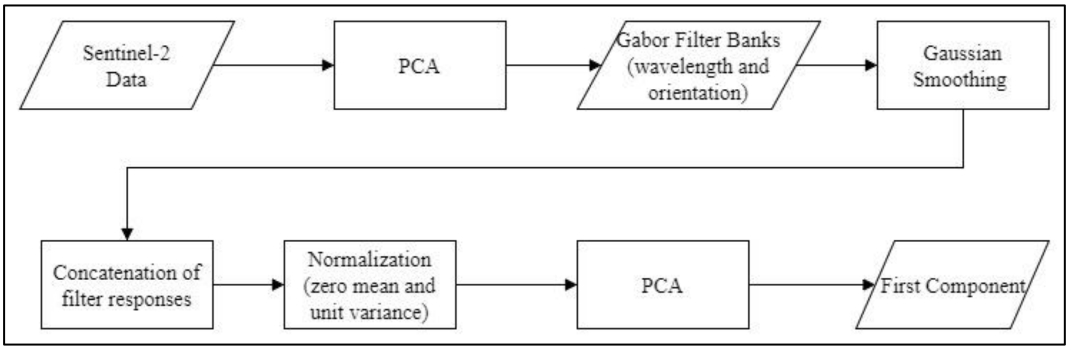


Figure 9: The utilized procedure for the extraction of textural features

3.1. Second Level Classification

In second level classification, all classes have their own masked image. For example, in water class, only the water containing areas had a normal pixel value and the others are zero, which means that all pixels appeared black during the visualization of the area. Those raw data are created before first level classification. Then, each class is divided into sub classes inside each other except the built-up region. Water is divided into inland water and marine water. Vegetation is divided into forest/meadow and vegetated agricultural land. Bare land is divided into barren land and non-vegetated agricultural land. Again, for second level classification, SVM is used and second level classes are created.

As done in the first level classification, textural bands are introduced again. The same procedure is applied in second level classification. First, only textural bands are classified and then a combination of multispectral data and textural bands are classified.

3.2. Accuracy Assessment

Last and most important part of the study is accuracy assessment. In Section 2.3, calculations of accuracy assessment were given. In order to verify that, this study is legitimate, accuracies and kappa coefficients of each test is calculated in Chapter 5 Results and Conclusion.

CHAPTER 4

IMPLEMENTATION OF METHODOLOGY

This study is performed for two cities of Republic of Turkey: Ankara, which is the capital and the second biggest city by population, and Izmir, which is the third biggest city by population. Ankara is located in central Anatolia and has a total area of 24,521 km^2. Izmir is located on the west coast of Turkey and has a total area of 7,340 km^2. Both cities have sufficient number of classes for LULC mapping. Study areas are shown in Figure 10.

Figure 10: Study Areas (retrieved from Yandex)

Proposed methodology contains a hierarchical classification method which is given in Figure 6. To see the effectiveness of chosen hierarchical classification methodology, non-hierarchical classification model is also studied. In Section 4.1 details and justification is given. Moreover, to see the success of the most used supervised classification algorithm, ML, instead of SVM, analysis and accuracy assessments are done. The reason why SVM is used in this study is given in Section 4.2 in details.

Thresholding for indexes, NDWI and NDVI, is mentioned in proposed methodology. Those thresholding are not done with a known methodology. Instead it is done by visually and subjective to the expert opinion. The values for İzmir, if NDWI pixel value is above 0.05 then pixel is water if not it is not water. For vegetation if NDVI pixel value is above 0.5 then pixel is vegetation if not, it is not vegetation. For Ankara, thresholding values for NDWI, if the pixel value is above 0.3 then the pixel is water if not it is not water. For vegetation, if NDVI pixel value is above 0.55 then it is vegetation if not it is not vegetation pixel.

Lastly, for all levels of classification, comparison for hierarchical and non-hierarchical methodology and comparison of different algorithms, same training set of pixels are used. In Figure 11 and Figure 12, training sets for Ankara and İzmir are given.

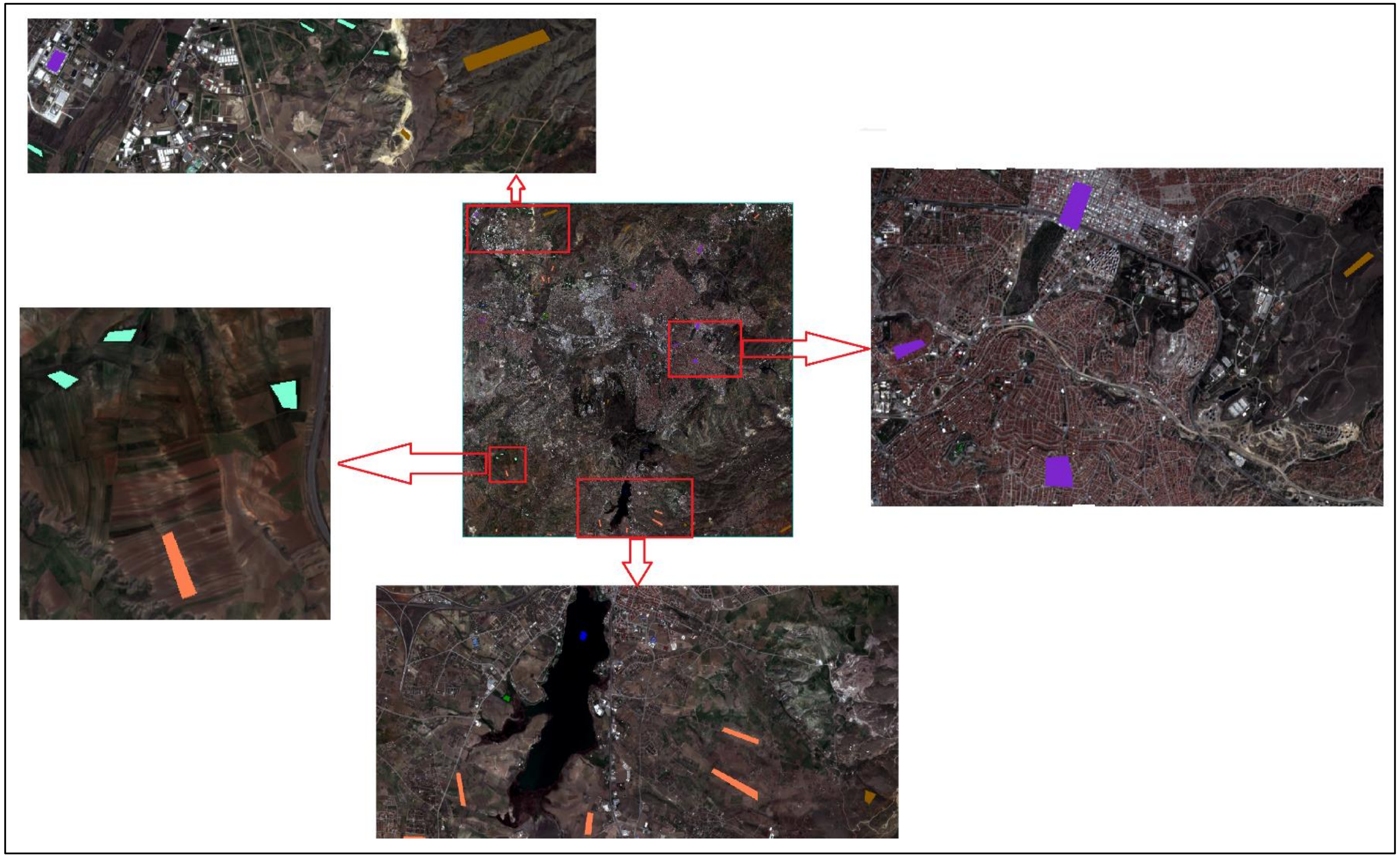


Figure 11: Training Set of Ankara

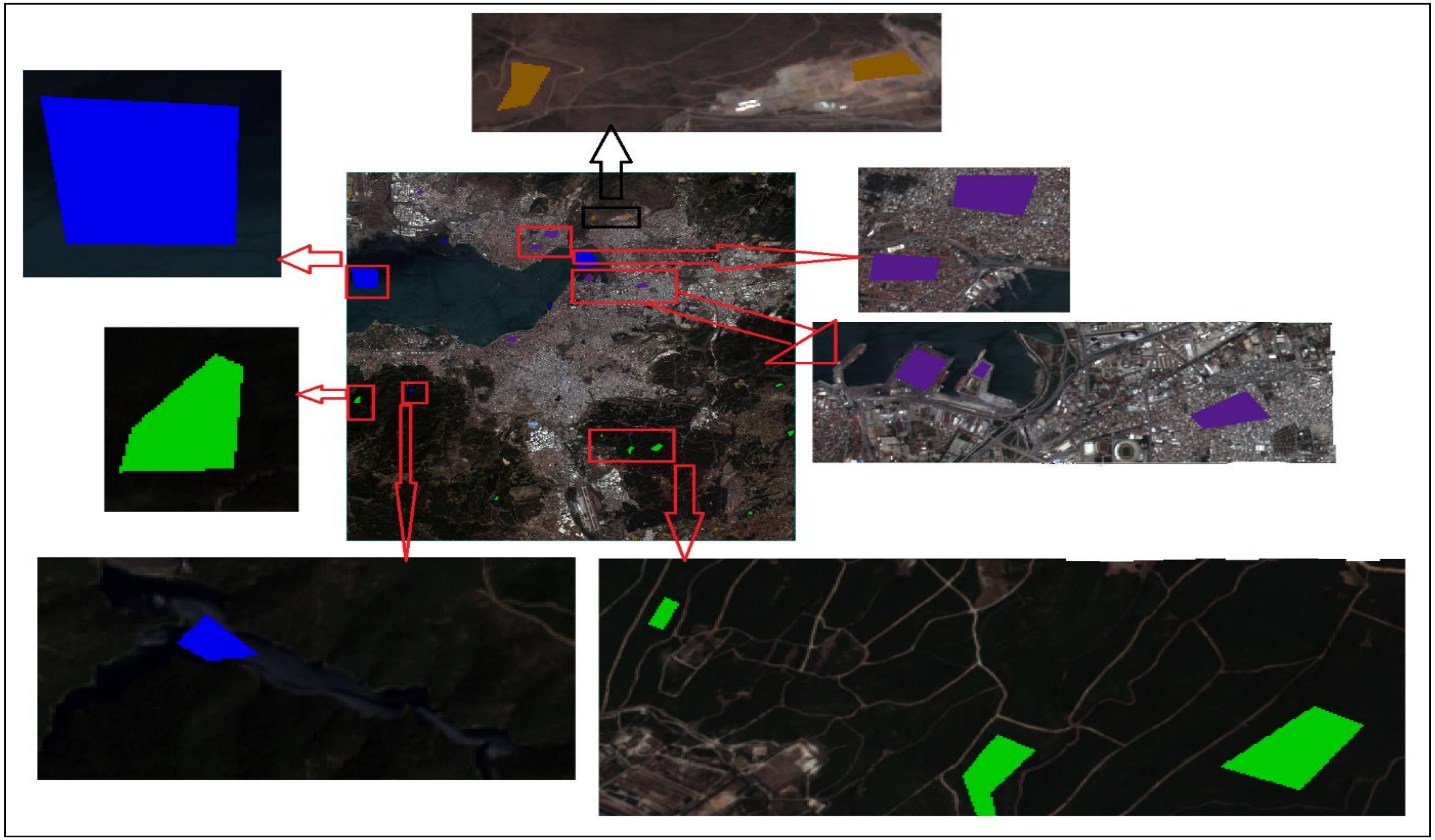


Figure 12: Training Set of İzmir

4.1. Comparison of Hierarchical Classification and Non-Hierarchical Classification

To come up with such a methodology, some pre-analyses are done. One is for hierarchical classification and the other one is for SVM algorithm. Instead of classifying the image with proposed methodology and hierarchy, ends up with better classification accuracy. In short, SVM algorithm is trained by all classes in one instance with same training set, instead of hierarchical classification of pixels. The analyses are done for both Ankara and İzmir. Classification results of non-hierarchical and hierarchical classification of Ankara and İzmir is given in Table 6, Table 7, Table 8 and Table 9 respectively. Accuracies of each city clearly shows that; hierarchical classification increases classification accuracy 4 percent and 10 percent respectively. Therefore, in this study, proposed method is chosen as hierarchical methodology.

Table 6:Non-Hierarchical Classification Results of Ankara

Non-Hierarchical Classification									
Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	11	3	3	1	0	18	61.11%
Forest	NA	0	2	14	0	0	0	16	87.50%
Barren Land	NA	0	0	2	58	10	5	75	77.33%
Non-Vegetated Agriculture	NA	0	0	3	34	27	10	74	36.49%
Built up	NA	0	0	0	6	0	41	47	87.23%
Sum	NA	20	13	22	101	38	56	250	Overall Accuracy
Users Accuracy	NA	100.00%	84.62%	63.64%	57.43%	71.05%	73.21%	Overall Accuracy	68.40%

Table 7: Hierarchical Classification of Ankara

Hierarchical Classification									
Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	10	3	0	0	0	13	76.92%
Forest	NA	0	3	19	0	0	0	22	86.36%
Barren Land	NA	0	0	0	61	11	3	75	81.33%
Non-Vegetated Agriculture	NA	0	0	0	33	27	10	70	38.57%
Built up	NA	0	0	0	7	0	43	50	86.00%
Sum	NA	20	13	22	101	38	56	250	Overall Accuracy
Users Accuracy	NA	100.00%	76.92%	86.36%	60.40%	71.05%	76.79%	Overall Accuracy	72.00%

Table 8: Non-Hierarchical Classification Results of İzmir

Non-Hierarchical Classification									
	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	20	0	0	0	0	0	0	20	100.00%
Inland Water	3	2	0	1	0	0	0	6	33.33%
Vegetated Agriculture	0	0	5	3	0	0	0	8	62.50%
Forest	0	0	7	39	3	1	1	51	76.47%
Barren Land	0	0	7	3	35	10	0	55	63.64%
Non-Vegetated Agriculture	0	0	0	0	6	10	0	16	62.50%
Built up	0	0	0	0	6	1	47	54	87.04%
Sum	23	2	19	46	50	22	48	210	Overall Accuracy
Users Accuracy	86.96%	100.00%	26.32%	84.78%	70.00%	45.46%	97.92%	Overall Accuracy	75.24%

Table 9: Hierarchical Classification of İzmir

Hierarchical Classification									
	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	20	0	0	0	0	0	0	20	100.00%
Inland Water	3	2	0	0	0	0	0	5	40.00%
Vegetated Agriculture	0	0	13	2	0	0	0	15	86.67%
Forest	0	0	6	44	0	0	0	50	88.00%
Barren Land	0	0	0	0	41	9	0	50	82.00%
Non-Vegetated Agriculture	0	0	0	0	4	11	0	15	73.33%
Built up	0	0	0	1	6	1	47	55	85.45%
Sum	23	2	19	47	51	21	47	210	Overall Accuracy
Users Accuracy	86.96%	100.00%	68.42%	93.62%	80.39%	52.24%	100.00%	Overall Accuracy	84.76%

4.2. Comparison of SVM and ML Classification Algorithms

Past studies with different algorithms given in Chapter 2 and shows that SVM gives better results instead of ML classification algorithm. Same as non-hierarchical classification comparison with hierarchical classification, different classification algorithms are tested before using in the proposed methodology. For that reason, ML, one of the most used algorithm in LULC mapping and SVM, success is proved over ML, algorithms are compared. Classification accuracy results of ML and SVM algorithms for Ankara and İzmir multispectral data is given in Table 10, Table 11, Table 12 and Table 13 respectively. It is clearly seen that in overall accuracy, SVM is overperformed ML. Moreover, investigating in class based accuracy, again SVM is better than ML.

Table 10: ML Classification Results of Ankara

ML									
Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	16	0	0	0	0	0	16	100.00%
Vegetated Agriculture	NA	0	9	3	1	0	0	13	69.23%
Forest	NA	1	4	14	2	1	0	22	63.64%
Barren Land	NA	0	0	0	39	11	3	53	73.58%
Non-Vegetated Agriculture	NA	0	0	0	38	20	1	59	33.90%
Built up	NA	0	0	0	19	6	62	87	71.26%
Sum	NA	17	13	17	99	38	66	250	Overall Accuracy
Users Accuracy	NA	94.12%	69.23%	82.35%	39.39%	52.63%	93.94%	Overall Accuracy	57.60%

Table 11: SVM Classification Results of Ankara

SVM									
Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	10	3	0	0	0	13	76.92%
Forest	NA	0	3	19	0	0	0	22	86.36%
Barren Land	NA	0	0	0	61	11	3	75	81.33%
Non-Vegetated Agriculture	NA	0	0	0	33	27	10	70	38.57%
Built up	NA	0	0	0	7	0	43	50	86.00%
Sum	NA	20	13	22	101	38	56	250	Overall Accuracy
Users Accuracy	NA	100.00%	76.92%	86.36%	60.40%	71.05%	76.79%	Overall Accuracy	72.00%

Table 12: ML Classification Results of İzmir

MAXIMUMLIKELYHOOD									
	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	19	0	0	0	0	0	0	19	100.00%
Inland Water	0	0	0	1	0	0	0	1	0.00%
Vegetated Agriculture	0	0	13	11	8	0	0	32	40.63%
Forest	0	0	2	29	3	0	0	34	85.29%
Barren Land	0	0	2	6	18	6	0	32	56.25%
Non-Vegetated Agriculture	0	0	0	0	8	12	0	20	60.00%
Built up	4	2	2	0	13	4	47	72	65.28%
Sum	23	2	19	47	50	22	47	210	Overall Accuracy
Users Accuracy	82.61%	0.00%	68.42%	61.70%	36.00%	54.55%	100.00%	Overall Accuracy	65.71%

Table 13: SVM Classification Results of İzmir

SVM									
	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built up	Sum	Producers Accuracy
Marine Water	20	0	0	0	0	0	0	20	100.00%
Inland Water	3	2	0	0	0	0	0	5	40.00%
Vegetated Agriculture	0	0	13	2	0	0	0	15	86.67%
Forest	0	0	6	44	0	0	0	50	88.00%
Barren Land	0	0	0	0	41	9	0	50	82.00%
Non-Vegetated Agriculture	0	0	0	0	4	11	0	15	73.33%
Built up	0	0	0	1	6	1	47	55	85.45%
Sum	23	2	19	47	51	21	47	210	Overall Accuracy
Users Accuracy	86.96%	100.00%	68.42%	93.62%	80.39%	52.38%	100.00%	Overall Accuracy	84.76%

4.3. İzmir

4.3.1. First Level Multispectral Classification of İzmir

In Section 3.1, first level classification steps, which are creating NDVI, NDWI and thresholding and masking image for each class, are introduced. After thresholding histograms, masking is done, SVM is used for classification of built up and bare land classes. Lastly, textural features are extracted and used in a way that proposed methodology shows.

4.3.1.1. Water and Vegetation Classification

The study area, NDVI and NDWI of Izmir are given in Figure 13, Figure 14 and Figure 15, respectively. After creating indices, vegetation and water are extracted by thresholding and the masking operation is done. Extraction of water, extraction of vegetation, the masked image of water and the masked image of vegetation are presented in Figure 16, Figure 17, Figure 18 and Figure 19, respectively. It is clearly seen that, index based classification and thresholding is successful while labeling vegetation and water classes.

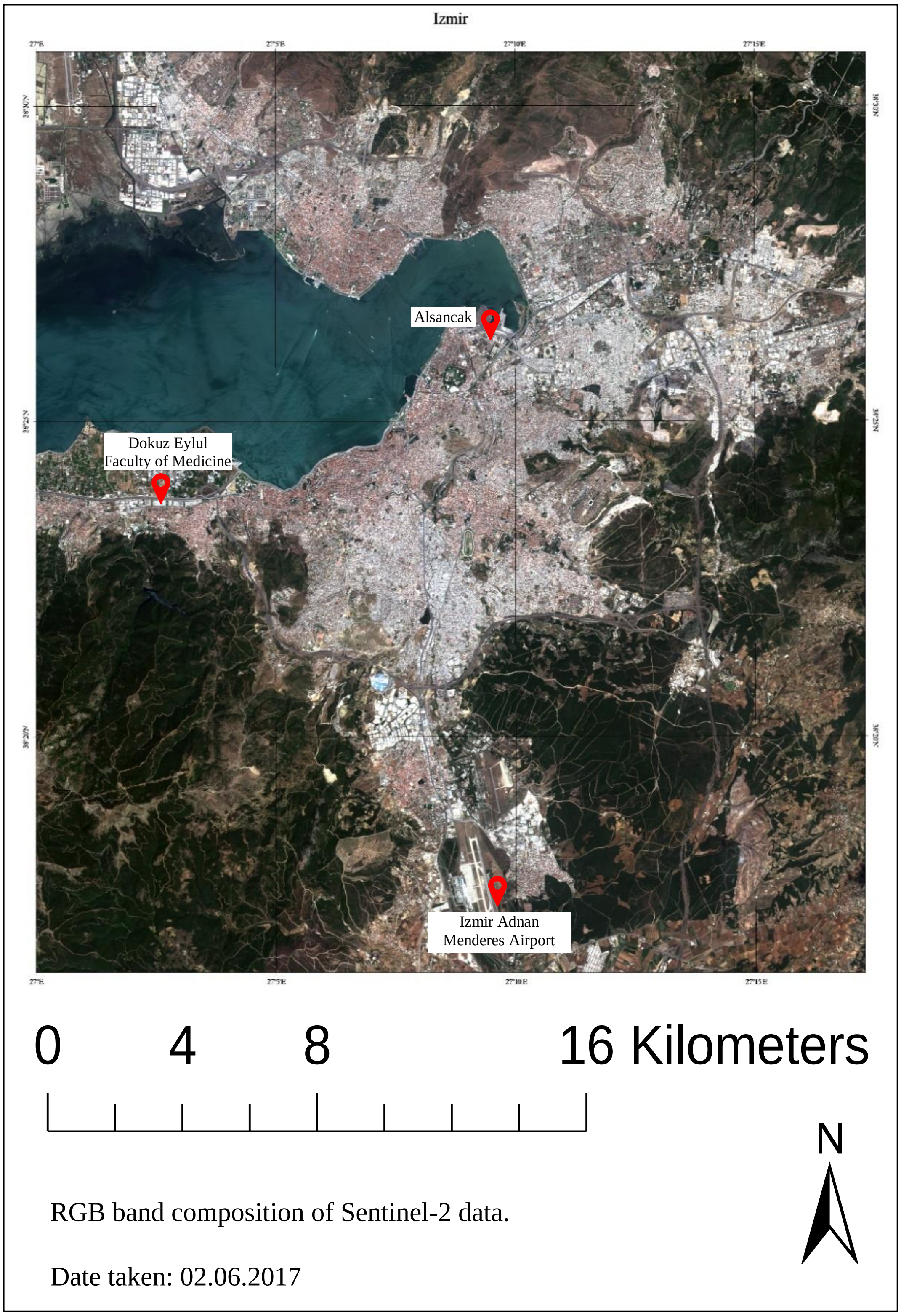


Figure 13: General View of İzmir

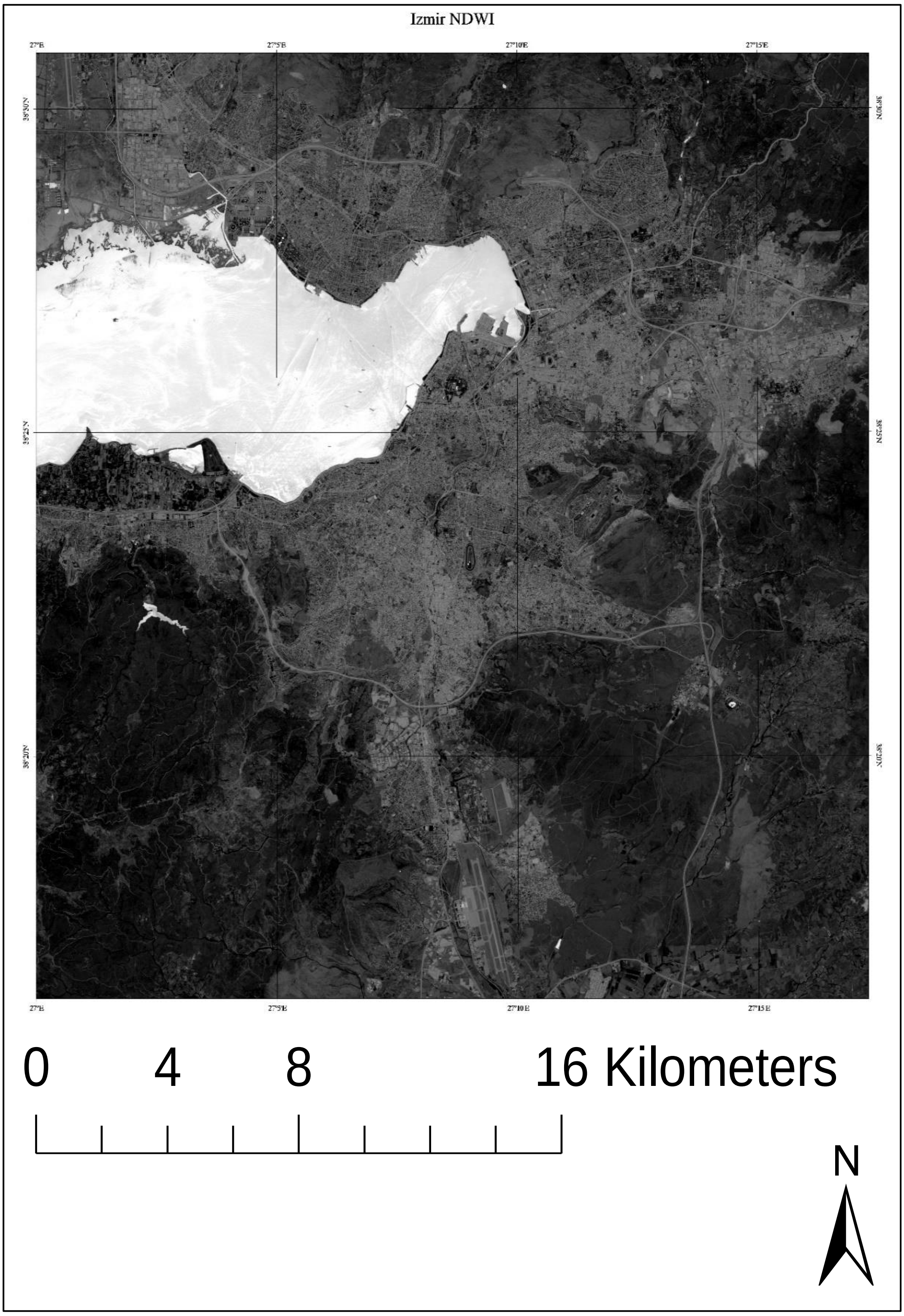


Figure 14: NDWI of Izmir

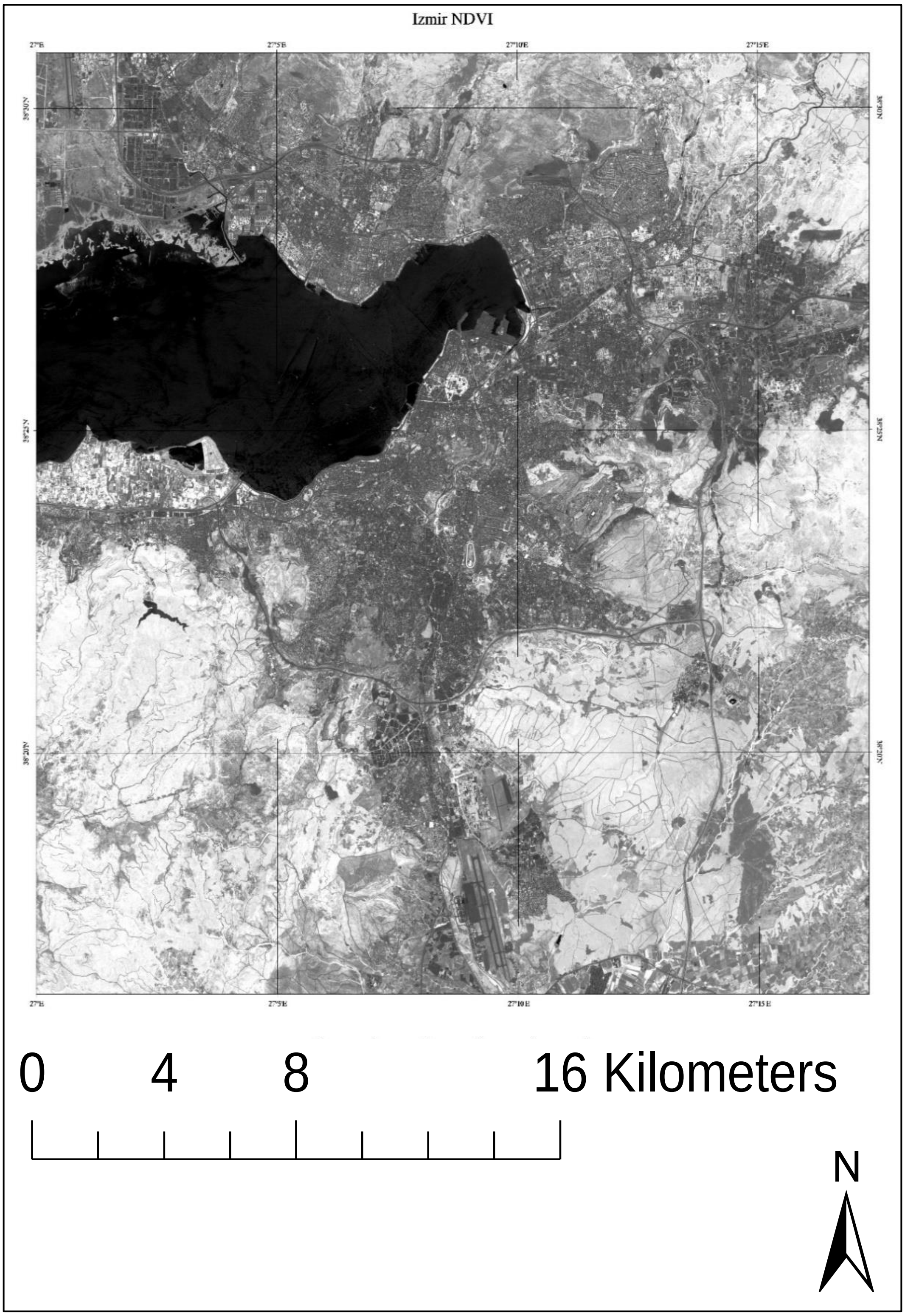


Figure 15: NDVI of İzmir

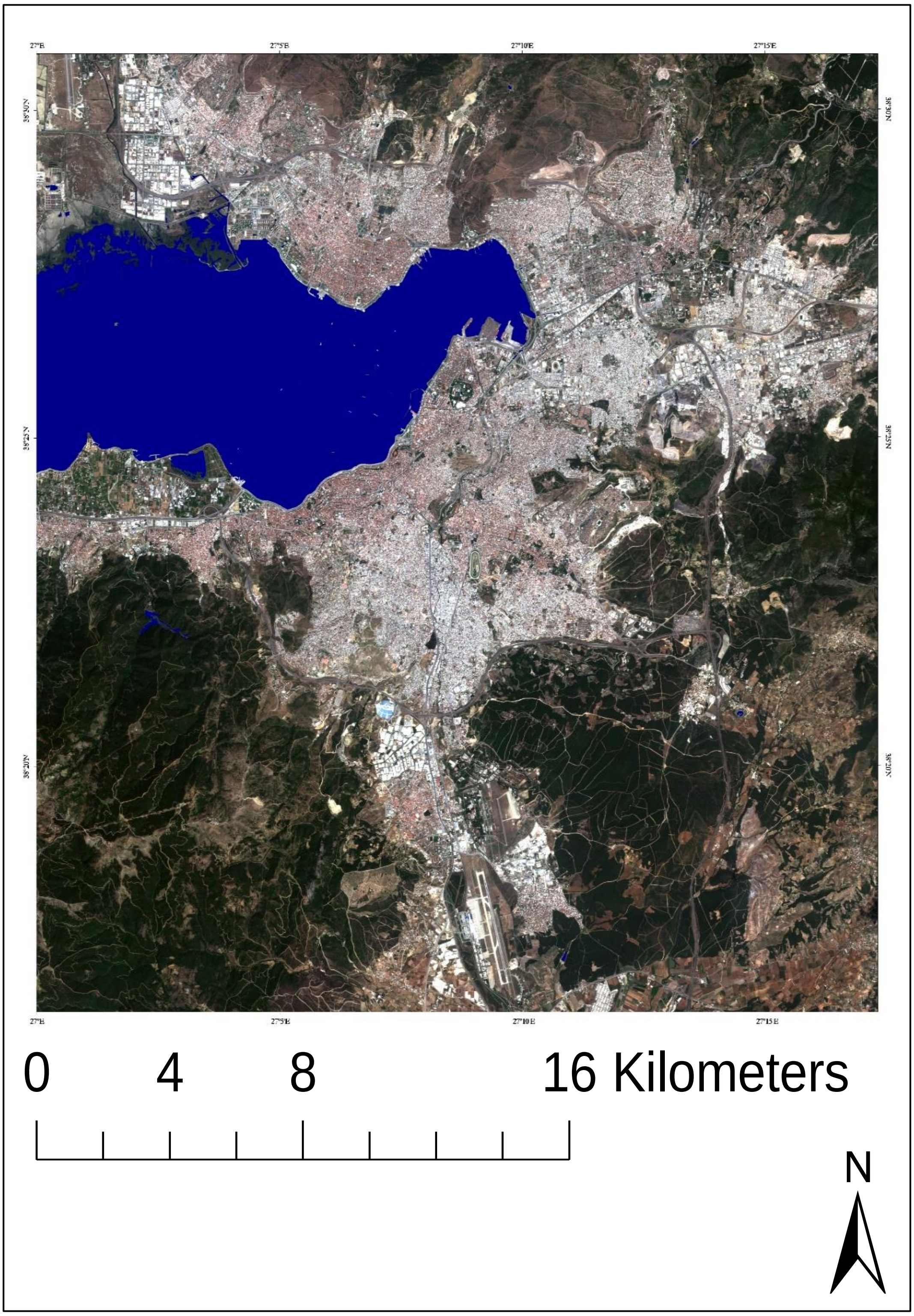


Figure 16: Extraction of Water

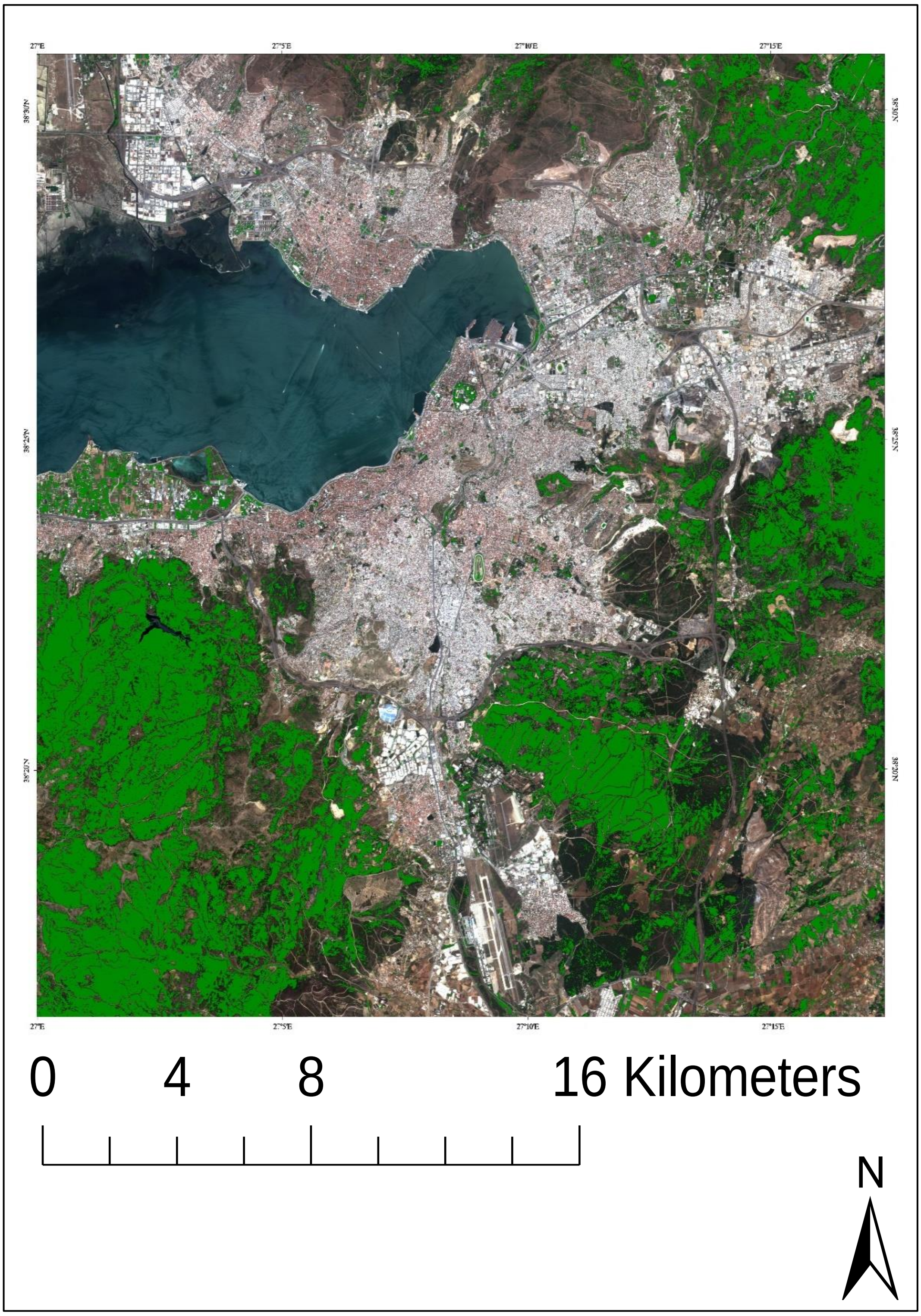


Figure 17: Extraction of Vegetation

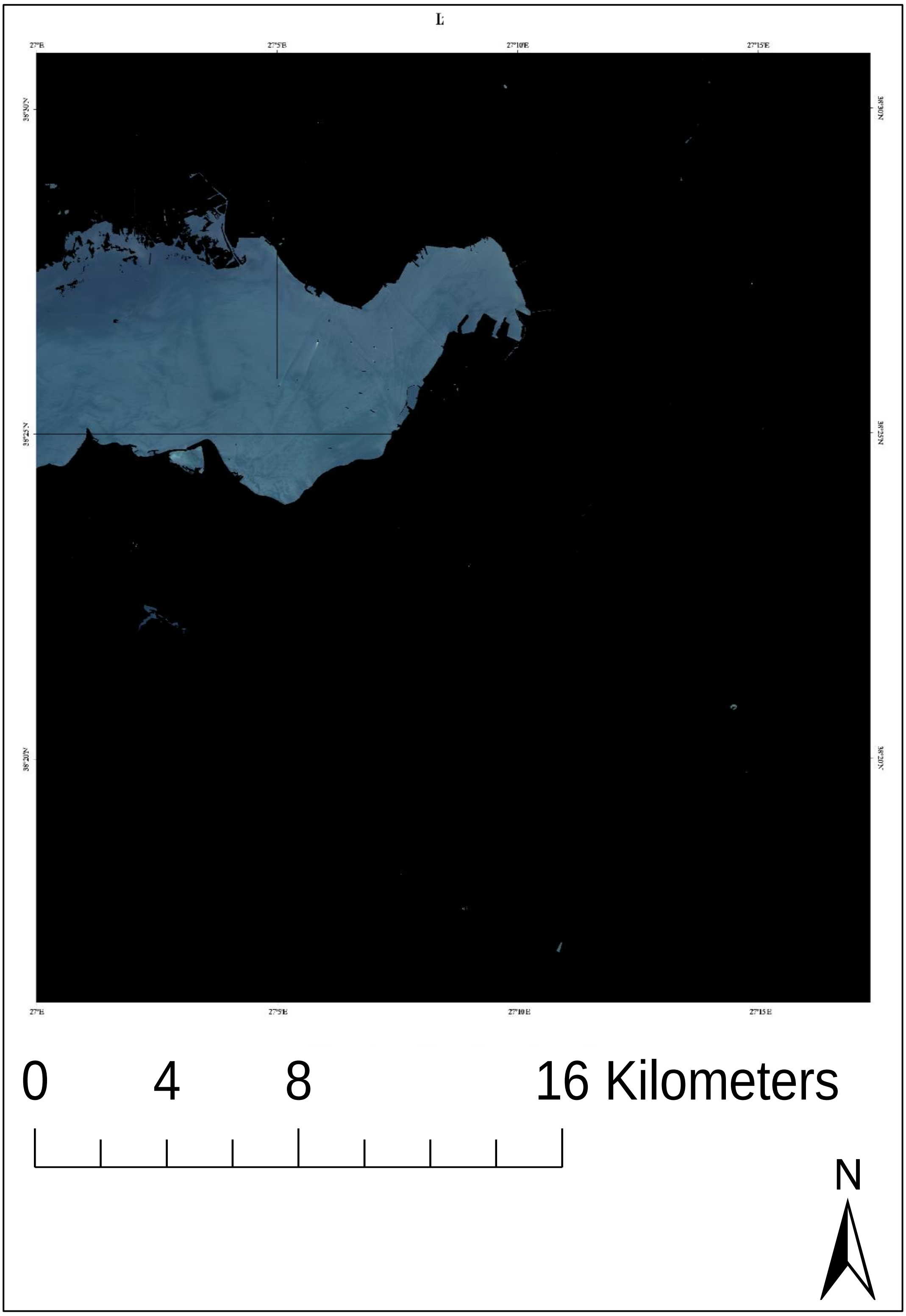


Figure 18: Masked Image for Water

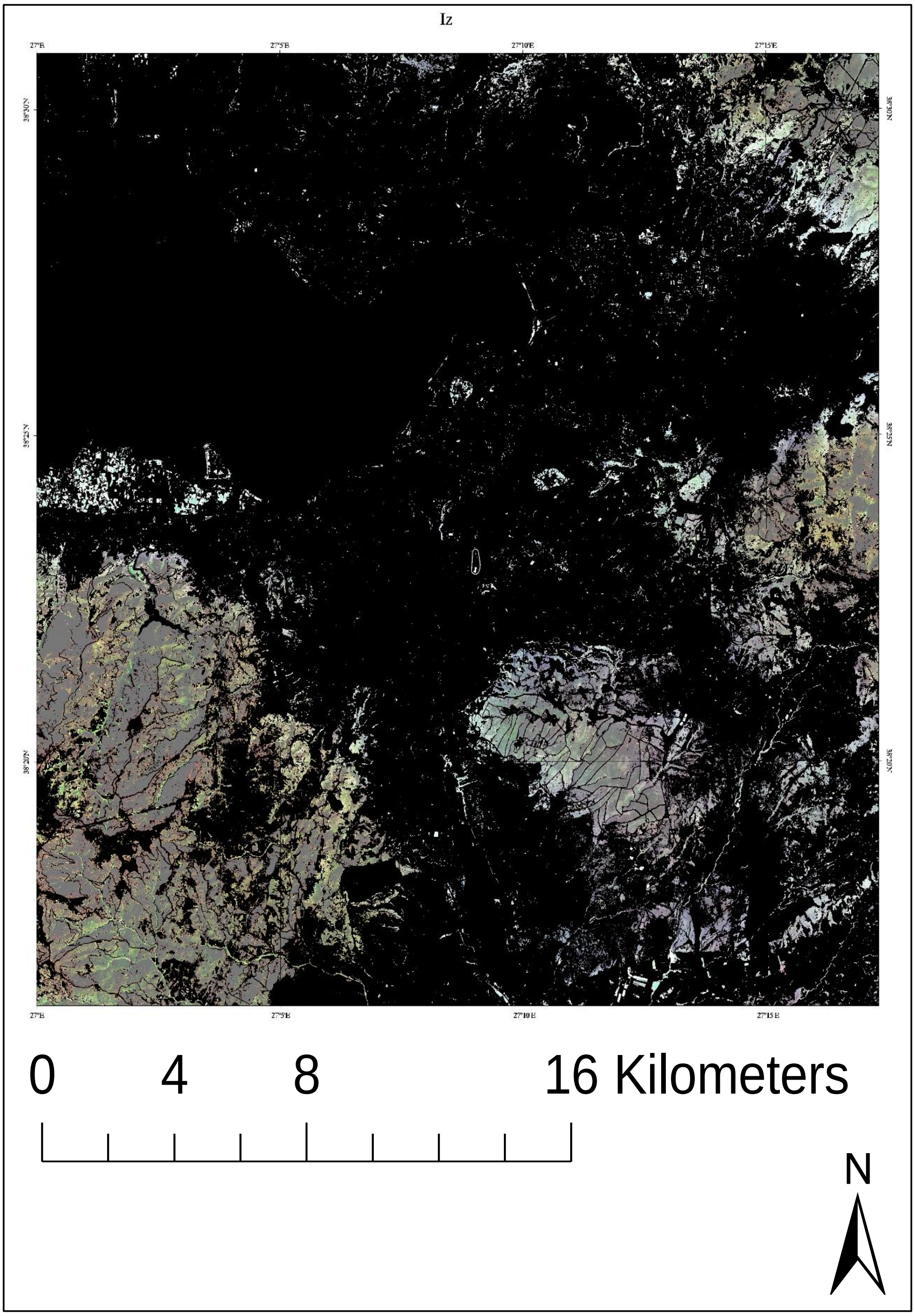


Figure 19: Masked Image for Vegetation

After thresholding the histograms, class labels are given as water and vegetation. The labeled classification results for water and vegetation are shown in Figure 20 and Figure 21, respectively. Water is represented by blue, vegetation is represented by green and masked pixels are represented by brown.

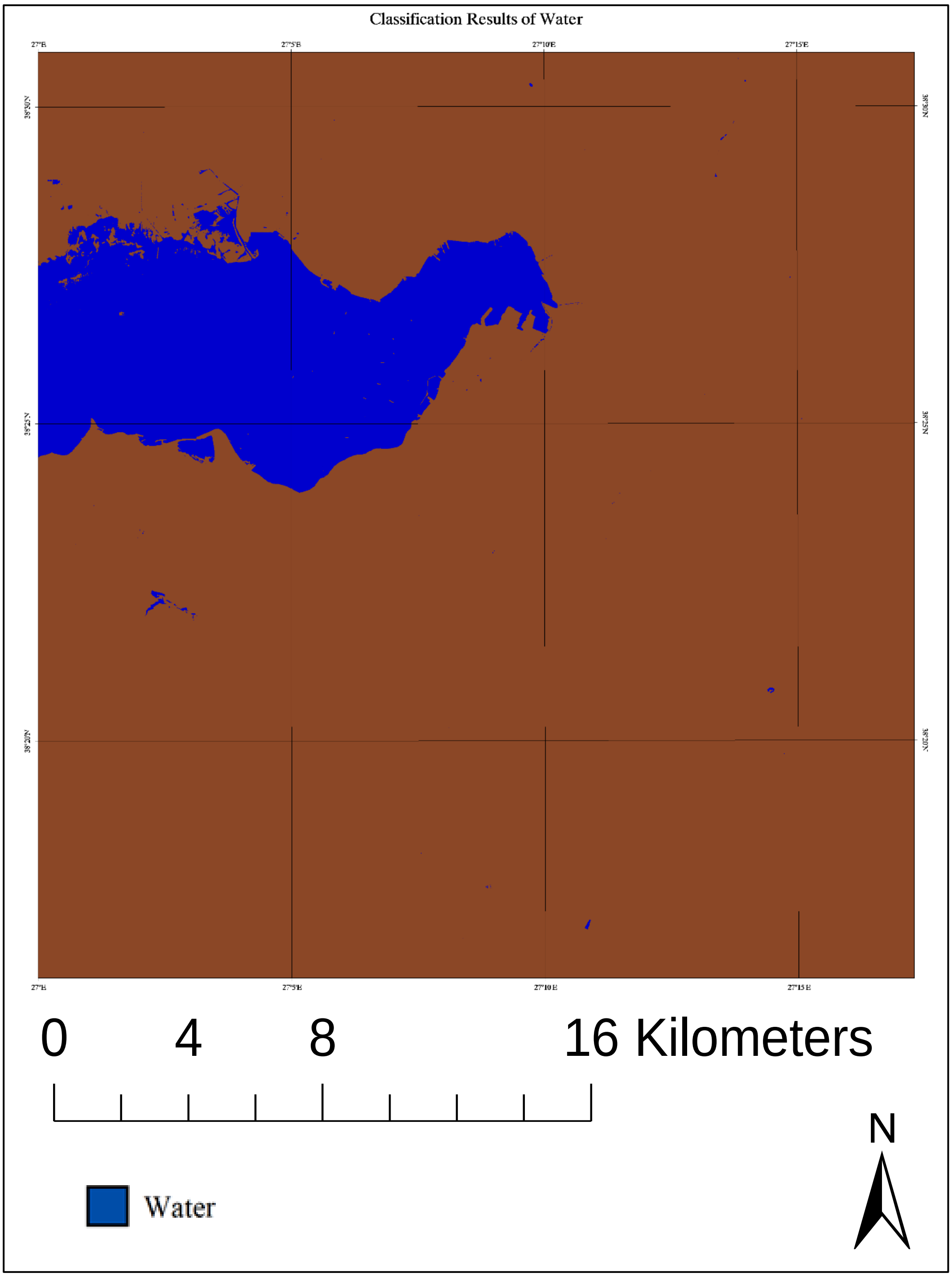


Figure 20: Classification Results of Water

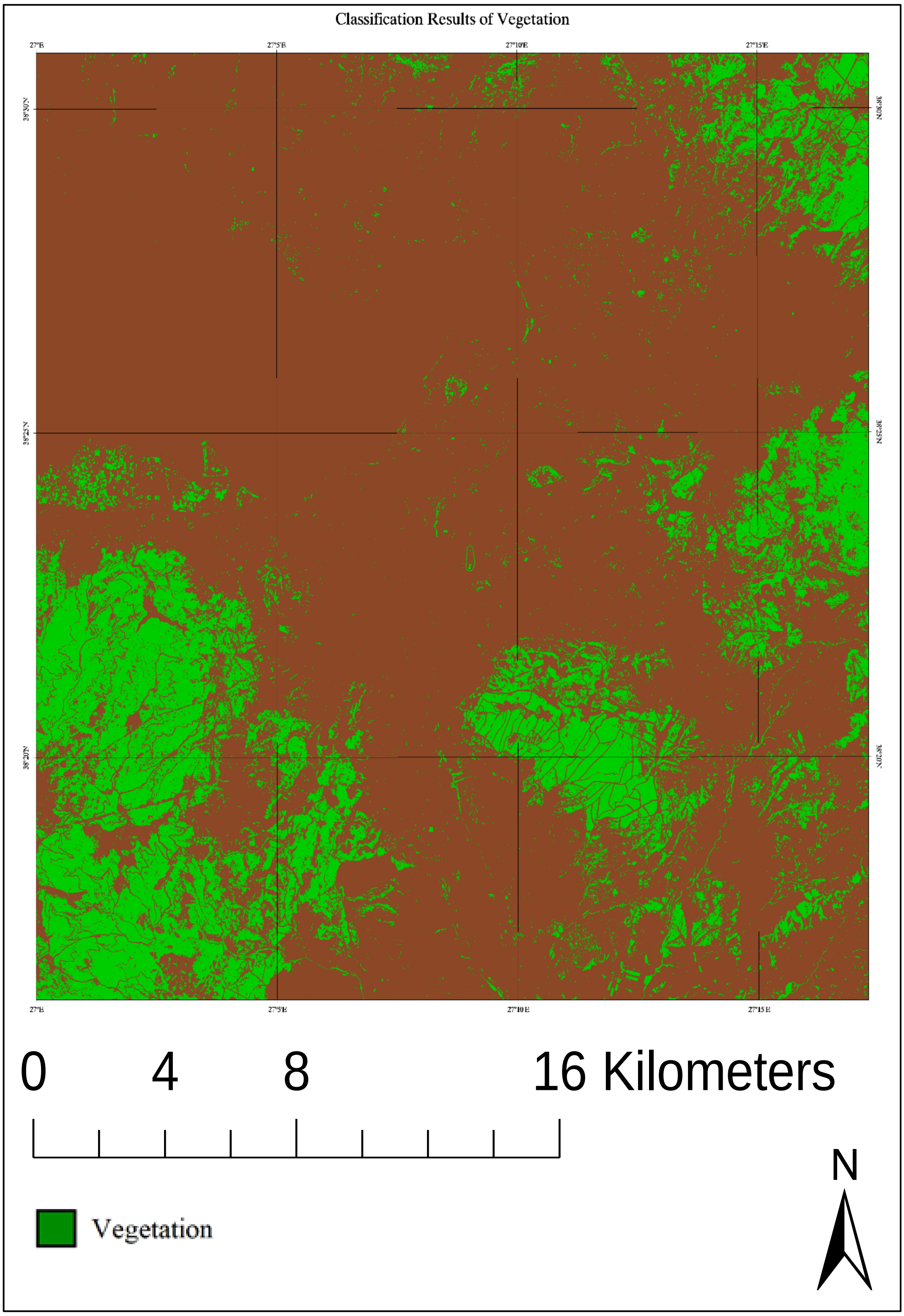


Figure 21: Classification Results of Vegetation

4.3.1.2. Built Up and Bare Land Classification

In the previous section, extraction of water and vegetation are presented separately. After that, masking was reversed, where water and vegetation pixels had 0 value, while bare land and built up areas had their original pixel values. Masked image for built up and bare land classification is given in Figure 22.

In this part, regions of interests are selected as built up and bare land to train the classifier. SVM algorithm is used for classifying the image. In Figure 23, results of SVM classification for built up and bare land is given.

After making the classification, all four classes were merged together for the accuracy assessment part, which is presented in Chapter 5. In Figure 24, combined classification results for the first level can be seen.

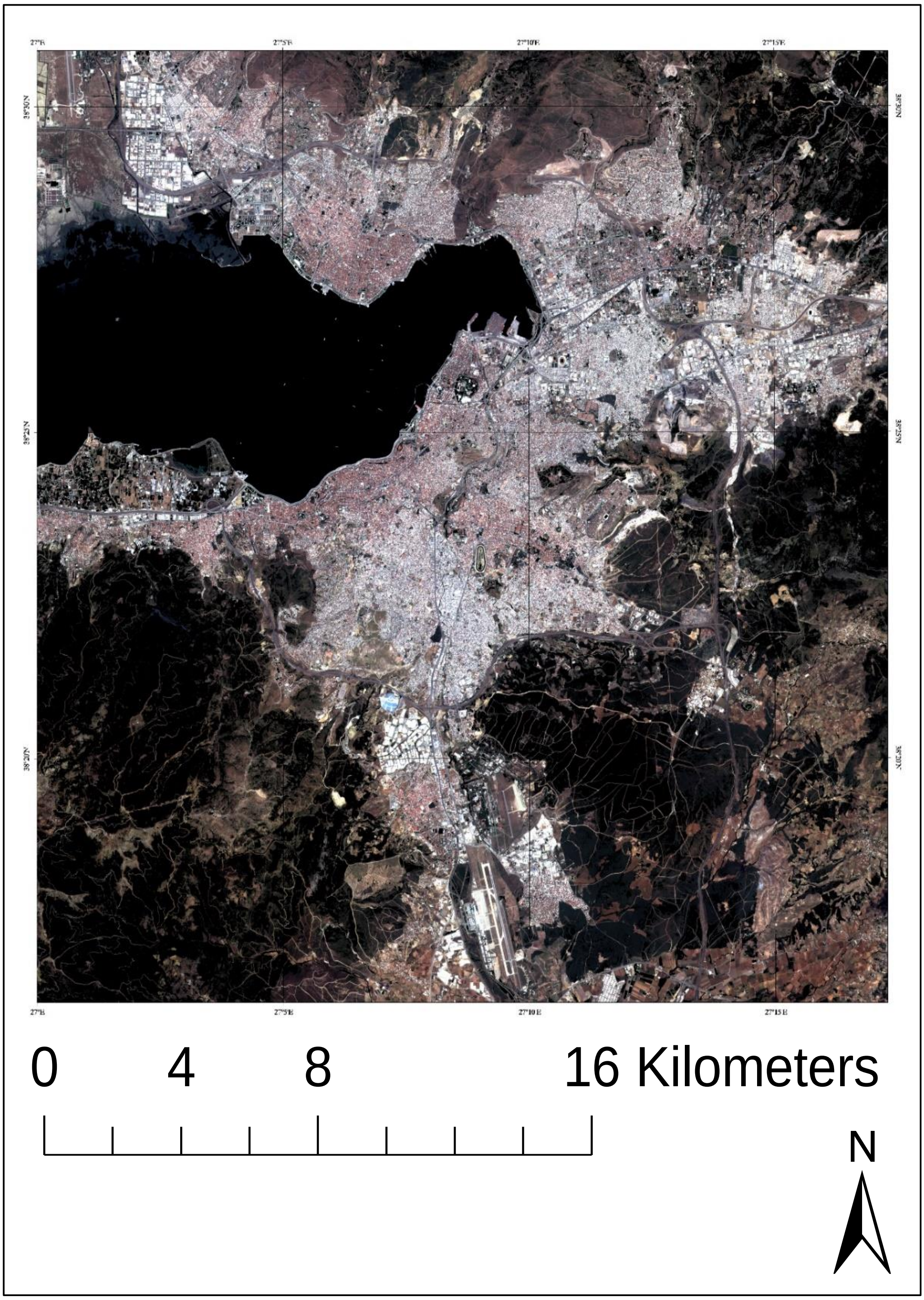


Figure 22: Masked Image for Built Up and Bare Land

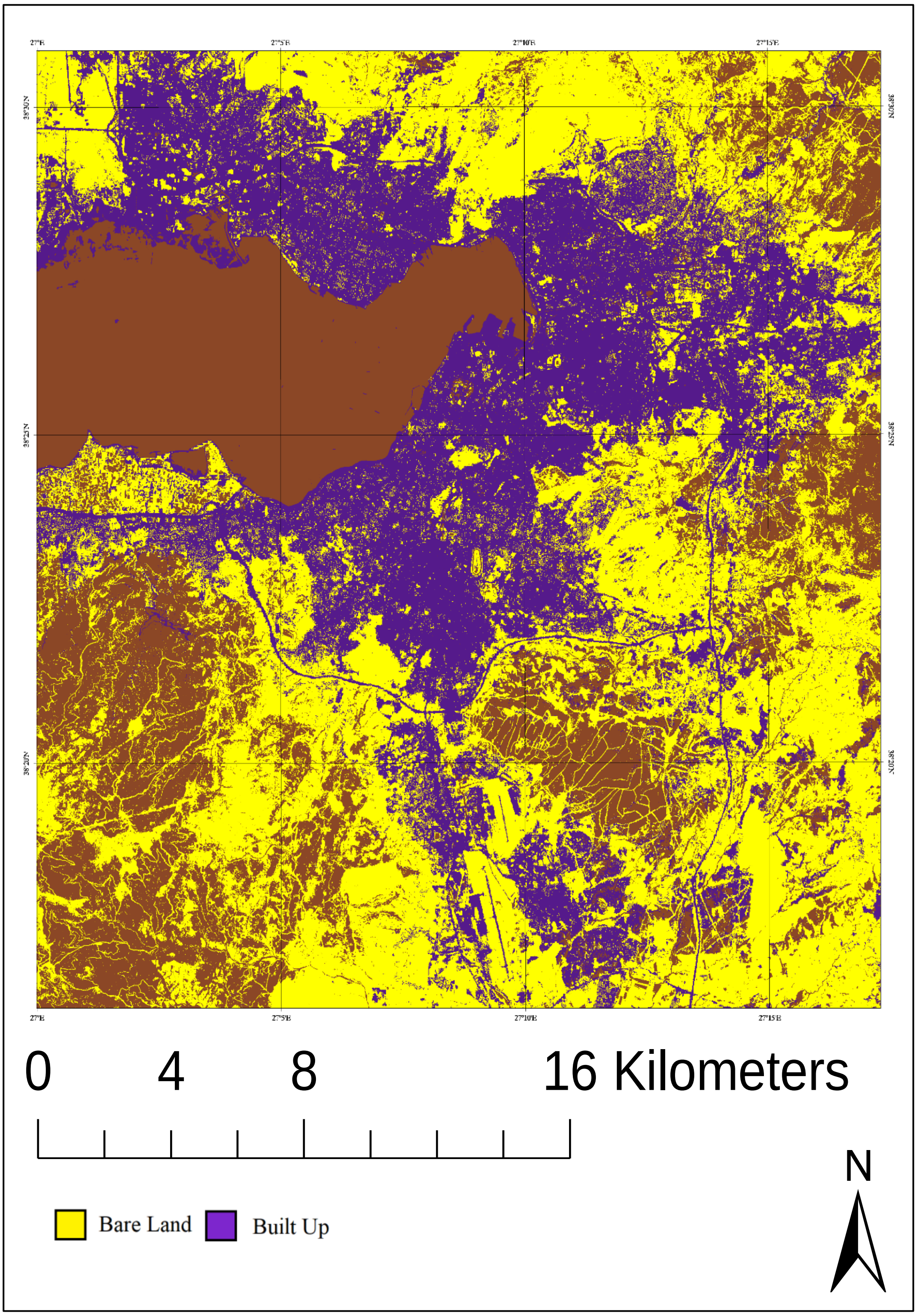


Figure 23: Classification Results of Bare Land and Built Up

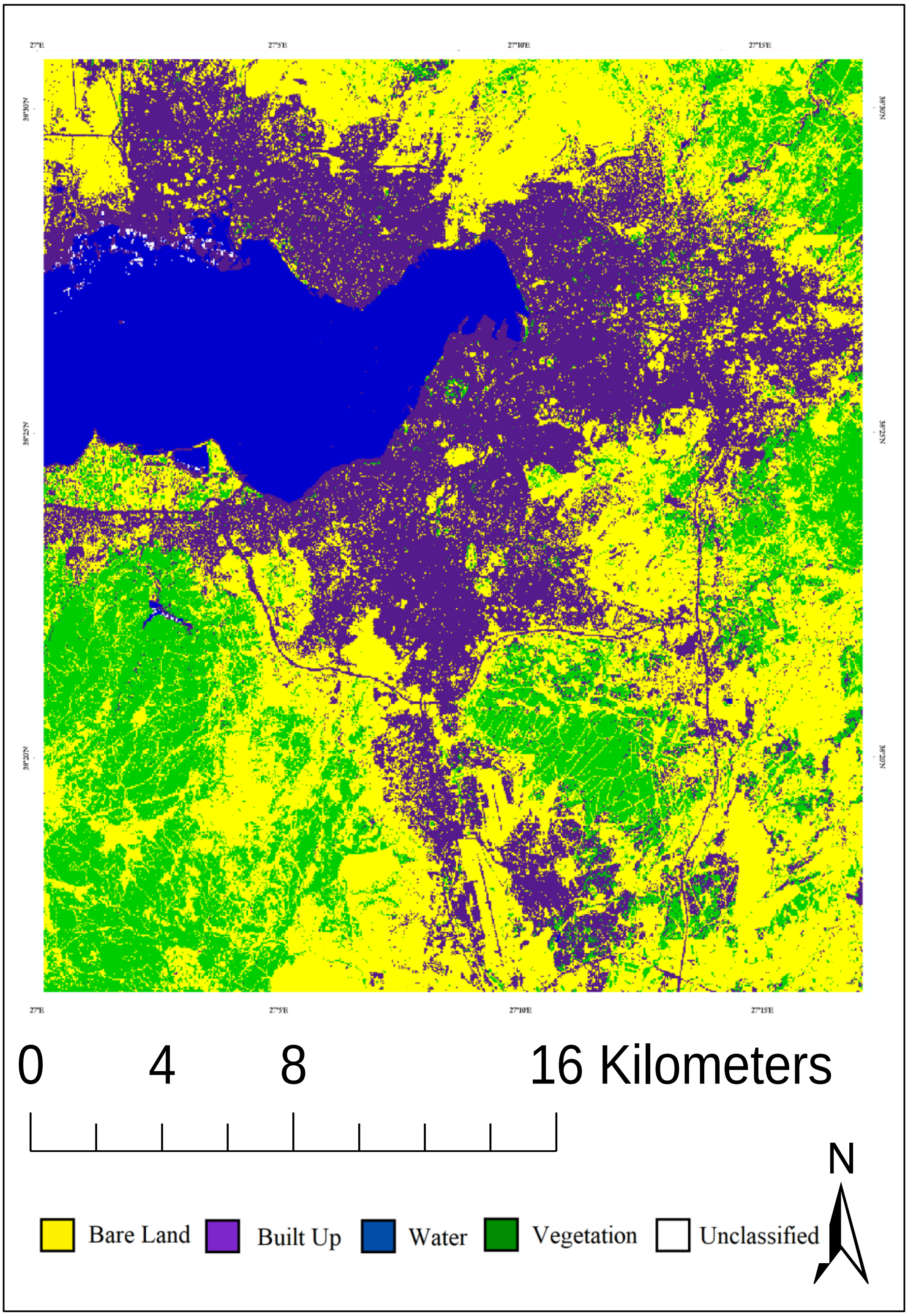


Figure 24: Combined Classification Results

4.3.2. First Level Textural Classification

In Section 3.1.2 and 0, extracting textural features are described in detail. In order to see if the accuracy is increased or not by using only textural features, classification of textural feature bands are done. For simplicity, masked images of gabor features are not presented since visualization is not an important factor. Only full images of textural features are given.

Extracting textural features with gabor filter is done on a software called MATLAB. First, the image data was introduced to the software. Since gabor algorithm can only work with two-dimensional data, there are some possible options to create the filtered image. These options include creating PCA components of the image or creating RGB (red green blue) image, turning it into gray scale; and then taking the maximum magnitudes of gabor. In this study, all options are used.

In PCA components, only first four PCA's are investigated because after that point there is not any valuable information left about the original data. RGB image filtering is applied by taking the gray scale of the three-dimensional image and then taking the maximum magnitudes.

RGB to gray image of gabor maximum magnitude filtered image is given in Figure 25 and then the first, second, third and fourth PCA component gabor filtered images are given in Figure 26, Figure 27, Figure 28 and Figure 29, respectively.

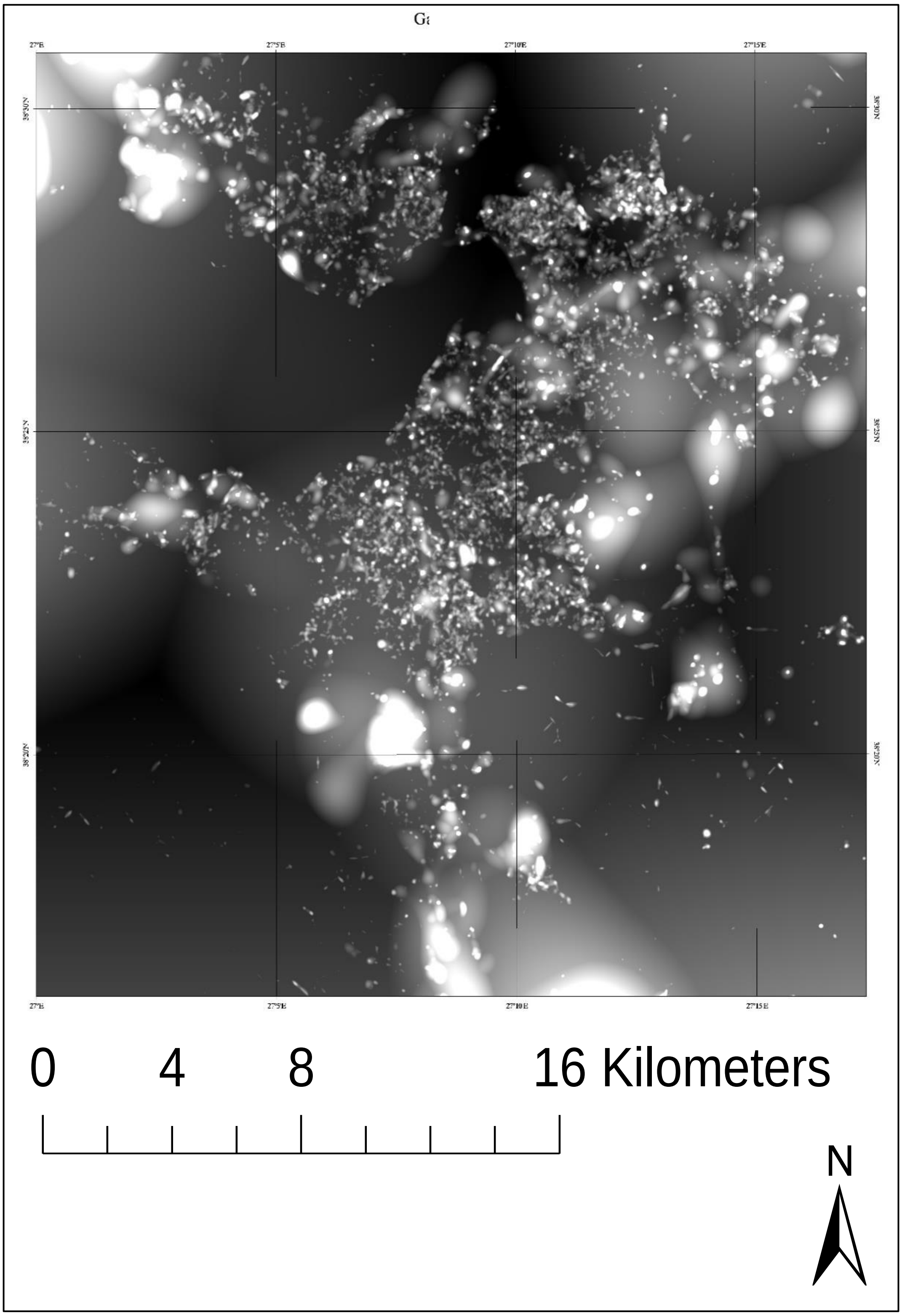


Figure 25: Gabor Maximum Magnitude Filtered Image

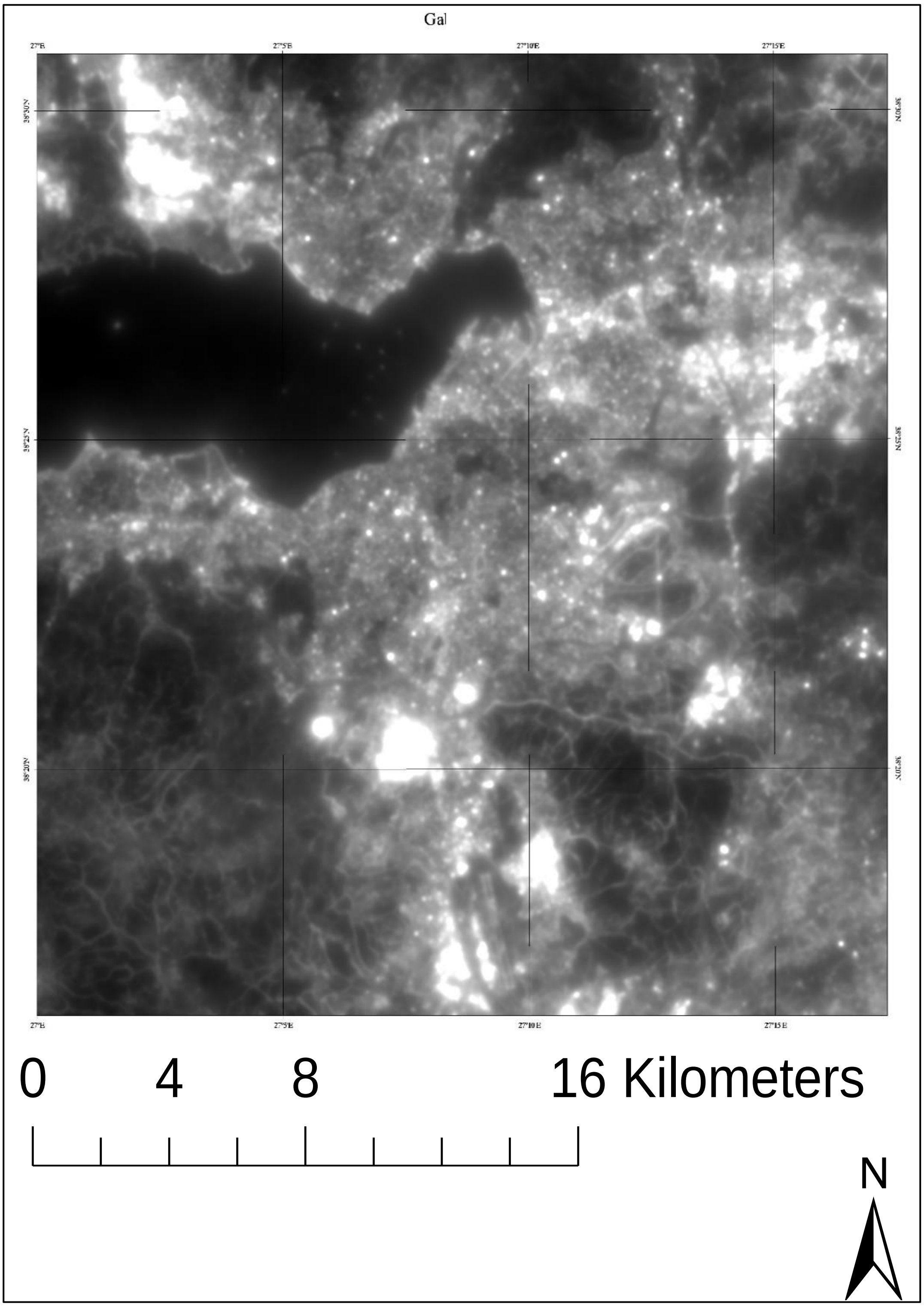


Figure 26: First PCA Gabor Filtered Image

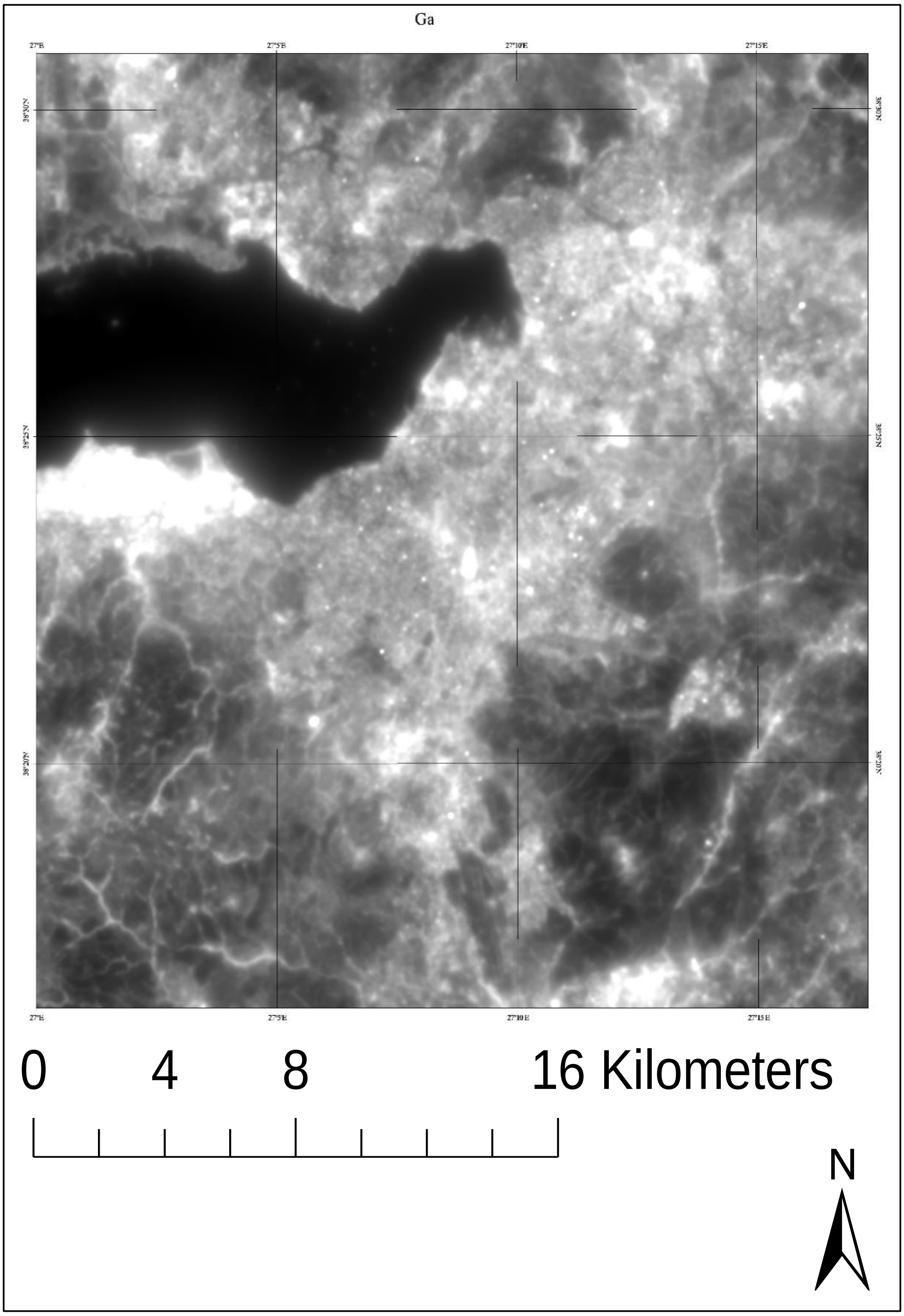


Figure 27: Second PCA Gabor Filtered Image

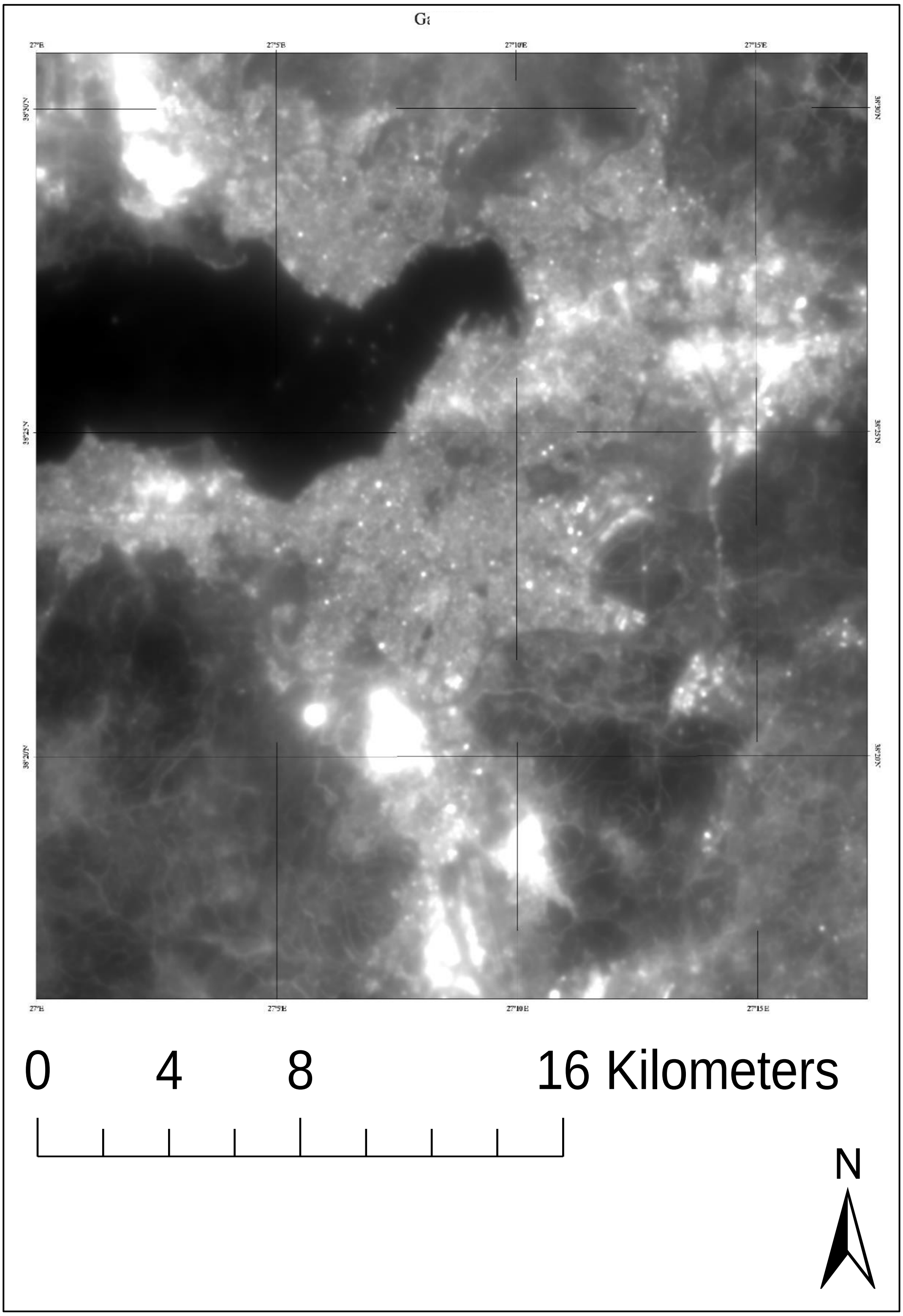


Figure 28: Third PCA Gabor Filtered Image

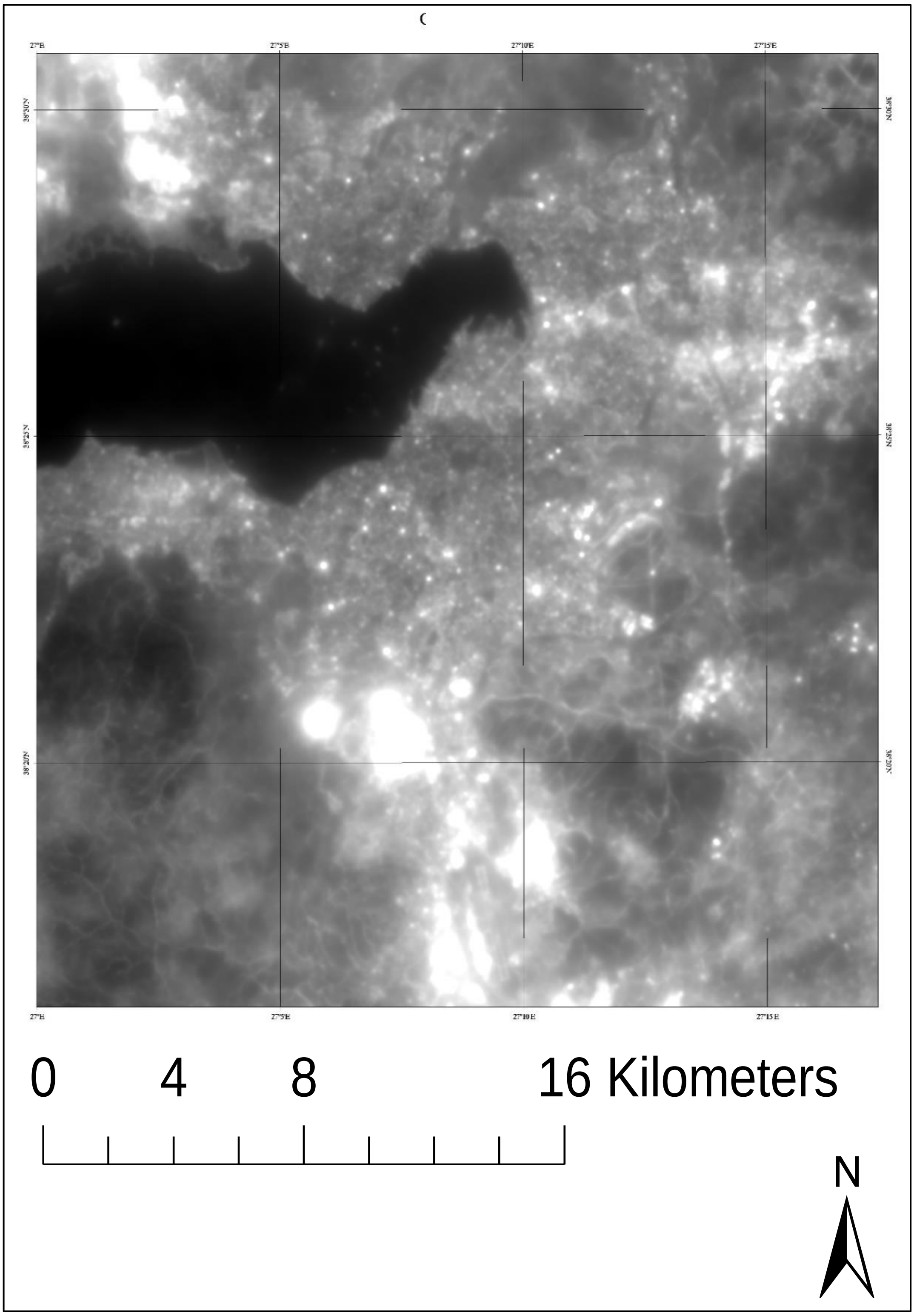


Figure 29: Forth PCA Gabor Filtered Image

All the filtered images are masked and classified with SVM with the same regions of interest used for training the algorithm in multispectral classification. The final combined classification for each type of filter is given in Figure 30, Figure 31, Figure 32, Figure 33, Figure 34 and Figure 35 respectively.

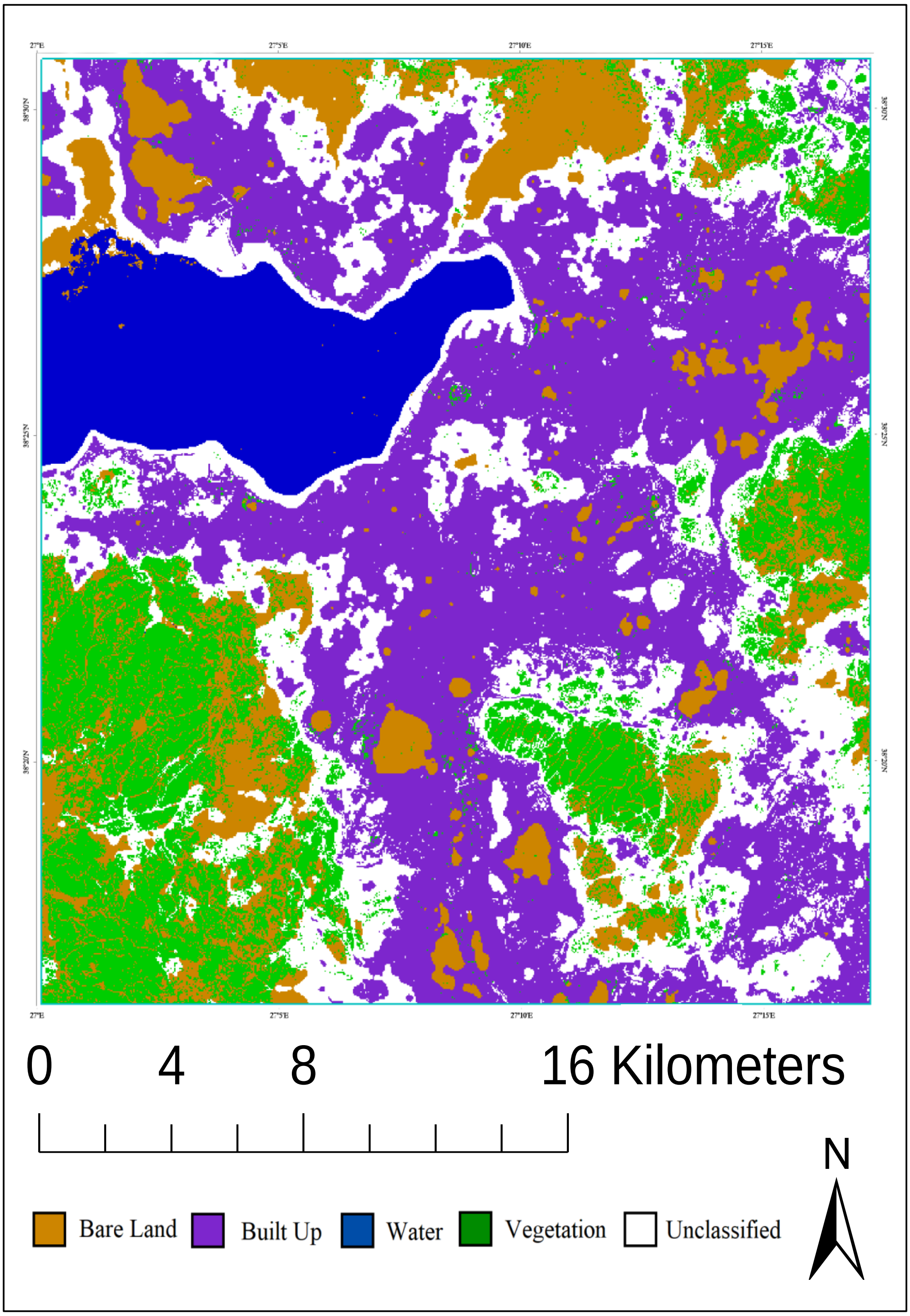


Figure 30: Classification Result of First PCA Gabor Filtered Image

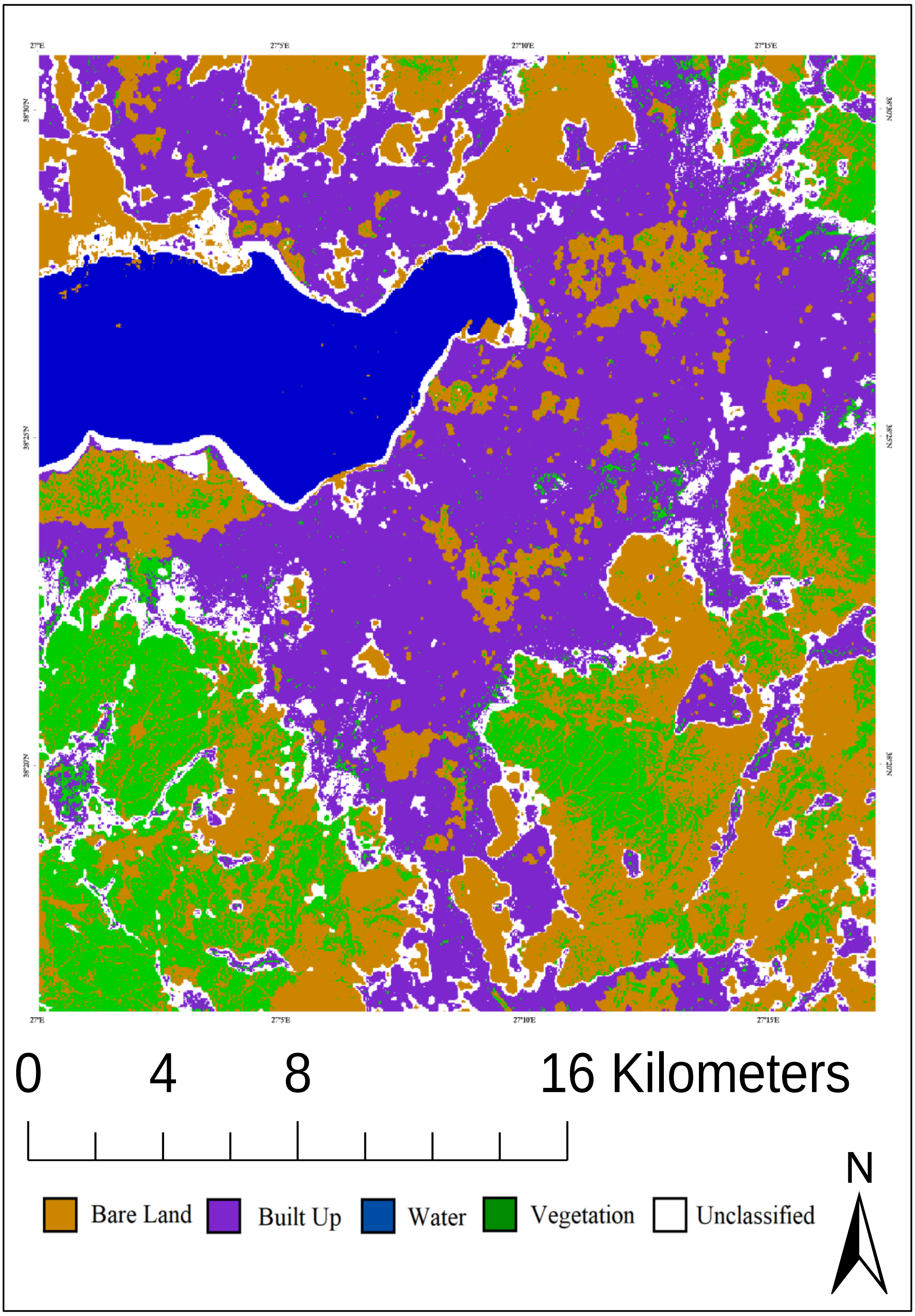


Figure 31: Classification Result of Second PCA Gabor Filtered Image

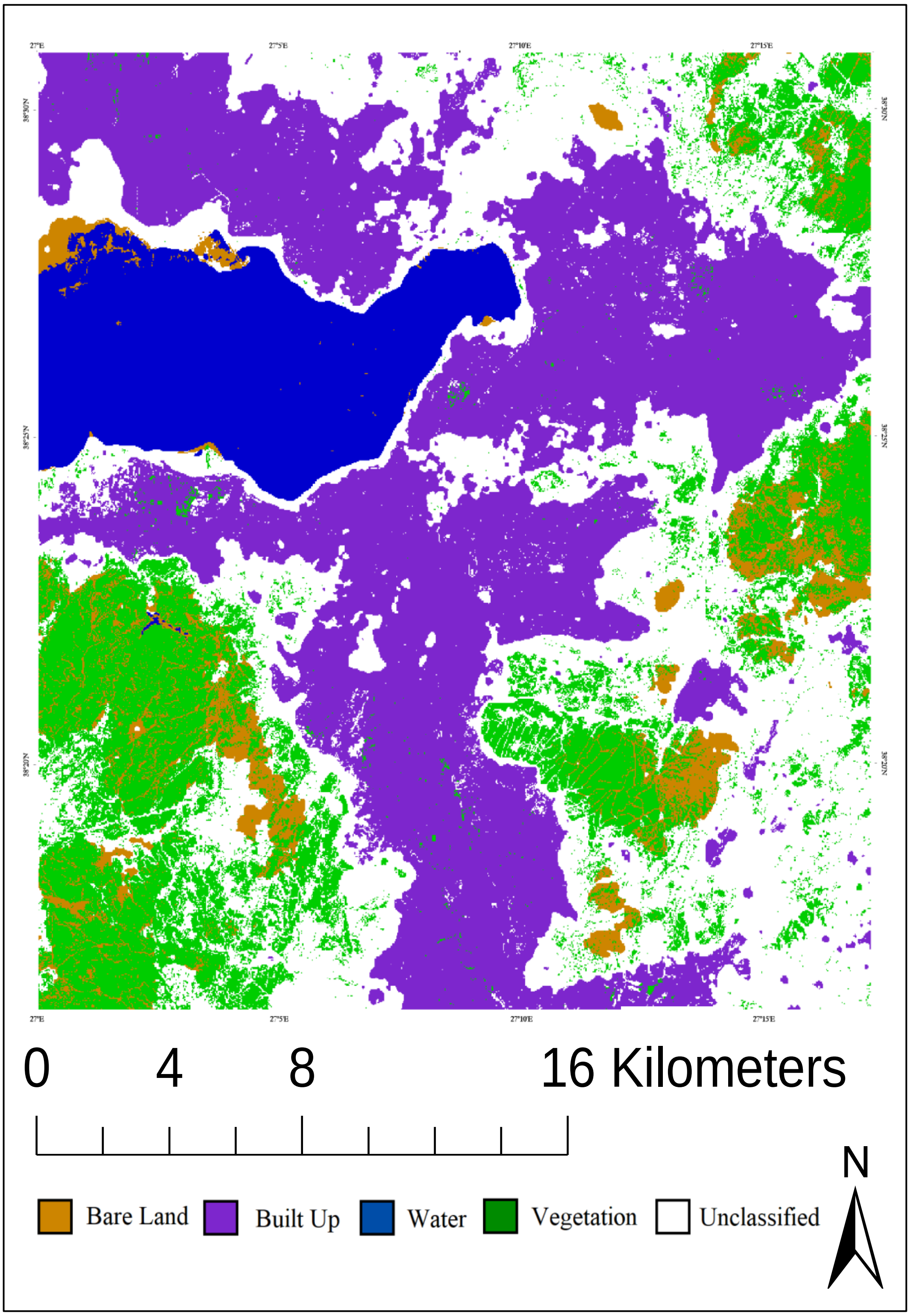


Figure 32: Classification Result of Third PCA Gabor Filtered Image

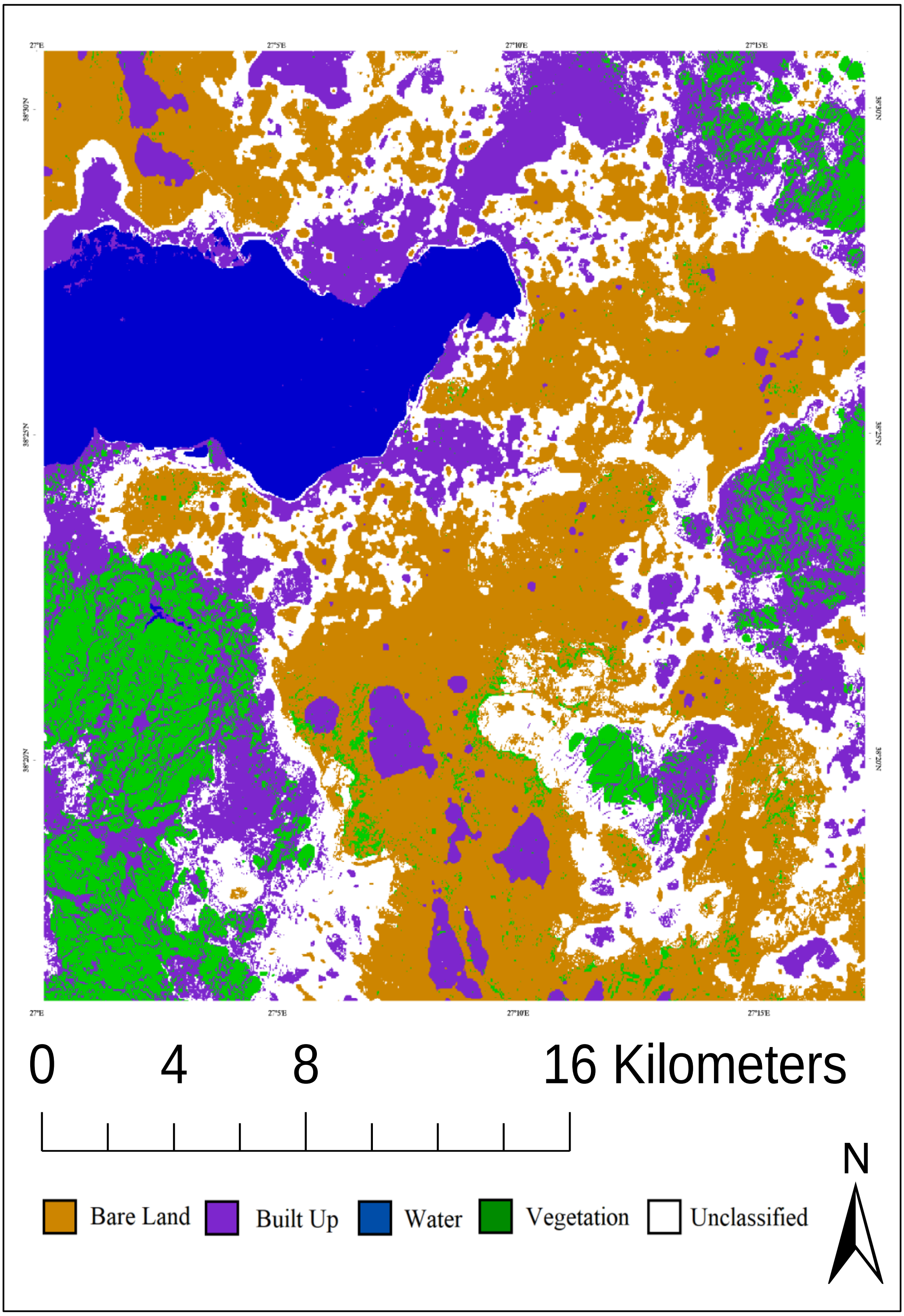


Figure 33: Classification Result of Forth PCA Gabor Filtered Image

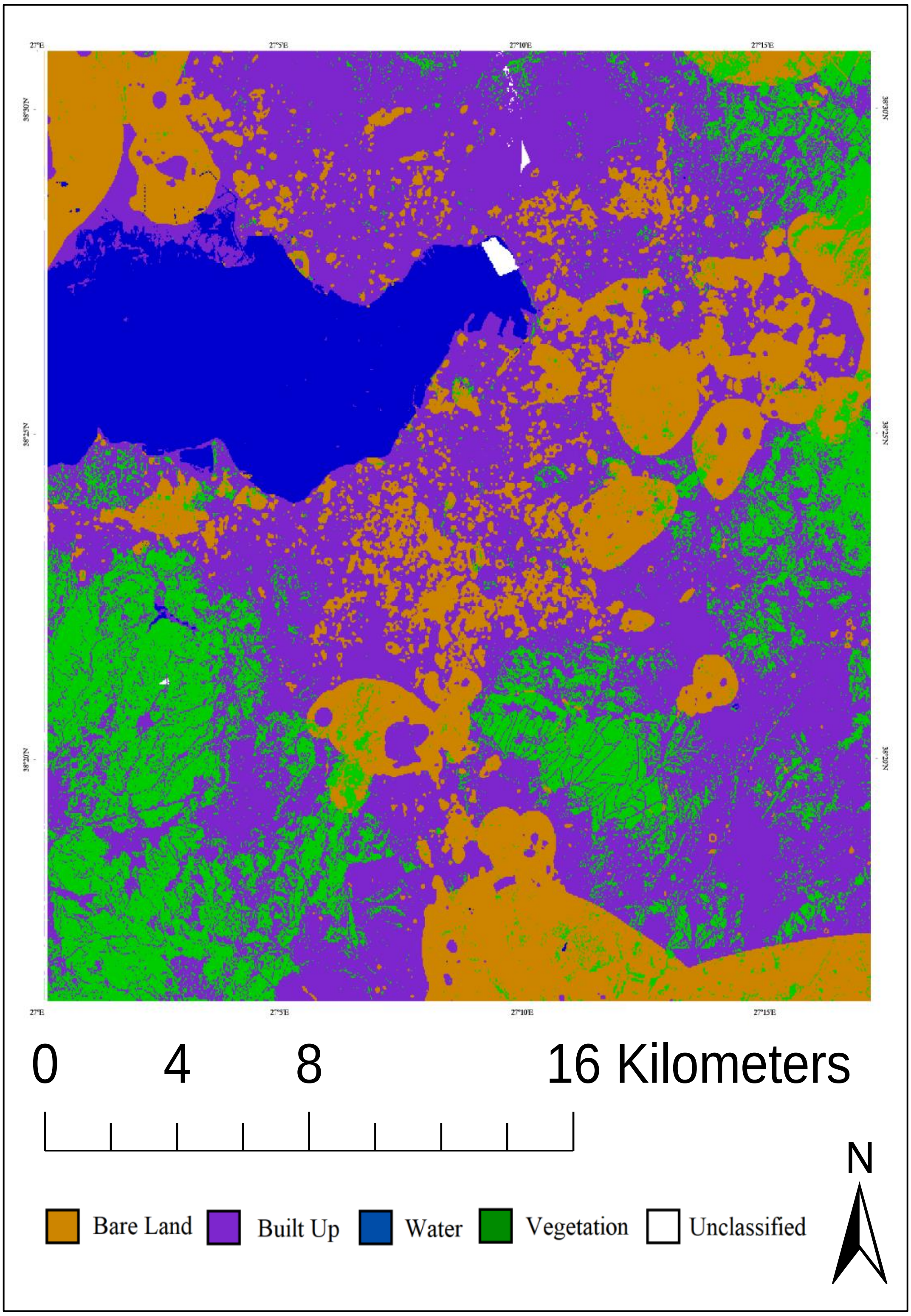


Figure 34: Classification Result of Maximum Magnitude Gabor Filtered Image

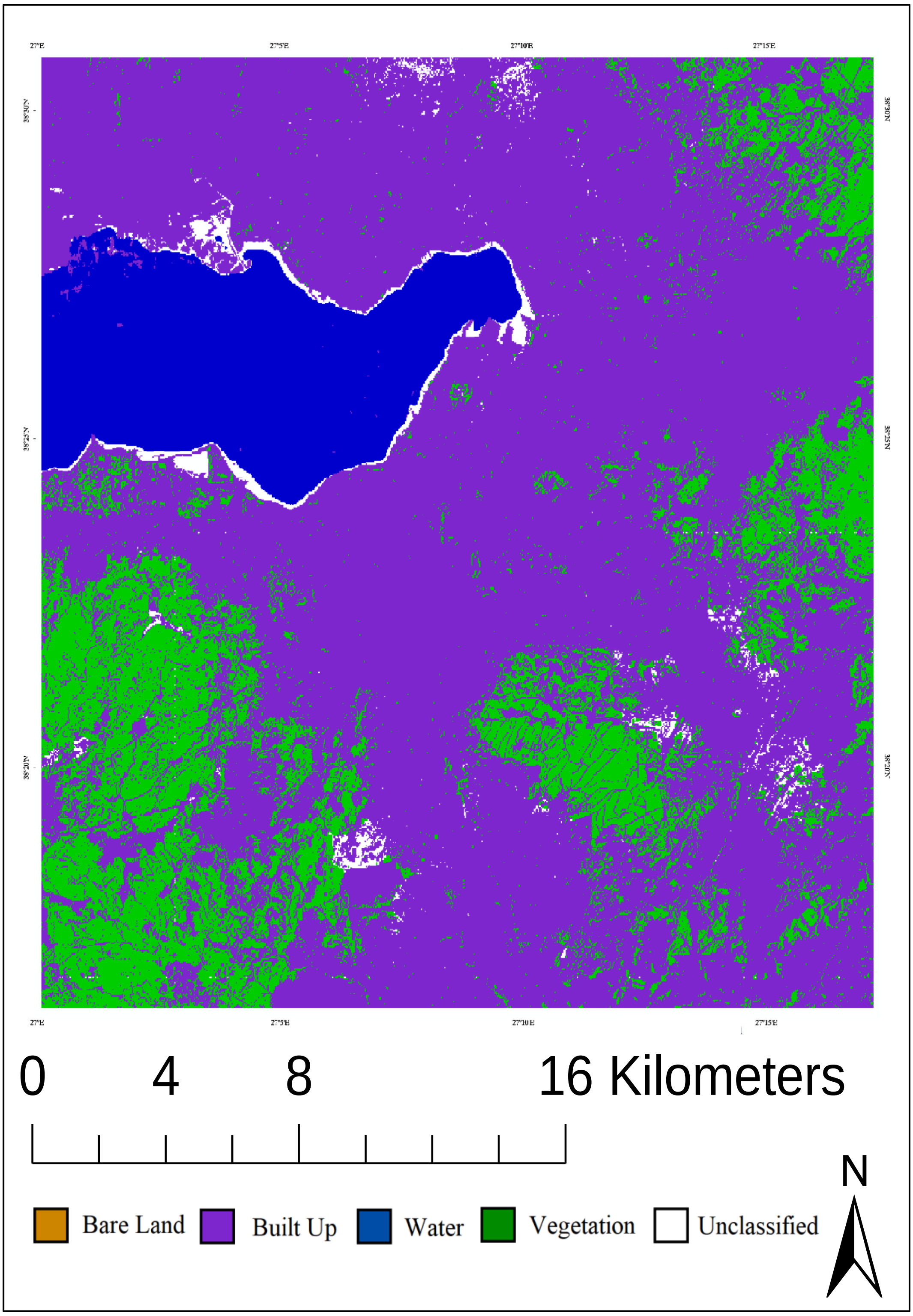


Figure 35: Combining All Texture Bands Together

As done in the multispectral classification part, accuracy assessment with stratified random sampling and then error matrix calculations are done and presented in Chapter 5. The results shows if only textural features can be used for a good classification or not.

4.3.3. First Level Multispectral and Textural Features Combined Classification

In this part, multispectral image data is merged with textural data extracted by Gabor filtering. The original data have 13 bands but for visualization, only RGB bands are used. Combining multispectral data with textural data does not change the RGB band composition. Therefore, visualization of data is the same as in Section 4.3.1. For this reason, no further figures were added before the classification steps.

In this part of the study, new data is used for first level classification is multispectral original data plus textural bands which are created in Section 4.3.2. Input data is now 18 band image data instead of 13 band multispectral data. Bands which merged with the original data are Gabor maximum magnitude filtered image of RGB, filtered first PCA component, filtered second PCA component, filtered third PCA component and filtered fourth PCA component. SVM algorithm is used again and classification results of merged data is given in Figure 36.

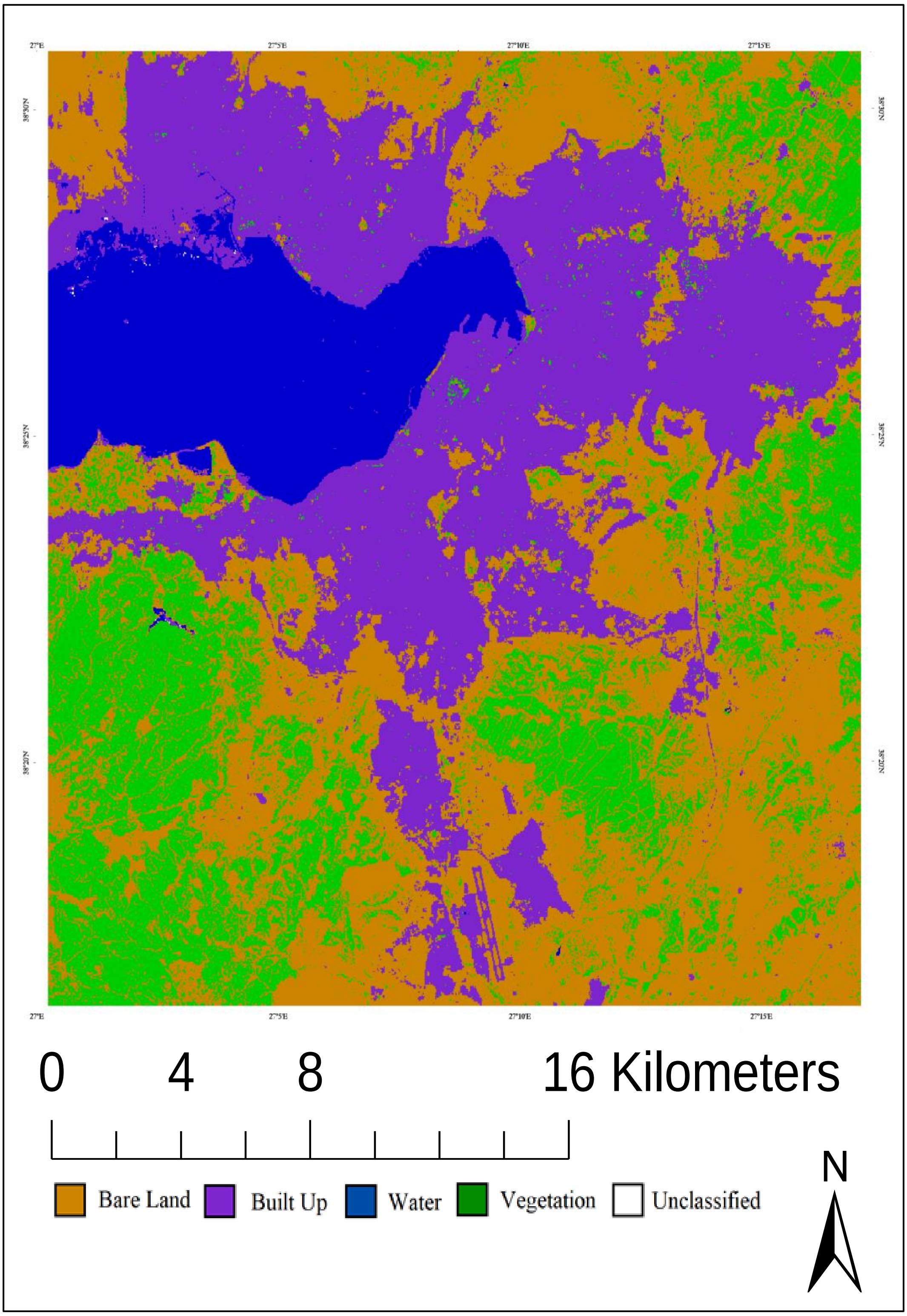


Figure 36: First Level Multispectral and Textural Classification Results

4.3.4. Second Level Multispectral Classification

In line with the methodology, classification levels are introduced in Chapter 3, Figure 6; second level classification steps are started after the first level classification is done. As it is mentioned before, the built-up regions are not divided any further. Water class is divided into marine water and inland water. Vegetation class is divided into vegetated agricultural land and forest/meadow. Bare land is divided into barren land and non-vegetated agricultural land. As done in the first level classification part, all classes are classified exclusively into their own masked data. Training pixel set of sub classes are created and used in all second level classification steps. Final classification result is given in Figure 37.

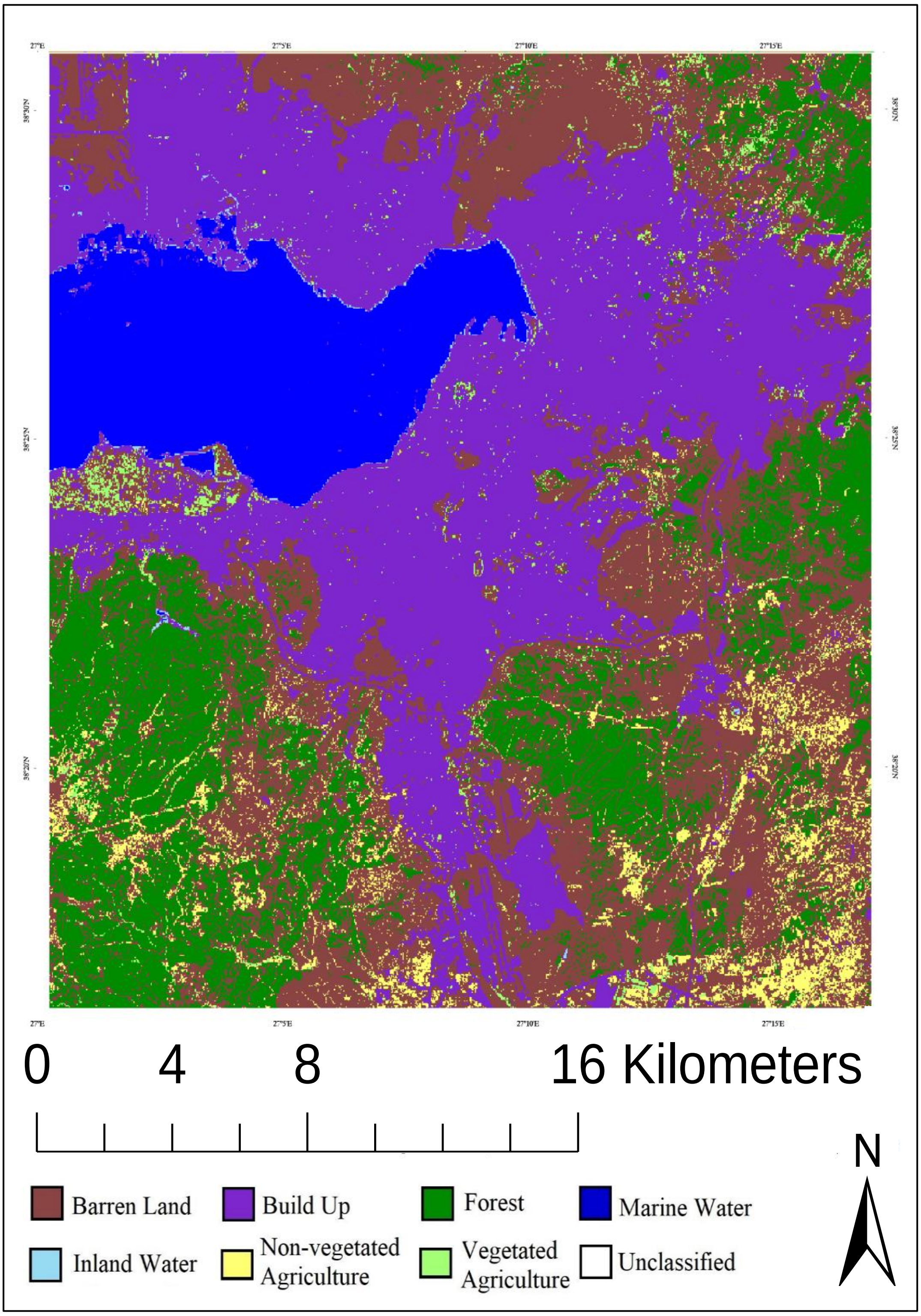


Figure 37: Second Level Multispectral Classification Results

4.3.5. Second Level Textural Classification

As it is done in multispectral classification, classes are classified with SVM with the same training samples. Maximum magnitude Gabor filtered image, first PCA filtered image, second PCA filtered image, third PCA filtered image and fourth PCA filtered image are given in Figure 38, Figure 39, Figure 40, Figure 41 and Figure 42, respectively.

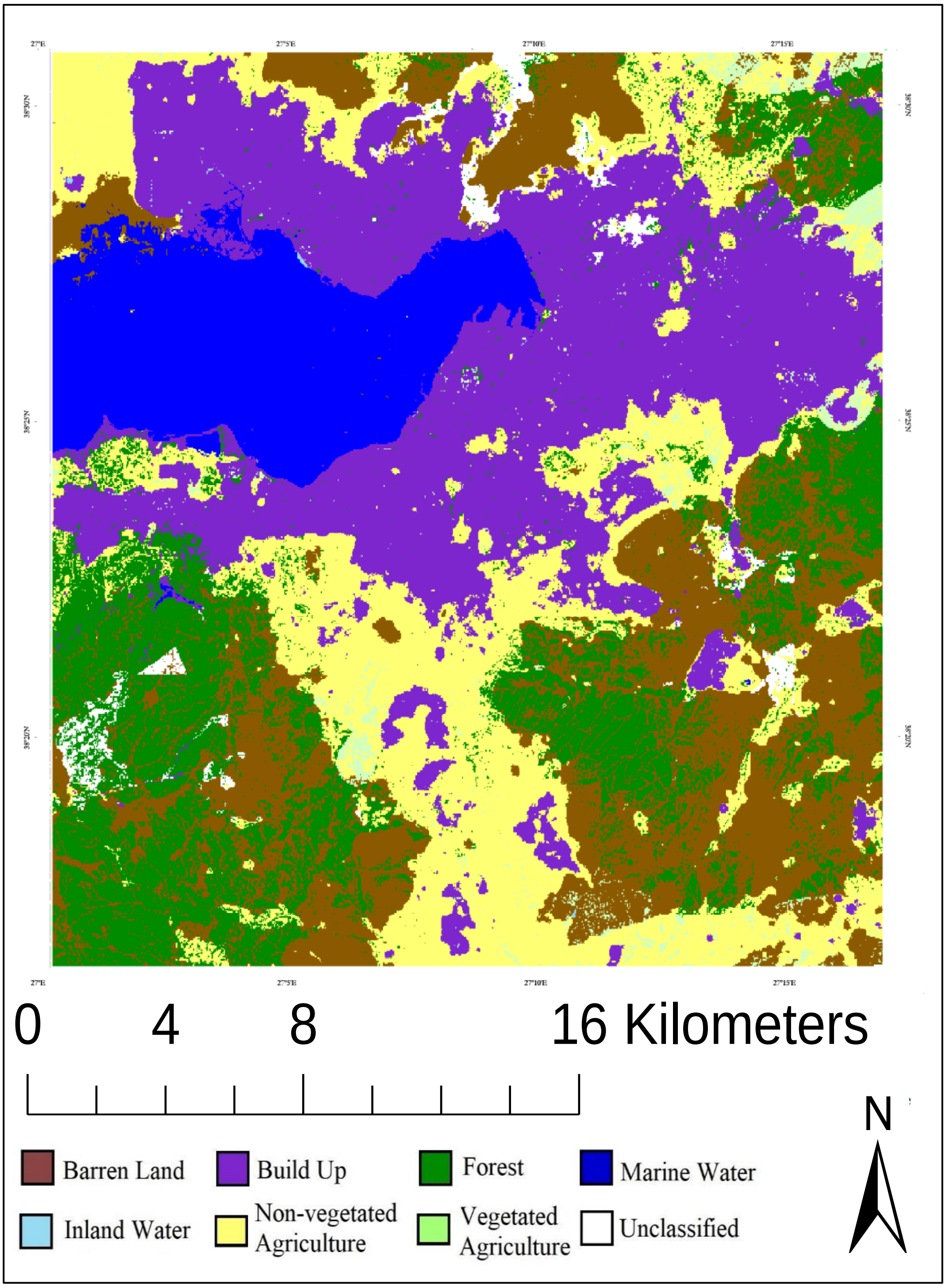


Figure 38: Maximum Gabor Feature Classification Results

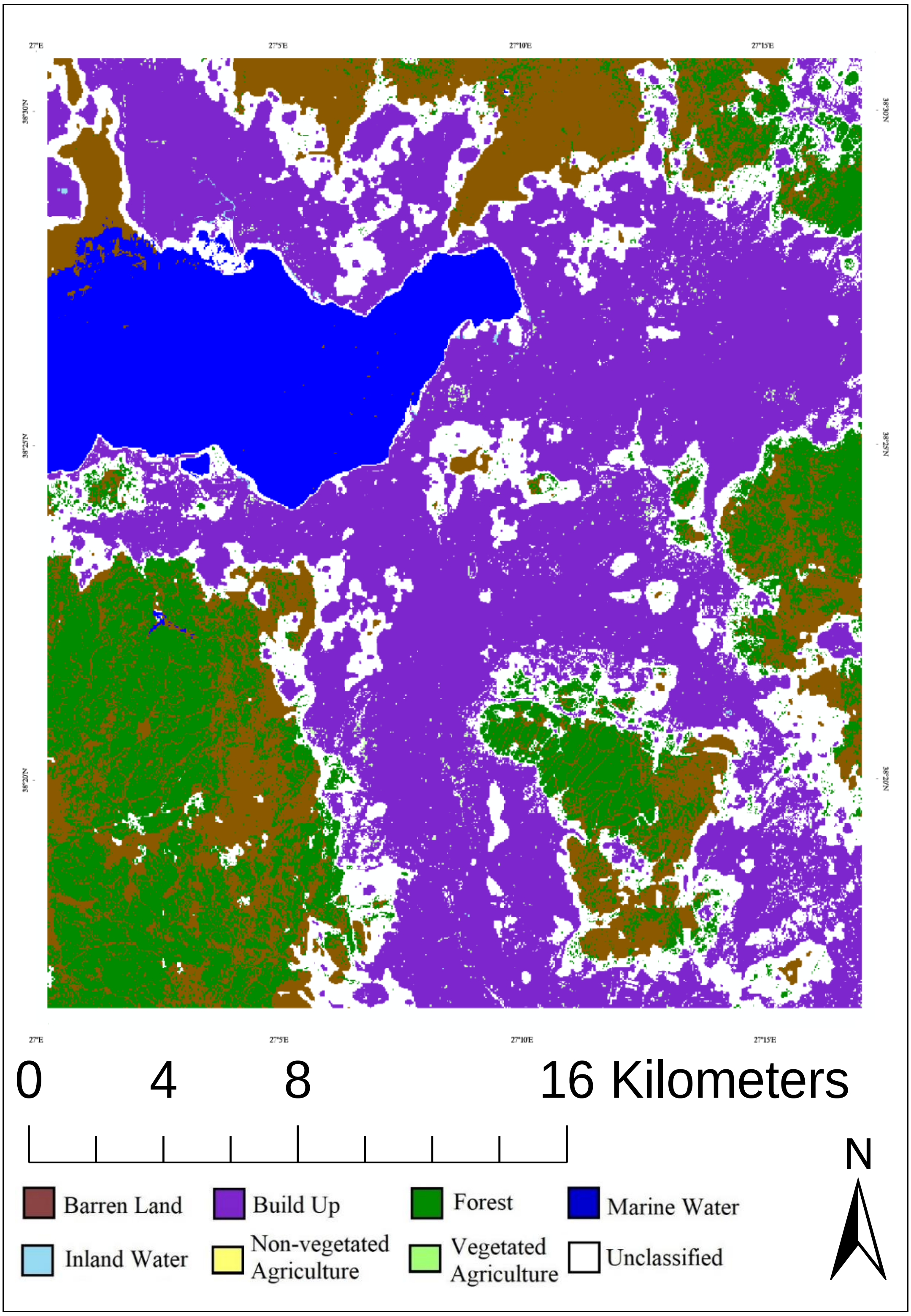


Figure 39: First PCA Component Classification Results

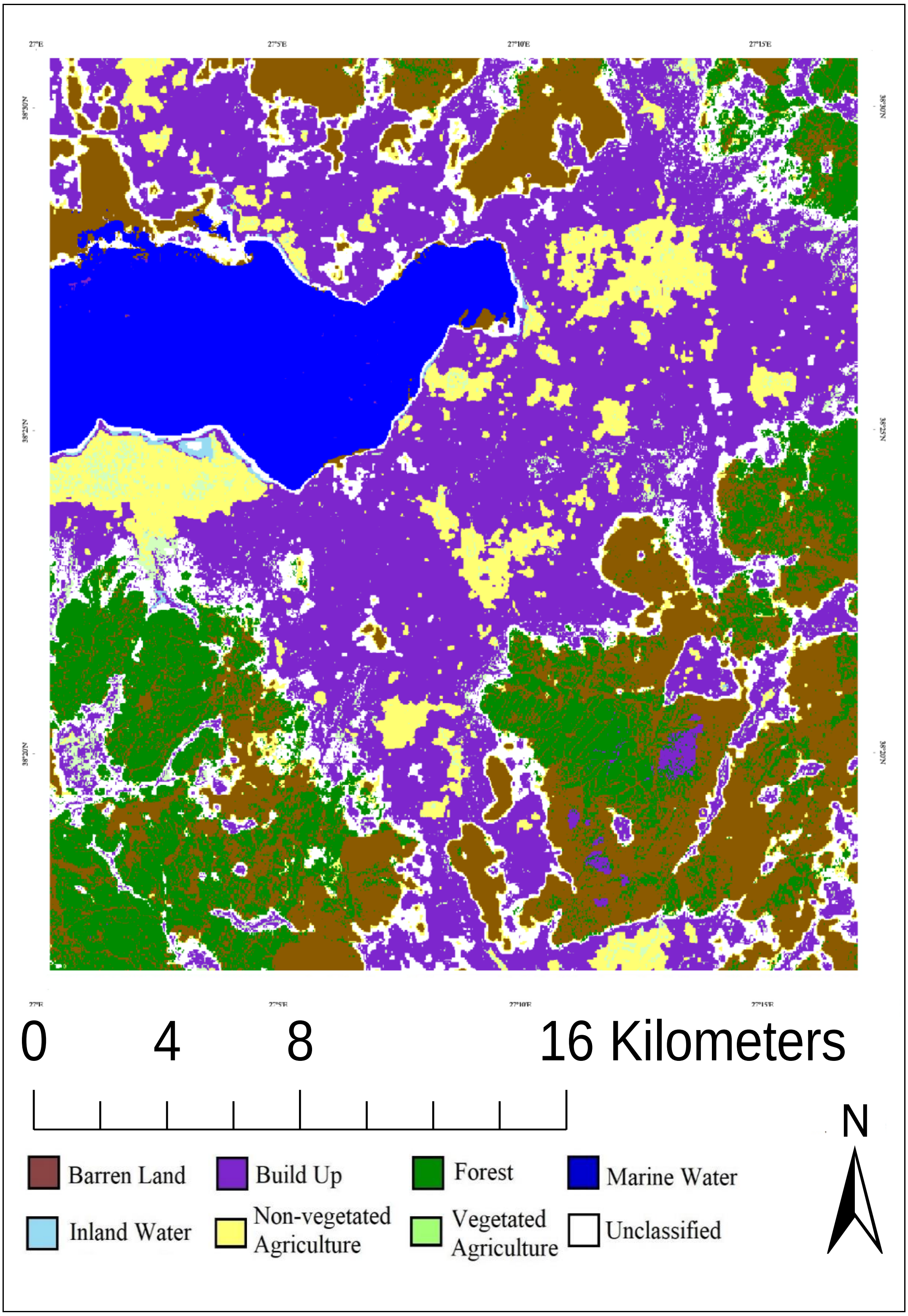


Figure 40:Second PCA Component Classification Results

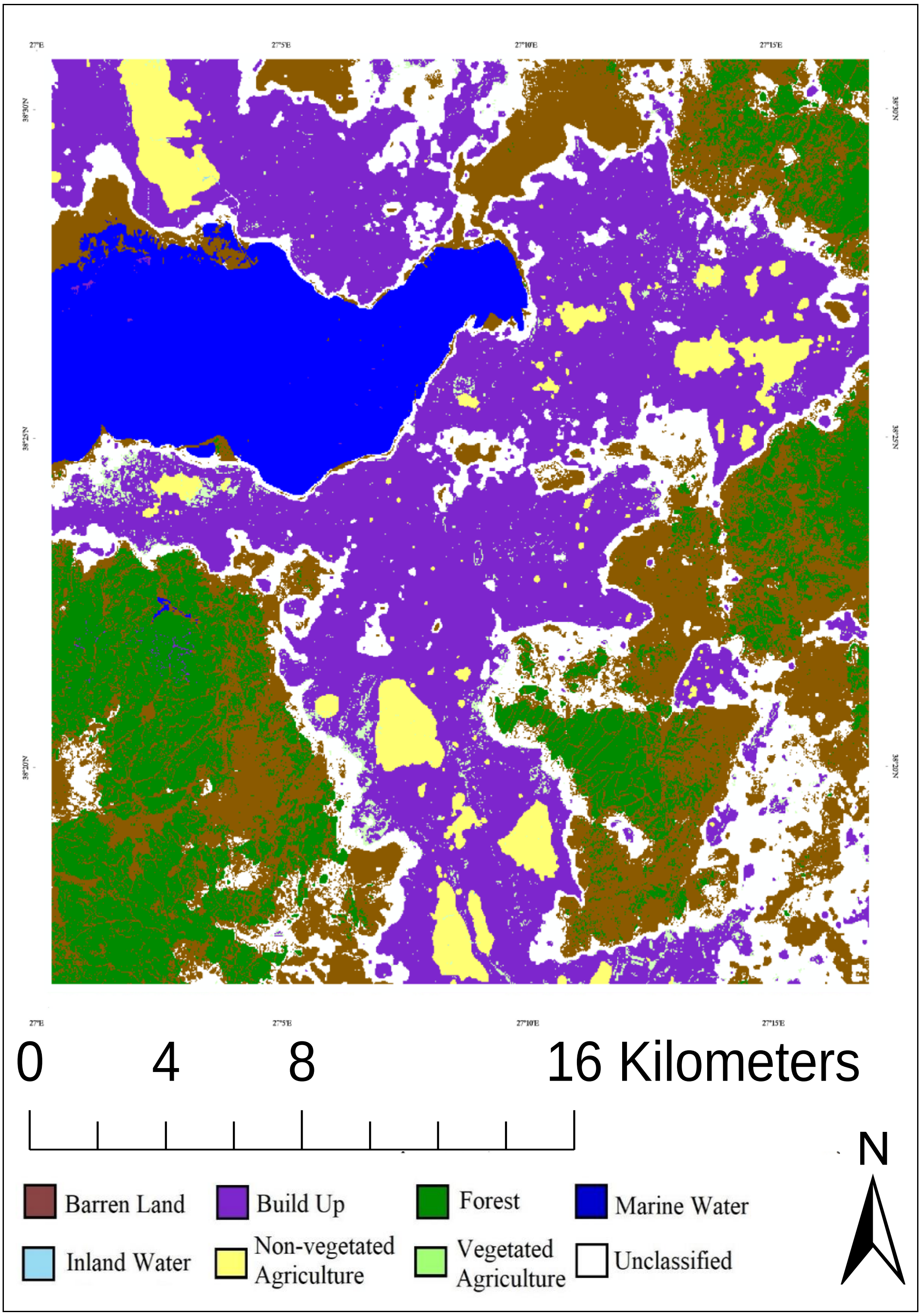


Figure 41:Third PCA Component Classification Results

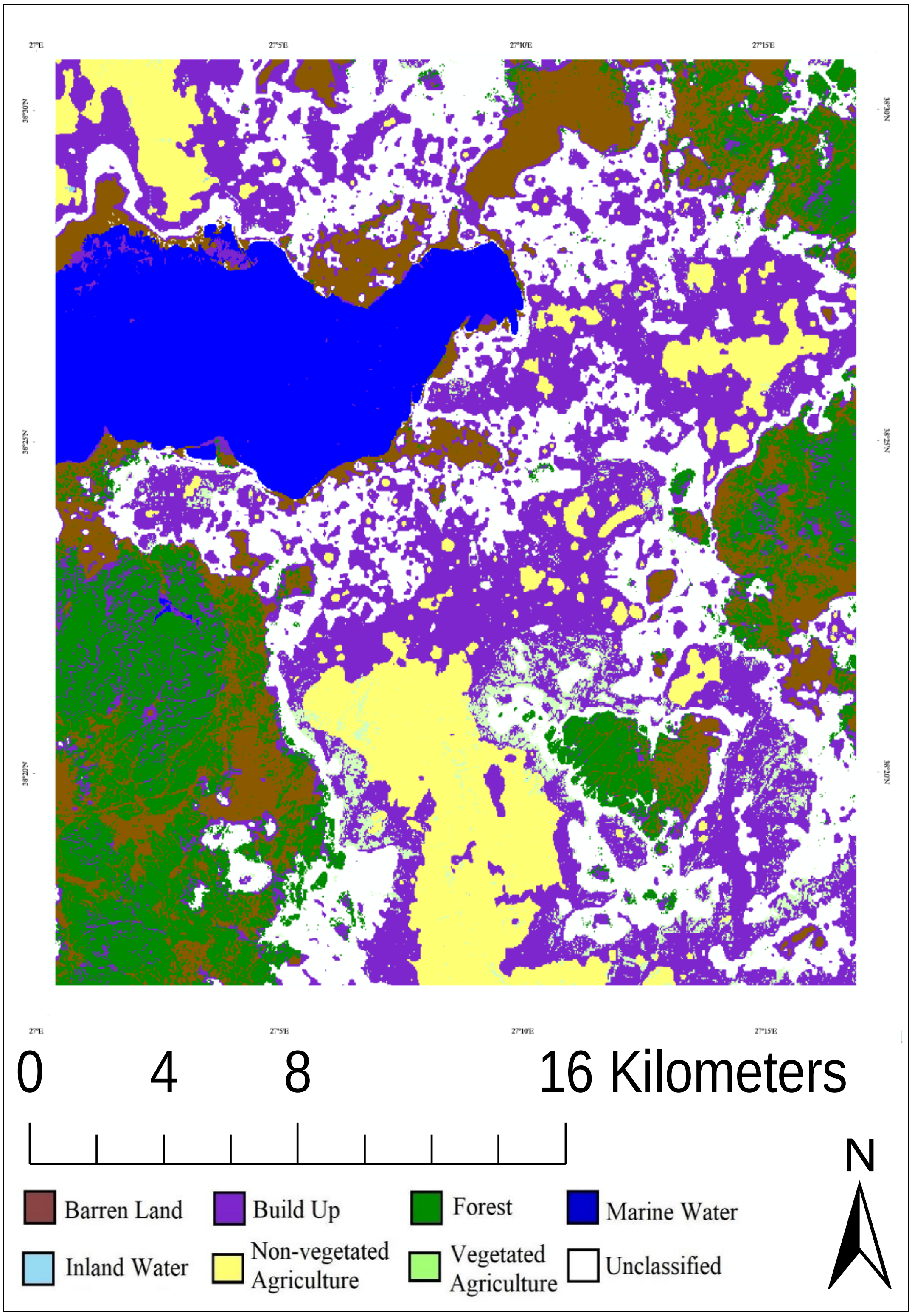


Figure 42:Fourth PCA Component Classification Results

4.3.6. Second Level Multispectral and Textural Features Combined Classification

As in the first level classification, in the second level, textural features are merged with the original data; and then SVM is applied. Classification results of combined classification is given in Figure 43.

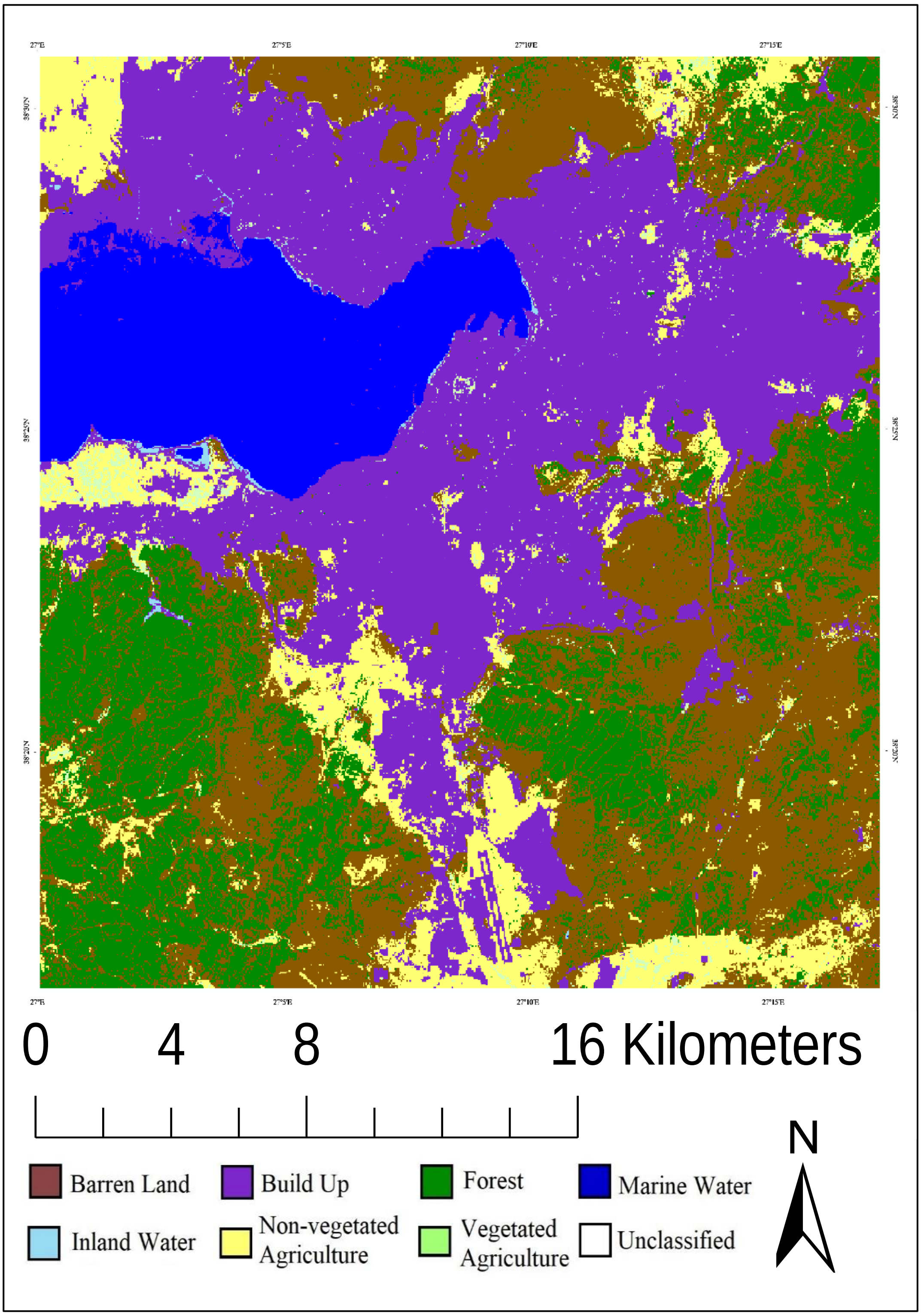


Figure 43: Multispectral and Textural Features Combined Classification Results

4.4. Ankara

Ankara data and Izmir data are similar to a great extent. The format and type of the data are the same; but there are also some differences. Firstly, although it does not effect the classification algorithm and methodology, Ankara area is larger than Izmir. Secondly Izmir is a coastal town while Ankara is not. Due to this fact, sub class of water, marine water class are omitted in second level classification of Ankara. Other parts and steps are the same.

4.4.1. First Level Multispectral Classification

Ankara data is treated in the same way as Izmir's. First, NDVI and NDWI are produced and then water and vegetation are extracted by thresholding the histograms. Masking is applied for further steps The study area of Ankara is given in Figure 44.

4.4.1.1. Water and Vegetation Classification

NDVI and NDWI of Ankara are given in Figure 45 and, Figure 46 respectively. After creating indices, vegetation and water were extracted; and then masking operation was done. Extraction of water, extraction of vegetation, the masked image of water and the masked image of vegetation is given in Figure 47, Figure 48, Figure 49 and Figure 50, respectively.

After completing indexes for water and vegetation, data became ready for thresholding. Extracting water and vegetation is done by thresholding and class labels are implemented as water and vegetation.

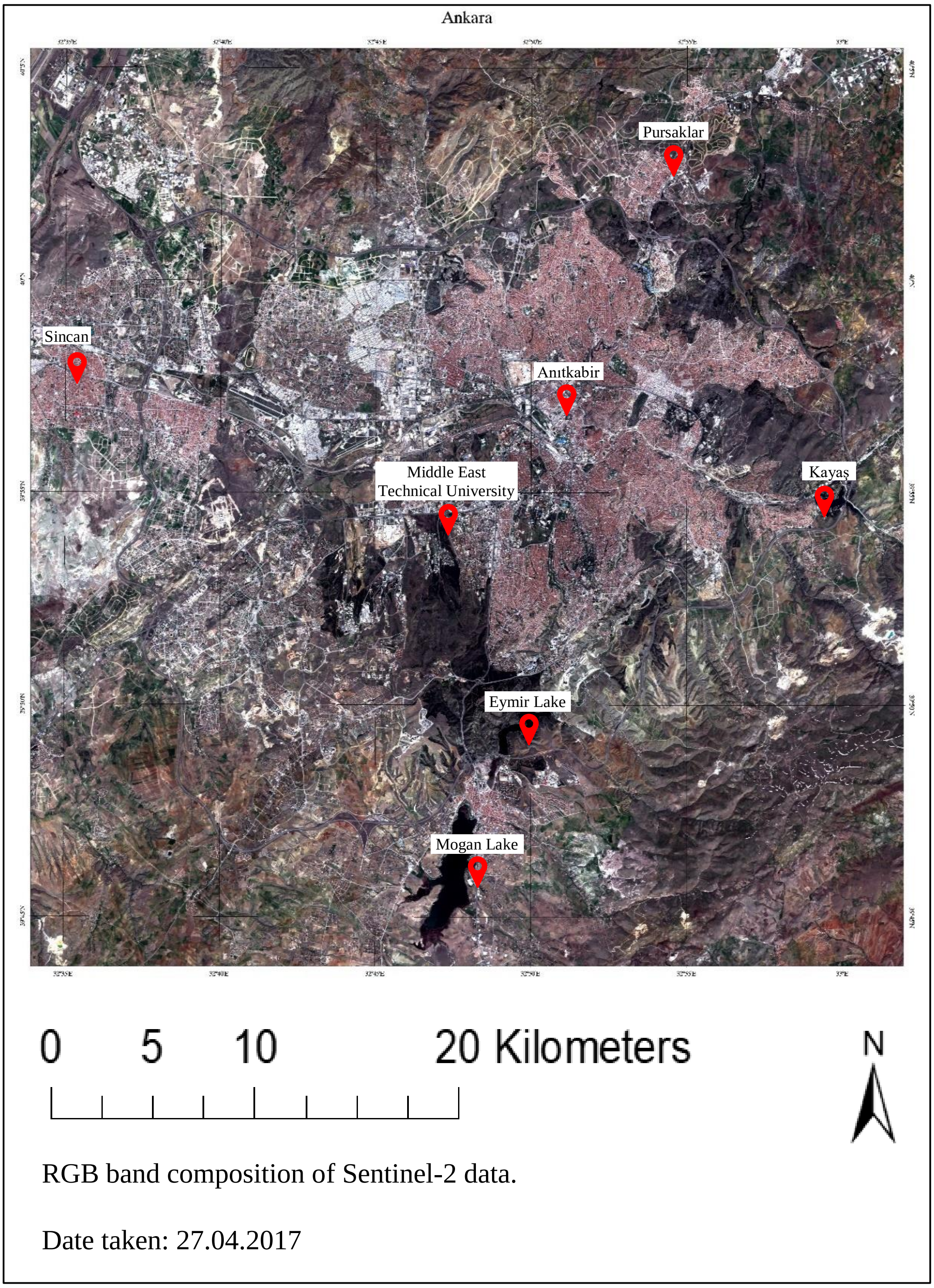


Figure 44: Study Area of Ankara

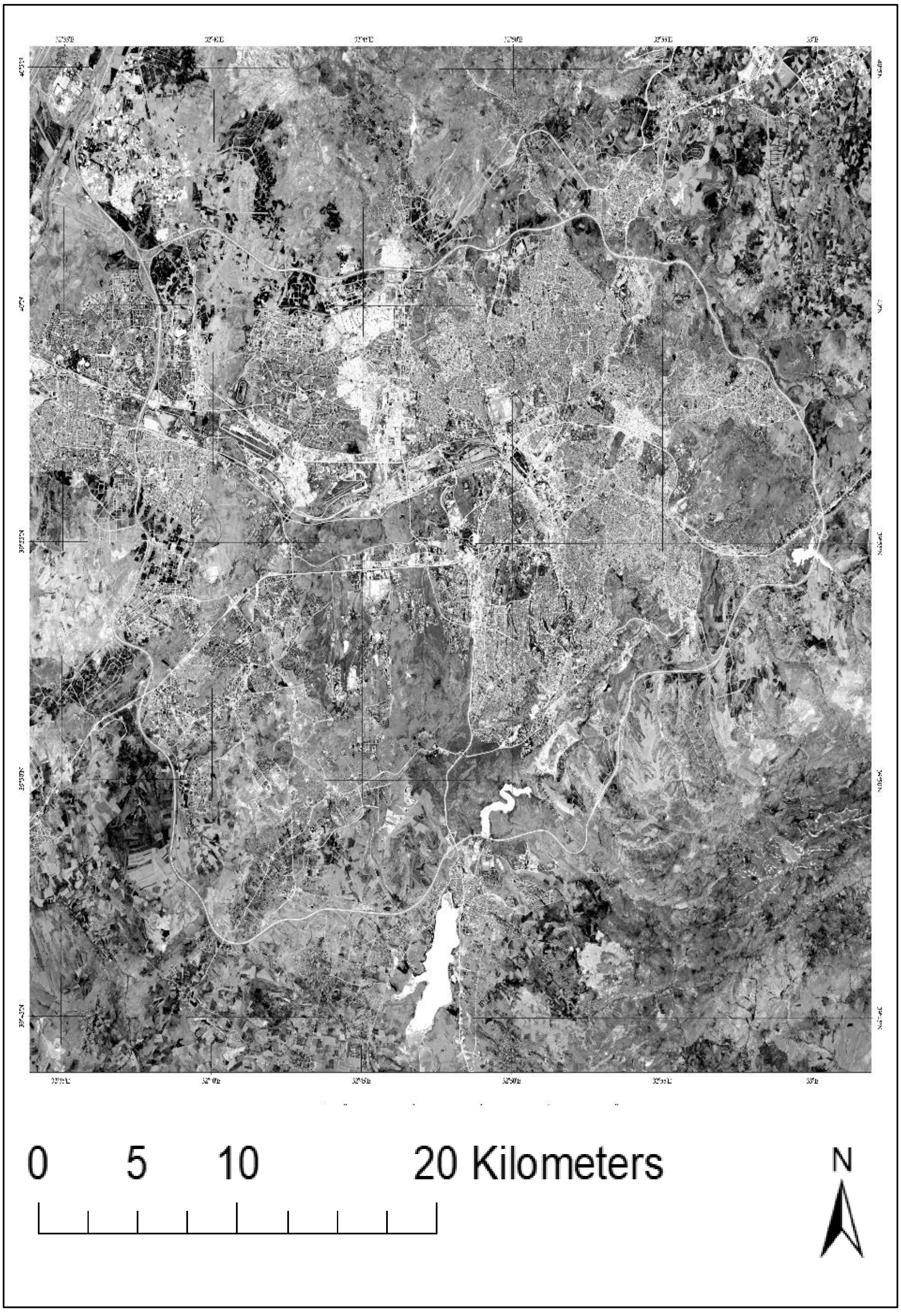


Figure 45: NDWI of Ankara

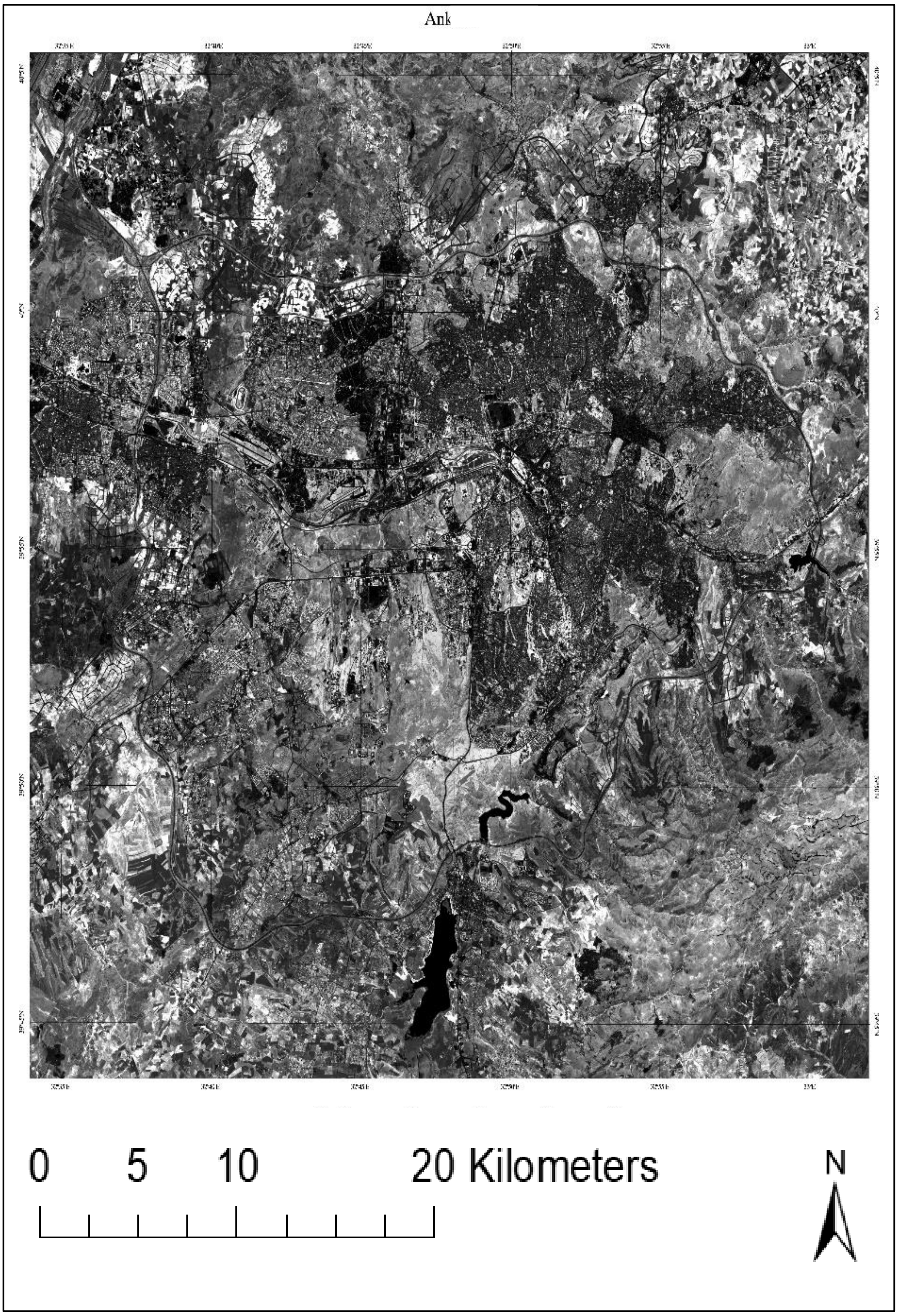


Figure 46: NDVI of Ankara

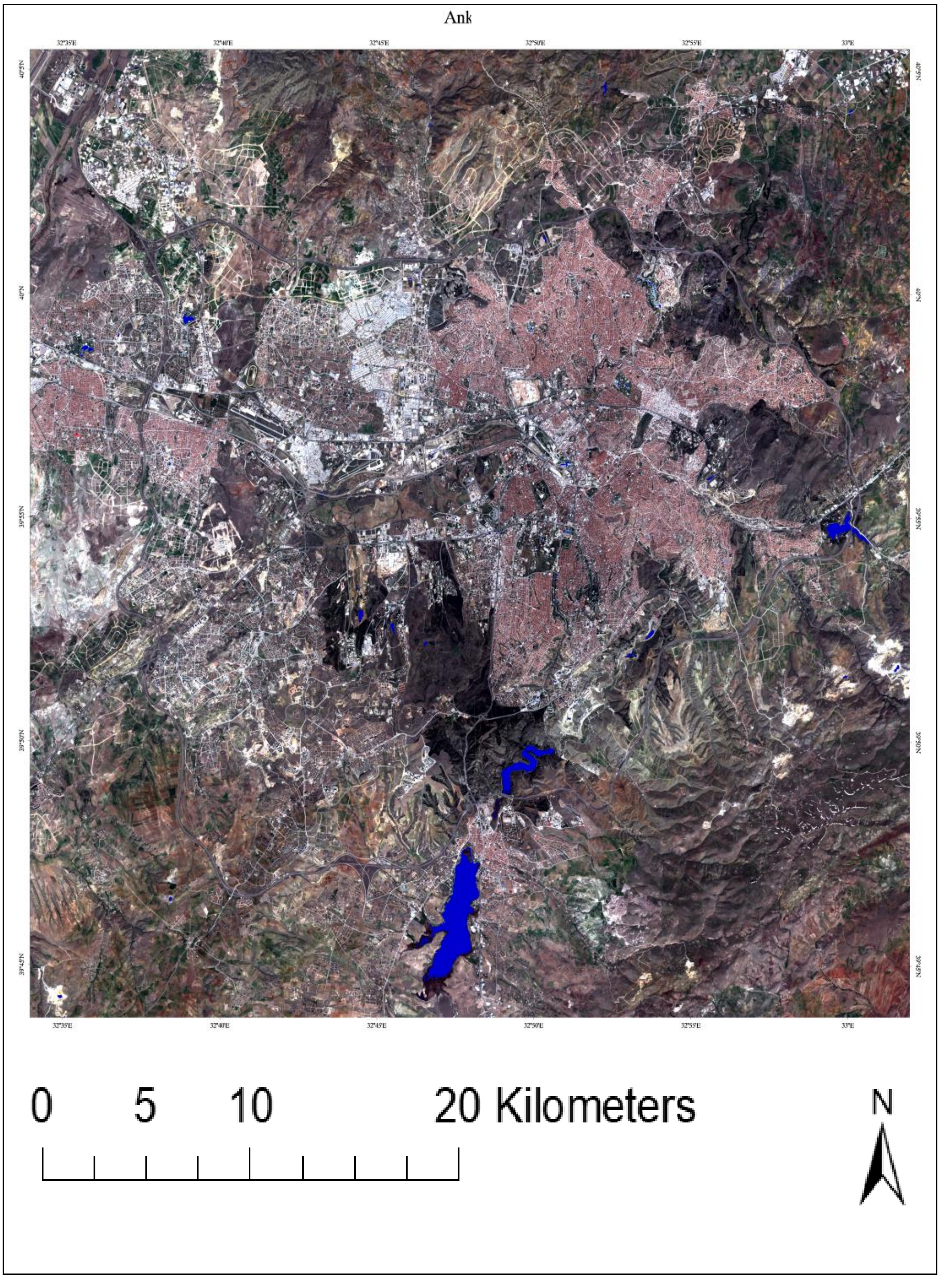


Figure 47: Region of Interest of Water in Ankara

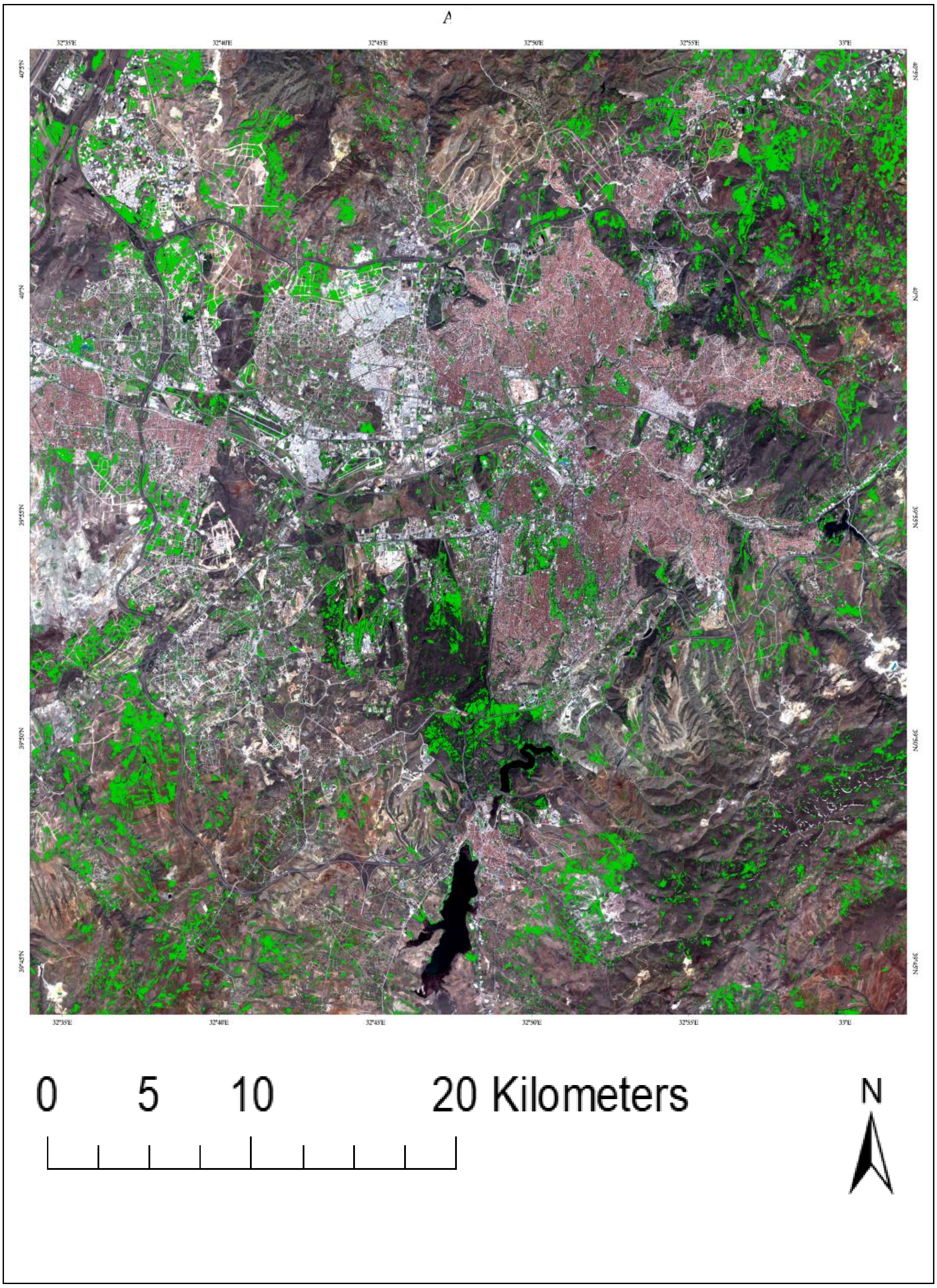


Figure 48:Region of Interest of Vegetation in Ankara

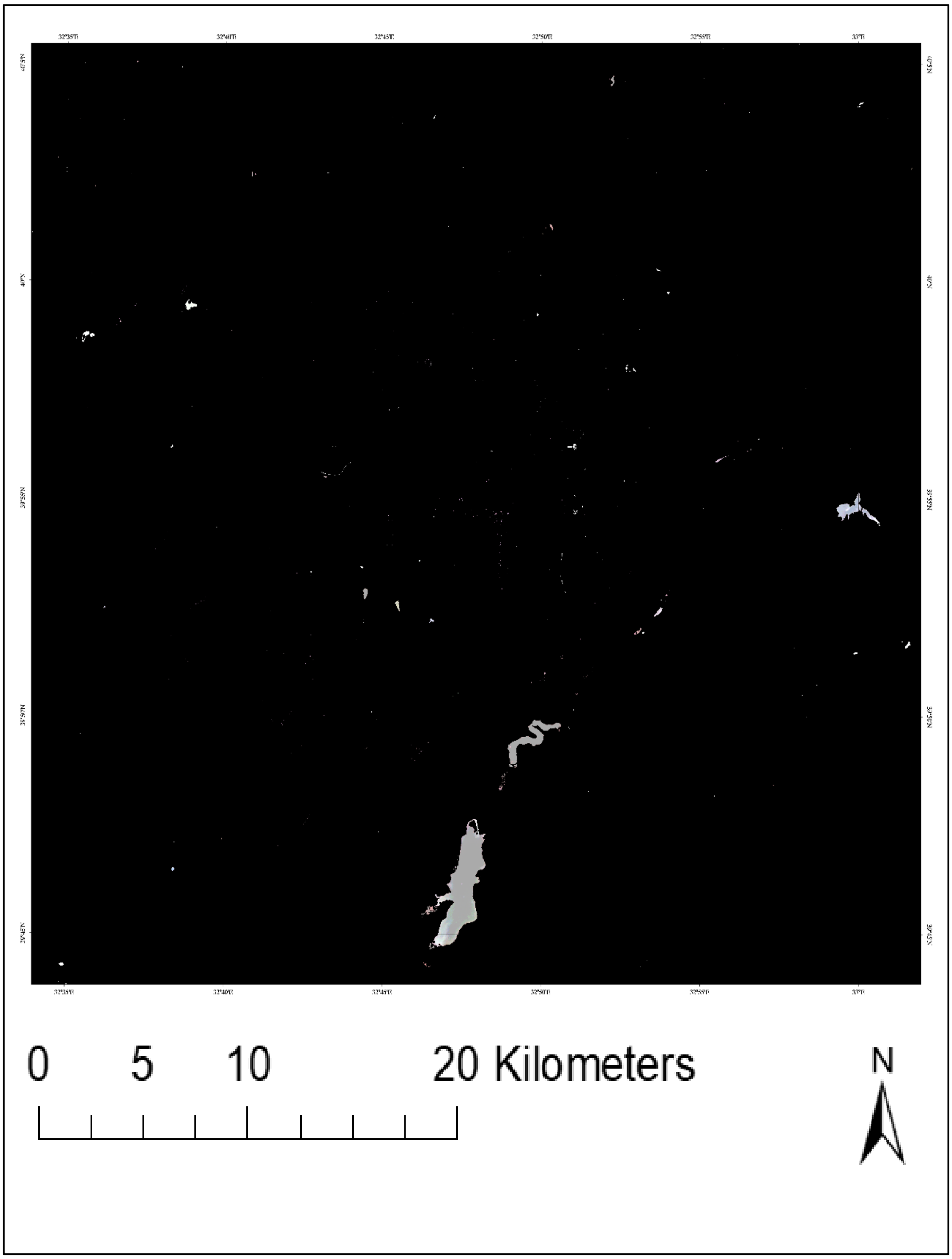


Figure 49: Mask for Water

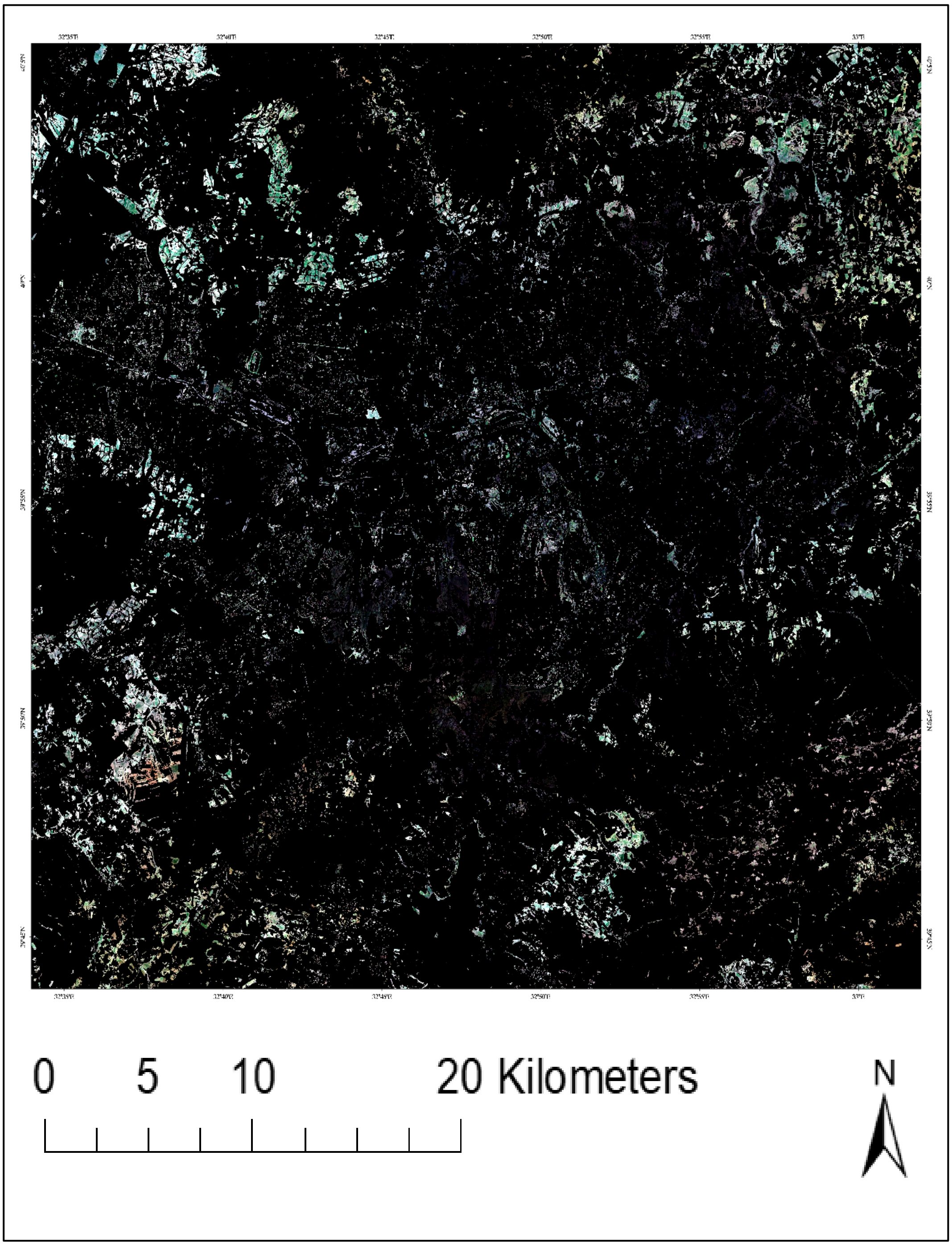


Figure 50: Mask for Vegetation

4.4.1.2. Built Up and Bare Land Classification

In previous section, separate masking of water and vegetation is explained. After that, masking is reversed, where water and vegetation pixels had zero value, while bare land and built up areas has their original pixel value, as it is done in İzmir and. In Figure 51, masked data for built up and bare land is shown.

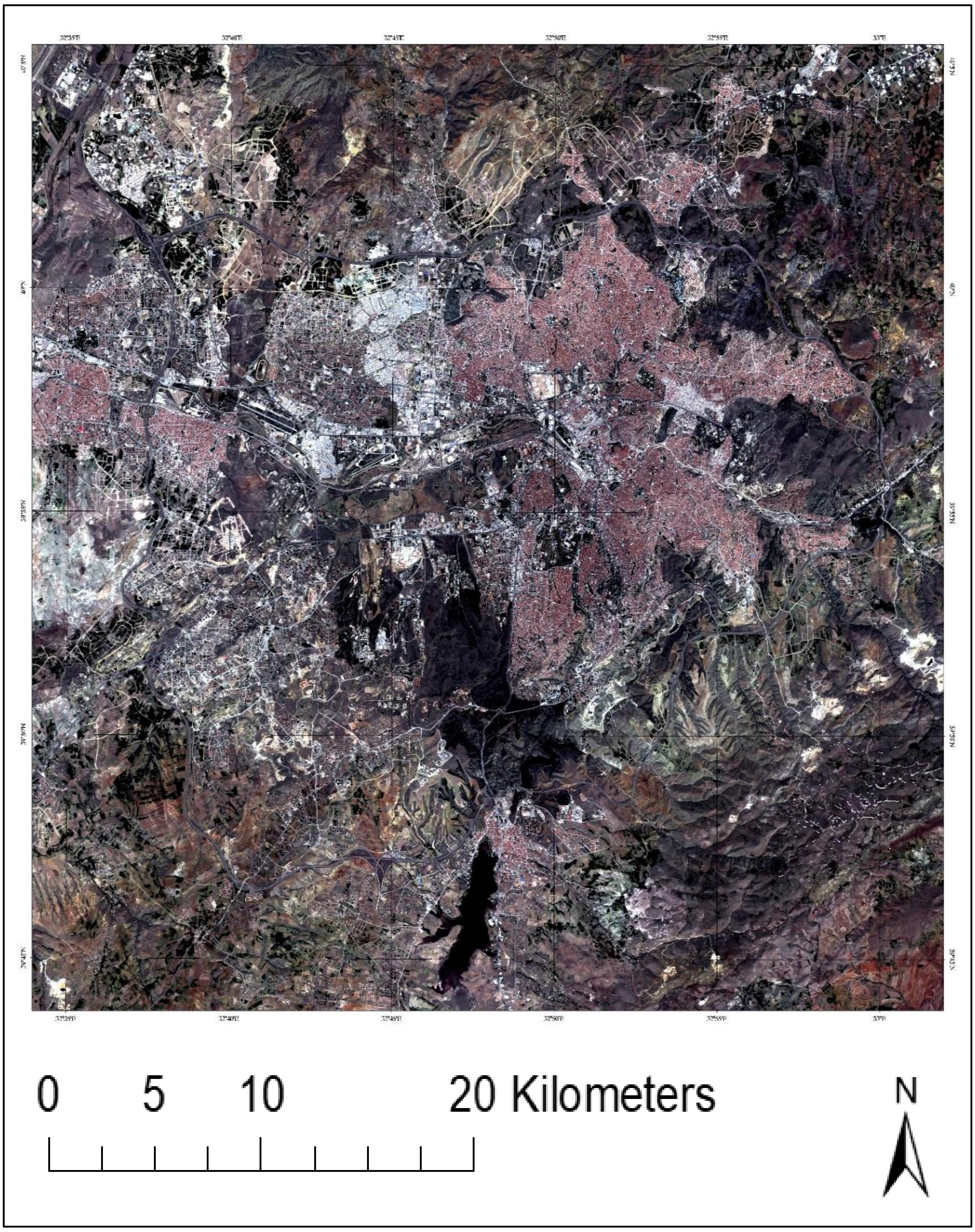


Figure 51: Masked Data for Bare Land and Built Up

After classification of built up and bare land is finished, all four classes are merged together. Accuracy assessment done for the first level classification of Ankara is presented in Chapter 5. In Figure 52, first level classification results of Ankara is given.

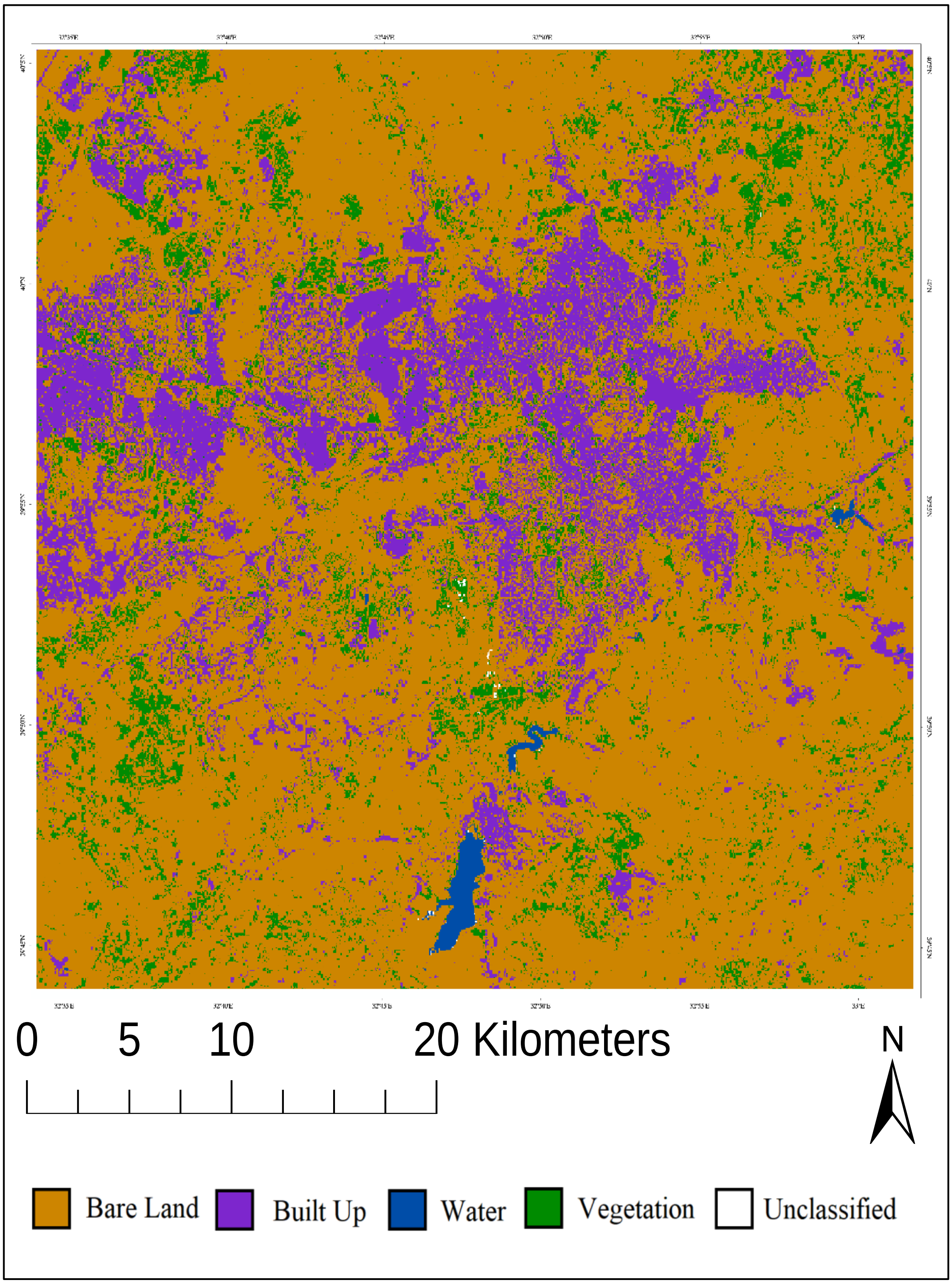


Figure 52: First Level Classification Results of Ankara

4.4.2. First Level Textural Classification

The same textural feature extraction approach is used for Ankara data. Same band extractions, first PCA, second PCA, third PCA, fourth PCA, and Gabor maximum magnitude of RGB to gray are investigated; as presented in this section and as can be seen in Figure 53, Figure 54, Figure 55, Figure 56 and Figure 57, respectively.

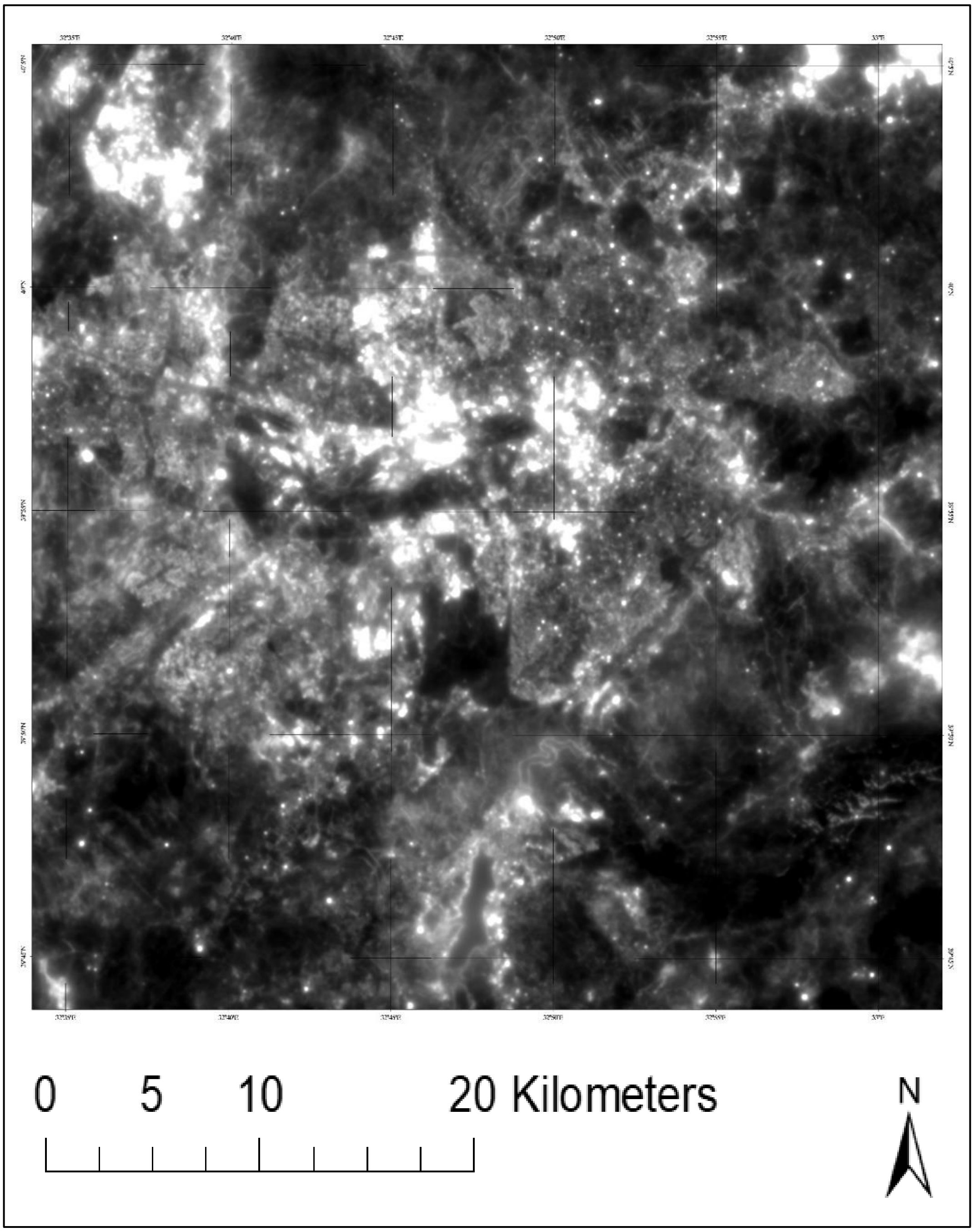


Figure 53: Gabor Filtered First PCA Band

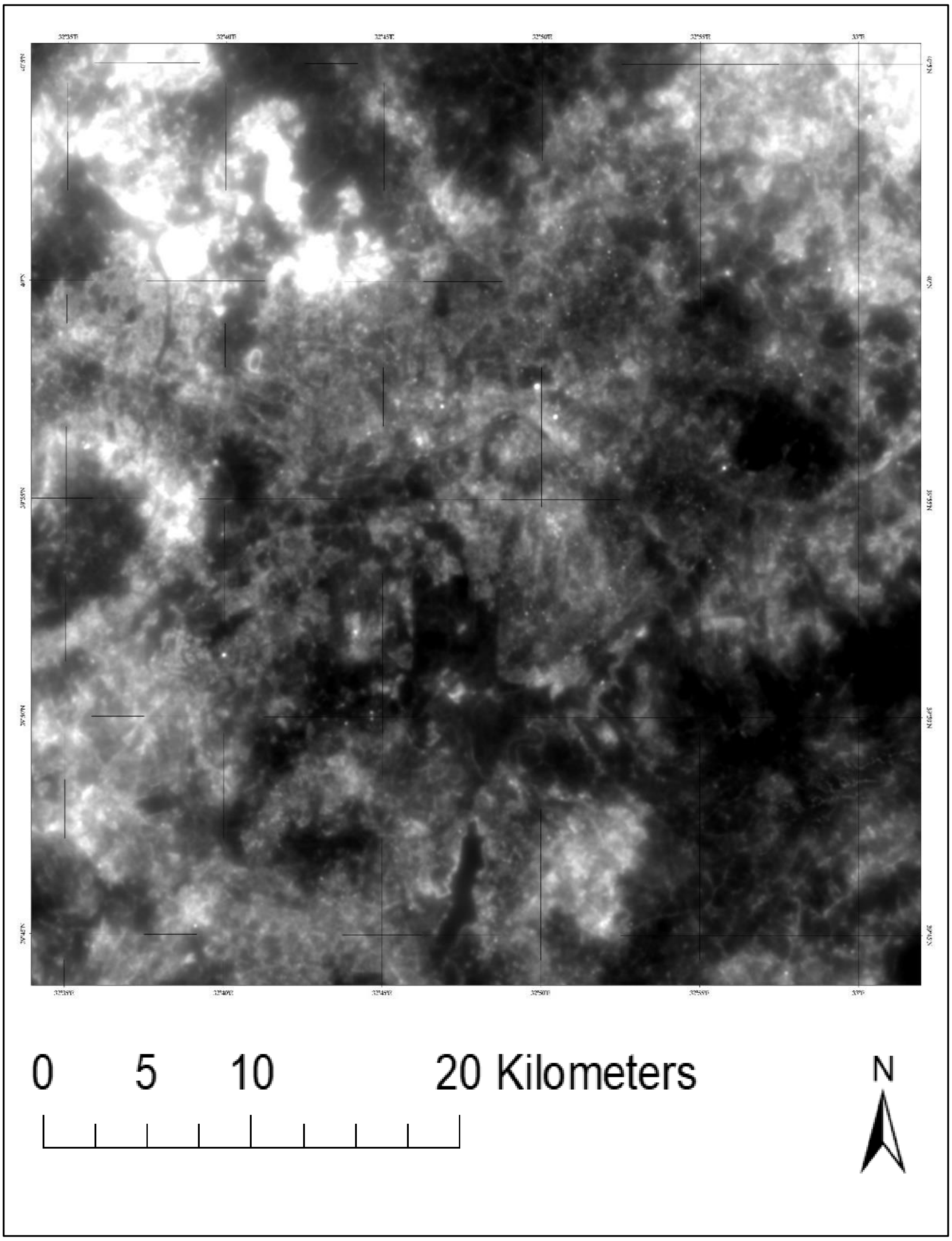


Figure 54: Gabor Filtered Second PCA Band

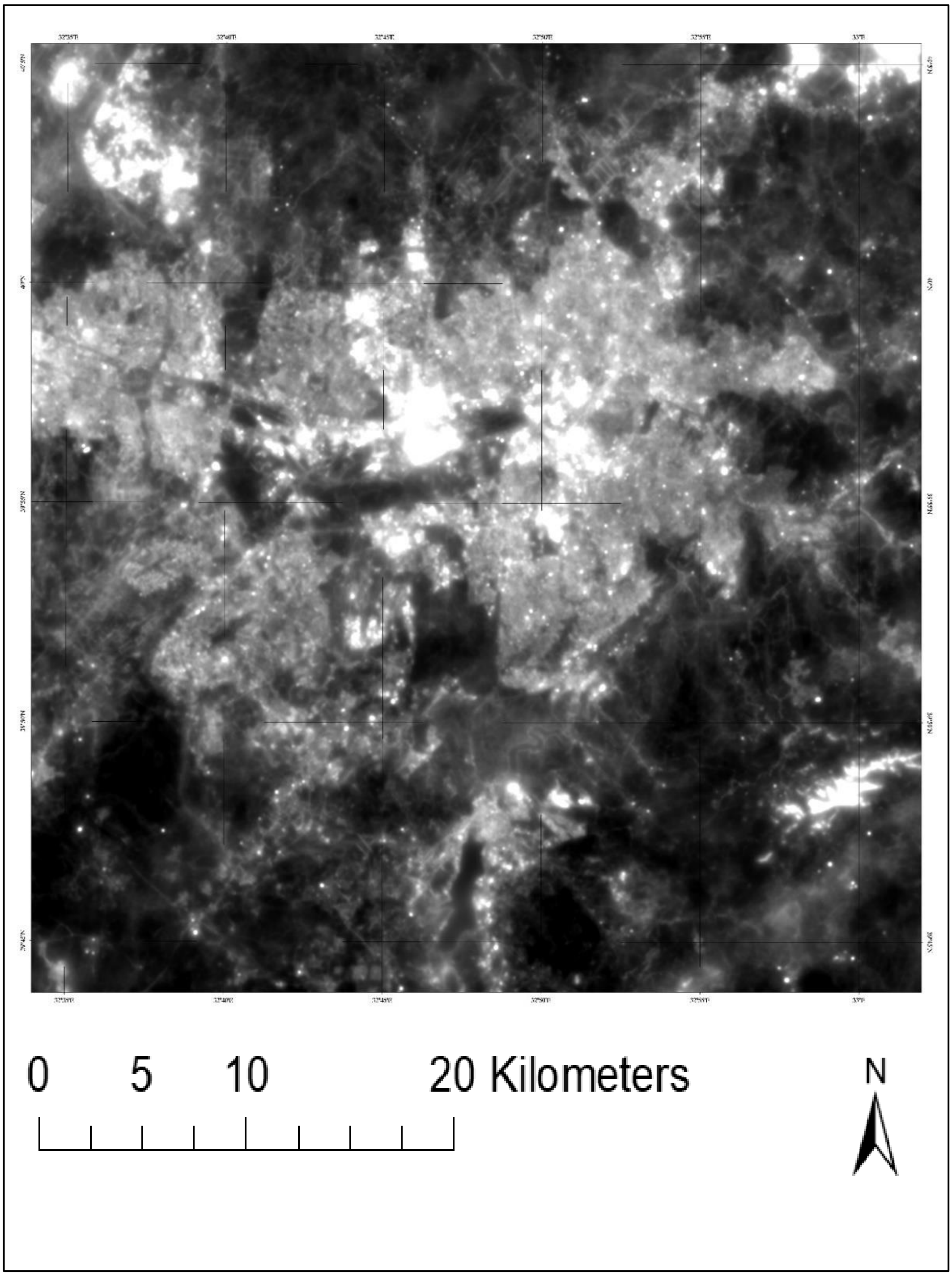


Figure 55: Gabor Filtered Third PCA Band

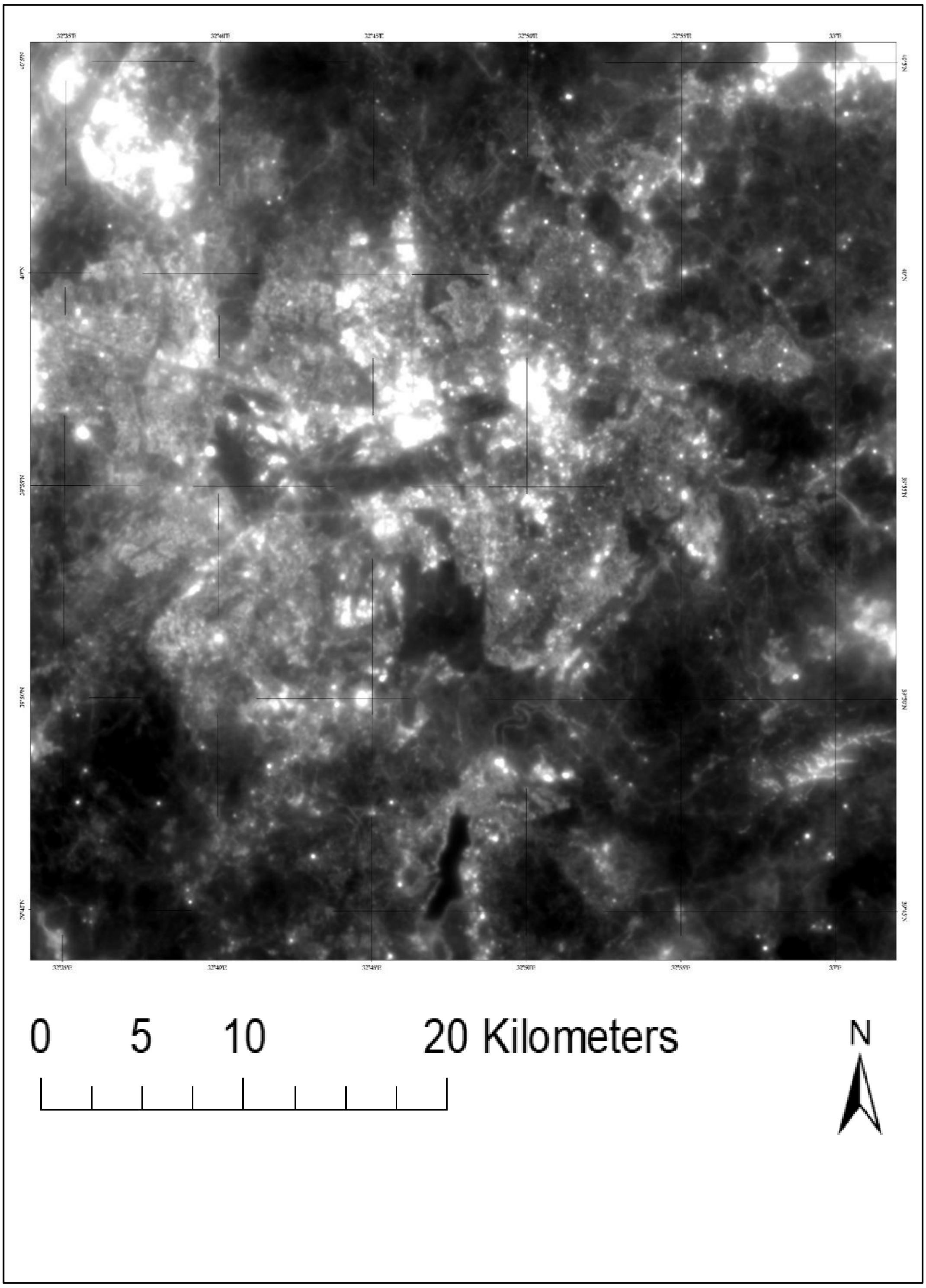


Figure 56: Gabor Filtered Fourth PCA Band

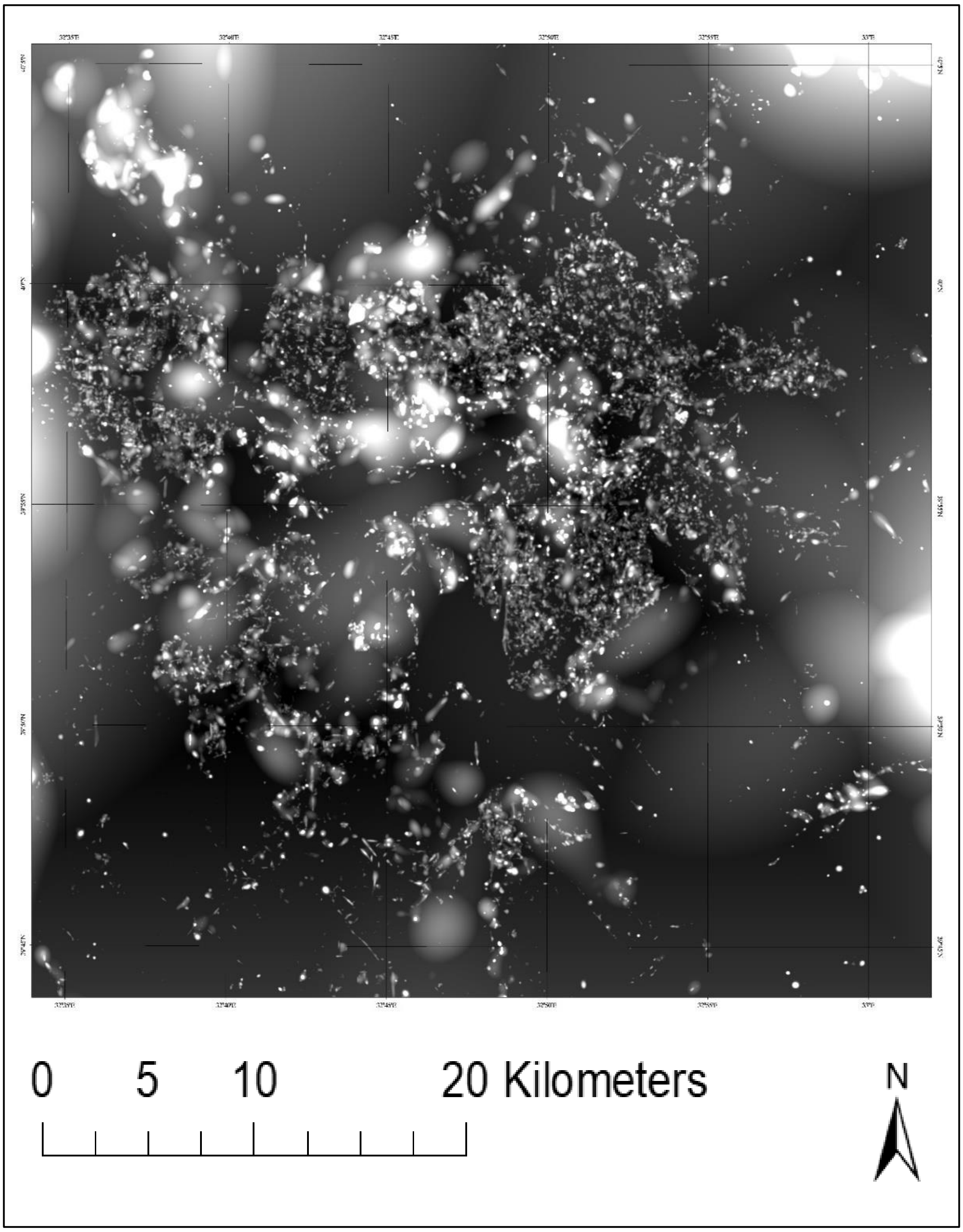


Figure 57: Maximum Gabor Magnitude Filtered RGB to Gray Image

The same training data used while classifying multispectral data is used for textural feature classification. Results of first PCA filtered image, second PCA filtered image, third PCA filtered image, fourth PCA filtered image and maximum magnitude filtered RGB to gray image and all textural features combined together are given in Figure 58, Figure 59, Figure 60, Figure 61, Figure 62 and Figure 63, respectively.

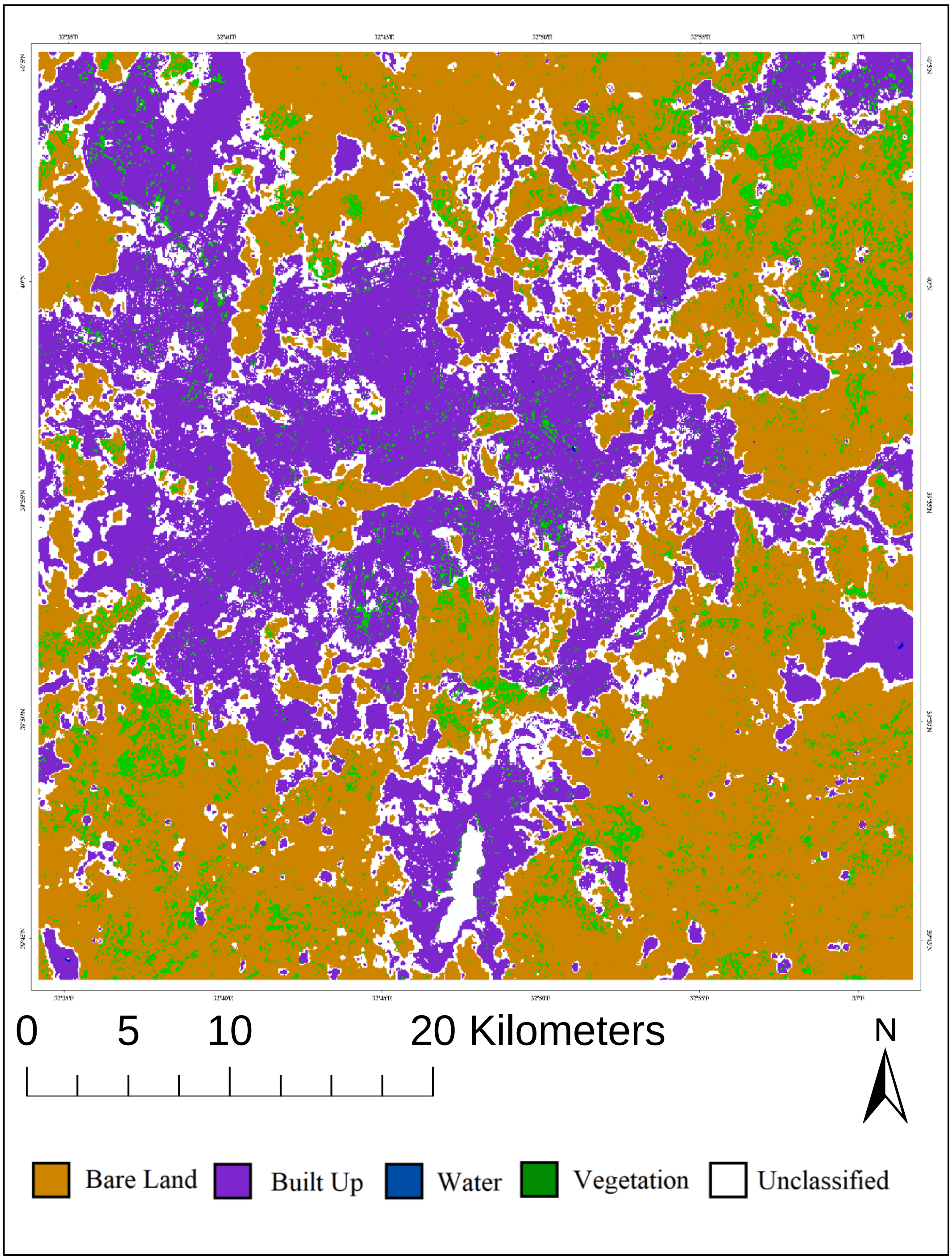


Figure 58: First PCA Filtered Classification Result

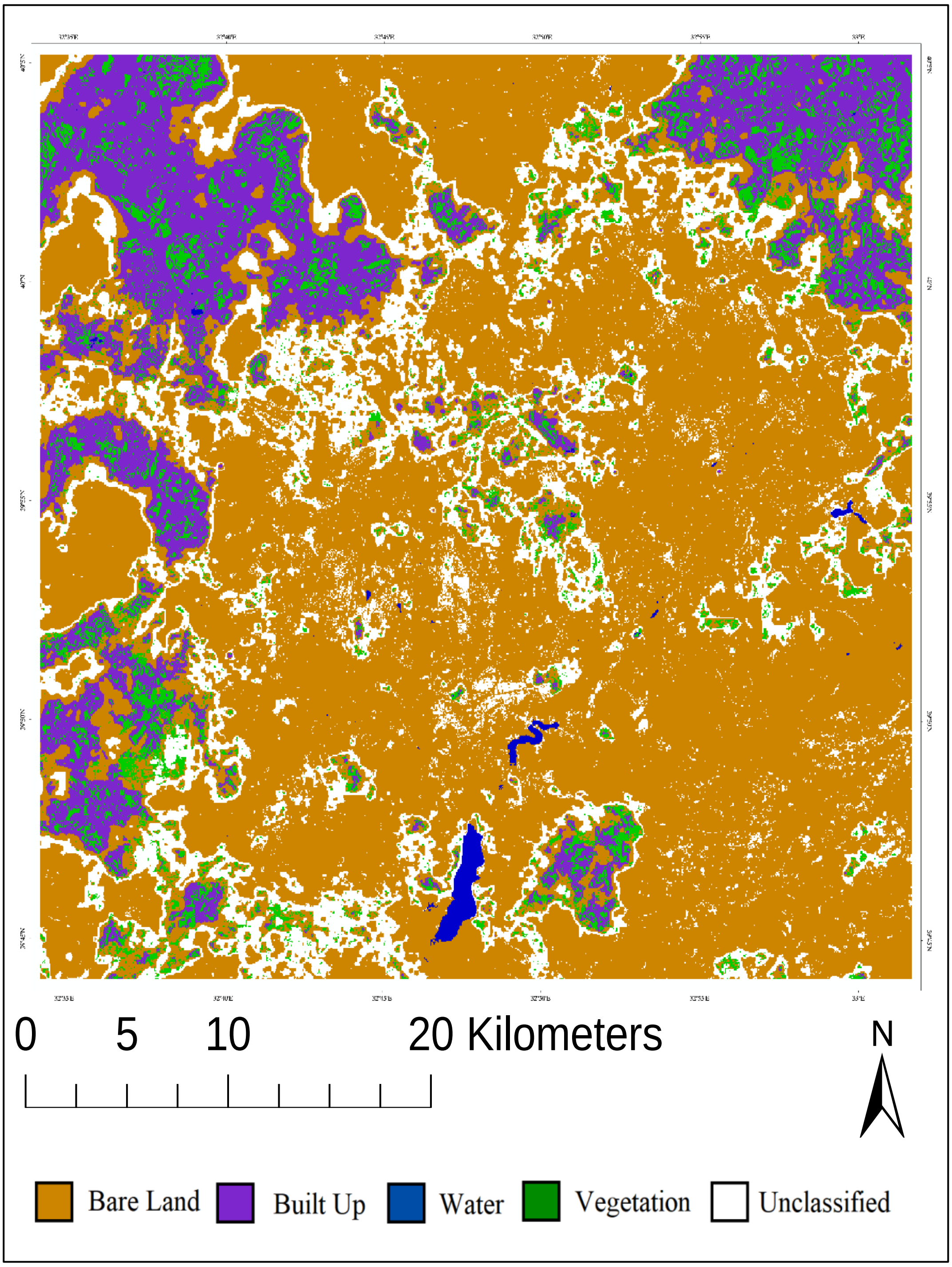


Figure 59: Second PCA Filtered Classification Result

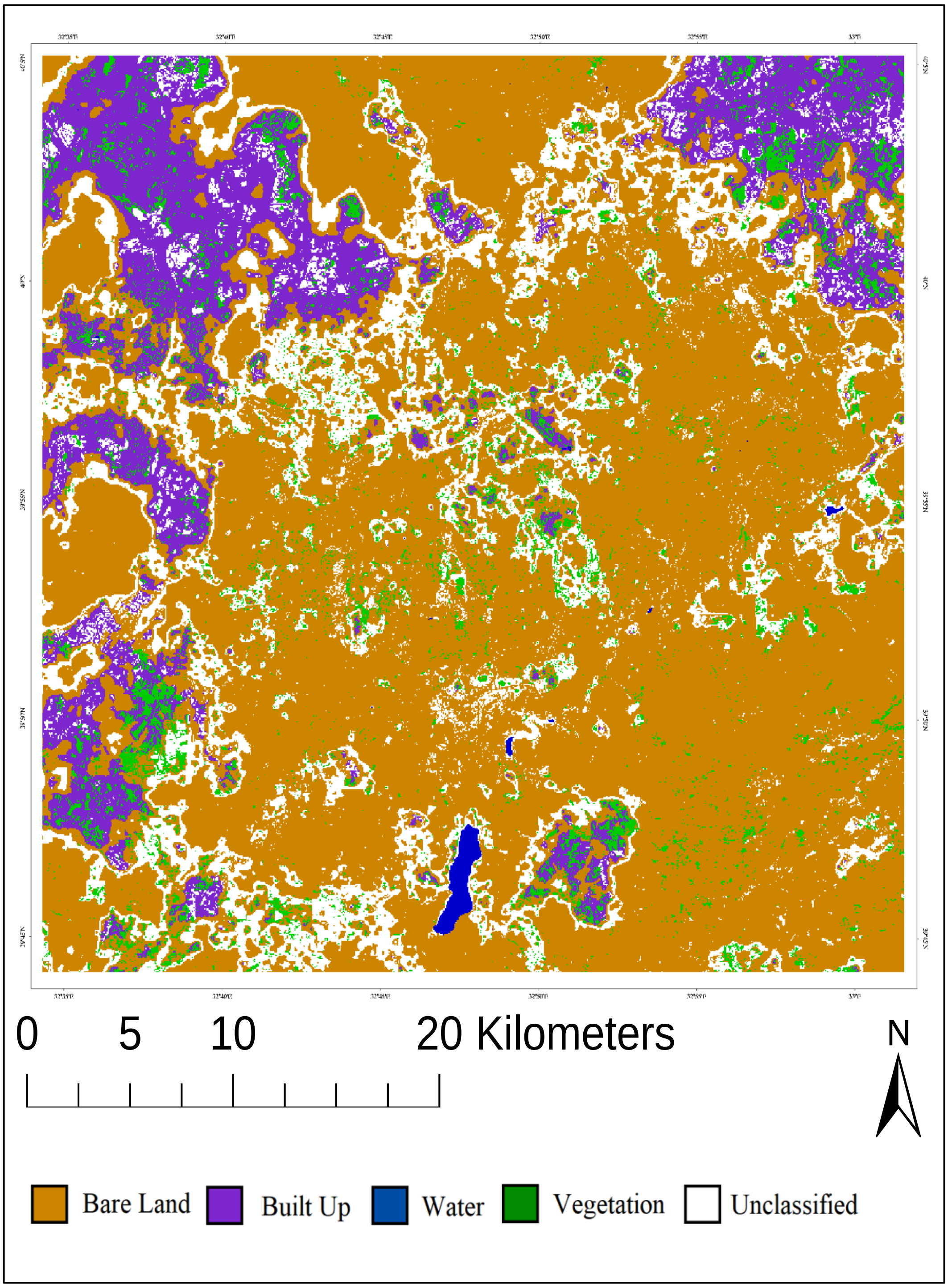


Figure 60: Third PCA Filtered Classification Result

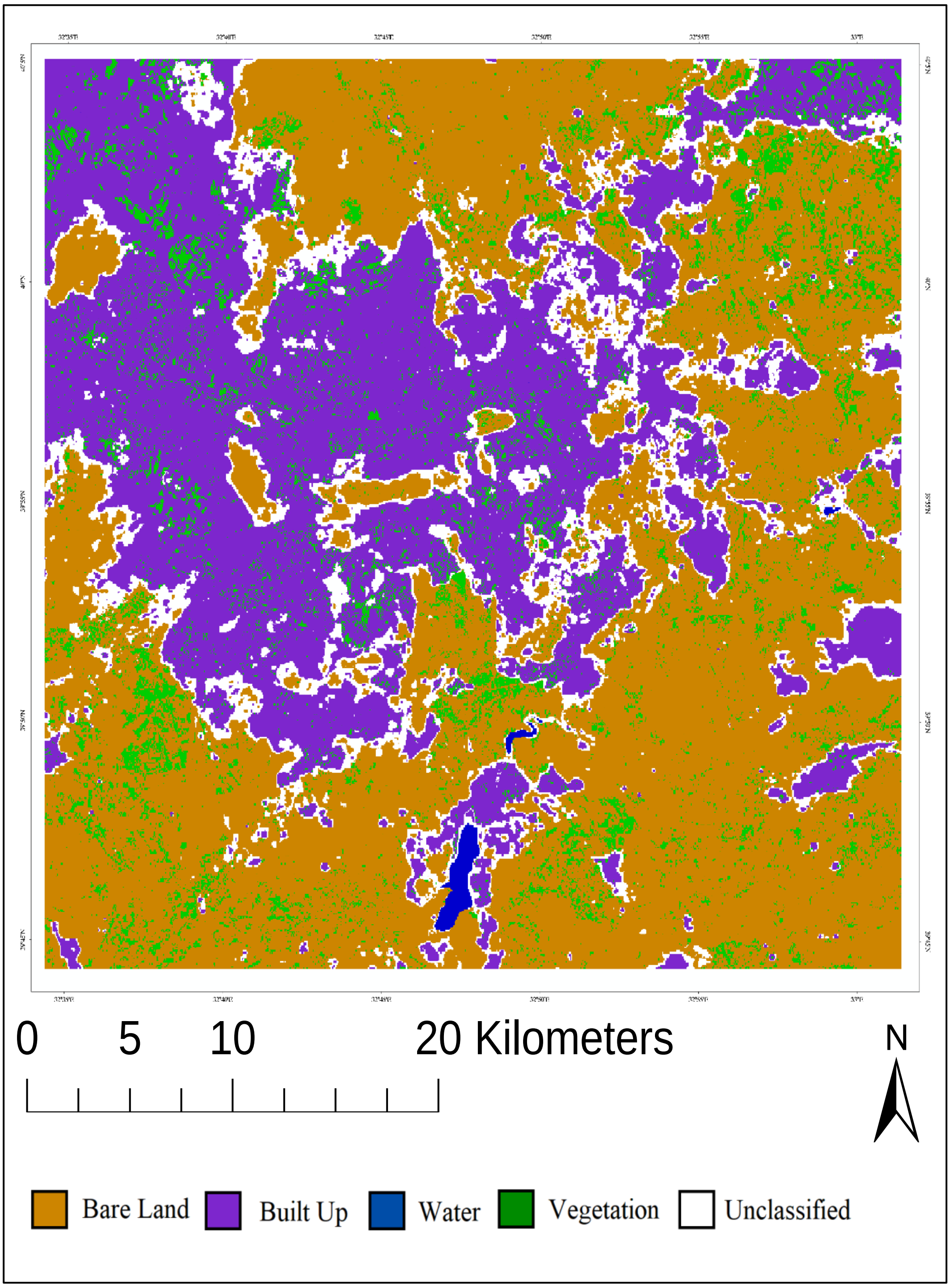


Figure 61: Fourth PCA Filtered Classification Result

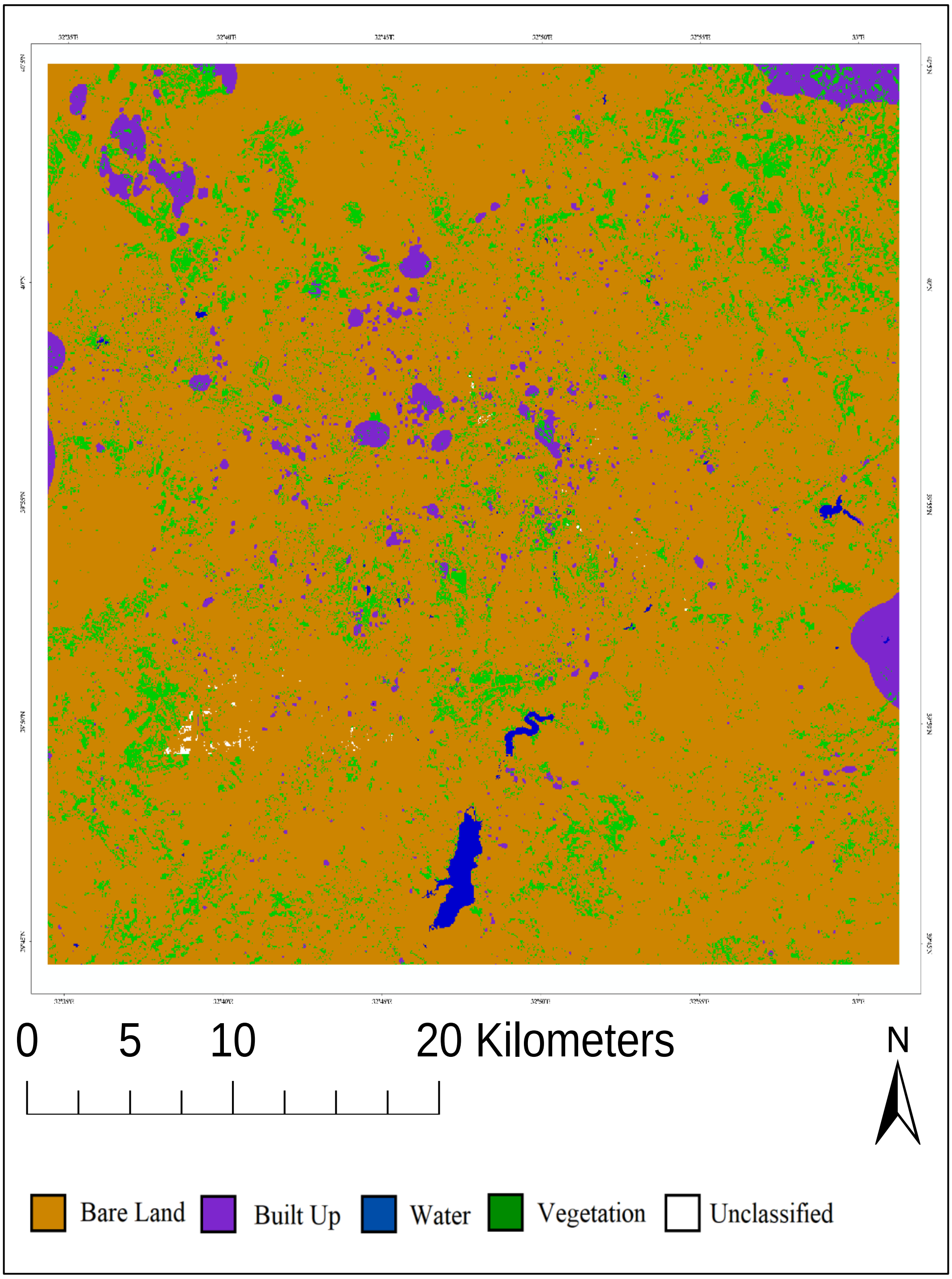


Figure 62: Gabor Maximum Magnitude of RGB to Gray Filtered Classification Result

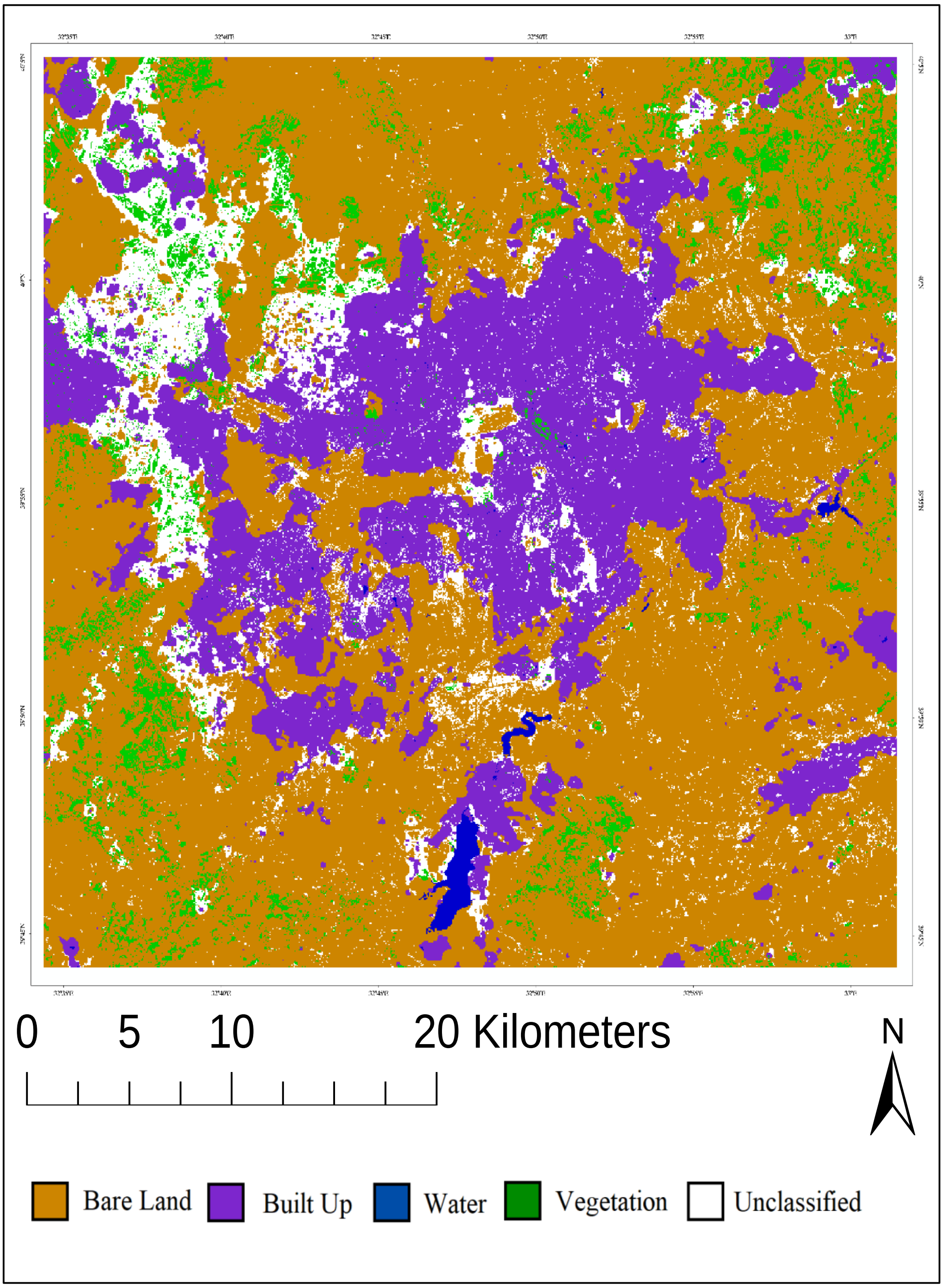


Figure 63: All Gabor Textural Features Combined Classification Results

4.4.3. First Level Multispectral and Textural Features Combined Classification

In this part, as it is done for Izmir, multispectral image data is merged with textural data extracted by Gabor filtering. SVM algorithm is used again and classification result of the merged data is given in Figure 64.

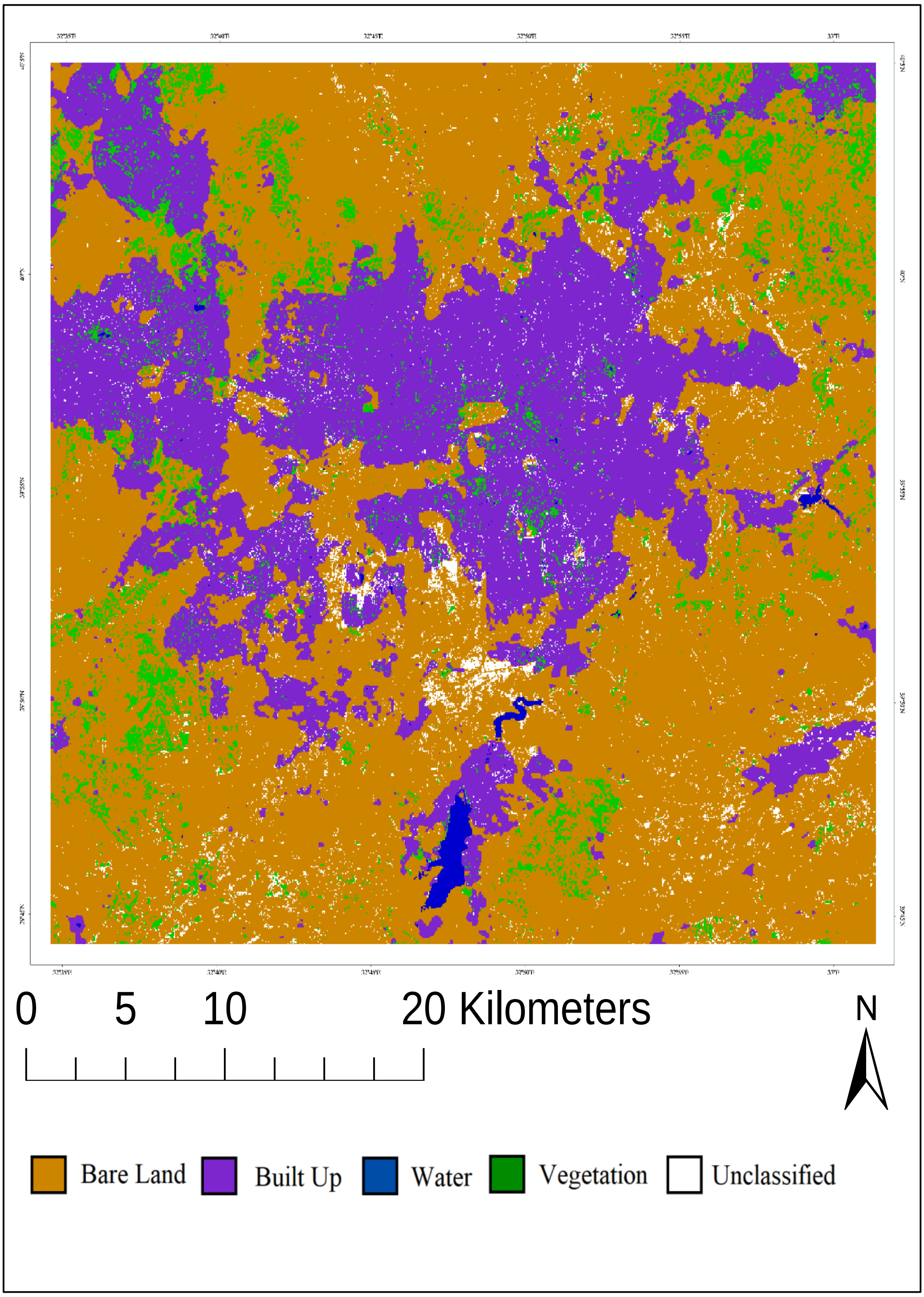


Figure 64: Combined Classification

4.4.4. Second Level Multispectral Classification

In the second level multispectral classification of Ankara, marine water class is omitted since Ankara is not a coastal city. Other than that, all remaining steps are the same. Second level classification result of Ankara is given in Figure 65.

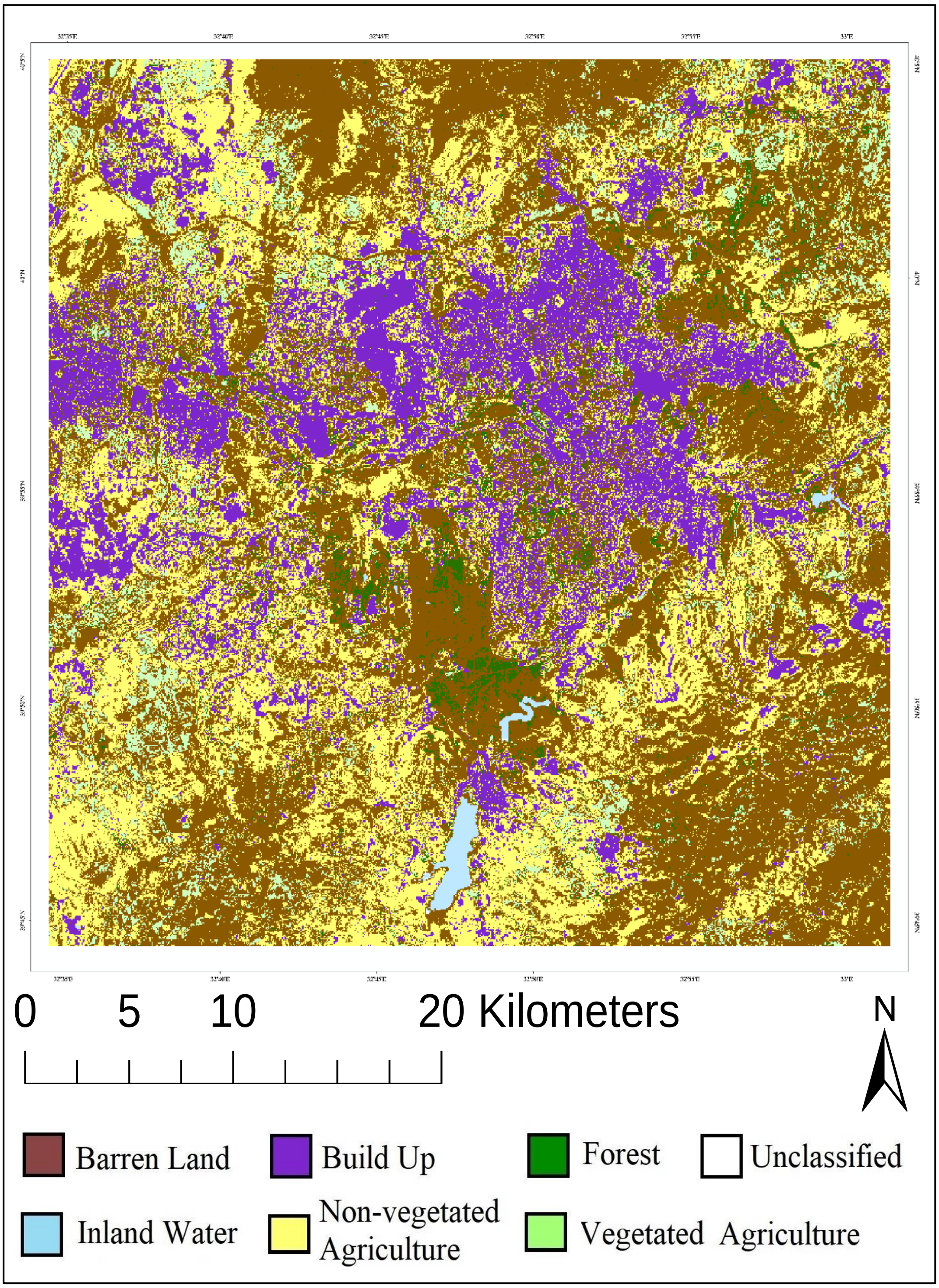


Figure 65: Second Level Multispectral Classification Results

4.4.5. Second Level Textural Classification

Again, the only difference from the steps followed for Izmir is omitting the marine water class. The same training data in multispectral classification is used for textural classification. Results of textural classification are presented in Figures 66 to 71.

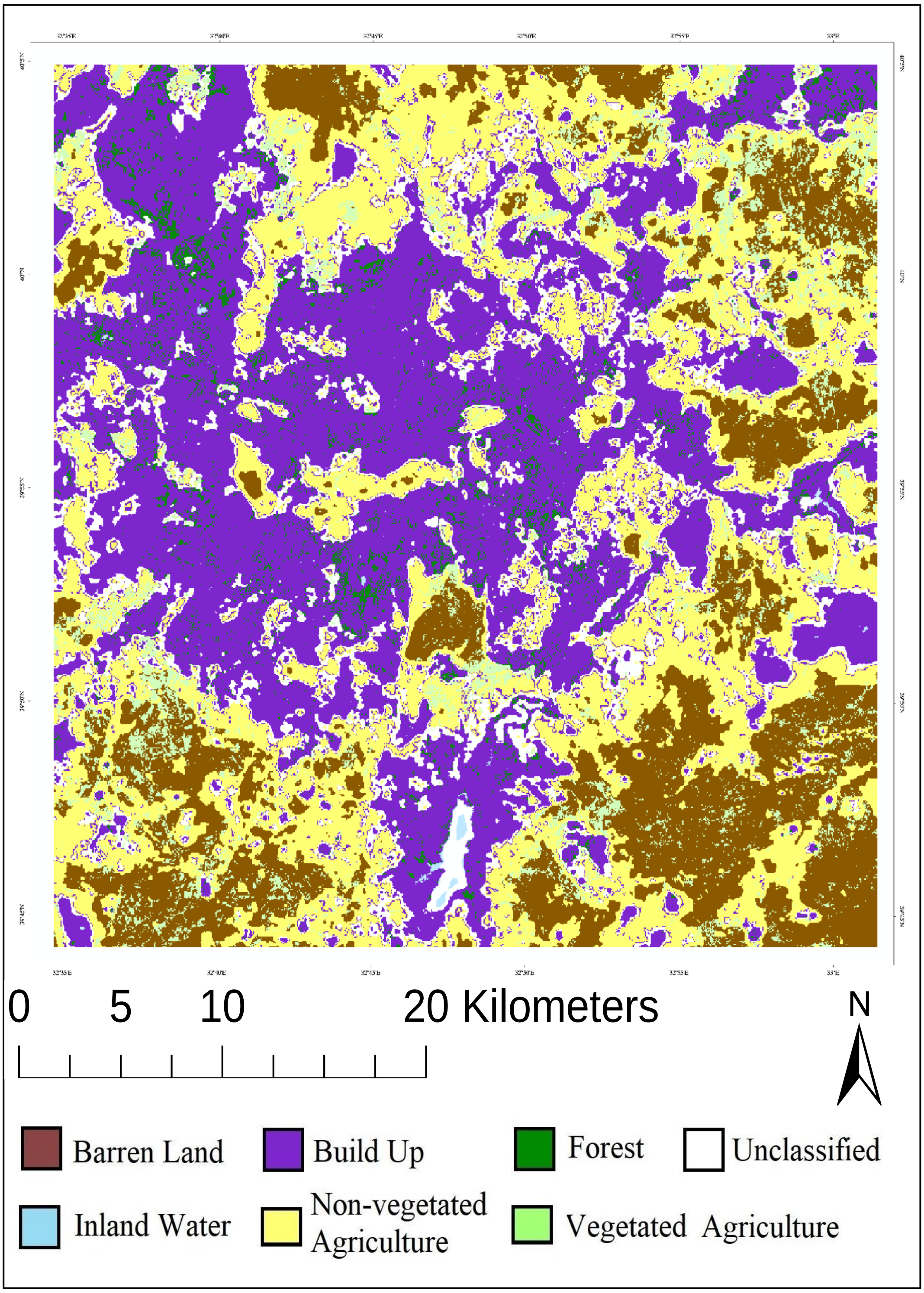


Figure 66: First PCA Component Classification Results

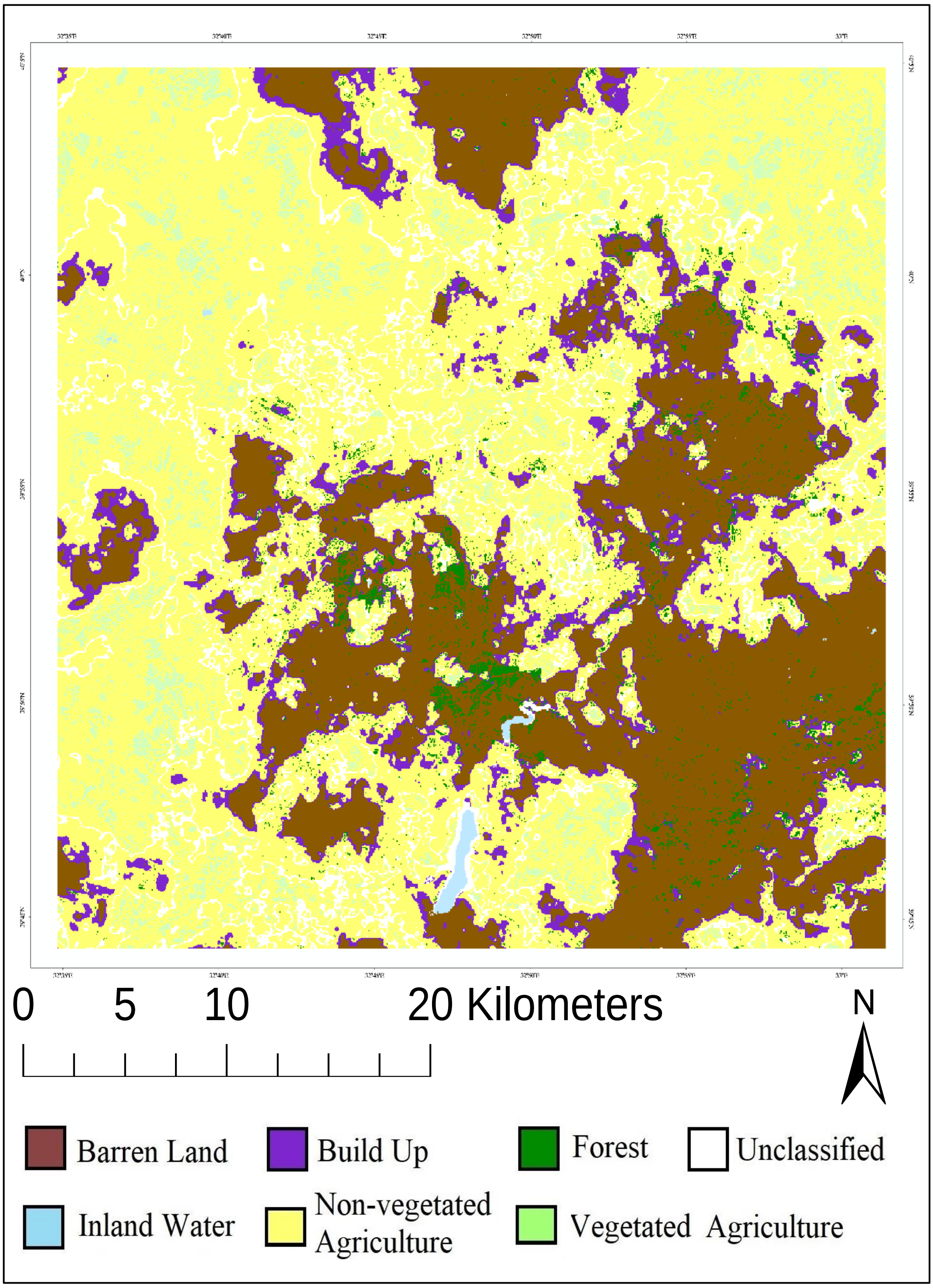


Figure 67: Second PCA Component Classification Results

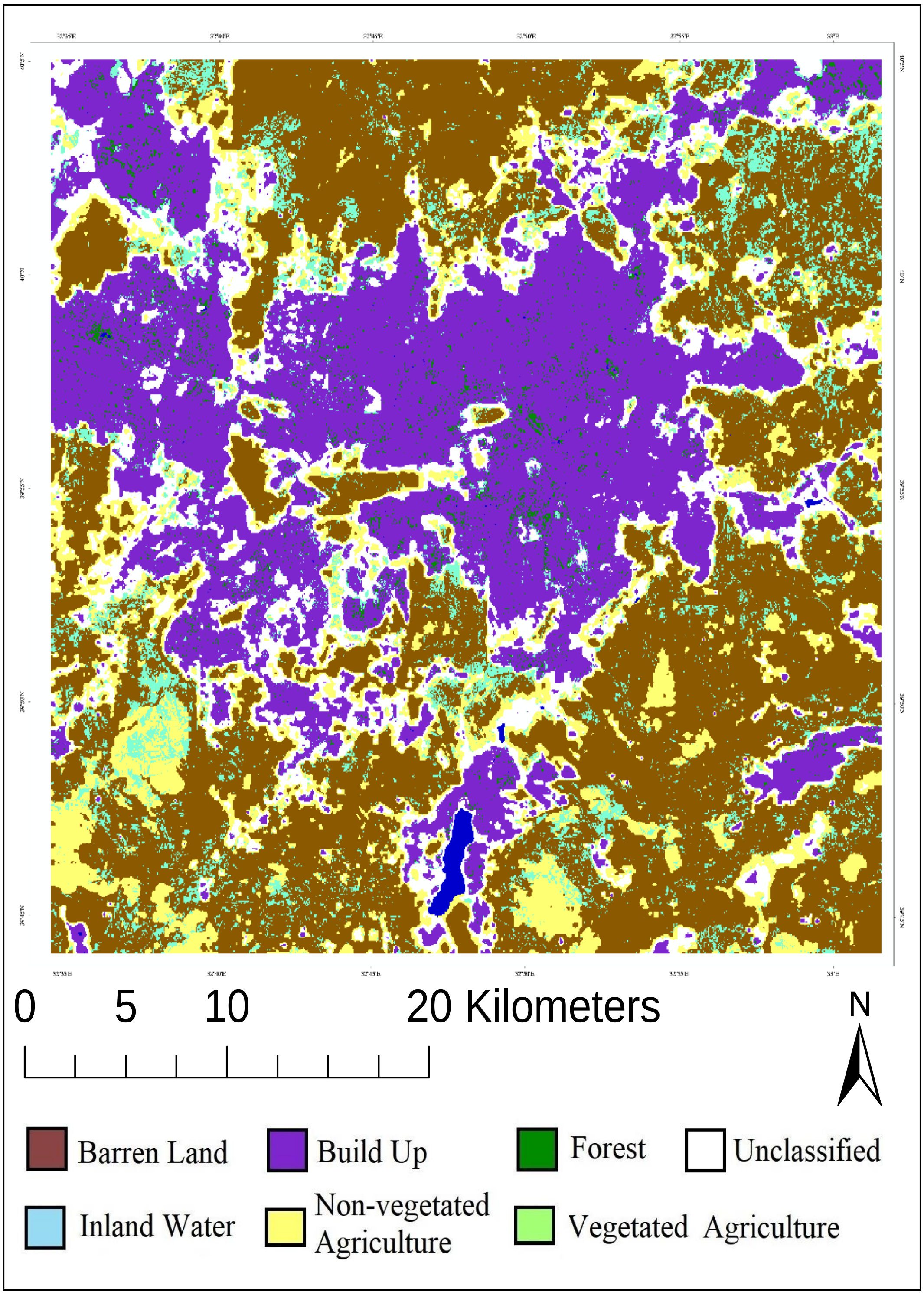


Figure 68: Third PCA Component Classification Results

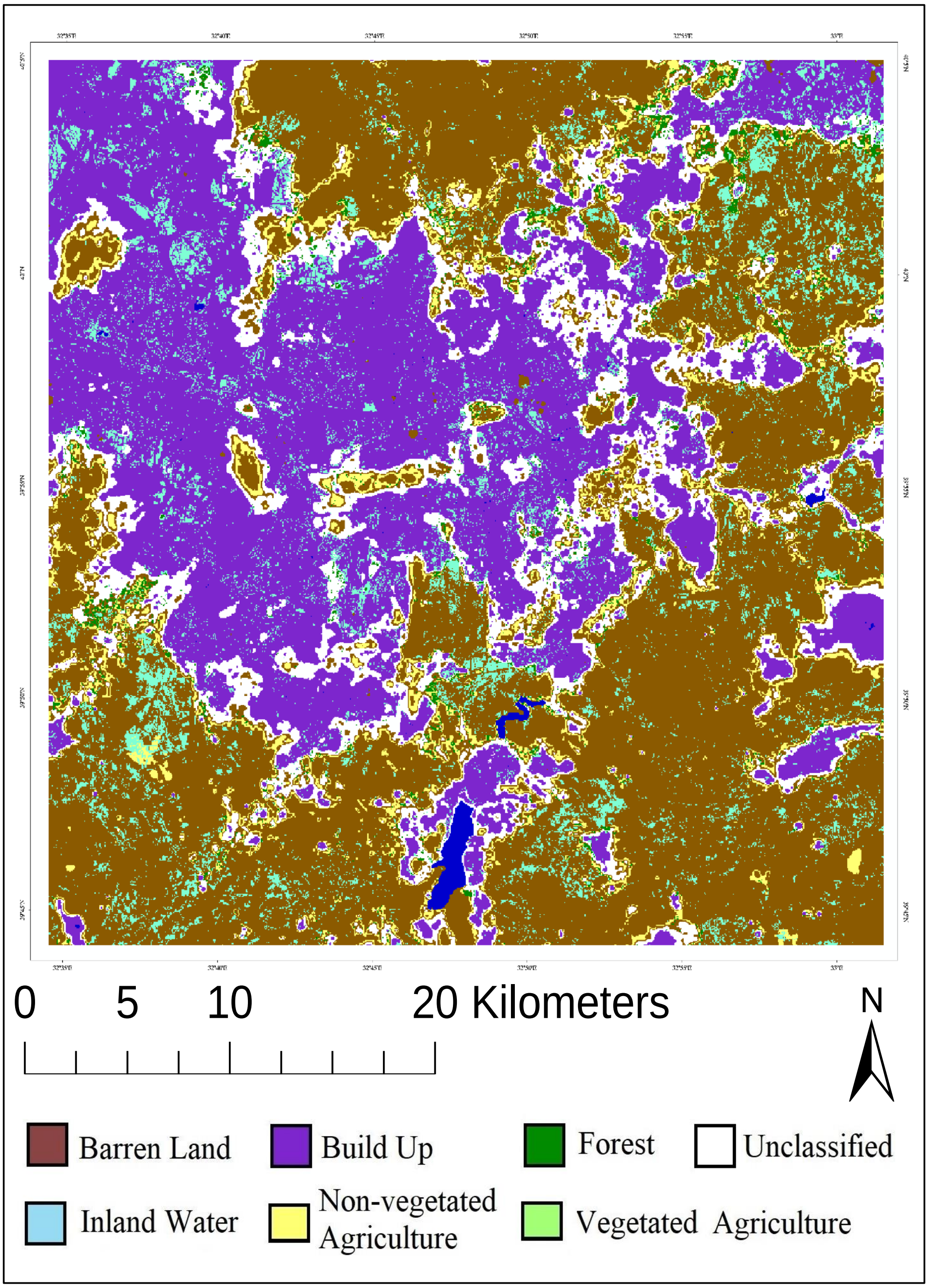


Figure 69: Fourth PCA Component Classification Results

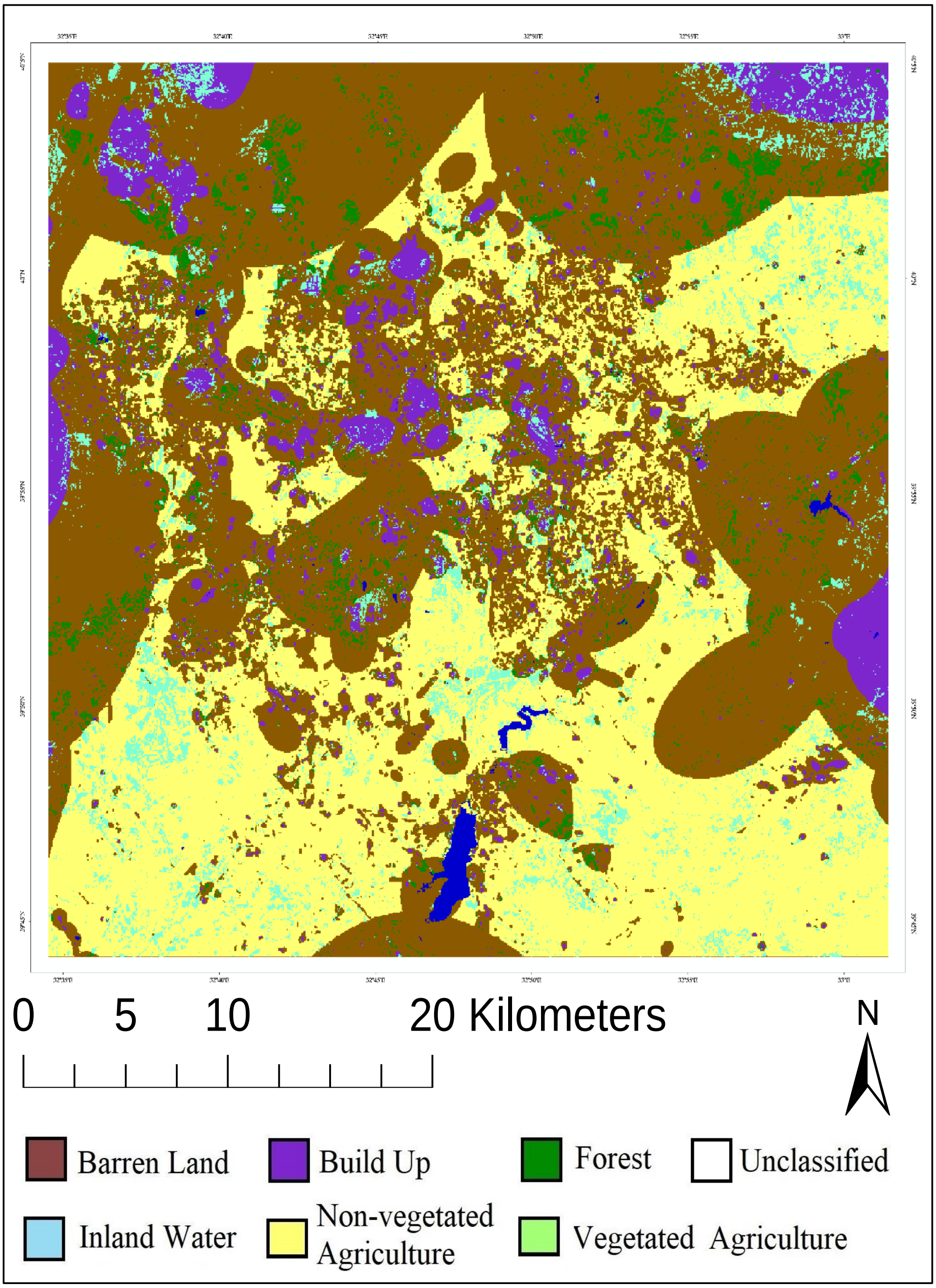


Figure 70: Gabor Maximum Magnitude Classification Results

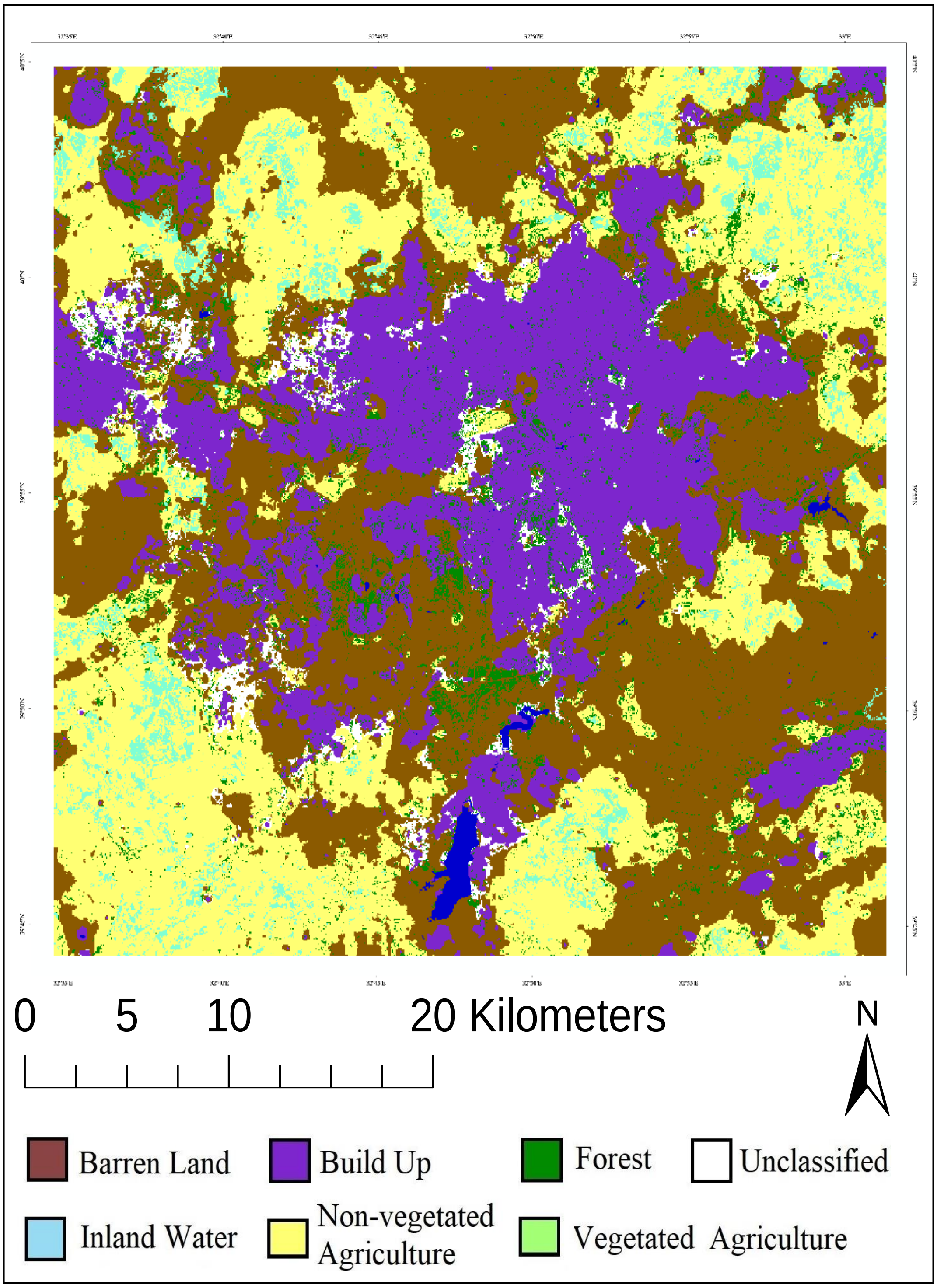


Figure 71: Combining All Texture Bands Together

4.4.6. Second Level Multispectral and Textural Features Combined Classification

In the second level, textural features are merged with the original data; and then SVM is applied as it was also done in the first level classification. Classification results of combined classification can be seen in Figure 72.

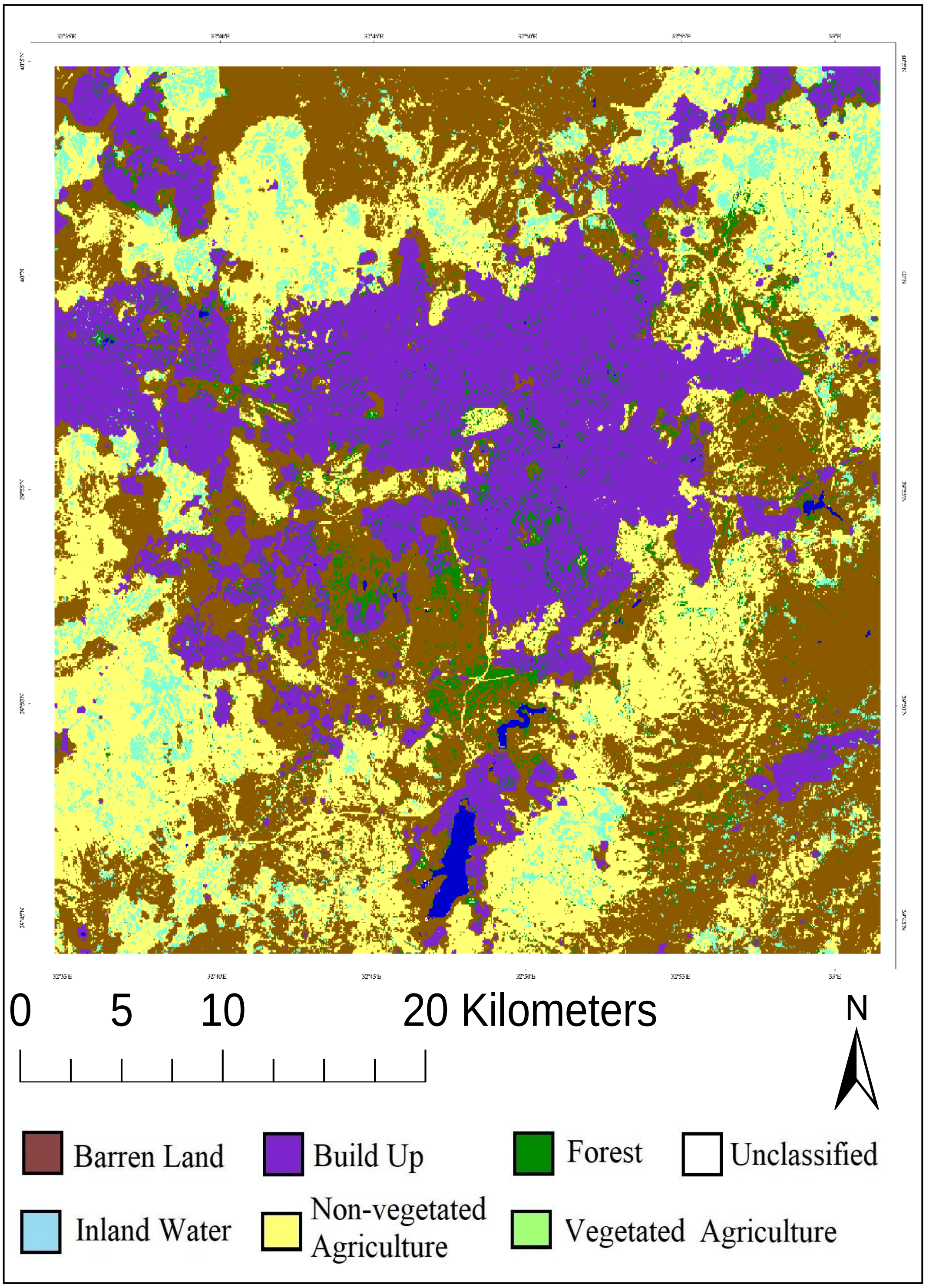


Figure 72: Multispectral and Textural Features Combined Classification Results

CHAPTER 5

RESULTS AND CONCLUSION

Even after an intensive analysis of data, classification results are not sufficient on their own. As stated in Section 2.3, accuracy assessment of the classification results is a must. For that purpose, random samples are created for first and second level classifications. As in the classification part of the study, the same training data is used for all different levels of classification; and only one random point sets are created for each level.

For cratering error matrices, ground truth data and class information are needed. The ground truth of each point is extracted from the original multispectral data via visual methods. If a pixel is a mixed pixel, majority rules are applied. Class information are taken from classification files. After getting these information, as explained in Section 2.3, error matrices are created, and accuracies were calculated with Kappa coefficient. Random points are created with ENVI software.

5.1. Results of İzmir

First level random points and second level random points are given in Figure 73 and Figure 74, respectively. Error matrices, accuracies and Kappa coefficients of first and second level classification of multispectral data are given in Table 14 and Table 15, respectively. Subsequently, the results of only textural data of first and second levels are given in Tables Table 16 to Table 27. Lastly, results for the combination of multispectral and textural features are given in Table 28 and Table 29, respectively.

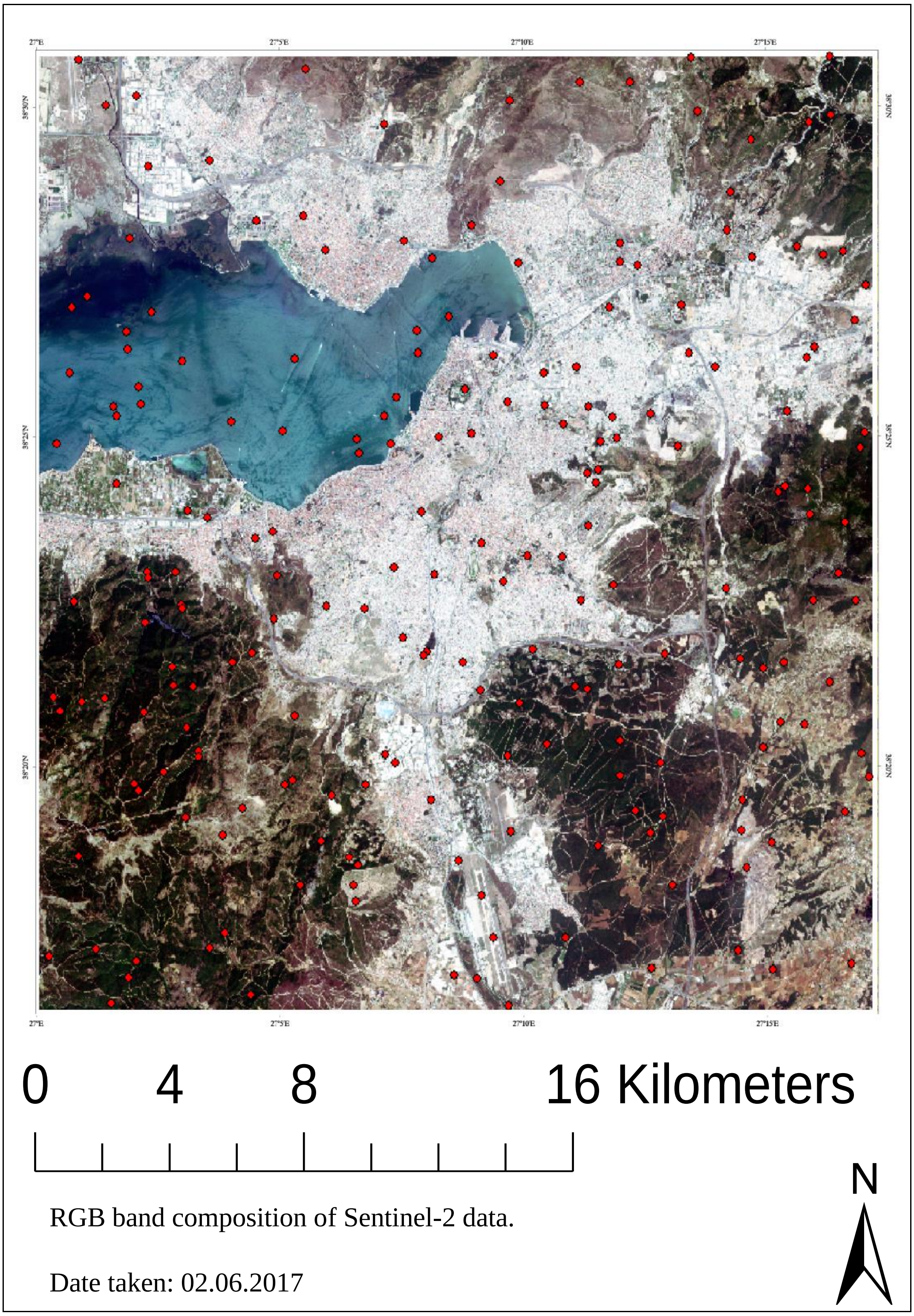


Figure 73: First Level Stratified Random Points

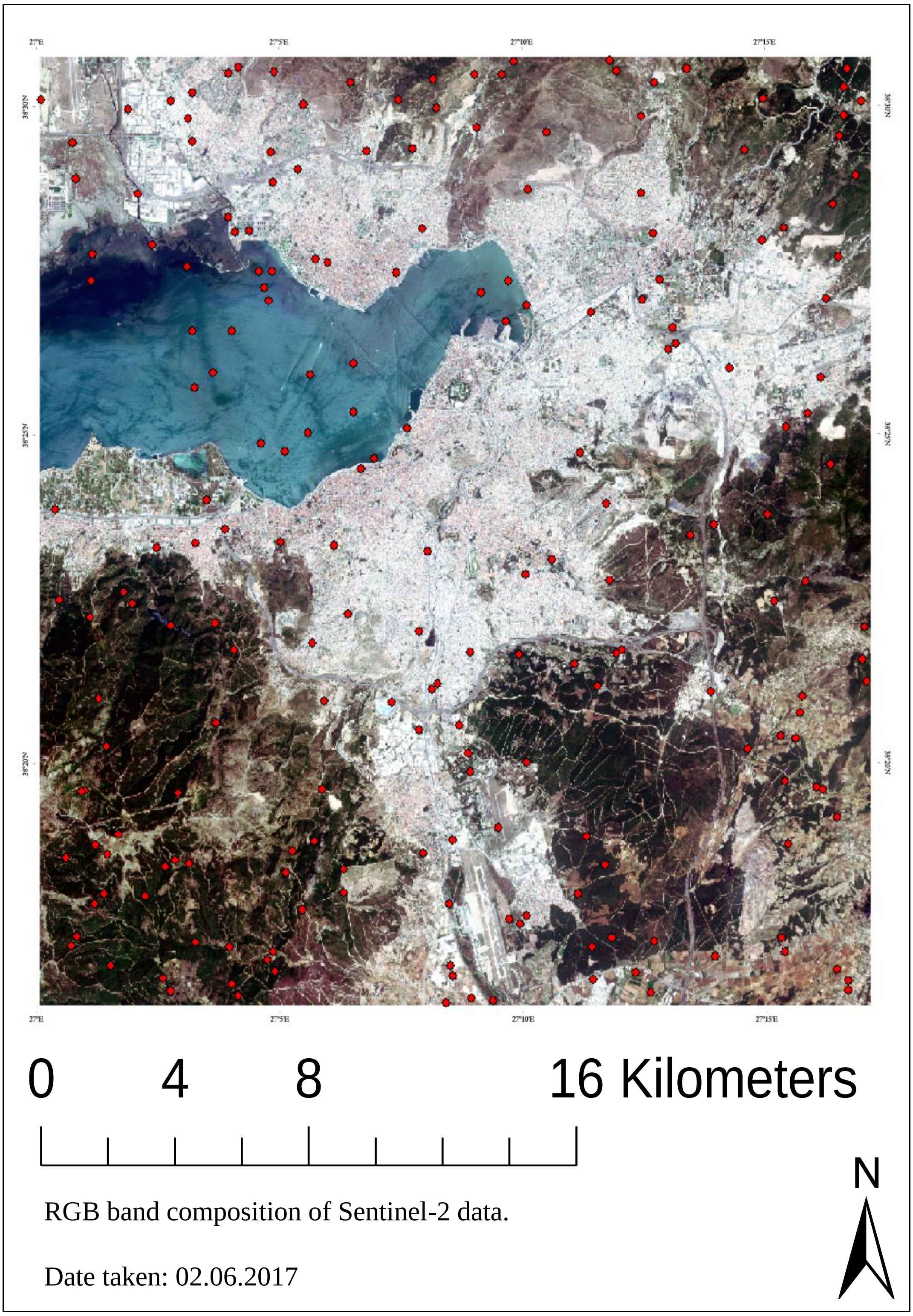


Figure 74: Second Level Stratified Random Points

Table 14: First Level Error Matrix of Multispectral Classification

Unclassified (0)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	25	0	0	0	25	100.00%
Vegetation	0	61	0	4	65	93.85%
Built Up	0	0	40	15	55	72.73%
Bare Land	0	6	6	53	65	81.54%
Sum	25	67	46	72	210	Overall Accuracy
Users Accuracy	100.00%	91.04%	86.96%	73.61%	Overall Accuracy	85.24% Kappa: 0.821

Table 15: Second Level Error Matrix of Multispectral Classification

Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	20	0	0	0	0	0	0	20	100.00%
Inland Water	3	2	0	0	0	0	0	5	40.00%
Vegetated Agriculture	0	0	13	2	0	0	0	15	86.67%
Forest	0	0	6	44	0	0	0	50	88.00%
Barren Land	0	0	0	0	41	9	0	50	82.00%
Non-Vegetated Agriculture	0	0	0	0	4	11	0	15	73.33%
Built Up	0	0	0	1	6	1	47	55	85.45%
Sum	23	2	19	47	51	21	47	210	Overall Accuracy
Users Accuracy	86.96%	100.00%	68.42%	93.62%	80.39%	52.38%	100.00%	Overall Accuracy	84.76% Kappa: 0.811

Table 16: First Level Error Matrix of All Gabor Textural Features Classification

Unclassified (0)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy	
Water	25	0	0	0	25		100.00%
Vegetation	0	60	0	2	62		96.77%
Built Up	0	7	46	70	123		37.40%
Bare Land	0		0	0	0		0.00%
Sum	25	67	46	72	210	Overall Accuracy	
Users Accuracy	100.00%	89.55%	100.00%	0.00%	Overall Accuracy	62.38%	Kappa: 0.506

Table 17: Second Level Error Matrix of All Gabor Textural Features Classification

Unclassified (12)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	22	0	0	0	0	0	0	22	100.00%
Inland Water	0	2	0	0	0	0	0	2	100.00%
Vegetated Agriculture	0	0	7	1	0	0	0	8	87.50%
Forest	0	0	6	41	0	0	0	47	87.23%
Barren Land	0	0	0	0	20	10	0	30	66.67%
Non-Vegetated Agriculture	0	0	1	0	20	9	11	41	21.95%
Built Up	0	0	0	1	9	2	36	48	75.00%
Sum	22	2	14	43	49	21	47	210	Overall Accuracy
Users Accuracy	100.00%	100.00%	50.00%	95.35%	40.82%	42.86%	76.60%	Overall Accuracy	65.24% Kappa: 0.584

Table 18: First Level Error Matrix of First PCA component Textural Features Classification

Unclassified (35)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	22	0	0	0	22	100.00%
Vegetation	0	49	0	1	50	98.00%
Built Up	0	1	35	35	71	49.30%
Bare Land	0	5	7	20	32	62.50%
Sum	22	55	42	56	210	Overall Accuracy
Users Accuracy	100.00%	89.09%	83.33%	35.71%	Overall Accuracy	60.00% Kappa: 0.533

Table 19: Second Level Error Matrix of First PCA component Textural Features Classification

Unclassified (37)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	20	0	0	0	0	0	0	20	100.00%
Inland Water	0	2	0	0	0	0	0	2	100.00%
Vegetated Agriculture	0	0	0	1	0	0	0	1	0.00%
Forest	0	0	12	36	0	0	0	48	75.00%
Barren Land	0	0	0	1	22	0	1	24	91.67%
Non-Vegetated Agriculture	0	0	0	0	0	0	0	0	0.00%
Built Up	0	0	0	0	22	14	42	78	53.85%
Sum	20	2	12	38	44	14	43	210	Overall Accuracy
Users Accuracy	100.00%	100.00%	0.00%	94.74%	50.00%	0.00%	97.67%	Overall Accuracy	58.10% Kappa: 0.507

Table 20: First Level Error Matrix of Second PCA component Textural Features Classification

Unclassified (20)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	23	0	0	0	23	100.00%
Vegetation	0	49	0	3	52	94.23%
Built Up	0	1	39	32	72	54.17%
Bare Land	0	6	7	30	43	69.77%
Sum	23	56	46	65	210	Overall Accuracy
Users Accuracy	100.00%	87.50%	84.78%	46.15%	Overall Accuracy	67.14% Kappa: 0.611

Table 21: Second Level Error Matrix of Second PCA component Textural Features Classification

Unclassified (26)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	22	0	0	0	0	0	0	22	100.00%
Inland Water	0	0	0	0	0	0	0	0	0.00%
Vegetated Agriculture	0	0	8	1	0	0	0	9	88.89%
Forest	0	0	7	33	0	0	0	40	82.50%
Barren Land	0	0	0	0	21	11	1	33	63.64%
Non-Vegetated Agriculture	0	0			2	1	11	14	7.14%
Built Up	0	0	0	1	23	9	33	66	50.00%
Sum	22	0	15	35	46	21	45	210	Overall Accuracy
Users Accuracy	100.00%	0.00%	53.33%	94.29%	45.65%	4.76%	73.33%	Overall Accuracy	56.19% Kappa: 0.482

Table 22: First Level Error Matrix of Third PCA component Textural Features Classification

Unclassified (61)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	24	0	0	0	24	100.00%
Vegetation	0	54	0	1	55	98.18%
Built Up	0	0	42	21	63	66.67%
Bare Land	0	2	0	5	7	71.43%
Sum	24	56	42	27	210	Overall Accuracy
Users Accuracy	100.00%	96.43%	100.00%	18.52%	Overall Accuracy	59.52% Kappa: 0.527

Table 23: Second Level Error Matrix of Third PCA component Textural Features Classification

Unclassified (45)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	21	0	0	0	0	0	0	21	100.00%
Inland Water	0	0	0	0	0	0	0	0	0.00%
Vegetated Agriculture	0	0	5	1	0	0	0	6	83.33%
Forest	0	0	5	38	0	0	0	43	88.37%
Barren Land	0	0	0	1	20	9	0	30	66.67%
Non-Vegetated Agriculture	0	0	0	0	1	4	8	13	30.77%
Built Up	0	0	0	0	15	3	34	52	65.38%
Sum	21	0	10	40	36	16	42	210	Overall Accuracy
Users Accuracy	100.00%	0.00%	50.00%	95.00%	55.56%	25.00%	80.95%	Overall Accuracy	58.10% Kappa: 0.519

Table 24: First Level Error Matrix of Fourth PCA component Textural Features Classification

Unclassified (55)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	24	0	0	0	24	100.00%
Vegetation	0	37	0	3	40	92.50%
Built Up	0	5	8	22	35	22.86%
Bare Land	0	0	28	28	56	50.00%
Sum	24	42	36	53	210	Overall Accuracy
Users Accuracy	100.00%	88.10%	22.22%	52.83%	Overall Accuracy	46.19% Kappa: 0.414

Table 25: Second Level Error Matrix of Fourth PCA component Textural Features Classification

Unclassified (46)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	21	0	0	0	0	0	0	21	100.00%
Inland Water	0	1	0	0	0	0	0	1	100.00%
Vegetated Agriculture	0	0	4	4	0	0	0	8	50.00%
Forest	0	0	9	40	0	0	0	49	81.63%
Barren Land	0	0	0	0	5	1	3	9	55.56%
Non-Vegetated Agriculture	0	0	0	0	7	5	12	24	20.83%
Built Up	0	0	0	1	17	10	24	52	46.15%
Sum	21	1	13	45	29	16	39	210	Overall Accuracy
Users Accuracy	100.00%	100.00%	30.77%	88.89%	17.24%	31.25%	61.54%	Overall Accuracy	47.62% Kappa: 0.403

Table 26: First Level Error Matrix of Maximum Gabor Magnitude Textural Features Classification

Unclassified (0)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy	
Water	25	0	0	0	25		100.00%
Vegetation	0	61	0	2	63		96.83%
Built Up	0	6	27	54	87		31.03%
Bare Land	0	0	19	16	35		45.71%
Sum	25	67	46	72	210	Overall Accuracy	
Users Accuracy	100.00%	91.04%	58.70%	22.22%	Overall Accuracy	61.43%	Kappa: 0.516

Table 27: Second Level Error Matrix of Maximum Gabor Magnitude Textural Features Classification

Unclassified (3)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	23	1	0	0	0	0	0	24	95.83%
Inland Water	0	1	0	0	0	0	0	1	100.00%
Vegetated Agriculture	0	0	5	2	0	0	0	7	71.43%
Forest	0	0	13	44	0	0	0	57	77.19%
Barren Land	0	0	0	0	20	10	0	30	66.67%
Non-Vegetated Agriculture	0	0	0	0	19	9	11	39	23.08%
Built Up	0	0	0	1	10	2	36	49	73.47%
Sum	23	2	18	47	49	21	47	210	Overall Accuracy
Users Accuracy	100.00%	50.00%	27.78%	93.62%	40.82%	42.86%	76.60%	Overall Accuracy	65.71% Kappa: 0.582

Table 28: First Level Error Matrix of Multispectral and Gabor Textural Features Together Classification

Unclassified (0)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	25	0	0	0	25	100.00%
Vegetation	0	61	0	1	62	98.39%
Built Up	0	0	41	9	50	82.00%
Bare Land	0	6	5	62	73	84.93%
Sum	25	67	46	72	210	Overall Accuracy
Users Accuracy	100.00%	91.04%	89.13%	86.11%	Overall Accuracy	90.00% Kappa: 0.880

Table 29: Second Level Error Matrix of Multispectral and Gabor Textural Features Together Classification

Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	22	0	0	0	0	0	0	22	100.00%
Inland Water	1	2	0	0	0	0	0	3	66.67%
Vegetated Agriculture	0	0	6	0	0	0	0	6	100.00%
Forest	0	0	13	46	0	0	0	59	77.97%
Barren Land	0	0	0	0	34	13	1	48	70.83%
Non-Vegetated Agriculture	0	0	0	0	10	8	0	18	44.44%
Built Up	0	0	0	1	2	1	50	54	92.59%
Sum	23	2	19	47	46	22	51	210	Overall Accuracy
Users Accuracy	95.65%	100.00%	31.58%	97.87%	73.91%	36.36%	98.04%	Overall Accuracy	80.00% Kappa: 0.750

By looking at all these accuracies, it is clearly seen that in some LULC classes, using only textural information makes a good classification. On the other hand, merging multispectral data with textural features makes an impressive increase in some classes. But sometimes only multispectral data is better.

Observing all the error matrices, for the first level of classification, water stands out as the easiest part. Any classification data which is tried in this study gives a hundred percent accuracy. NDWI thresholding can be a reason for this, since itis a strong indicator by itself for extracting water. For the final table, data chosen to be used while classification does not matter for water class. For the second class, i.e., vegetation, combined data of multispectral and textural features increases the total accuracy. For the final table, merged data is recommended for use. For third class, i.e., built up using combined data gives better results in classification as it does in vegetation. For the last class, i.e., bare land, what are said for vegetation and built up applies. Using combined data gives a better result. Final table for the first level classification is given in Table 30.

For the second level classification of Izmir, total number of classes is seven, excluding unclassified class. Error matrices were observed one by one; and the best classification data was tried to be chosen for each class. It can be seen that all data used in this study gives a perfect classification accuracy for marine water class, too. For inland water class, accuracy results provide a better performance when only textural information is used. For vegetated agricultural land and built up area, combined data gives a better performance. On the other hand, for forest, bare land and non-vegetated agricultural land, multispectral data performs better alone. Final table for the best results in second level classification is presented in Table 31 below.

Table 30: First Level Classification Final Results

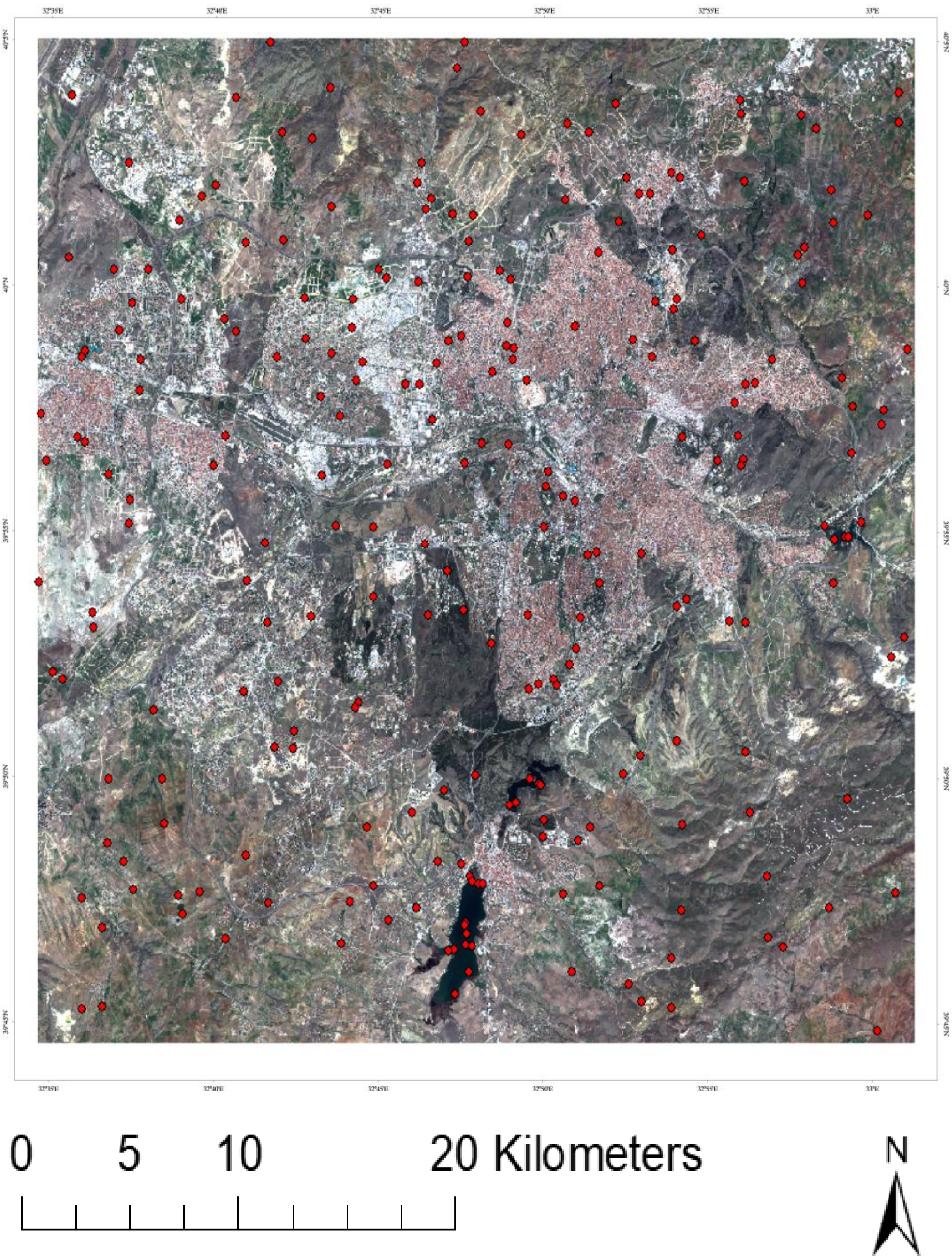
Unclassified (0)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	25	0	0	0	25	100.00%
Vegetation	0	61	0	1	62	98.39%
Built Up	0	0	41	9	50	82.00%
Bare Land	0	6	5	62	73	84.93%
Sum	25	67	46	72	210	Overall Accuracy
Users Accuracy	100.00%	91.04%	89.13%	86.11%	Overall Accuracy	90.00% Kappa: 0.880

Table 31: Second Level Classification Final Results

Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	22	0	0	0	0	0	0	22	100.00%
Inland Water	0	2	0	0	0	0	0	2	100.00%
Vegetated Agriculture	0	0	6	0	0	0	0	6	100.00%
Forest	0	0	6	44	0	0	0	50	88.00%
Barren Land	0	0	0	0	41	9	0	50	82.00%
Non-Vegetated Agriculture	0	0	0	0	4	11	0	15	73.33%
Built Up	0	0	0	1	2	1	50	54	92.59%
Sum	22	2	12	45	47	21	50	199	Overall Accuracy
Users Accuracy	100.00%	100.00%	50.00%	97.78%	87.23%	52.38%	100.00%	Overall Accuracy	88.44% Kappa: 0.854

5.2. Results of Ankara

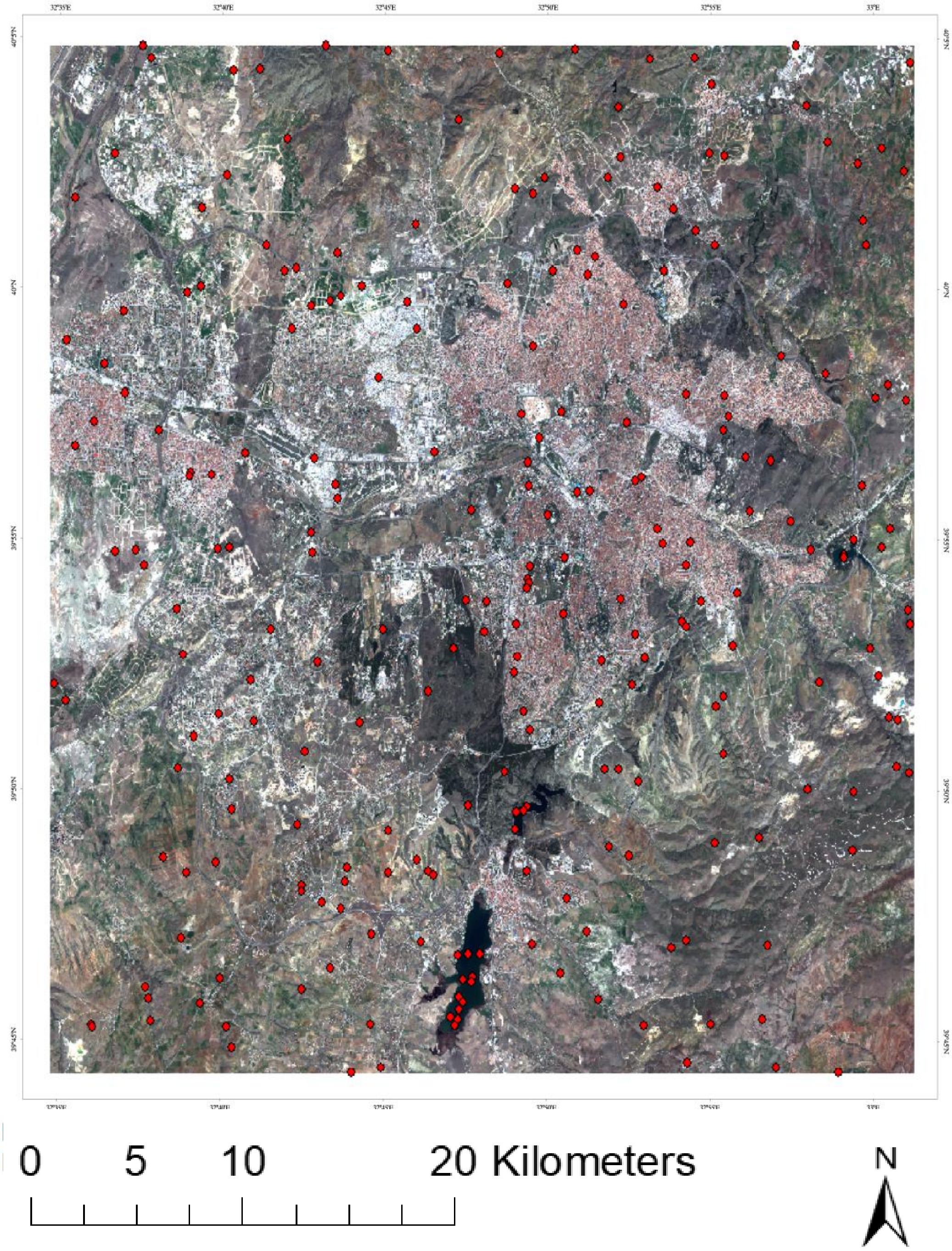
The same method applied for Izmir is also applied for accuracy assessment of Ankara. First level random points and second level random points are given in Figure 75 and Figure 76 respectively. Error matrices, accuracies and Kappa coefficients of first and second level classifications of multispectral data are given in Table 32 and Table 33, respectively. Subsequently, the results of only textural data of first and second levels are given in Table 34 to Table 45. Lastly, the results for the combination of multispectral and textural features are given in Table 46 and Table 47.



RGB band composition of Sentinel-2 data.

Date taken: 27.04.2017

Figure 75: First Level Random Points



RGB band composition of Sentinel-2 data.

Date taken: 27.04.2017

Figure 76: Second Level Random Points

Table 32: First Level Error Matrix of Multispectral Classification

Unclassified (1)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	20	0	0	0	20	100.00%
Vegetation	0	32	0	2	34	94.12%
Built Up	0	0	39	9	48	81.25%
Bare Land	0	9	19	119	147	80.95%
Sum	20	41	58	130	250	Overall Accuracy
Users Accuracy	100.00%	78.05%	67.24%	91.54%	Overall Accuracy	84.00% Kappa: 0.857

Table 33: Second Level Error Matrix of Multispectral Classification

Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	10	3	0	0	0	13	76.92%
Forest	NA		3	19				22	86.36%
Barren Land	NA	0	0	0	61	11	3	75	81.33%
Non-Vegetated Agriculture	NA	0	0	0	33	27	10	70	38.57%
Built Up	NA	0	0	0	7	0	43	50	86.00%
Sum	NA	20	13	22	101	38	56	250	Overall Accuracy
Users Accuracy	NA	100.00%	76.92%	86.36%	60.40%	71.05%	76.79%	Overall Accuracy	72.00% Kappa: 0.639

Table 34: First Level Error Matrix of All Gabor Textural Features Classification

Unclassified (28)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	19	0	0	0	19	100.00%
Vegetation	0	20	0	1	21	95.24%
Built Up	0	2	41	18	61	67.21%
Bare Land	0	8	8	105	121	86.78%
Sum	19	30	49	124	250	Overall Accuracy
Users Accuracy	100.00%	66.67%	83.67%	84.68%	Overall Accuracy	74.00% Kappa: 0.721

Table 35: Second Level Error Matrix of All Gabor Textural Features Classification

Unclassified (3)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	10	1	0	0	0	11	90.91%
Forest	NA	0	3	21	0	0	0	24	87.50%
Barren Land	NA	0	0	0	58	11	10	79	73.42%
Non-Vegetated Agriculture	NA	0	0	0	27	26	3	56	46.43%
Built Up	NA	0	0	0	15	0	42	57	73.68%
Sum	NA	20	13	22	100	37	55	250	Overall Accuracy
Users Accuracy	NA	100.00%	76.92%	95.45%	58.00%	70.27%	76.36%	Overall Accuracy	70.80% Kappa 0.622

Table 36: First Level Error Matrix of First PCA component Textural Features Classification

Unclassified (62)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	0	0	0	0	0	0.00%
Vegetation	0	14	0	1	15	93.33%
Built Up	0	6	41	29	76	53.95%
Bare Land	0	6	10	81	97	83.51%
Sum	0	26	51	111	250	Overall Accuracy
Users Accuracy	0.00%	53.85%	80.39%	72.97%	Overall Accuracy	54.40% Kappa:0.509

Table 37: Second Level Error Matrix of First PCA component Textural Features Classification

Unclassified (33)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	5	0	0	0	0	0	5	100.00%
Vegetated Agriculture	NA	0	9	4	0	0	0	13	69.23%
Forest	NA	0	4	15	0	0	0	19	78.95%
Barren Land	NA	0	0	0	24	13	0	37	64.86%
Non-Vegetated Agriculture	NA	0	0	0	39	14	8	61	22.95%
Built Up	NA	0	0	0	29	9	44	82	53.66%
Sum	NA	5	13	19	92	36	52	250	Overall Accuracy
Users Accuracy	NA	100.00%	69.23%	78.95%	26.09%	38.89%	84.62%	Overall Accuracy	44.40% Kappa: 0.333

Table 38: First Level Error Matrix of Second PCA component Textural Features Classification

Unclassified (36)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	16	0	0	0	16	100.00%
Vegetation	0	17	0	2	19	89.47%
Built Up	0	6	8	22	36	22.22%
Bare Land	0	8	39	96	143	67.13%
Sum	16	31	47	120	250	Overall Accuracy
Users Accuracy	100.00%	54.84%	17.02%	80.00%	Overall Accuracy	54.80% Kappa: 0.527

Table 39: Second Level Error Matrix of Second PCA component Textural Features Classification

Unclassified (25)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	13	0	0	0	0	0	13	100.00%
Vegetated Agriculture	NA	0	12	9	0	0	0	21	57.14%
Forest	NA	0	0	5	0	0	0	5	100.00%
Barren Land	NA	0	0	0	41	5	12	58	70.69%
Non-Vegetated Agriculture	NA	0	0	0	28	27	56	111	24.32%
Built Up	NA	0	0	0	11	3	3	17	17.65%
Sum	NA	13	12	14	80	35	71	250	Overall Accuracy
Users Accuracy	NA	100.00%	100.00%	35.71%	51.25%	77.14%	4.23%	Overall Accuracy	40.40% Kappa: 0.287

Table 40: First Level Error Matrix of Third PCA component Textural Features Classification

Unclassified (43)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	10	0	0	0	10	100.00%
Vegetation	0	17	0	2	19	89.47%
Built Up	0	6	8	22	36	22.22%
Bare Land	0	7	39	96	142	67.61%
Sum	10	30	47	120	250	Overall Accuracy
Users Accuracy	100.00%	56.67%	17.02%	80.00%	Overall Accuracy	52.40% Kappa: 0.503

Table 41: Second Level Error Matrix of Third PCA component Textural Features Classification

Unclassified (36)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	15	0	0	0	0	0	15	100.00%
Vegetated Agriculture	NA	0	7	9	0	0	0	16	43.75%
Forest	NA	0	1	10	0	0	0	11	90.91%
Barren Land	NA	0	0	0	51	26	1	78	65.38%
Non-Vegetated Agriculture	NA	0	0	0	18	7	3	28	25.00%
Built Up	NA	0	0	0	16	2	48	66	72.73%
Sum	NA	15	8	19	85	35	52	250	Overall Accuracy
Users Accuracy	NA	100.00%	87.50%	52.63%	60.00%	20.00%	92.31%	Overall Accuracy	55.20% Kappa: 0.450

Table 42: First Level Error Matrix of Fourth PCA component Textural Features Classification

Unclassified (37)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	11	0	0	0	11	100.00%
Vegetation	0	29	0	2	31	93.55%
Built Up	0	3	42	27	72	58.33%
Bare Land	0	6	9	86	101	85.15%
Sum	11	38	51	115	252	Overall Accuracy
Users Accuracy	100.00%	76.32%	82.35%	74.78%	Overall Accuracy	66.67% Kappa: 0.637

Table 43: Second Level Error Matrix of Fourth PCA component Textural Features Classification

Unclassified (30)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	18	0	0	0	0	0	18	100.00%
Vegetated Agriculture	NA	0	12	20	0	0	0	32	37.50%
Forest	NA	0	0	0	0	0	0	0	#DIV/0!
Barren Land	NA	0	0	0	53	29	5	87	60.92%
Non-Vegetated Agriculture	NA	0	0	0	10	1	3	14	7.14%
Built Up	NA	0	0	0	25	5	39	69	56.52%
Sum	NA	18	12	20	88	35	47	250	Overall Accuracy
Users Accuracy	NA	100.00%	100.00%	0.00%	60.23%	2.86%	82.98%	Overall Accuracy	49.20% Kappa: 0.370

Table 44: First Level Error Matrix of Maximum Gabor Magnitude Textural Features Classification

Unclassified (0)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	20	0	0	0	20	100.00%
Vegetation	0	28	0	2	30	93.33%
Built Up	0	0	5	3	8	62.50%
Bare Land	0	14	53	125	192	65.10%
Sum	20	42	58	130	250	Overall Accuracy
Users Accuracy	100.00%	66.67%	8.62%	96.15%	Overall Accuracy	71.20% Kappa: 0.700

Table 45: Second Level Error Matrix of Maximum Gabor Magnitude Textural Features Classification

Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	11	10	0	0	0	21	52.38%
Forest	NA	0	2	11	0	0	0	13	84.62%
Barren Land	NA	0	0	1	60	15	35	111	54.05%
Non-Vegetated Agriculture	NA	0	0	0	34	23	14	71	32.39%
Built Up	NA	0	0	0	7	0	7	14	50.00%
Sum	NA	20	13	22	101	38	56	250	Overall Accuracy
Users Accuracy	NA	100.00%	84.62%	50.00%	59.41%	60.53%	12.50%	Overall Accuracy	52.80% Kappa: 0.370

Table 46: First Level Error Matrix of Multispectral and Gabor Textural Features Together Classification

Unclassified (12)	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	20	0	0	0	20	100.00%
Vegetation	0	17	0	2	19	89.47%
Built Up	0	5	52	22	79	65.82%
Bare Land	0	8	6	106	120	88.33%
Sum	20	30	58	130	250	Overall Accuracy
Users Accuracy	100.00%	56.67%	89.66%	81.54%	Overall Accuracy	78.00% Kappa: 0.757

Table 47: Second Level Error Matrix of Multispectral and Gabor Textural Features Together Classification

Unclassified (0)	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	10	1	0	0	0	11	90.91%
Forest	NA	0	3	21	0	0	0	24	87.50%
Barren Land	NA	0	0	0	60	19	1	80	75.00%
Non-Vegetated Agriculture	NA	0	0	0	32	19	3	54	35.19%
Built Up	NA	0	0	0	14	0	47	61	77.05%
Sum	NA	20	13	22	106	38	51	250	Overall Accuracy
Users Accuracy	NA	100.00%	76.92%	95.45%	56.60%	50.00%	92.16%	Overall Accuracy	70.80% Kappa: 0.618

By looking at all these accuracies, it is clearly seen that in some LULC classes, using only textural information makes a good classification. On the other hand, merging multispectral data with textural features makes an impressive increase in some classes. However, sometimes multispectral data alone is a better choice.

Observing all the error matrices, for the first level of classification, water stands out as the easiest part. Any classification data, which is tried in this study, gives a hundred percent accuracy except the first PCA component. NDWI thresholding can be a reason for this, since it is a strong indicator by itself for extracting water. For the final table, data chosen to be used while classification does not matter for water class. The second and third class, vegetation, gives good results when only multispectral data is used, as done for built up. For the last class, bare land, textural data gives better results when used alone. The final table for the first level classification is given in Table 48.

For the second level classification of Ankara, total number of classes is six, excluding unclassified class and marine water class. Error matrices are observed one by one; and the best classification data is tried to be chosen for each class. It can be seen that all data used in this study gives a 100 percent classification accuracy for inland waters. For vegetated agricultural land, forest and built up area, combined data gives a better performance. On the other hand, for barren land, multispectral data performs better alone. For non-vegetated agricultural land, a better performance is achieved when only textural data is used. The final table for the best results in second level classification is presented in Table 49.

Table 48: First Level Classification Final Results

	Water	Vegetation	Built Up	Bare Land	Sum	Producers Accuracy
Water	20	0	0	0	20	100.00%
Vegetation	0	32	0	2	34	94.12%
Built Up	0	0	39	9	48	81.25%
Bare Land	0	8	6	106	120	88.33%
Sum	20	40	45	117	222	Overall Accuracy
Users Accuracy	100.00%	80.00%	86.67%	90.60%	Overall Accuracy	88.74% Kappa: 0.877

Table 49: Second Level Classification Final Results

	Marine Water	Inland Water	Vegetated Agriculture	Forest	Barren Land	Non-Vegetated Agriculture	Built Up	Sum	Producers Accuracy
Marine Water	NA	NA	NA	NA	NA	NA	NA	NA	NA
Inland Water	NA	20	0	0	0	0	0	20	100.00%
Vegetated Agriculture	NA	0	10	1	0	0	0	11	90.91%
Forest	NA	0	3	21	0	0	0	24	87.50%
Barren Land	NA	0	0	0	61	11	3	75	81.33%
Non-Vegetated Agriculture	NA	0	0	0	27	26	3	56	46.43%
Built Up	NA	0	0	0	14	0	47	61	77.05%
Sum	NA	20	13	22	102	37	53	247	Overall Accuracy
Users Accuracy	NA	100.00%	76.92%	95.45%	59.80%	70.27%	88.68%	Overall Accuracy	74.90% Kappa: 0.674

5.2. Conclusion and Recommendations

The main objective of this study is to create a LULC map and to test the newly launched Sentinel-2 sensor capabilities for EO. For that reason, hierarchical classification of CRINE is adapted and SVM algorithm is used for classification. Moreover, textural features are extracted and implemented to the data for testing the effect on accuracies.

For the main objective, Sentinel-2 capabilities for EO, only multispectral data should be considered. By looking at the accuracies of Izmir and Ankara in first level, one can see that the overall accuracies are 85.24% and 84.00%; and the Kappa coefficients are 0.821 and 0.827, respectively. As it is mentioned in Table 3: Suggested Ranges for Kappa Coefficient (Richards & Jia, 2006), first level classification is almost perfect based on the values of kappa coefficients. Overall accuracies also indicate a good classification result. Considering each class one by one, water class can easily be extracted from NDWI and yields perfect classification results. It should be kept in mind that thresholding from histograms is subjective; therefore, small changes can occur if thresholds are changed. For vegetation, accuracies are above 93%, as a result of NDVI, which is a good indicator for extracting vegetation. Thresholding is subjective in NDVI too; therefore, it needs to be handled carefully. Bare land class in Izmir and Ankara both have above 80% accuracy. SVM algorithm worked well while creating hyperplane to separate built up and bare land. The last and least accurate class of level one is built up where accuracies are 72% and 81% for Izmir and Ankara, respectively. While training the classifier, pure pixels are chosen. Built up fabric can either be discontinuous or continuous. Since Izmir is a smaller town than Ankara and its population is nearly half of Ankara’s; built up fabric is observed to be rather discontinuous. This can be the reason for the lower accuracy of Izmir. However, in overall, accuracies are very promising for using Sentinel-2 to create LULC map.

In the second level of multispectral data, overall accuracy of Izmir is 84.76%, Ankara is 72.00% and Kappa coefficients are 0.811 and 0.639, respectively. Again, Table 3, demonstrates that Izmir has “almost perfect” classification results while Ankara has “good” classification results. One by one investigation of classes shows that, for Izmir, marine water has perfect classification, but inland water has 40% classification accuracy. It is clearly seen that inland water was confused with shallow water if the classification maps are investigated in detail. Ankara has no marine water so there is not any confusion between shallow water and inland water. Classification accuracy of inland water is 100%. Both in Izmir and Ankara, vegetated agricultural lands and forests have above 75% accuracy. Checking past studies, it was seen that “fairly good” accuracy is achieved for remotely sensed data. Barren land and built up areas have above 80% classification accuracy in both cities. The last class of second level classification is non-vegetated agricultural lands. In Izmir, it is 73.33% but in Ankara 38.57%. Izmir results again are “fairly good”; but Ankara has “low” classification accuracy. All in all, by looking at the overall results, Sentinel-2 data can be used for LULC maps successfully.

After the main objective is tested, textural data was introduced to see whether only textural data is sufficient for classification or not. For the first level, water and vegetation accuracies are above 90%, again since the NDVI and NDWI indices are working well. Built up classification results for textural features are not as good as the results of multispectral data alone. Bare land accuracy is not as high as of other classes in Izmir; but in Ankara fairly good results are observed.

To see the errors in specific classes for İzmir and Ankara, brief error matrixes are created. In Table 50 and Table 51 each tested methodology and algorithms errors specify is shown. It can guide for further application. For example, in İzmir, built up area has the worst accuracy. With some modification or addition to the algorithm or data, accuracies can be go up.

Table 50: Error Matrix for Each Class for İzmir

İzmir				
SVM	Number of Pixels	True	False	Percent
Water	25	25	0	100.00%
Vegetation	65	61	4	93.85%
Built Up	55	40	15	72.73%
Bare Land	65	53	12	81.54%
ML	Number of Pixels	True	False	Percent
Water	19	19	0	100.00%
Vegetation	57	55	2	96.49%
Built Up	79	45	34	56.96%
Bare Land	55	46	9	83.64%
No Hierarchy	Number of Pixels	True	False	Percent
Marine Water	20	20	0	100.00%
Inland Water	5	2	3	40.00%
Vegetated Agriculture	15	5	10	33.33%
Forest	50	38	12	76.00%
Baren Land	50	35	15	70.00%
Non-Vegetated Agriculture	15	10	5	66.67%
Built Up	55	47	8	85.45%

Table 51: Error Matrix for Each Class for Ankara

Ankara				
SVM	Number of Pixels	True	False	Percent
Water	20	20	0	100.00%
Vegetation	34	32	2	94.12%
Built Up	48	39	9	81.25%
Bare Land	147	119	28	80.95%
ML	Number of Pixels	True	False	Percent
Water	14	14	0	100.00%
Vegetation	24	22	2	91.67%
Built Up	112	58	54	51.79%
Bare Land	100	85	15	85.00%
No Hierarchy	Number of Pixels	True	False	Percent
Marine Water	20	20	0	100.00%
Inland Water	5	2	3	40.00%
Vegetated Agriculture	15	5	10	33.33%
Forest	50	38	12	76.00%
Barren Land	50	35	15	70.00%
Non-Vegetated Agriculture	15	10	5	66.67%
Built Up	55	47	8	85.45%

After the main objective is tested, textural data was introduced to see whether only textural data is sufficient for classification or not. For the first level, water and vegetation accuracies are above 90%, again since the NDVI and NDWI indices are working well. Built up classification results for textural features are not as good as the results of multispectral data alone. Bare land accuracy is not as high as of other classes in Izmir; but in Ankara fairly good results are observed.

Looking at the use of textural features alone for second level, sub classes of water and vegetation have above 85% accuracy. Other classes, non-vegetated agricultural land, barren land and built up, are not as successful as they are with multispectral data. All three accuracies of both cities are below 75%.

Purpose of combining the data is to observe whether the classification accuracies will increase or not. For Izmir and Ankara combined data, overall accuracies are

90% and 78%; and the Kappa coefficients are 0.880 and 0.757, respectively. Table 3 shows almost perfect classification for Izmir and excellent classification for Ankara. Considering the classes one by one, water class has 100% accuracy in classification. For vegetation, accuracies are 98.39% and 89.47% for Izmir and Ankara, respectively. Bare land class in Izmir and Ankara both have above 84% accuracy. SVM algorithm functioned well while creating hyperplane to separate built up and bare land. The last and least accurate class of level one is built up, where accuracies are 82% and 65% for Izmir and Ankara, respectively.

In second level of multispectral and textural combined data, overall accuracy of Izmir is 80.00% and of Ankara is 70.80% while the Kappa coefficients are 0.750 and 0.618, respectively. According to Table 3, Izmir and Ankara have "good" classification results. One by one investigation of classes shows that, for Izmir, marine water has perfect classification, but inland water has 66.67% classification accuracy. It is clearly seen that inland water was confused with shallow waters once again. Classification accuracy of inland water was 100% for Ankara. Both in Izmir and Ankara, vegetated agricultural lands have above 90% accuracy and forests have above 77%. Barren land and built up areas have above 70% classification accuracy in both cities. The last class of second level classification is non-vegetated agricultural lands; accuracy of which is 44.44% in Izmir and 35.19% in Ankara. It can also be seen that barren land has low classification accuracy.

Effect of texture is not stable in both cities. In Izmir, combining textural data with multispectral data decreases the accuracy for built up and non-vegetated agricultural lands. On the other hand, in Ankara, it increases the accuracy. Vegetation and sub classes perform better with multispectral data alone in the first level. When it comes to the second level of combined data, textural data increases the accuracy of forest and vegetated agricultural area. For bare land in Izmir, combined data increases the accuracy; but in Ankara textural data alone performs better as it does with non-vegetated agricultural lands.

Consequently, it can be said that the methodology worked successfully for creating LULC maps with Sentinel-2 data. Its success is proven with the case study accuracy results and Kappa coefficients. Using textural features for some classes increases accuracy; and they can be used for different satellites too. As textures change in every scene, detailed textural analysis should be done.

- One of the main contribution of this thesis is to, compare the effectiveness of hierarchical classification system on Sentinel-2 data with one-step non-hierarchical classification system. It is clearly seen that; hierarchical classification methodology outperforms non-hierarchical classification methodology.
- The second contribution of this thesis is to compare basic supervised classification methods, namely support vector machine and maximum likelihood classification and to reveal the better methods to be utilized with Sentinel-2 data. It is clearly seen that, SVM is performed better while testing the Sentinel-2 data.
- Third, the effects of integrating the textural features to Sentinel-2 data. In this study gabor filtering is used. Main objective of this study is not study textural feature effects on image data, therefore, only the analysis are interpreted. As seen in results part, for some classes, textural features improve the results.
- Potential of Ankara and İzmir in creating LULC maps. The cities shows that, enough classes are existed for a detailed hierarchical classification.
- Last but not least, specify and compare the performances of suggested methodology on Corine subclasses. All Corine hierarchical classes level 1 to level 3 are included in this studies classes. The methodology can be used for creating LULC map according to Corine hierarchy.

For the further studies, 3rd level of Corine classes are included in this thesis 2nd level classes. It can be developed furthermore to extract Corine's 3rd level classes. For example, built up class in this study represents Corine's 2nd level classes. With a suitable algorithm it can represent Corine's 3rd level classes. In more detailly, 2nd level classes are the last step of methodology. Those 2nd level classes are contains

Corine's hierarcical classes. Inland water class contains Corine's 41 and 51 and corresponding 3^{rd} level, marine water class contains Corine's 42 and 52 and corresponding 3^{rd} level classes, forest/meadow class contains Corine's 141, 142, 221, 222, 223, 231, 311, 312, 313, 321, 322, 323 and 324, vegetated agricultural lands contains Corine's 241, 242, 243 and 244, built up class contains Corine's 2^{nd} level 11, 12 and 13 and corresponding 3^{rd} level classes, barren land class contains Corine's 331, 332, 333, 334 and 335, non-vegetated agricultural land class class contains Corine's 211, 212 and 213. This methodology is specify only 2^{nd} level of Corine hierarchy. Further implementations for this methodology can further specify all 3^{rd} level of Corine hierarcy.

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