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SOIL SEALING AND LAND USE CHANGE DETECTION APPLYING GEOGRAPHIC OBJECT BASED IMAGE ANALYSIS (GEOBIA) TECHNIQUE

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وَقُلِ اعْمَلُواْ فَسَيَرَى اللّهُ عَمَلَكُمْ وَرَسُولُهُ وَالْمُؤْمِنُونَ
وَسَتُرَدُّونَ إِلَى عَالِمِ الْغَيْبِ وَالشَّهَادَةِ فَيُنَبِّئُكُم بِمَا كُنتُمْ
تَعْمَلُونَ.

التوبة (105)

Soon will Allah observe your work, and His Messenger, and the Believers: Soon will you be brought back to the knower of what is hidden and what is open: then will He show you the truth of all that you did.

Quran-[At-Tauba (9:105)]

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ABBREVIATIONS

AHP	analytical hierarchy process
DEM	Degital Elevation Model
DOC	Controlled Designation of Origin (Denominazione di Origine Controllata)
EC	Electrical Conductivity
FAO	Food and Agriculture Organization
GCP	GroundControl Points
GEOBIA	Geographic Object Based Image Analysis
GIS	Geographic Information Systems
GPS	Global Positioning System
IGM	Italian Military Geographical Institute
ISTAT	National Institute for Statistics (Istituto nazionale di statistica)
KIA	Kappa Index of Agreement
LIDAR	Light Detection and Ranging
LULC	Land Use and Land Cover
LULCC	Land Use and Land Cover Change
MCDM	Multi Criteria Decision Making
MCE	Multi Criteria Evaluation
OC	Soil organic carbon
OM	soil organic matter
RGB	Image Composition of Red, Green and Blue layers
RMSE	root mean square error
TDS	Total Dissolved Solids
USDA	United States Department of Agriculture

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INTRODUCTION

1. INTRODUCTION

1.1. Statement of the Problem

It is believed that the name of our planet “Earth” is at least 1000 years old. It comes from the Old English words 'ertha' and 'eor(th)e' and it is a German/English name, which basically means ‘ground’ or ‘soil’. Naming the planet after soil may reflect how important soil to our planet and to humans. Human history, religions and myths are all talking about the importance of soil or land. For example, the Quran (Muslims Holy Book) describes that GOD “Allah” created the first man from clay, while the Bible says out of soil, which are both representation for earth. Earth is also one of the four classical elements in history of the medieval and Greek models. In addition, it is one of the five elements in Hinduism and in the Chinese philosophy. Even the ancient Egyptians had a unique god of the Earth named “Geb”. It was believed in ancient Egypt that Geb allowed crops to grow and that Geb's laughter was earthquakes. This tells us how our ancestors highly valued soil and land. On the contrary, in the last few decades humans seemed to have forgotten the value of soil and a huge area of soils were destroyed.

Theoretically, soil is a renewable resource. However, as coarse estimate, ten centimeters of fertile soil are created in 2000 years (Jenny, 1941). This means that soils we deplete by human activities are gone forever relative to human lifespan; thus, one can conclude that soil is not a renewable resource (see Soil Thematic Strategy COM 231/2006). It is manifested today that soil is as important as other natural resources to human kind, just like the sun, water and air. As a natural resource, soil provides an ecological capacity through securing a variety of functions including environmental services, raw materials, physical platforms for the built environment, fiber and food production, biodiversity pool, landscape and heritage. Consequentially, protection and optimum use of the soil resources is a serious mission for sustainable development goals. Every year 13 million hectares of forests are cut down worldwide (FAO, 2010). In addition, only in Europe, an area as large as the city of Berlin is transformed into urban areas every year. The projections (Alexandratos & Bruinsma, 2012) reveal that the available arable land per earth inhabitant will be reduced by half by 2050. This is probably due to the fact that urbanization has taken place at an accelerated rate since the last century. The

United Nations suggested that over 50% of the current world population live in the urban areas.

Nowadays, urbanization is one of the major problems facing environment due to its several impacts on the environment. One of these impacts is lose of soil due to soil sealing by urban settings. So, the increase in soil sealing problem is associated with the urbanization growth rate. Soil sealing is covering of the surface of the soil with impermeable materials such as stones, asphalt and concrete, as a result of new roads, buildings, parking places and other private and public spaces. Recently, the impacts of soil sealing became known to the scientific community. Lose of soil functions is a very important impact of soil sealing. Biomass production is one of the important soil functions and is most likely the first function lost by soil sealing. From the beginning of the human civilization, biomass production became a key factor for the continuity of civilized life. It is useable as energy source, body cover, food, construction material and much other uses. With the growing attention to the effects of soil sealing, scientists raced to study the various impacts on different soil functions; however, so far there is no solid methodology to estimate the loss in biomass production as a soil function lost by soil sealing. Therefore, there is an urgent need to develop a novel method to evaluate and quantify the lost biomass production by soil sealing. To study a phenomenon such as soil sealing growth and its impacts, it is important to understand the history, rates and trends of the problem. In order to do so, a land use and land cover change detection analysis is considered necessary. In this analysis, a comparison between the past and present land use and land cover is conducted to study the quantity and type of change during a certain period of time. Land use and land cover change refers to changes made to the Earth’s surface through human impact. Historically, humans have made many changes arising from the need to exploit resources and through agricultural expansion. However, the present rate of Land use and land cover change (e.g. transformation from agricultural/forested areas to urban areas) is much greater than ever recorded previously, resulting in rapid changes to ecosystems at local to global scales. The spatial analysis of land use and land cover change detection comprises the use of historical maps to judge against recent maps of land use and land cover. The weak point here is the quality of the classification in the old maps which in turn will affect the quality of the analysis results. As a result, enhancing the quality of the classification for old land use and land cover maps will enhance the final results of the change detection analysis. The recent remote sensing techniques provide a great opportunity to improve the classification quality of old maps. Geographic object based image analysis (GEOBIA) is a novel remote sensing technique that can be used to classify images based on objects characteristics. GEOBIA is a newly developed area of Geographic Information Science and remote sensing, in which automatic segmentation of images into objects of similar spectral, temporal and spatial characteristics of these objects is undertaken. Using GEOBIA technique to reclassify old aerial photographs may produce a more coherent classification and improve the old land use and land cover map enabling in turn - for instance - a better evaluation of soil sealing dynamics.

For the application of this study, arises the need to find a study area with particular specifications. A study area was chosen in Telesina Valley (Valle Telesina), located in Benevento in the Campania region of central Italy. The reason behind the selection of this region lies in the diversity of land use and land cover such as forests, different types of agriculture, pasture and urban settlements. As well as, the variety of change types of land use and land cover in the last few decades, which vary between deforestation, agriculture intensification and extensification, abandonment, afforestation and urbanization. In addition, the area is interesting because it represents a case study where agriculture (namely high quality viticulture) can potentially compete against urbanization processes. Add to this, the area is characterized by the availability of data and information necessary to carry out the study because this region has been subject to several of the previous studies.

1.2. Purpose of the Study

Then, to summarize the preceding ideas, to study the impact of soil sealing on the biomass production there is a need for a fine quality of land use and land cover change detection analysis. In order to obtain this quality, it is necessary to improve the old classification of land use and land cover areas using one of the most recent remote sensing techniques. Consequently, the final results of the change detection analysis will be improved and therefore, the quantification of the lost biomass production by soil sealing will be improved.

Therefore, the study had different objectives, which can be summarized as follows:

- investigate the land use and land cover change in the study area between 1954 and 2009 as a long term change detection analysis;
- develop a novel methodology for the classification of old gray scale aerial photographs using geographic object based image analysis (GEOBIA) technique to generate an improved land use and land cover map of the study area for the year 1954;
- conduct a comparison of the capability of change detection between old and improved "GIOBIA" land use and land cover classifications of the year 1954 regarding three main change types i.e., afforestation and deforestation; agricultural development; and urbanization to study the effect of enhancing historical data on the modeling process;
- introduce a novel land suitability evaluation index;
- evaluate the amount of lost soil by soil sealing during the period between 1954 and 2011; and
- develop a novel GIS based method for modeling soil functions loss by soil sealing to quantify the losses in biomass production.

REVIEW OF THE LITERATURES

2. REVIEW OF THE LITERATURES

2.1. Long term detection of land use and land cover change

Land use and land cover change (LULCC) is one of the most notable modifications occur on the Earth's land surface (Lambin et al., 2001). Many studies revealed that, in the last few decades landscape transformation rate was increased significantly (Antrop, 2005; Ewert et al., 2005). Therefore, studying the factors that control these changes and their impacts has become extremely essential for those how are involved in defending water resources from non-point pollution (Ripa et al., 2006), biodiversity conservation, land use planning, and landscape ecology (Etter et al., 2006). Knowing of land cover does not automatically determine the land use. So, to understand the changes in the land cover it is important to define the land use under investigation (Lambin & Geist, 2001). There are several definitions of land cover (Meyer, & Turner, 1994) and land use (Jansen, 2006). Land cover is known as ''the observed (bio) physical cover on the earth's surface'' (Di Gregorio & Jansen, 2000); while land use defines how the people use this part of the earth's surface (Cihlar & Jansen, 2001).

Satellite remote sensing is the most usable data source for recognition, determination, and mapping land use and land cover (LULC) outlines and changes because of its accurate georeferencing procedures, digital format suitable for computer processing and successive data acquisition, (Jensen, 1996; Lu et al., 2004; Chen et al., 2005). Remote sensing and Geographic information systems (GIS) are used to create maps of land cover but only serves as one input to land use mapping and change detection, which requires a more multi-disciplinary approach to its definition, integrating both physical and social sciences. This might include interviews with land owners of similar land cover types to determine the types of activities that are being undertaken (Ellis & Pontius, 2013). For example, natural grasslands and grazing land might have similar spectral signals and although the similarity of land covers types, yet they have quite different land uses. Consequently, the discipline of land change science has evolved with the need now to integrate both the physical and social sciences in understanding the drivers and resulting impacts of LULCC (Ellis & Pontius, 2013).

2.1.1. Land use and land cover change (LULCC)

Land use and land cover change (LULCC) refers to changes made to the Earth's surface through human impact. Historically, humans have made many changes arising from the need to exploit resources and through agricultural expansion. However, the present rate of LULCC is much greater than ever recorded previously, with rapid changes to ecosystems occurring at local to global scales (Ellis & Pontius, 2013). Land cover consists of the physical and biological cover that can be found on the surface of the land. Examples include water bodies, vegetation, bare soils and urban areas. The term land use is much more complex and additionally includes human activities such as cultivation, livestock grazing and managed forests, all of which can modify existing processes on the surface of the land such as the hydrology or the biodiversity of species (Di Gregorio & Jansen, 2000). From the perspective of social scientists or land managers, land use is also defined in terms of the socio-economic purpose for which the land is managed, e.g. subsistence agriculture vs. large scale commercial farming, land that is rented vs. land that is owned, etc. (Anderson et al., 2001).

Land use change information is very important, especially to urban planners. Multi-temporal change analysis may assist the planners in determining spatial growth trends. Studies verified the need for assembling and summarizing land use data. It also illustrated the need for construction of systematic procedures for keeping account of changes (Ross, 1985). Although this is an important aspect of urban planning, it is more important aspect from the environmental point of view, given that urbanization is causing soil functions losses by sealing this soil with impermeable substances. Change detection is valuable for several applications associated with land use and land cover changes (LULCC), such as urban sprawl and coastal change (Shalaby & Tateishi, 2007), desertification and land degradation (Adamo & Crews-Meyer, 2006; Gao & Liu, 2010), landscape changes and shifting cultivation (Imbernon, 1999; Serra et al., 2008;Abd El-Kawy et al., 2011), habitat and landscape fragmentation (Munroe et al., 2005; Nagendra et al., 2006), change of urban landscape pattern (Batisani & Yarnal, 2009; Dewan & Yamaguchi, 2009; Long-qian et al., 2009), quarrying activities (Mouflis et al., 2008), and deforestation (Schulz et al., 2010; Wyman & Stein, 2010). Land use conversions are defined and classified as the changes in land use class that occurred in a given area and time. These classes identify the typology of changes by assigning a land use conversion code to each intersection created by the overlay of successive land use maps, allowing a thematic representation of the spatial distribution of changes. The method is based on the previous generalization of land use categories and offers a quantitative and qualitative measure of conversion that occurred in the study area, allowing the spatial distribution of land use changes to be reported on a unique map (Benini et al., 2010).

2.2. Automatic land use and land cover classification using GEOBIA technique

Ecosystem functions can be affected by land use and land cover change (LULCC), which is in turn dependent upon the provision, regulation and support of cultural ecosystem services. Thus, strategic planning and LULC interventions are necessary for ensuring the health and sustainability of an ecosystem. In order to make appropriate LULC decisions, accurate assessments of LULCC are needed, in particular to identify crucial zones of environmental vulnerability or those which provide valuable ecosystem services, e.g. the identification of a zone that is essential for the filtering of runoff or the abstraction of potable water in a watershed. Another example would be the identification and monitoring of the LULCC between certain land cover/land use types, e.g. the change from agricultural lands to urban, which can provide an important indication of the social and economic drivers that lead to such a change (Van-Camp et al., 2004). Since land change detection is highly dependent on the accuracy of the historical data input, improving data accuracy is likely to improve the final land change detection result (Pipino et al., 2002; Chapman, 2005; Salmons & Dubenion-Smith, 2005). Moreover, it was demonstrated (Fritz et al., 2013) that when comparing even more recent global land cover maps, a high amount of spatial disagreement can be found.

GEOBIA is a newly developed area of Geographic Information Science and remote sensing in which automatic segmentation of images into objects of similar spectral, temporal and spatial characteristics of these objects is undertaken (Hay & Castilla, 2008). GEOBIA is a subset of a larger field referred to as Object Based

Image Analysis (OBIA), which has been the subject of many research studies in the last decade (Benz et al., 2004; Blaschke et al., 2000; Blaschke et al., 2004; Blaschke & Strobl, 2001; Burnett & Blaschke, 2003; Flanders et al., 2003; Hay et al., 2003; Hay & Castilla, 2008; Koch et al., 2003; Lang et al., 2008; Liu et al., 2006; Navulur, 2007; Schiewe, 2002; Zhang et al., 2005) and which consists of numerous procedures including segmentation, classification, feature extraction and edge detection processes that have been applied in remote sensing image analysis for decades (Aplin et al., 1999; Baltsavias, 2004; Câmara et al., 1996; Haralick, 1983; Haralick & Shapiro, 1985; Hay et al., 1996; Kettig & Landgrebe, 1976; Levine & Nazif, 1985; Lobo et al., 1996; McKeown et al., 1989; Pal & Pal, 1993; Ryherd & Woodcock, 1996; Strahler et al., 1986; Wulder, 1998).

Using GEOBIA technique, we move up from pixel based analysis of remote sensing images to object based analysis (Ardila et al., 2012; Hay et al., 2001; Hay & Castilla, 2008; Johansen et al., 2011; Marpu et al., 2010) where new characteristics are obtained for each object not only from its pixels but also from the surrounding objects and sub and super-objects to generate new results or geo-intelligence (Aubrecht et al., 2008; Benz et al., 2004; Blaschke et al., 2004; Blaschke, 2010; Chen & Hay, 2011; Hay & Blaschke, 2010; Jobin et al., 2008; Kim et al., 2009; Laliberte et al., 2007; Langanke et al., 2007; Möller et al., 2007; Navulur, 2007; Stow et al., 2008; Tiede et al., 2008; Trias-Sanz et al., 2008; van der Werff & van der Meer, 2008; Weinke et al., 2008). These advances have also occurred as a result of the growing accessibility to very high resolution (VHR) earth imagery such as Ikonos and QuickBird (Jacobsen, 2004) and of highly sophisticated software such as Definiens eCognition Developer 8 (Neubert et al., 2008).

The GEOBIA technique consists of two main steps: segmentation and classification (Hay& Castilla, 2008, Kim et al., 2009). Segmentation is a clustering process meant to cluster homogeneous pixels based on predefined features (such as spectral, thematic or spatial values) to obtain homogeneous image objects (or segments). A supervised or knowledge-based image classification follows this segmentation process to categorize each image object in different classes. Since the quality of the segmentation results will affect all subsequent steps in the classification process, producing a high quality segmentation process is a basic requirement (Addink et al., 2007; Blaschke, 2003; Dorren et al., 2003; Hofmann et al., 2008; Meinel & Neubert, 2004; Singh et al., 2005). Although previous studies have attempted to find an optimal segmentation (Feitosa et al., 2006; Kim & Madden, 2006; Kim et al., 2008; Wang et al., 2004), there is no method available for doing this and therefore the feature thresholds involved in this procedure remain highly dependent on trial-and-error (Definiens, 2004; Meinel & Neubert, 2004). GEOBIA applications can be found in a range of spatially-related fields including forestry (Chen et al., 2012; Kim et al., 2009), natural resource management (Johansen et al., 2011; Willhauck, 2000; Whiteside et al., 2011), urban planning (Ardila et al., 2011) and change detection (Jensen, 2005, Lizarazo, 2011).

2.3. Modeling of Soil functions loss (biomass production) by soil sealing

Soil sealing has been cited for its negative impacts on natural resources, economic health, and community character (Herold et al., 2001, Wilson et al., 2003). Urban sprawl was earlier defined by Ewing (1997), where he defined it as a form of low density spatial development, single and segregation land uses, always characterized by scattered and discontinuous leapfrog expansion. Due to its complexity, still there is ongoing discussion on urban sprawl definition and there is no truthful and commonly accepted definition and measures (Sutton, 2003; Galster et al., 2001; Wolman et al., 2005). Several studies showed that urban sprawl has significant negative impacts on natural and semi-natural ecosystems such as social isolation and environmental degradation (e.g. Breuste, 1996; Burchell et al., 2002; Squires, 2002). Also it was plainly demonstrated that the urban sprawl affects the respective site in terms of, say, biodiversity (Löfvenhaft et al., 2002), habitat suitability (Hirzel et al., 2002), water balance (Interlandi & Crockett, 2003), microclimate (Pauleit et al., 2005), or photosynthesis (Imhoff et al., 2000; Haase & Nuissl, 2007). According to Burghardt et al., 2004, there are hardly any internationally recognized definitions of soil sealing. The European Union (EU) revealed that "soil sealing refers to changing the nature of the soil such that it behaves as an impermeable medium and describes the covering or sealing of the soil surface by impervious materials by, for example, concrete, metal, glass, tarmac and plastic" (EEA glossary, 2006). Monitoring soil sealing is critical to ecological

& sustainable development goals. It provides basic indicators of the urban ecology because of its negative effect on the soil water balance, microclimate, flora and fauna (destruction of habitats), noise and the urban heating (Giridharan et al., 2004). Developments in soil sealing are largely determined by spatial planning strategies, where unfortunately the effects of irreplaceable soil losses are often not sufficiently taken into account (Sulzer et al., 2006). It was demonstrated that, (Meinel & Hernig, 2005; Rodríguez & González, 2007) only with a survey of the temporal and the local development (monitoring) of the total and partly urban soil sealing, one is able to measure and judge the real success of a sustainable coordinated land use policy. This has to be done in different spatial resolutions independency on the type of problem. They showed that the application of geobasic data for determining special data is very useful. Several methods have been proposed to characterize land use and land cover at the sub-pixel level, including Linear Mixture Models (Lu & Weng, 2004; Verhoeye & De Wulf, 2000), Artificial Neural Networks (Paola & Schowengerdt, 1995; Swinnen et al., 2001), Fuzzy Classifiers (Zhang & Foody, 1998), Maximum Likelihood Classifiers (Häme et al., 2001), Hierarchical Linear Unmixing (Newland, 1999), Support Vector Machines (Brown et al., 1999) and soil indexes and classifications of sealed soils (Blume, 1989; Bohl & Roth, 1993). Using IKONOS images, Lackner and Conway (2008) were able to automatically delineate and classify land-use polygons in Ontario, Canada, within a diverse urban setting. They obtained high overall accuracies for six- and ten-class maps, with 90% and 86% accuracy respectively. By using landsat images, Rodríguez and González (2007) revealed that of all the band combinations, the 4-5-1 is the one that best distinguishes the urban areas, though any combination including channels 1 and 5 shows this distinction. Kong et al. (2006) also employed an OBIA (object based image analysis) approach to extract urban land-use information from a high-resolution image. In another Chinese urban dynamic monitoring study in Beijing, An et al. (2007) found the overall accuracy and the Kappa Index of Agreement (KIA) to be significantly higher when using OBIA methods compared with traditional approaches. In addition, Im et al. (2008) compared three different change detection techniques, based on object/neighborhood correlation, image analysis and image segmentation, with two different per-pixel approaches, and found that object based change classifications were superior (KIA up to 90%) compared to the other change detection results

(KIA 80 to 85%). Zhou and Troy (2008) presented an object-oriented approach for analyzing and characterizing the urban landscape structure at the parcel level, using high-resolution digital aerial imagery and LIDAR data for the Baltimore area. They incorporated a three-level hierarchy in which objects were classified differently at each level. The overall accuracy of the classification was 92.3%, and the overall Kappa statistic was 0.89. Automated object based classification of the aerial photography proved to be an accurate method to map sealed and green areas at garden level scale. The overall accuracy is affected by the level of thematic detail. The accuracy average of 84% increased to 92% when a simply binary map of sealed-unsealed surfaces was produced. The use of elevation information (i.e. LIDAR data) is necessary to discriminate low from high vegetation (Kampouraki & Gitas, 2009). Alternatively, the urban growth map is a powerful visual and quantitative assessment of the kinds of urban growth that have occurred across a landscape. Urban growth further can be characterized using a temporal sequence of urban growth maps to illustrate urban growth dynamics. Beyond analysis, the ability of remote sensing-based information to show changes to a community's landscape, at different geographic scales and over time, is a new and unique resource for local land use decision makers as they plan the future of their communities.

Development associated with urbanization not only decreases the amount of forest area (Macie & Moll, 1989), farmland, woodlots, and open space but also breaks up what is left into small chunks that disrupt ecosystems and fragment habitats (Maine State Planning Office, 1997; Lassila, 1999). Remote sensing data in the form of historical time series is an important data source for the parameterization and calibration of urban growth models and an essential condition for the prediction of future development and scenario modeling (Herold et al., 2001). The information about dynamic processes occurring in the pilot area can be extrapolated to the surroundings of other cities and especially to municipalities which are experiencing similar pressures (Rodríguez & González, 2007).

2.3.1. Land suitability analysis for wheat production

The term “Land suitability assessment” refers to the investigation of the appropriateness of a certain part of land to a specific type of land use. This assessment involves many factors that directly or indirectly control the ability of this part of land to host the land use under investigation. Performing land suitability evaluation and generating maps of land suitability for different land use types will facilitate to reach sustainable agriculture (Vargahan et al., 2011). An ecosystem needs an estimation of quantity and quality of its resources and the suitability of these resources for a certain range of land uses in order to assure its future sustainability for productivity and biodiversity (kilic et al., 2005). In general, land suitability analysis can answer the questions “which” and “where”; which land use is to apply under certain conditions and where is the best site to apply this land use. Enormous number of studies has been done to assess the land suitability for different land uses such as different agriculture crops (Van lanen et al., 1992, Jalalian et al., 2008, Zhang et al., 2004, Rabia, 2012a), comparing irrigation systems (Landi et al., 2008, Rabia et al., 2013a), trees plantation (Menjiver et al., 2003), landscape planning and evaluation (Miller et al., 1998) and environmental impact assessment (Moreno & Seigel, 1988).

Land suitability assessment methods can be divided into relative limitation scale approach (Simple limitation; limitation regarding number and intensity) and parametric approach (Storie; square root) (Sys et al., 1991). Many researchers have conducted comparison studies between the different land suitability assessment methods (Hopkins, 1977; Anderson, 1987; Steiner, 1983 and 1987, Rabia & Terribile, 2013a). Although the outcome of the different land suitability methods usually correlated to each other (Ashraf, 2010), the square root parametric method commonly gives higher results than the storie method. A study was carried out (Vargahan et al., 2011) to compare four land suitability methods (Simple limitation, limitation regarding number and intensity, Storie and Square root) and revealed that, square root parametric method is mainly better and more commonly used method in qualitative evaluation. However, it was clear from results that the predicted values were always lower than the observed, which gives the impression that both parametric methods (Storie and Square root) normally underestimates the potentiality of investigated land (Vargahan et al., 2011). The study also recommended that utilizing the outcome of this method in quantitative evaluation gives more realistic results.

Wheat is one of the fundamental food crops and is an essential component in food industry. It has been used in several studies as a reference crop for land productivity evaluation (Ashraf et al., 2010; Dumanski & Onofrei, 1989; Jafarzadeh et al., 2008). Of the most important factors that affect wheat production are $CaCO_3$, pH, organic matter content, topology, texture, drainage, soil depth, EC and altitude (Ashraf, 2010; Ashraf, et al., 2010; Mokarram et al., 2010; Mustafa et al., 2011; Vargahan et al., 2011). The analytical hierarchy process (AHP), which has been proposed by Saaty (1977), has been used through a pairwise comparison technique to assign individual parameter's weights for each factor. Numerous studies have documented the (AHP) methodology (Mendoza, 1997; Mendoza & Sprouse, 1989; Saaty, 1980 and 1995; Kangas, 1992 and 1993; Peterson et al., 1994; Reynolds & Holsten, 1994; Pukkala & Kangas, 1996) and it is not suitable to be discussed in this study. Additionally, a number of studies on applications of (AHP) in suitability evaluation have been done (Banai-Kashani, 1989; Eastman et al., 1992 and 1993; Mustafa et al., 2011; Xiang & Whitley, 1994). AHP depends on Pairwise Comparison Matrices to assign weights for every factor controlling the suitability analysis.

2.3.2. Biomass production loss

The nation destroys its soils, destroys itself (Franklin D. Roosevelt, 1937). When soil is sealed with impermeable surfaces it can no longer be used for biomass, food and fiber production and therefore its capacity to support ecosystems, habitats, biodiversity and crops is affected. Burghardt (2006) and Rabia (2012b) demonstrated that sealed areas are still increasing, and it is often the most fertile soils which are sealed. Soil presents a large number of functions that are essential for human life. In addition to providing biomass, food and raw materials, soil performs also various services such as being a habitat host and a gene pool. The soil also has the functions of processing, filtering and storage in addition to cultural and social functions. Therefore, the soil plays a key role in regulating natural and socio-economic processes that are necessary for human survival, as the water cycle and climate system (Jones et al., 2012). European Commission (EC, 2006) identified eight categories of soil threats, which are soil sealing, biodiversity loss, erosion, floods and landslides, salinization, contamination, compaction, and loss of organic material. Deteriorated soil quality because of soil sealing can be related with:

loss of organic matter, which reduces particle aggregation, water holding capacity, water infiltration, and increase compaction (Baumgartl, 1998);

water and wind erosion, increasing the atmospherical dust in dry climatic conditions (Pilgrim & Schroeder, 1997);

increasing of soil hydromorphic condition related with poor drainage problems (Wilcke et al., 1999); and

acidification and other soil chemical modification (Zhu & Carreire, 1999).

So, if we assumed that the fertile soils would produce biomass two or three times "sometimes more" the unfertile soils, in this way all this biomass production will be lost by sealing those soils. Hu et al., 2009, show that the photosynthetic activity of vegetation decreased in the urban rural fringe largely, reflecting the dramatic urban expansion over the period. On different aspect, the phenological events of flowering permitted scientists to study net primary productivity (Badeck et al., 2004; Schwartz et al., 2002). Phenology shifts towards earlier springtime flowering in urbanized areas compared to surrounding rural areas (Roetzer et al., 2000; Wilby & perry, 2006). Earlier springs, longer frost-free seasons (Mitchell & Hulme, 2002; Wilby, 2001), and reduced snowfall have affected the dates of emergence, first flowering and health of leafing or flowering plants in many parts of the world (e.g., Sparks & Smithers, 2002). Cape (2003) also discusses the potential impacts of volatile organic compounds (VOCs) on agriculture—specifically on plants grown for their flowers. The economic costs of increased allergy problems should also be considered. Many of the potential consequences of phenological changes based on studies of global climate changes. Their relevance here rests on the assumption that urbanization and global climate change are similar (Beckroege 1984;Landsberg 1981; Ziska et al., 2003) in ways of affecting plant phenology through increasing temperature accompanied by elevated CO_2 (Neil & Wu, 2006). Changes in flowering phenology across an urban landscape have the potential to affect plant population dynamics. Early and late flowering have been correlated with decreased seed set (Rathcke & Lacey, 1985; Santandreu & Lloret, 1999). Urbanization effects on flowering phenology may become important at the community level, effects on other plant species, pollinators, herbivores, secondary consumers and pathogens due to changes in flowering phenology must be considered. Urbanization effects on flowering phenology may also result in unpredictable changes in ecosystem structure because species previously able to coexist due to niche differentiation may interact differently (Fitter & Fitter, 2002).

Because the soil is the basis of various human activities and provides a number of valuable ecological services, it has a significant economic value. Various attempts have been made by economists to estimate the environmental and agricultural land value. The costs of soil sealing can be substantial, both in terms of costs directly to users (agriculture), and in terms of indirect costs caused such loss of ecological functions of soil. However, not all of these functions are of direct economic or social value, and not all are sufficiently investigated. Also, many soil functions may be interdependent. So far, there is no firm methodology for the quantification of soil functions loss. Therefore, there is a great need that the scientific community gives more attention to develop different methods for the evaluation of the different soil functions and quantification of the losses due to the diverse soil destroying causative factors such as soil sealing.

MATERIALS AND METHODS

3. MATERIALS AND METHODS

3.1. Description of the study area

The study was carried out in Telesina Valley (Valle Telesina), located in Benevento in the Campania region of central Italy (Fig. 1). The area is characterized by a diversity of land cover and land use types, including urban settlements, forests, pasture and different types of agriculture. Despite the land cover and land use change that has occurred during the last century, the study has maintained a rich diversity in land use and land cover types. Telesina Valley is a traditional area with vineyards producing high quality wines including three with DOC designation (Guardiolo, Solopaca and Sannio) (Bonfante et al., 2005).

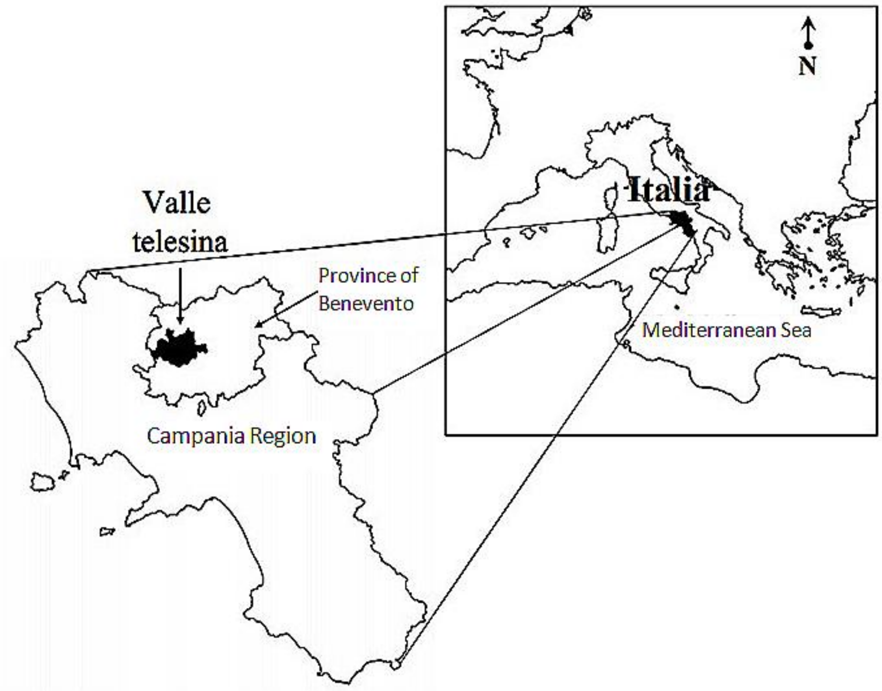

Fig. 1. The study area of Telesina Valley in Campania Region, southern Italy.

The landscape has a complex geomorphology and is characterized by an E-W elongated graben into which the river Calore flows (Fig. 2) (Magliulo et al., 2007). The area includes five different pedo-environments: i) mountains (limestone relieves); ii) hills; iii) pediment plains (slope fan of limestone reliefs); iv) ancient fluvial terraces; and v) alluvial plains (Fig. 3) (Scaglione et al., 2008).

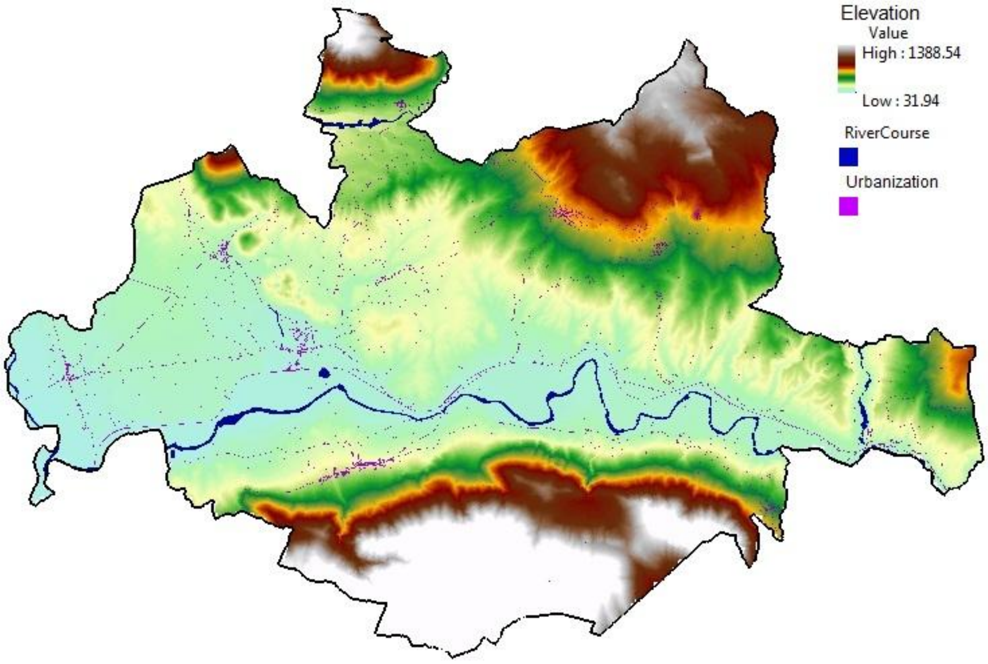

Fig. 2. A sketch of the study area of Telesina Valley representing the digital elevation model (elevation in meters above sea level), river network and urban infrastructure. Source: the study area profile created in arcScene 10 (ESRI, 2012).

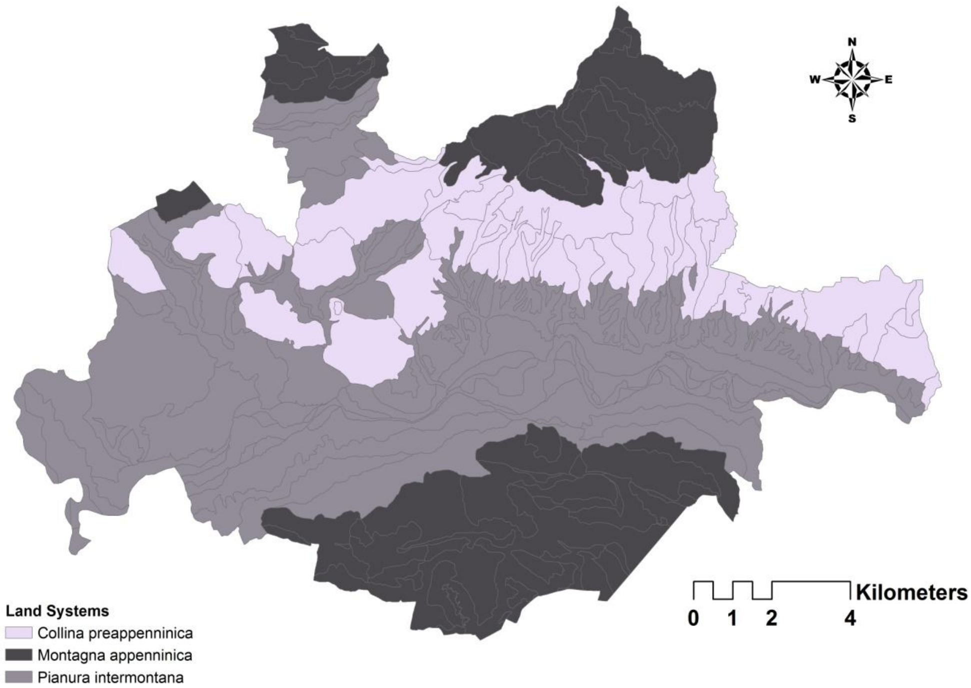

Fig. 3. Land systems of the study area (Telesina Valley).

3.2. Soil sampling and analysis

As part of the study, a review was carried out to integrate previous study of soil maps of Telesina Valley in scale 1:25000 (Terribile et al., 1996) in collaboration with the CNR-ISAFoM of Ercolano in Naples. All the soil profiles of the study area were described as reported in the "Guide to the Soil Survey - Project UOT" (ISSDS, 1997). All profiles were sampled for routine analyses. The dissolved samples were air-dried and sieved (r <2 mm). The main physicochemical and chemical analyses were performed according to the methods of MiRAAF (1992), except granulometric analysis of andic soils properties (estimated in advance with the field test) that was performed on wet sample with the method of the pipette at pH 9.5 (Mizota & van Reeuwijk, 1989); the pH was measured in a soil suspension: water 1:2.5; the organic substance was determined by oxidation with potassium dichromate; the cation exchange capacity (CEC) was determined by $BaCl_2$. Some extra-routine analyses were also carried out on the soil samples; in particular, extractions of iron, aluminum and silicon in oxalate (Feo, Alo, Sio) and in dithionite (Fed, Ald, Sid) were carried out according to the method of Schwertmann (1964) and MiPAF (2000), respectively. These analyzes were performed, as well as for purposes of classification of the different pedo-types. The iron and aluminum extracted in oxalate are used as a criterion in the classification of soils (McKeague & Day, 1966). Scarcity of organic matter, however, prevailed in the area of interest. The soils were classified according to Soil Taxonomy of the USDA, (Soil Survey Staff, 1998). Sixty complete profiles were accomplished to cover the study area and to obtain the edaphological data. The profiles were distributed randomly in the study area (Carter & Gregorich, 2008). The exact location of each sampling point was detected directly in the field with the aid of a GPS; the coordinates of the points were subsequently entered into the GIS database in order to pinpoint the position of sampling on a point shapfile (Fig. 4).

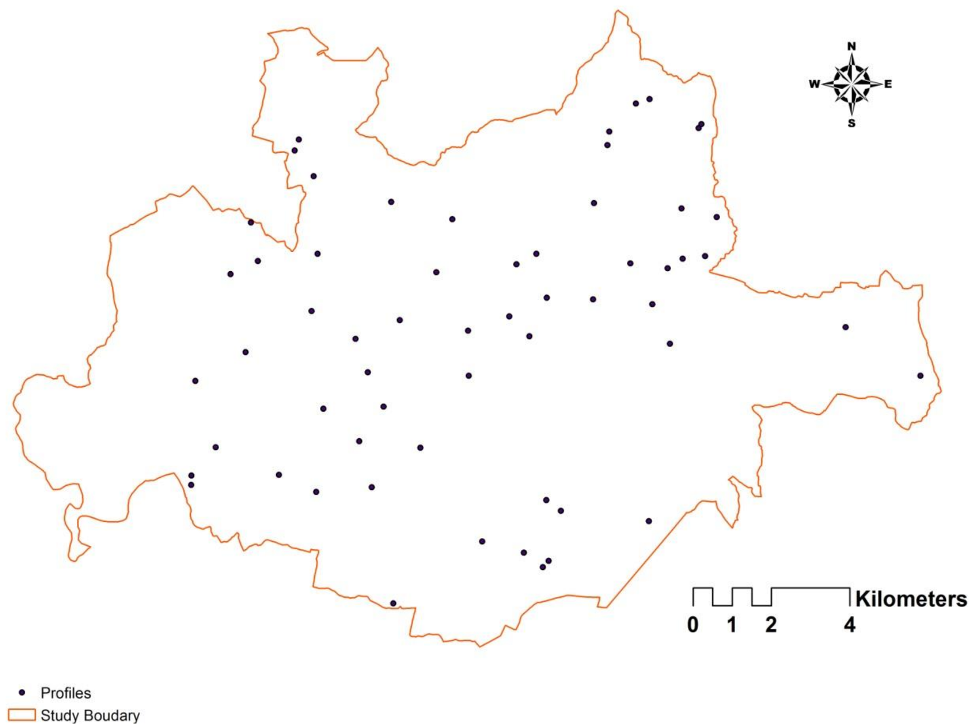

Fig. 4. Representative soil profiles distribution in the study area

A total of 207 land units were recognized in the study area (Appendix I). Figs 5 and 6 show the soil map and legend of the study area which reveal that the area is characterized by fourteen soil groups (i.e. Hapludands, Udivitrands, Eutrudepts, Haplustepts, Calciustepts, Hapludolls, Ustorthents, Melanudands, Ustifluvents, Ustivitrands, Vitraquands, Calciustolls, Hapludolls and Haplustalfs) (Terribile et al., 1996). Climatic conditions are homogenous over the study area. The digital elevation model (DEM) was obtained from the digitalization of topographic maps, produced by the Istituto Geografico Militare Italiano at 1:25,000 scale, producing a Digital Elevation Model (DEM) having a 20×20 m resolution (IGM, 1954).

Fig. 5. Map of soil classes in the study area following the USDA soil taxonomy (Soil Survey Staff, 1998).

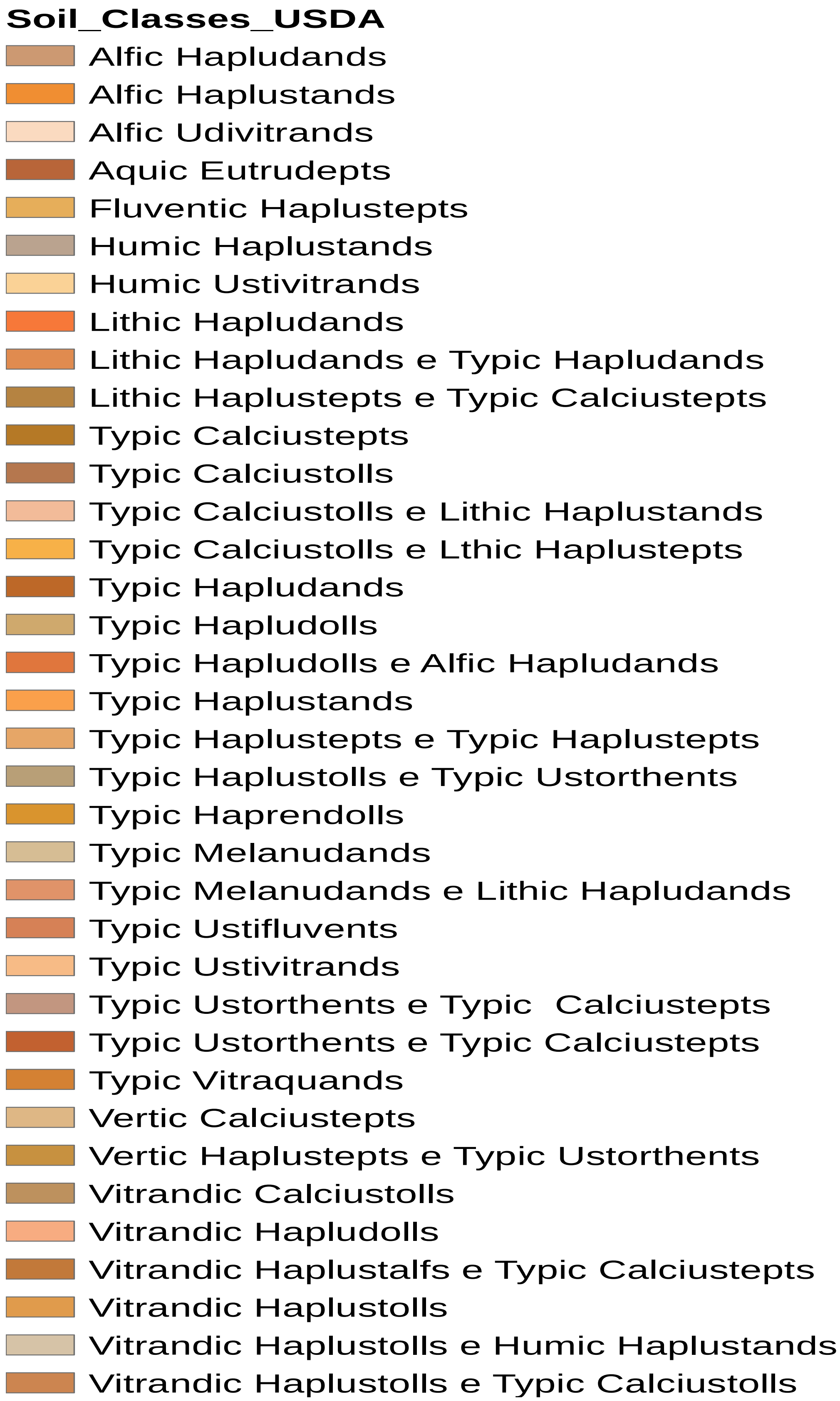

Fig. 6. Soil classes in the study area following the USDA soil taxonomy (Soil Survey Staff, 1998).

3.3. Main work frame

As proposed in the introduction section, the work was divided into three major phases. In the first phase, long term detection for land use and land cover change was done for the period from 1954 to 2009 in order to understand the history, rates and trends of the soil sealing in the study area (Fig. 7). In the second phase, an automatic LULC classification of the 1954 aerial photographs using GEOBIA technique was conducted. The logical reason behind this phase is the assumption that improving the quality of the classification for old land use and land cover maps will improve the final results of the change detection analysis. Consequently, the quantification of the lost biomass production by soil sealing will be improved. Finally, in the third phase, a modeling of soil function loss by soil sealing was made to quantify the losses in one of the soil functions i.e., biomass production. In the following paragraphs, a detailed description of the methodology is given for each of the three phases.

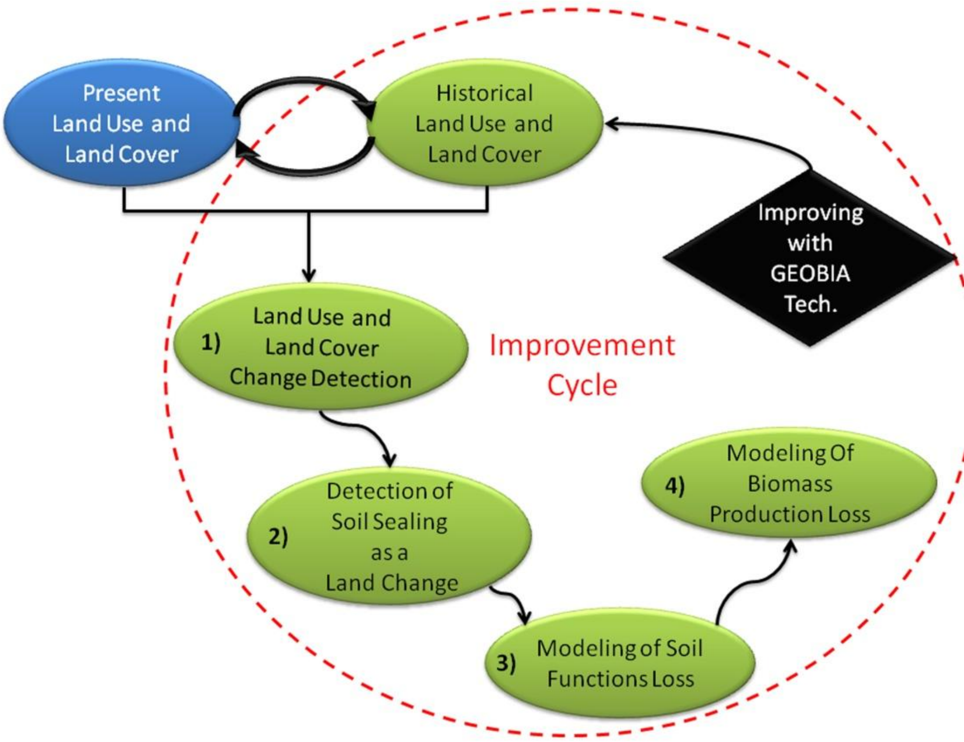

Fig. 7. Main work frame of the study

3.3.1. Long term detection for land use and land cover change (1954 – 2009)

3.3.1.1. Data Sources

Maps of land use and land cover (LULC) were obtained for Telesina Valley, where four LULC maps from the years 1954, 1990, 2000 and 2009 were used in this study (Figs. 8, 9, 10 and 11). The first map is a detailed Land cover map (nominal scale of 1:100,000) provided by the cartographic office of the "Touring Club Italiano" and dating back to 1954, was acquired, georeferenced, digitized and clipped as a 1954 LULC map of the study area (CNR & Directorate General of Cadastre, 1956-1960). The resolution of the clipped map is dependent on the accuracy of the original Touring Club map, which is reflected in the relatively coarse legend with only 9 classes and the resulting large areas of individual polygons. The LULC maps for 1990 and 2000 were generated from the Corine's LULC classification for Europe (EEA, 2000). Each map has 24 classes and therefore contains a more complex and detailed legend. The 2009 map is the most recent and detailed map, and is based on the LULC classification adapted from corine with 25 classes (SeSIRCA, 2009).

3.3.1.2. Change Detection Analysis

As can be observed in Figs. 8, 9, 10 and 11, the four LULC maps, all differ in their legend definitions and the number of classes. Land use changes were defined and classified as the changes in a land use class that occurred in a given area and time. These classes identify the typology of changes by assigning a land use change code to each intersection created by the overlay of successive land use maps, allowing a thematic representation of the spatial distribution of changes (Abd El-Kawy et al., 2011). The method is based on the previous generalization of land use categories and offers a quantitative and qualitative measure of conversion that occurred in the study area, allowing the spatial distribution of land use changes to be reported on a unique map. Land use change has been evaluated for three periods: from 1954 to 1990, 1990 to 2000 and from 2000 to 2009.

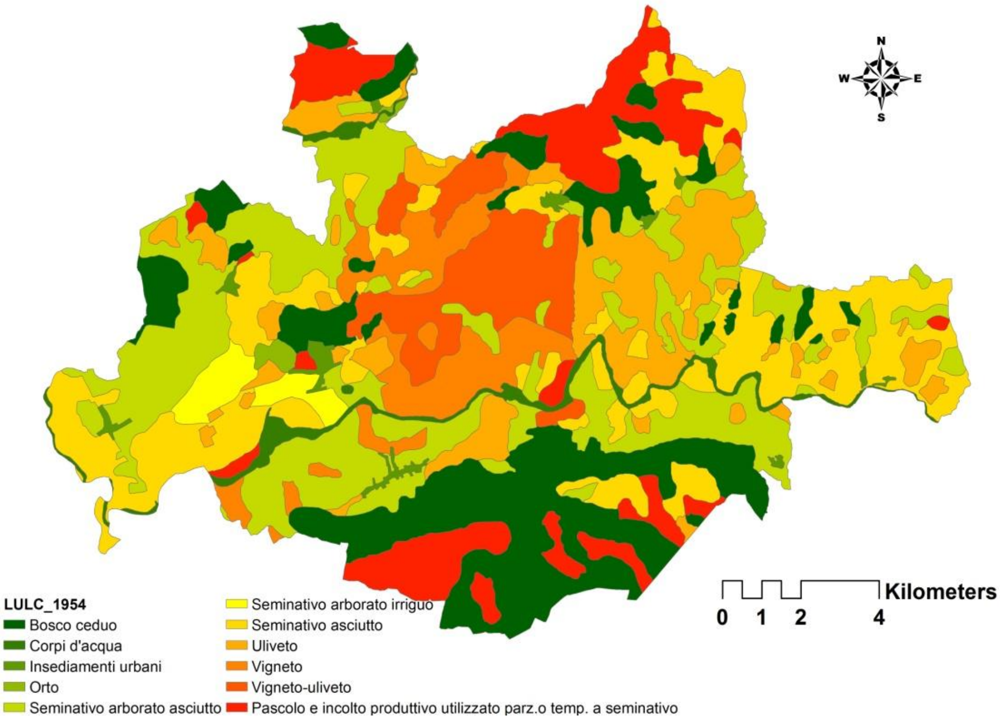

Fig. 8. Land use and land cover map of the study area for the year 1954 (CNR & Directorate General of Cadastre, 1956-1960).

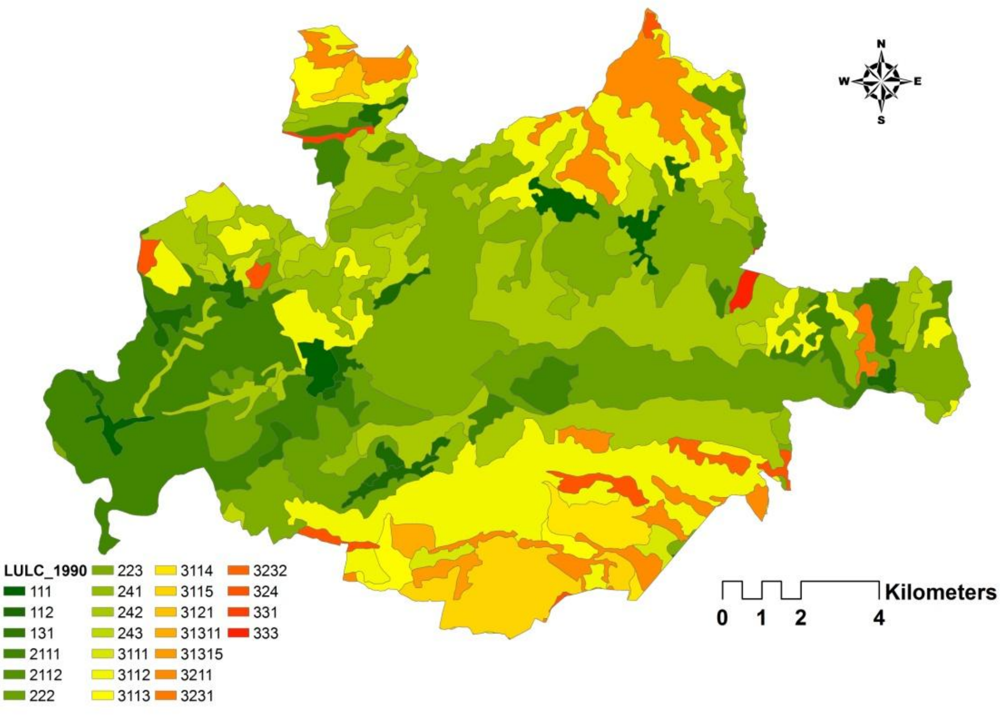

Fig. 9. Land use and land cover map of the study area for the year 1990 (EEA, 2000).

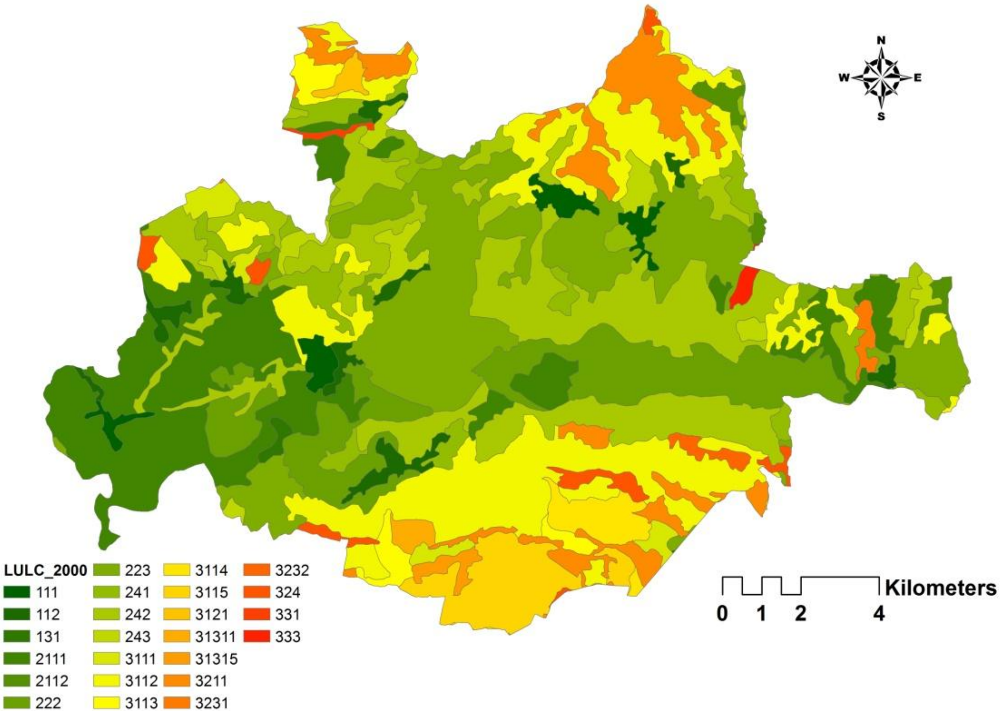

Fig. 10. Land use and land cover map of the study area for the year 2000 (EEA, 2000).

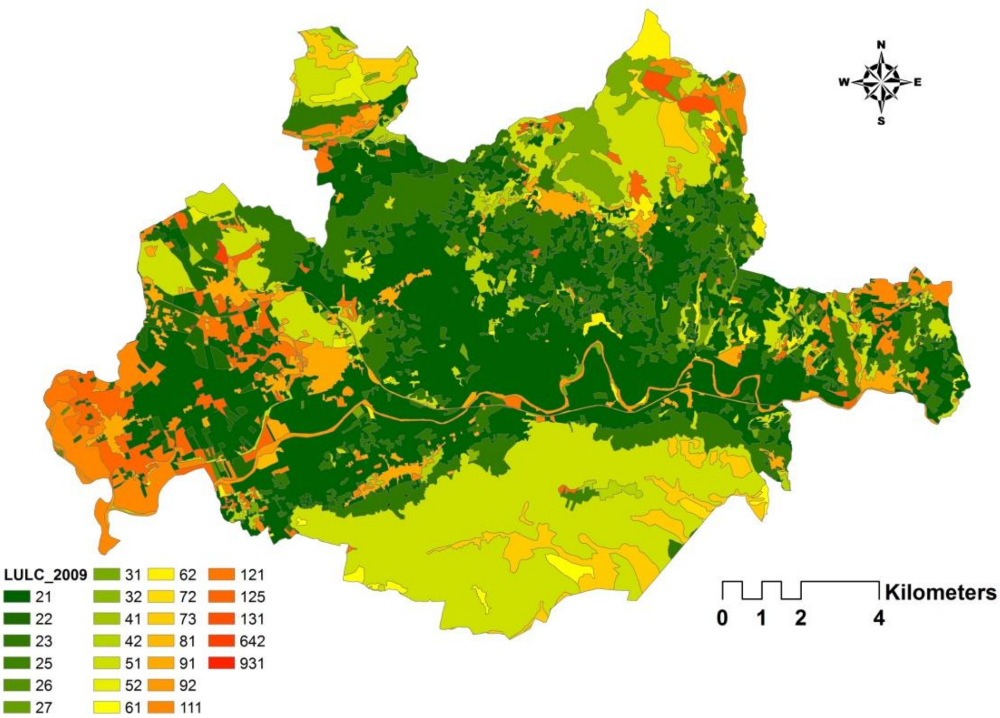

Fig. 11. Land use and land cover map of the study area for the year 2009 (SeSIRCA, 2009).

To detect the land change in the study area during the period from 1954 to 2009, possible types of changes that may occur in the study area were determined based on the LULC classes from the four maps. Fifteen land use change categories were identified (Table 1). Codes were assigned to each new polygon created by the intersection (Benini et al., 2010), using a reference matrix that expresses the typology of land use change that occurred on the basis of previous and successive land use category comparison (Tables 2, 3 and 4). The resulting map represents the land use change that occurred in every patch during the period taken into account, and spatially identifies what has occurred in the area. Each pair of maps was overlaid to generate a set of land change polygons with attribute information from both set of classifications in the pair. This information was used together with the change matrix to assign each polygon with a change code. Finally, land change maps were created for each time period.

Table1. Possible change classes and change codes in the study area (Benini et al., 2010).

Change codes	Land use change class	Description
Pu	Urban persistence	Areas where settlements persist during time
Ui	Urban intensification	Areas converted to urban
E	Exceptionality	Unusual conversion
P	Persistence	Areas with no change in land use
Ai	Agrarian intensification	Areas where agricultural activities substitute previous land use
Ic	Intensive conversion	Agricultural areas where an intensive conversion has occurred
Ec	Extensive conversion	Agricultural areas where an extensive conversion has occurred
R	Afforestation	Areas where other land uses are converted into woodland
D	Deforestation	Wooded areas converted to other land uses
Nd	Natural dynamic	Areas where natural changes occurred
A	Abandonment	Urban and agricultural areas converted to shrubs and rugged areas
St	Stabilization	Rugged areas that are converted to shrubs or grassland
De	Degradation	Shrub areas converted to rugged
Pa	Agriculture Persistence	Areas where agriculture persist during time include intensification and extensification
Pf	Forest Persistence	Areas where forests persist during time

Table 2. Change matrix for LULC changes from 1954 to 1990.

Land Use	New Class	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23	B24
Old Class	Num	111	112	131	2111	2112	222	223	241	242	243	3111	3112	3113	3114	3115	3121	31311	31315	3211	3231	3232	324	331	333
A1	1	Ui	Ui	Ui	D	D	D	D	D	D	D	Pf	Pf	Pf	Pf	Pf	Pf	Pf	Pf	D	D	D	Pf	D	D
A2	2	Ui	Ui	Ui	Ai	Ai	Ai	Ai	Ai	Ai	Ai	E	E	E	E	E	E	E	E	E	E	E	E	Nd	E
A3	3	Pu	Pu	Pu	E	E	E	E	E	E	E	R	R	R	R	R	R	R	R	A	A	A	R	E	A
A4	4	Ui	Ui	Ui	Ic	Ic	Ic	Ic	Ic	Ic	Ic	R	R	R	R	R	R	R	R	A	A	A	R	E	A
A5	5	Ui	Ui	Ui	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	R	R	R	R	R	R	P	P	P	R	E	P
A6	6	Ui	Ui	Ui	Ic	Pa	Pa	Pa	Pa	Pa	Pa	R	R	R	R	R	R	R	R	A	A	A	R	E	A
A7	7	Ui	Ui	Ui	Pa	Ec	Ec	Ec	Ec	Ec	Ec	R	R	R	R	R	R	R	R	A	A	A	R	E	A
A8	8	Ui	Ui	Ui	Ic	Pa	Pa	Pa	Pa	Pa	Pa	R	R	R	R	R	R	R	R	A	A	A	R	E	A
A9	9	Ui	Ui	Ui	Ic	Pa	Pa	Pa	Pa	Pa	Pa	R	R	R	R	R	R	R	R	A	A	A	R	E	A

Table 3: Change matrix for LULC changes from 1990 to 2000.

Land Use	New Class	B1	B2	B3	B4	B5	B6	B7	B8	B9	B10	B11	B12	B13	B14	B15	B16	B17	B18	B19	B20	B21	B22	B23	B24
Old Class	Num	111	112	131	2111	2112	222	223	241	242	243	3111	3112	3113	3114	3115	3121	31311	31315	3211	3231	3232	324	331	333
B1	111	Pu	Pu	E	E	E	E	E	E	E	E	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B2	112	Pu	Pu	E	E	E	E	E	E	E	E	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B3	131	Ui	Ui	Pu	E	E	E	E	E	E	E	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B4	2111	Ui	Ui	Ui	Pa	Ec	Ec	Ec	Ec	Ec	Ec	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B5	2112	Ui	Ui	Ui	Ic	Pa	Ic	Ic	Pa	Pa	Pa	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B6	222	Ui	Ui	Ui	Ic	Ec	Pa	Pa	Ec	Ec	Ec	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B7	223	Ui	Ui	Ui	Ic	Ec	Pa	Pa	Ec	Ec	Ec	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B8	241	Ui	Ui	Ui	Ic	Pa	Ic	Ic	Pa	Pa	Pa	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B9	242	Ui	Ui	Ui	Ic	Pa	Ic	Ic	Pa	Pa	Pa	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B10	243	Ui	Ui	Ui	Ic	Pa	Ic	Ic	Pa	Pa	Pa	R	R	R	R	R	R	R	R	A	A	A	A	E	A
B11	3111	Ui	Ui	Ui	D	D	D	D	D	D	D	Pf	Nd	Nd	Nd	Nd	Nd	Nd	Nd	D	D	D	Pf	E	D
B12	3112	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Pf	Nd	Nd	Nd	Nd	Nd	Nd	D	D	D	Pf	E	D
B13	3113	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Nd	Pf	Nd	Nd	Nd	Nd	Nd	D	D	D	Pf	E	D
B14	3114	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Nd	Nd	Pf	Nd	Nd	Nd	Nd	D	D	D	Pf	E	D
B15	3115	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Nd	Nd	Nd	Pf	Nd	Nd	Nd	D	D	D	Pf	E	D
B16	3121	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Nd	Nd	Nd	Nd	Pf	Nd	Nd	D	D	D	Pf	E	D
B17	31311	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Nd	Nd	Nd	Nd	Nd	Pf	Nd	D	D	D	Pf	E	D
B18	31315	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Nd	Nd	Nd	Nd	Nd	Nd	Pf	D	D	D	Pf	E	D
B19	3211	Ui	Ui	Ui	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	R	R	R	R	R	R	P	Nd	Nd	R	E	De
B20	3231	Ui	Ui	Ui	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	R	R	R	R	R	R	Nd	P	Nd	R	E	De
B21	3232	Ui	Ui	Ui	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	R	R	R	R	R	R	Nd	Nd	P	R	E	De
B22	324	Ui	Ui	Ui	D	D	D	D	D	D	D	Nd	Nd	Nd	Nd	Nd	Nd	Nd	Nd	D	D	D	Pf	E	D
B23	331	Ui	Ui	Ui	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	R	R	R	R	R	R	St	St	St	R	P	St
B24	333	Ui	Ui	Ui	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	R	R	R	R	R	R	St	St	St	R	E	P

Table 4. Change matrix for LULC changes from 2000 to 2009.

Land Use	New Class	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17	C18	C19	C20	C21	C22	C23	C24	C25
Old Class	Num	21	22	23	25	26	27	31	32	41	42	51	52	61	62	72	73	81	91	92	111	121	125	131	642	931
B1	111	E	E	E	E	E	E	A	A	E	E	R	R	A	A	A	A	A	Pu	E	E	E	E	A	R	E
B2	112	E	E	E	E	E	E	A	A	E	E	R	R	A	A	A	A	A	Pu	E	E	E	E	A	R	E
B3	131	E	E	E	E	E	E	A	A	E	E	R	R	A	A	A	A	A	Pu	E	E	E	E	A	R	E
B4	2111	Pa	Pa	Pa	Ec	Ec	Ec	A	A	Ec	Ec	R	R	A	A	A	A	A	Ui	E	Pa	Pa	Pa	A	R	Pa
B5	2112	Ic	Ic	Ic	Pa	Pa	Pa	A	A	Pa	Pa	R	R	A	A	A	A	A	Ui	E	Pa	Pa	Pa	A	R	Ic
B6	222	Pa	Pa	Pa	Ec	Ec	Ec	A	A	Ec	Ec	R	R	A	A	A	A	A	Ui	E	Pa	Pa	Pa	A	R	Ic
B7	223	Pa	Pa	Pa	Ec	Ec	Ec	A	A	Ec	Ec	R	R	A	A	A	A	A	Ui	E	Pa	Pa	Pa	A	R	Ic
B8	241	Pa	Pa	Pa	Pa	Pa	Pa	A	A	Pa	Pa	R	R	A	A	A	A	A	Ui	E	Pa	Pa	Pa	A	R	Ic
B9	242	Pa	Pa	Pa	Pa	Pa	Pa	A	A	Pa	Pa	R	R	A	A	A	A	A	Ui	E	Pa	Pa	Pa	A	R	Ic
B10	243	Ic	Ic	Ic	Pa	Pa	Pa	A	A	Pa	Pa	R	R	A	A	A	A	A	Ui	E	Pa	Pa	Pa	A	R	Ic
B11	3111	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B12	3112	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B13	3113	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B14	3114	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B15	3115	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B16	3121	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B17	31311	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B18	31315	D	D	D	D	D	D	D	D	D	D	Pf	Pf	D	D	D	D	D	Ui	D	D	D	D	D	R	D
B19	3211	Ai	Ai	Ai	Ai	Ai	Ai	P	P	Ai	Ai	R	R	P	Nd	De	P	Nd	Ui	E	Ai	Ai	Ai	Ai	R	Ai
B20	3231	Ai	Ai	Ai	Ai	Ai	Ai	Nd	Nd	Ai	Ai	R	R	Nd	P	De	De	Nd	Ui	E	Ai	Ai	Ai	Ai	R	Ai
B21	3232	Ai	Ai	Ai	Ai	Ai	Ai	Nd	Nd	Ai	Ai	R	R	Nd	P	De	P	Nd	Ui	E	Ai	Ai	Ai	Ai	R	Ai
B22	324	D	D	D	D	D	D	D	D	D	D	Nd	Nd	D	D	D	D	D	Ui	D	D	D	D	D	D	D
B23	331	Ai	Ai	Ai	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	St	St	Nd	St	Nd	Ui	Nd	Ai	Ai	Ai	Ai	R	Ai
B24	333	Ai	Ai	Ai	Ai	Ai	Ai	Ai	Ai	Ai	Ai	R	R	St	St	De	P	Nd	Ui	E	Ai	Ai	Ai	Ai	R	Ai

In this study, the focus was on three types of land change for which specific land change maps from 1954 to 2009 were created:

- afforestation and deforestation;
- agricultural development; and
- urbanization.

The land change trends were then examined using a line of best fit to estimate potential future land changes in Telesina Valley (Moore & Moffat, 2007).

3.3.2. Automatic land use and land cover classification of 1954 aerial photographs using GEOBIA technique

The understanding of land change based on past maps is inherently limited by their original classification and the granularity of their legends. Older maps often have a less detailed and accurate legends, which results in a map with large polygons that in reality contain a mix of classes. Furthermore, different resolutions and accuracies associated with different maps used to detect land use change further hampers additional model processing, predictions or calculations. Enhancing the quality and accuracy of older maps will thus be beneficial to land change detection, land use and land cover change modeling and future predictions of land change. In this study, GEOBIA technique is applied to old aerial photographs to reclassify the land use and land cover of the study area for the year 1954. The objects detected by GEOBIA are represented in a type of hierarchy or taxonomy that shows the structural relations between the objects (Booch, 1991). GEOBIA is not intended to replace humans but is a support tool to produce better classifications in an incremental approach (Leckie et al., 1998; Castilla & Hay, 2007). Aerial photographs of Telesina Valley were obtained for the year 1954. Using the object-oriented eCognition software, the LULC of the study area was reclassified. Using the eCognition 8.7 software (Trimble, 2012), it was then possible to extract land cover data from the aerial photographs using different features such as the tone, brightness, border contrast, roundness and many other features available in the software. An example of a result produced by the software is shown in Fig. 12. The idea was to compare the original 1954 map with the reclassified LULC map to determine whether the reclassified map will improve land change estimates.

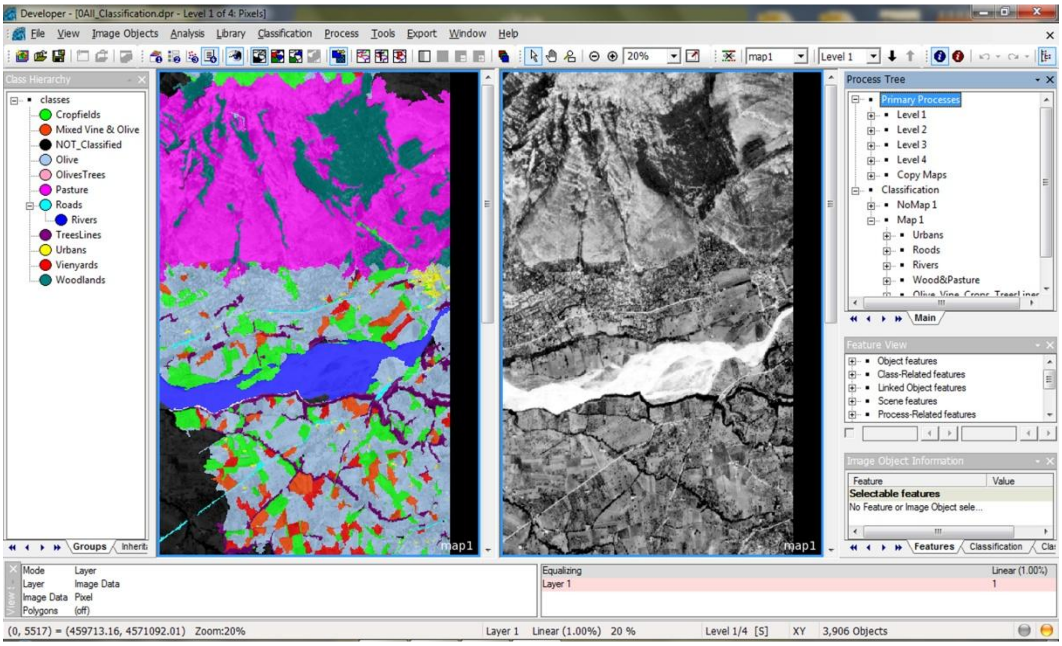

Fig. 12. Screenshot of the GEOBIA classification process using eCognition software (Trimble, 2012).

3.3.2.1. Preprocessing of aerial photographs

Gray scale erial photographs of 1954 that cover the study area were obtained (Fig. 13). The black and white aerial photographs of the study area for the year 1954, which were part of Volo GAI 1954, were produced by the Italian Air Group between 1954 and 1956 under the authority of the Italian Military Geographical Institute (IGM). The format of the original sheets is 24x24 cm or 20x20 cm with an average scale of 1: 33,000 and an average altitude of 4800-5500 m (IGM, 1954). All the aerial photographs were scanned with high resolution (800 pixel per inch) to provide a high quality digital form of the images (Appendix II).

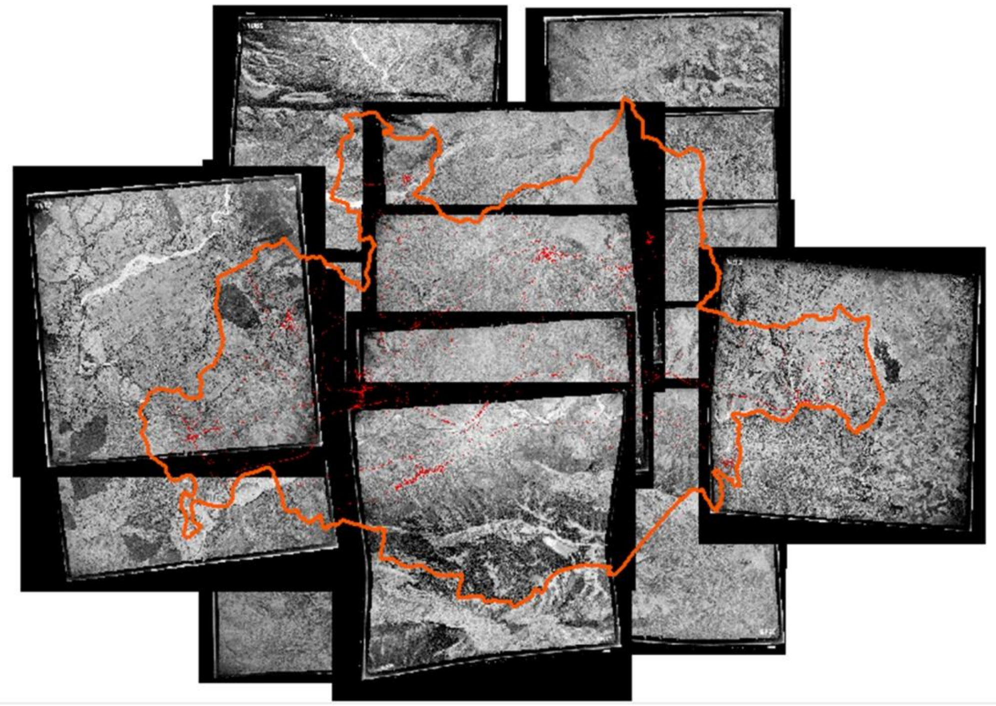

Fig. 13. A number of 17 aerial photographs covering the study area.

The procedure proposed for using the GEOBIA technique for the land use and land cover classification consists of six sequential steps: (1) Aerial photographs orthorectification; (2) Orthophotos homogenization; (3) Enhanced orthophotos cropping and filtering, (4) Object-based approach for images segmentation; (5) Photo interpretation and land cover map building, and (6) Map Accuracy assessment test. All these six steps are described in the following paragraphs and summarized in Fig. 14.

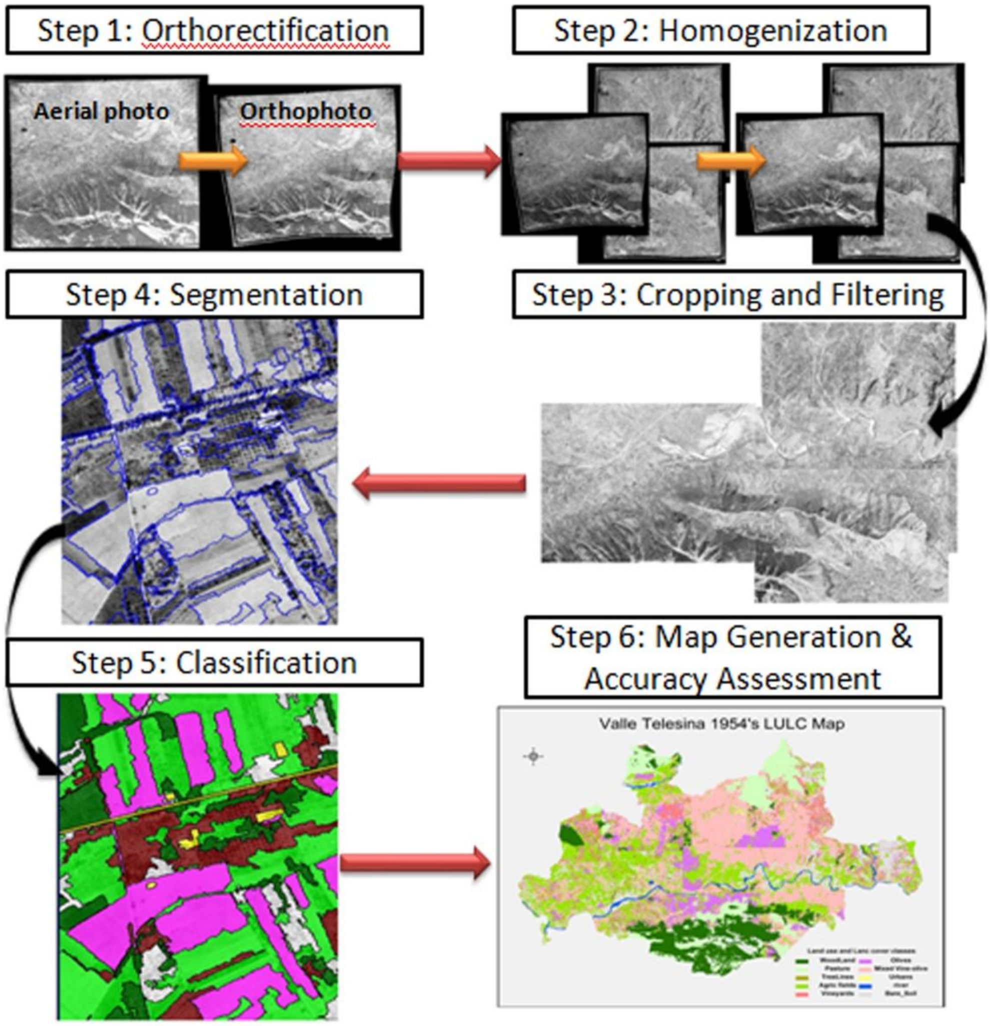

Fig. 14. A summary flow chart of all the six steps of the procedure proposed for using GEOBIA technique for land use and land cover classification.

3.3.2.1.1. Step 1: Aerial photographs orthorectification

In this step, in order to make the 1954 aerial photographs georeferentiated, geometrically correct and uniform in scale, a procedure was applied using the rectify photo module in ArcGIS 10 software using spline function (ESRI, 2011). The orthorectification process of the GAI flight images has been broadly discussed in earlier studies (Pelorosso et al., 2007; Pelorosso, 2008). The orthorectification process is a procedure used to convert raw remote sensing images to georeferenced data. It is based on the acquisition of points that have been selected on the reference layer (i.e. Topographic map of 1954) (IGM, 1954) and recognized on the images to be orthorectified. The selected points are used in the aerial triangulation algorithms and they are called GCP (Ground Control Points). A number of GCPs between 10 and 30 points were selected for each aerial photograph. The selected points varied between Bridges, road crosses, building corners and small isolated trees. All the photographs were assigned to a UTM coordinate system (WGS 1984 UTM, Zone 33North) and WGS 1984 Datum. The root mean square error (RMSE) index of the GCP position has been used to verify the orthorectification process accuracy (Weeks, 2011). For each coordinate axis (X, Y), the RMSE was considered separately. The RMSE index is an evaluation of the deviation between selected and expected position of each GCP and it can be calculated using the Equation (1).

$$\boldsymbol{RMSE} = \sqrt{\frac{\sum_{i=1}^{n} r_i^2}{n}} \qquad (1)$$

Where:

n: is the number of GCP used for the orthorectification process

r: is "residue" the difference between the real value of the coordinate (X or Y) of a point i and the value obtained by aerial triangulation.

At this point all aerial photographs became orthorectified and georeferenced and ready to start next step of the image pre-processing (Fig. 15).

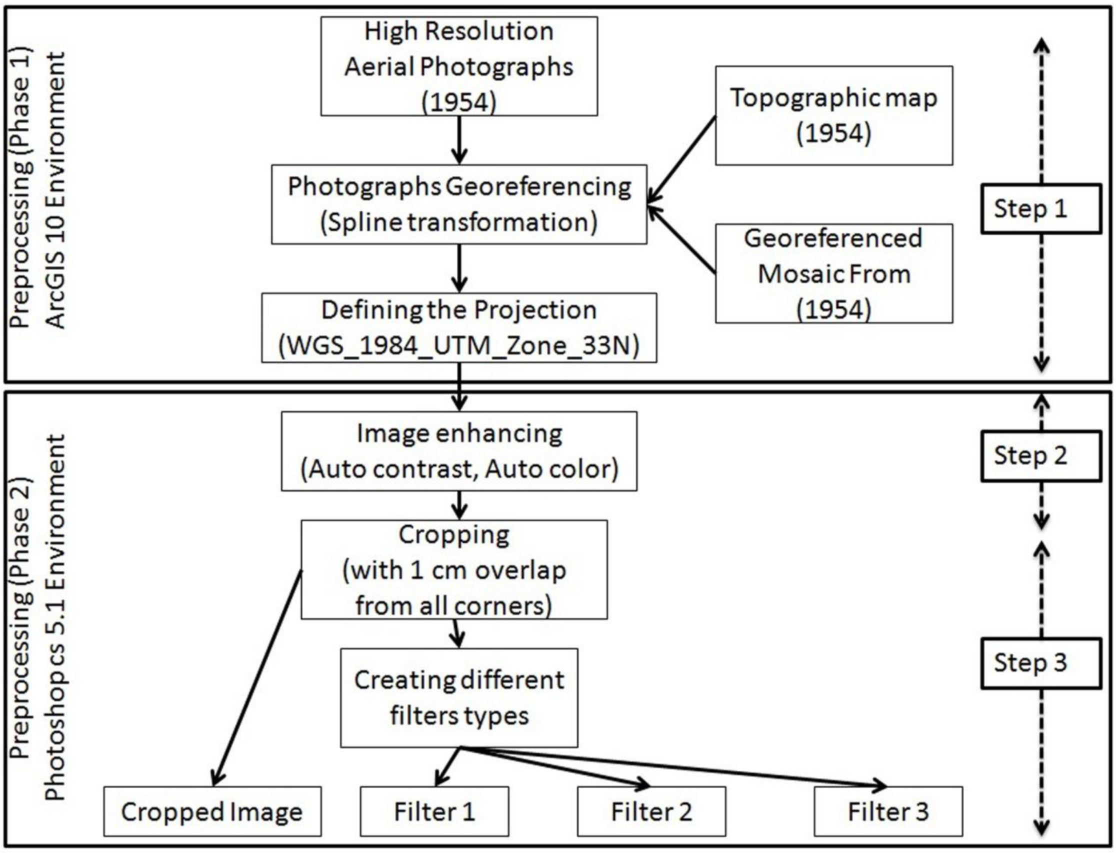

Fig. 15. A summary diagram of steps 1, 2 and 3 of GEOBIA classification process.

3.3.2.1.2. Step 2: Orthophotos homogenization

The evaluation of land cover changes based on remote sensing images without homogenization can lead to unrealistic results (Paolini et al., 2006). The method proposed by Seitz et al. (2010) was adapted to present a procedure for the homogenization of 1954 aerial photographs in order to overcome the brightness and scanning errors (Fig. 15). This method is based on a linear transformation in order to soften differences in contrast and tonality between orthophotos. In order to achieve images homogeneity, all aerial photographs have been set to the auto tone and contrast using geographic imager software (Avenza Systems Inc., 2012). Fig. 16 shows the differences between adjacent two images prior and after the homogenization process. This way all photographs became homogenized and ready for the next step.

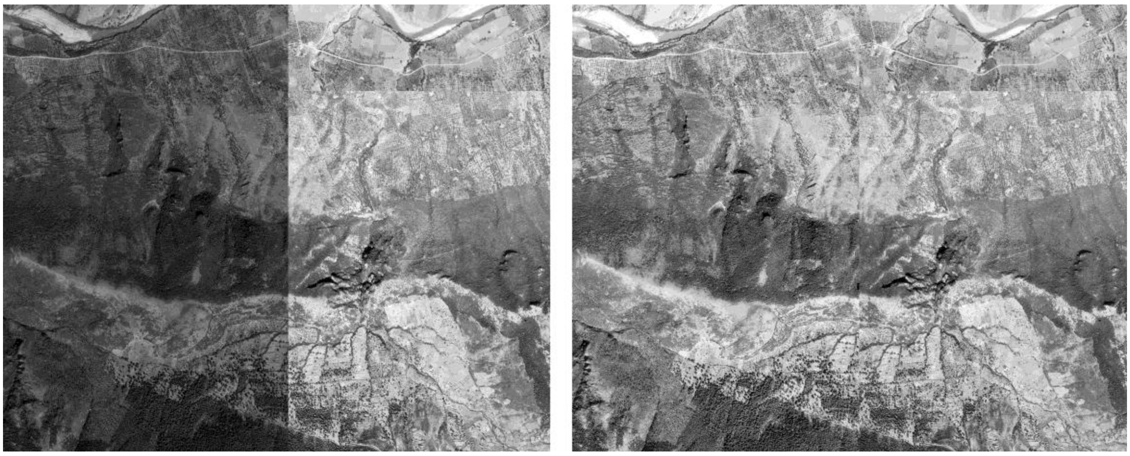

Fig. 16. Homogenization of adjacent orthophotos, left side: original photographs before homogenization; right site: homogenized photographs.

3.3.2.1.3. Step 3: Clipping and filtering of enhanced orthophotos

The aerial photographs are usually obtained in strips creating blocks. In the same strip, two successive photos have an overlapping area of 60%. In addition, there is a 20% overlap between photos from two adjacent strips which means 40% cumulative overlap in both sides of the photo. For this reason, the study area can fall in different orthoimages with wide overlapping zones. Therefore, a cropping process has been conducted over all aerial photographs using geographic imager software (Avenza Systems Inc., 2012) taking into account leaving 1 cm of overlap from each side to be used later in the mosaicing process (Fig. 15). In addition, different filters were developed from the clipped aerial photographs to be used later in the segmentation and classification process. This proposed approach may help in enhancing both the visualization and the classification procedures capabilities. After trying different filters, finally three filters have been found favorable to be used in the segmentation and classification process. These filters are ink-out, water and find-edges which were created using the geographic imager software (Avenza Systems Inc., 2012). Fig. 17 shows an example of an aerial photo with the three corresponding filters which are georeferenced same as the original aerial photo. By this step, the preprocessing stage has ended and each aerial photograph is orthorectified along with three filters and ready for the segmentation and classification process.

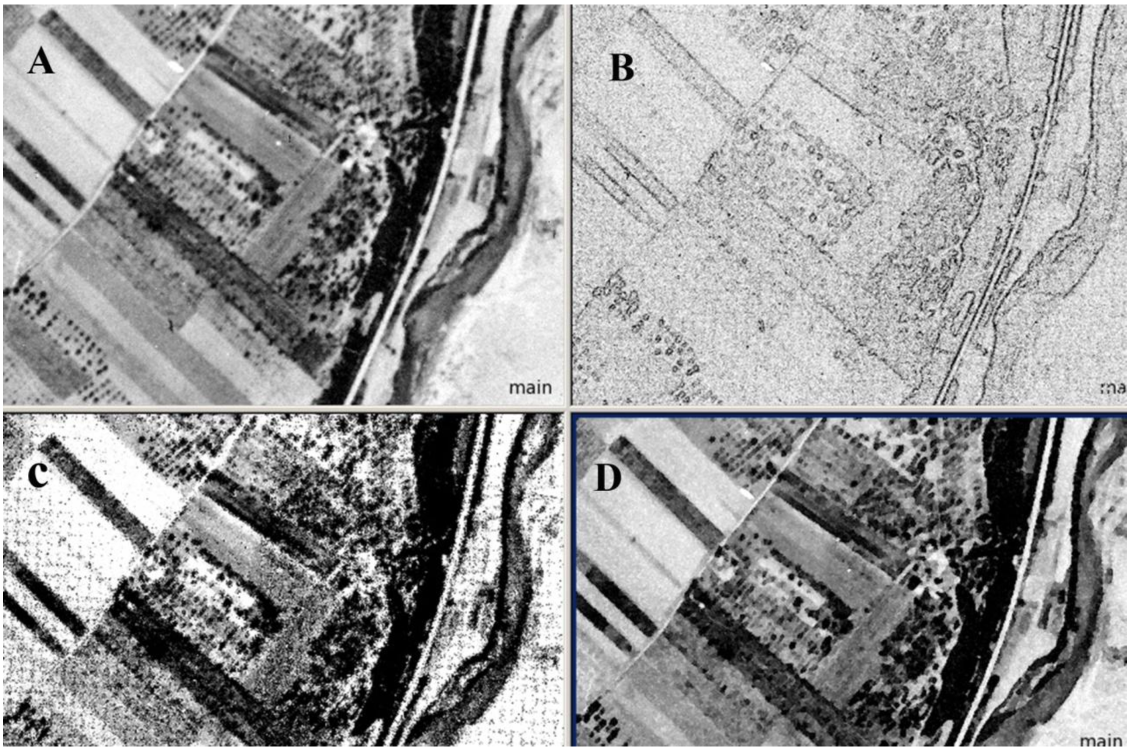

Fig. 17. An aerial photograph (A) with the three corresponding filters, find-edges (B), ink-out (C), and water (D).

3.3.2.1.4. Step 4: Semi-automated Object-based approach for images segmentation

In eCognition software environment, a semi-automated procedure was applied to generate the LULC map of the study area for the year 1954. The procedure is based on the following two steps: first, applying an automated segmentation, and secondly, assigning a class to the extracted polygons by semi-automated photo classification (Fig. 18) (Geri et al., 2008).

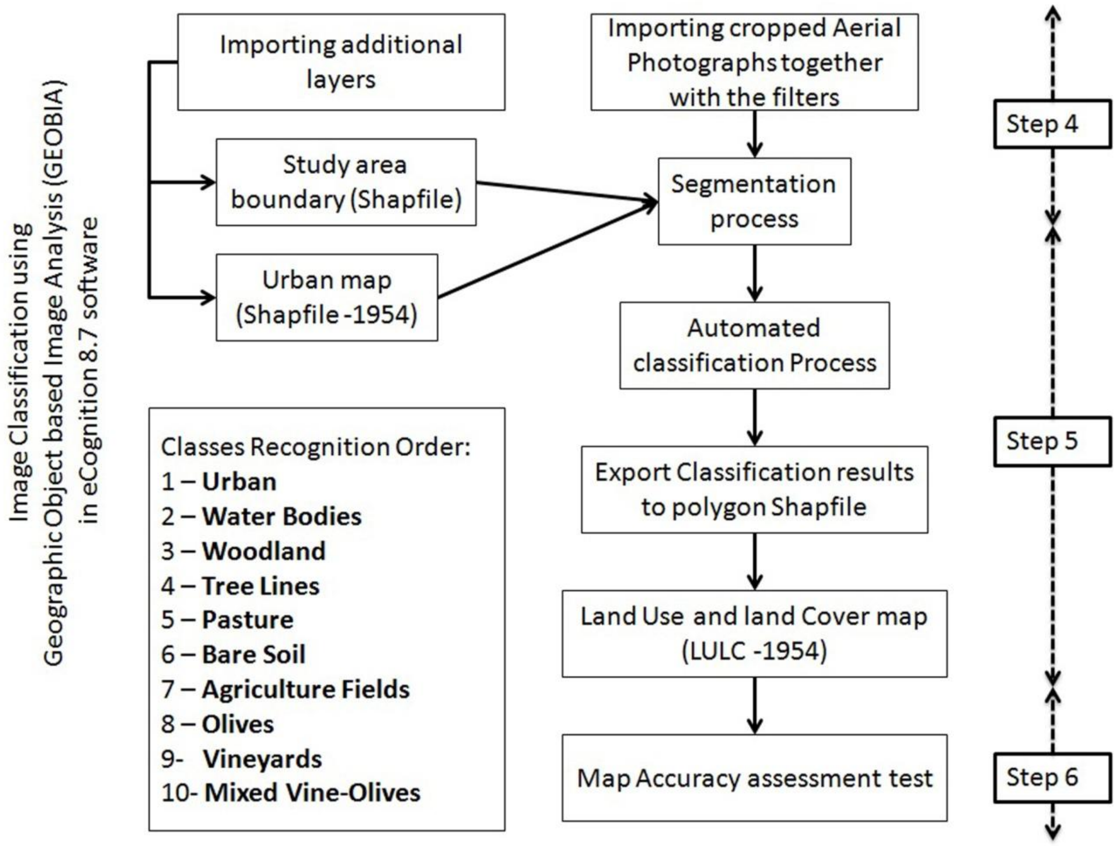

Fig. 18. A summary diagram of steps 4, 5 and 6 of GEOBIA classification process.

Clipped orthophotos were imported to eCognition software along with the corresponding filters to be subjected to the segmentation process. Segmentation process was carried out for 1954 aerial photographs individually, in addition to their filters, using the algorithms embedded in eCognition Developer 8.7 software (Trimble, 2012). The multi-resolution segmentation algorithm was chosen as the principal segmentation algorithm that works by achieving a mutual-best-fitting approach. This algorithm repeatedly merges pixels and then objects through an optimization procedure, which gives preference to certain unions generating a minimum level of heterogeneity in the produced objects. The algorithm uses an upper threshold of homogeneity to repetitively merge single image objects of one pixel in several loops in pairs until it reaches the homogeneity threshold limit. The calculation of homogeneity criterion (σ) (Fig. 19) in eCognition 8.7 is based on selecting a scale parameter value and choosing weights to four other criteria (shape, color, smoothness and compactness), which are embedded in the algorithm.

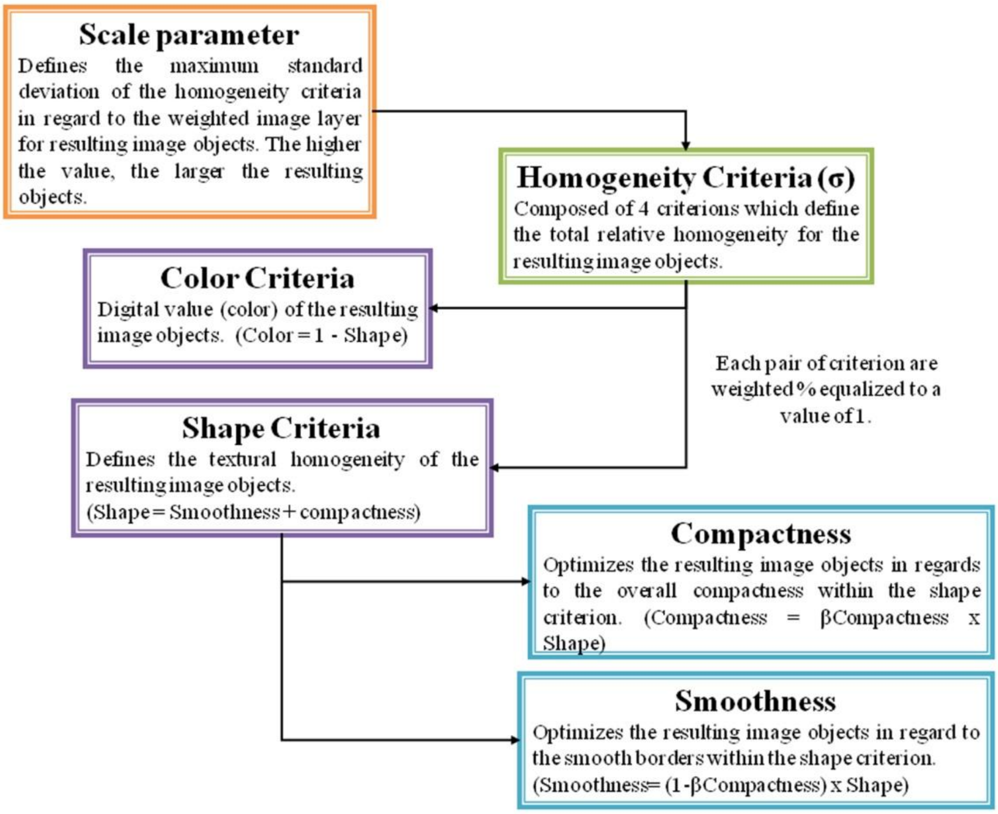

Fig. 19. Multi-resolution segmentation concept flow diagram.

The scale defines the maximum standard deviation of the homogeneity criteria for the resulting image objects, while the homogeneity criterion defines the characteristics of the objects (Trimble, 2012). Assigning different values to these segmentation parameters produces different sizes and shapes of image objects. Therefore, it is a critical decision to choose these parameters values to acquire the maximum accuracy in segmentation. Based on the procedure proposed by Meinel and Neubert (2004) and Neubert et al. (2006), the most favorable values of segmentation parameters were selected through comparison between manually extracted sample polygons and objects derived from different segmentations (Fig. 20). The optimal segmentation parameters values is a compromise between a reduced number of the resulting image objects and a high quality division of the surface in land cover classes.

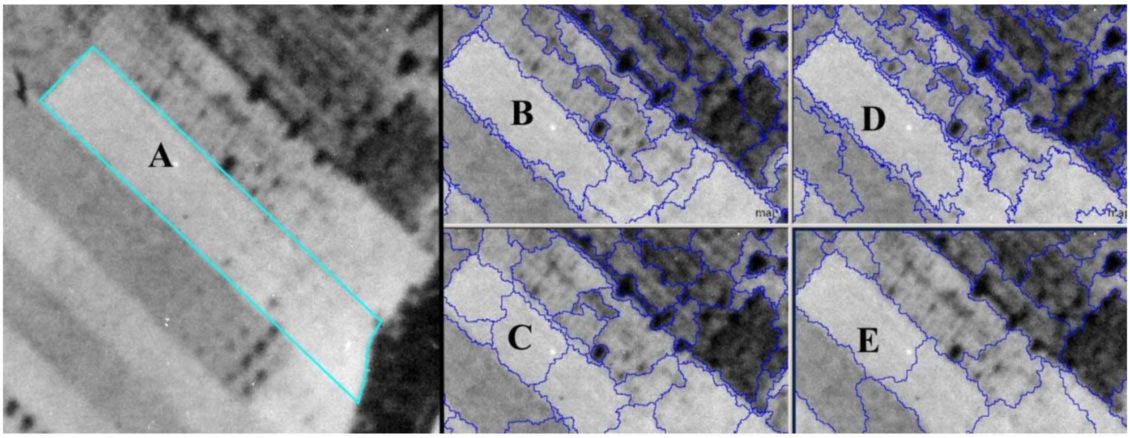

Fig. 20. Comparison between a sample polygon (A) and objects derived from different segmentations trials (B, C, D and E).

A visual evaluation was conducted in comparison with the manually extracted sample polygons taking into account different criteria as the segmentation of linear objects, the overall delineation of different land cover types and the occurrence of faulty segmentations. This evaluation was used to provide a decisional support to the selection of the optimal parameters values in case of similar segmentation results (Gennaretti et al., 2011). Whenever a segmentation was completed with a new combination of parameters, its performance was evaluated in relation to the former ones. This procedure was carried on until a significant sample of the possible parameter combinations was tested and the optimal one could be selected.

3.3.2.1.5. Step 5: Classification of orthophotos and generation of LULC map

During this step, a land cover class was given to each polygon obtained by the segmentation process. In the 1954 orthophotos, due to their low spatial resolution and their monochrome grayscale, it was difficult to detect some cover classes. For this reason, generating different filters from each orthophoto were a very useful aid for the identification and the classification of deferent objects as road networks, buildings and other classes. The legend for land cover classes was adapted from the legend of 1954 touring map of Italy (CNR & Directorate General of Cadastre, 1956-1960) with appropriate changes (Fig. 18). A full record of the process tree and the algorithms used in the classification can be found in appendix III (Fig. 21).

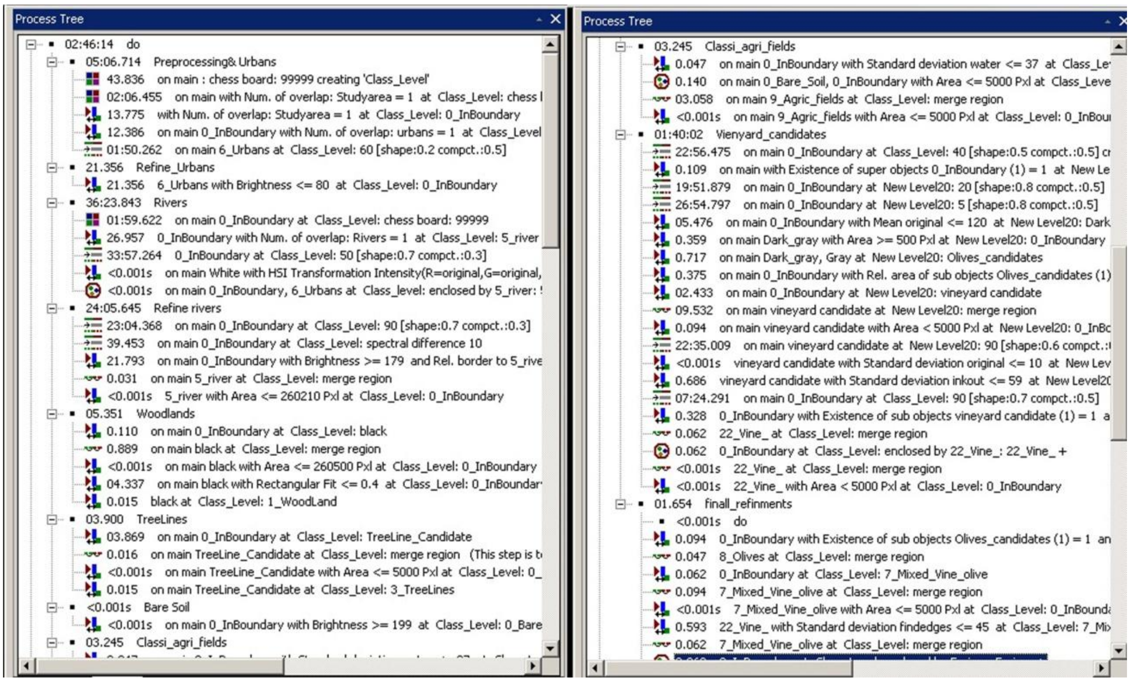

Fig. 21. A screenshot of the GEOBIA classification process tree.

3.3.2.1.6. Step 6: Map accuracy assessment

The quality of spatial data sets is a very broad issue which may depend on different characteristics (Worboys, 1998) but frequently, and in this case also, the map or classification accuracy is the characteristic of interest. Many map accuracy assessment measures can be derived from a confusion matrix (Lark, 1995; Stehman, 1997). However, many researchers have suggested that measures such as the kappa coefficient should be adopted as a standard (e.g., Smits et al., 1999). The classification accuracy assessment compiles a spatial comparison between the classified point on the map and the real class in the validation point in the field. Finally, these classified point and validation points are compiled in a confusion matrix. Using this confusion matrix, deferent accuracy assessment percentages can be developed (Fig. 18). Overall accuracy (Equation 2) defines how well the developed classification map identifies all land cover types on the ground (Foody, 2002). Producer's accuracy (Equation 3) expresses how well the map producer identified a land cover type on the map from the remote sensing imagery data. User's accuracy (Equation 4) explains how well a person using this map will find that land cover type on the ground. Finally, Kappa analysis (Equation 5) measures the difference between actual agreement and chance (or random) agreement between the map and validation data on the ground (Congalton, 1991). In order to apply the accuracy assessment test to the generated classification map, 292 validation points were selected randomly in the study area to be used in the comparison (Fig. 22). Stereoscopic view was used to validate the classification in the selected points. After running the validation procedures, the collected data were inserted in the confusion matrix to calculate the percentages of accuracy assessment.

$$\text{Overall Accuracy} = \frac{\text{sum of diagonal tallies (correctly identified)}}{\text{total number of samples}} \times 100 \qquad (2)$$

$$\text{User's Accuracy} = \frac{\text{Samples correctly identified in the row}}{\text{Row Total}} \times 100 \qquad (3)$$

$$\text{Producer's Accuracy} = \frac{\text{Samples correctly identified in the Column}}{\text{Column Total}} \times 100 \qquad (4)$$

$$\textit{Kappa}\ \text{coefficient}\ (\hat{K}) = \frac{\text{observed accuracy } (p_0) - \text{chance agreement } (p_e)}{1 - \text{chance agreement } (p_e)} \times 100$$

(5)

Where, Observed accuracy (P_0) determined by diagonal in error matrix; and Chance agreement (P_e) incorporates off diagonal, Sum of Product of row and column totals for each class (Foody, 2002).

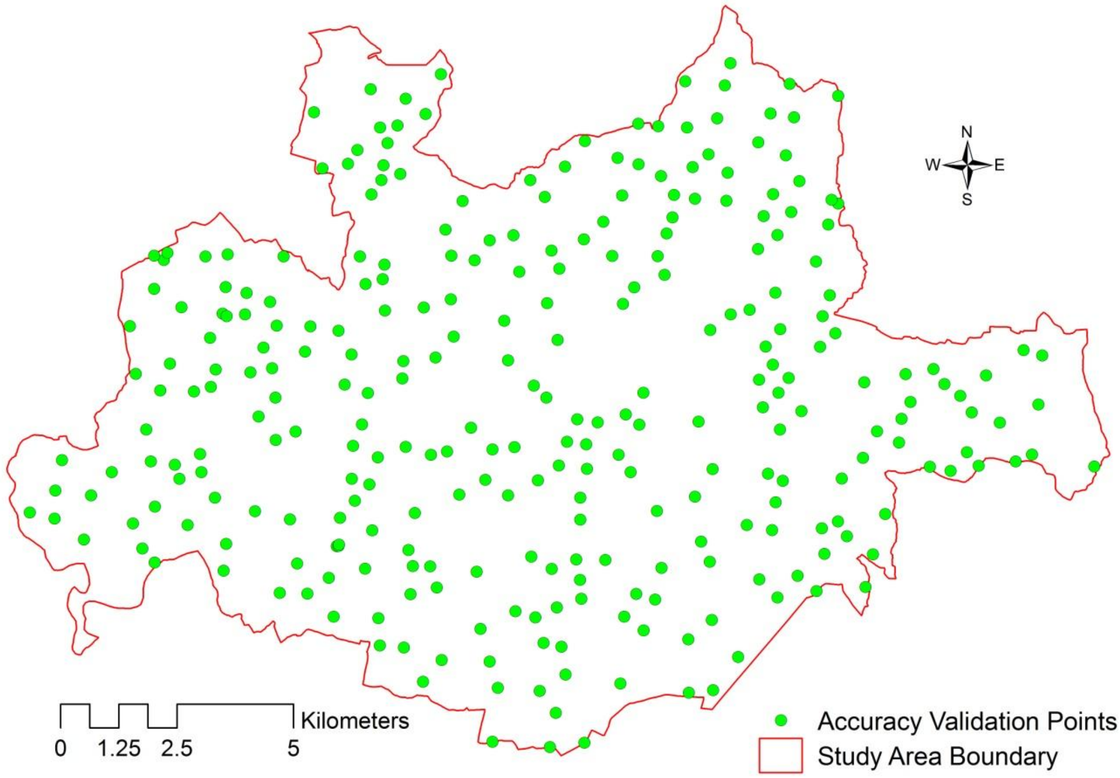

Fig. 22. Random validation points covering the study area.

3.3.3. Modeling of Soil functions loss (biomass production) by soil sealing

Biomass production is one of the most important soil functions and losing this function for any reason is a contribution to the hunger problem. Until now, from literature review, there is no solid methodology to evaluate soil functions loss. In this study, a novel methodology for evaluating soil function loss, after soil sealing, is proposed (Fig. 23) with respect to biomass production. The proposed methodology consists of different sequential stages starting with data collection arriving to a quantification of the biomass production loss. The methodology is mainly based on conducting a land suitability evaluation for wheat production. Then, using the wheat production statistic averages from statistical reports, it is possible to assign a production rate for different suitability classes and generate a land productivity map for wheat. Wheat crop is used here as a standard international land productivity measure and a reference crop for land productivity evaluation (Dumanski & Onofrei, 1989; Jafarzadeh et al., 2008; Ashraf et al., 2010). However, any other crop is suitable for the proposed method. Next, using the generated land productivity map along with soil sealing map (i.e. map of urbanization in the study area) we can quantify the lost biomass production due to soil sealing. In the next few paragraphs, a detailed explanation of the proposed methodology is given.

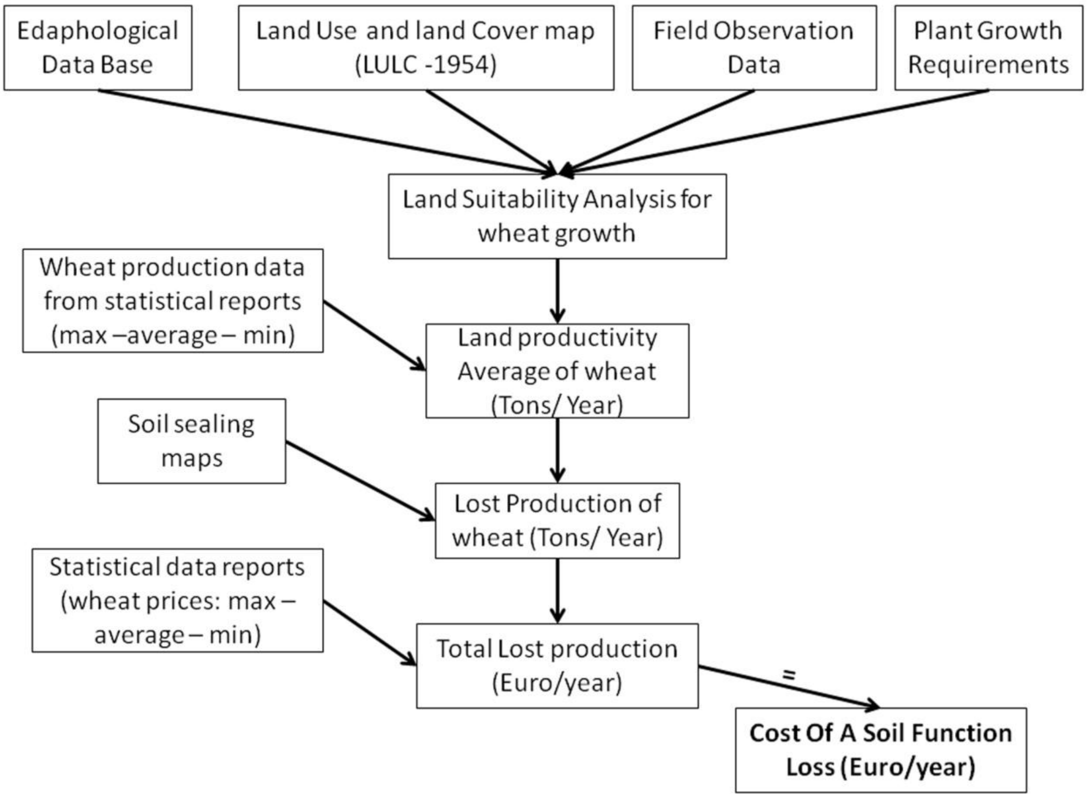

Fig. 23. Proposed scheme for soil function loss evaluation (Biomass production loss by soil sealing).

3.3.3.1. Land suitability analysis for wheat

Basically, land suitability assessment is a multi-criteria problem, as the analysis is a decision/evaluation problem concerning a number of parameters. A presentation of the analysis complexity can be shown in (Fig. 24). In general, the land suitability problem can be summarized in a generic model as in the following function (Equation 6):

$$S = f(x_1, x_2, \ldots\ldots, x_n) \qquad (6)$$

where, S is suitability level and x_1., x_2,..., x_n are the factors affecting land suitability.

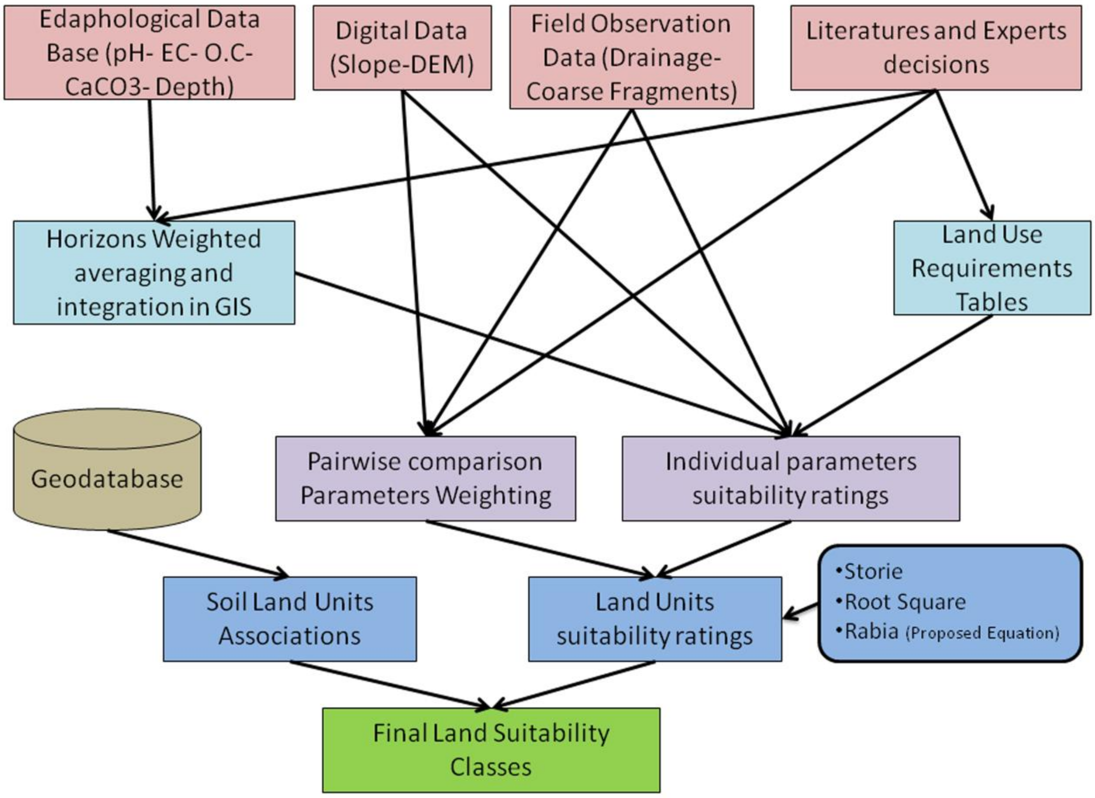

Fig. 24. Diagram of land suitability evaluation Process for wheat production.

Among the different land suitability assessment methods, this work is interested in the parametric methods. The two classical parametric methods (Storie and square root) have been used in comparison with the proposed method (Rabia method). The land suitability parametric approach can be summarized in six steps as shown in Fig. 25, following FAO framework for land evaluation (FAO, 1976) and the procedures proposed by Sys et al. (1991).

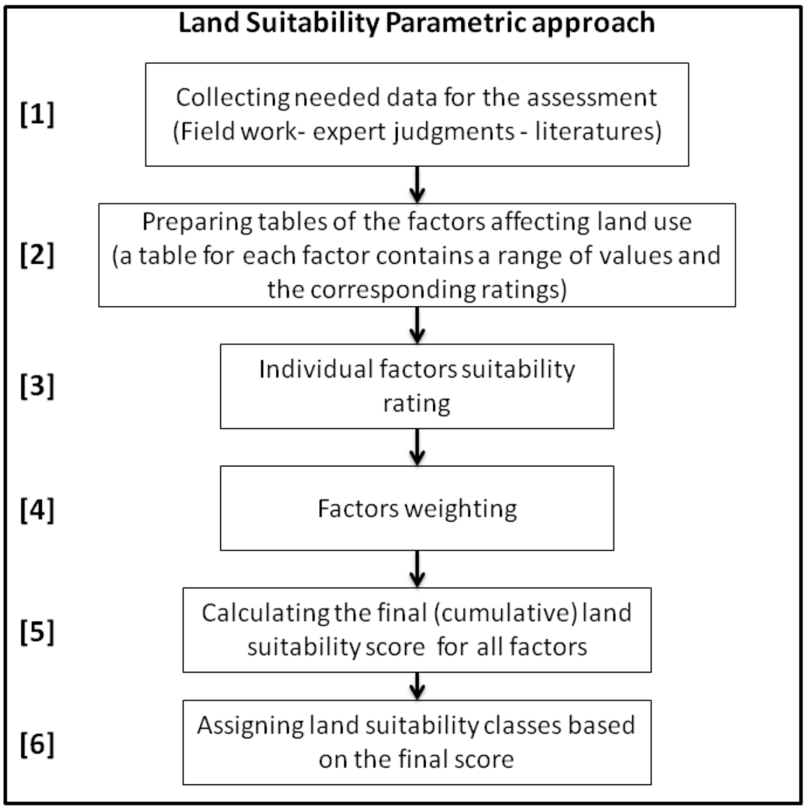

Fig. 25. Flowchart of Parametric approach procedures (Rabia & Terribile, 2013a).

First step of the parametric approach comprise collecting the fieldwork data and judgments from literatures and experts opinions needed for the later evaluation steps. In this stage, the parameters or factors that affect the land use under investigation should be defined. The number of the considered factors has to be reduced to a strict minimum to avoid repetition of related characteristics in the calculation, which will lead to a reduction in value of the final suitability index (Sys et al., 1991). Previous studies suggested that the number of the factors should range between seven and nine to achieve truthful results (Ashraf, 2010; Mokarram et al., 2010; Mustafa et al., 2011; Rezaei et al., 2010). Nine parameters have been named in this work to study land suitability for wheat production. These parameters are soil organic carbon, $CaCO_3$, pH, drainage, texture, EC, slope, altitude and soil depth (Ashraf, 2010; Ashraf et al., 2010; Mokarram et al., 2010; Mustafa et al., 2011; Vargahan et la., 2011). Full record of the soil analysis for these parameters in the study area can be found in appendix IV. In the second step, rating tables for each factor are to be prepared where each table has some values of a factor and the corresponding ratings for these values (usually range from 0 to 100). If the feature is highly suitable, a rating of 100 is to be assigned and if it is not suitable, a minimal rating will be assigned to that feature. In this study the rating tables were adapted from the tables prepared by Sys et al. (1993). These tables will be used in the third stage to specify ratings for individual parameters in all the sampling sites in the study area. In this step, researchers usually rate the parameters based on the situation of study area, experts' suggestions and review of literatures (Ashraf, 2010).

The following step is to calculate weights for different factors in order to use these weights in the later stages. The analytical hierarchy process (AHP) has been used commonly in Multi Criteria Decision Making (MCDM) or Multi Criteria Evaluation (MCE) (Mustafa et al., 2011). Several studies have documented the (AHP) methodology (Mendoza & Sprouse, 1989; Mendoza, 1997; Saaty, 1980; Saaty, 1995; Kangas, 1992; Kangas, 1993; Peterson et al., 1994; Reynolds & Holsten, 1994; Pukkala & Kangas, 1996) and it is not suitable to be portrayed in this study. On the other hand, a number of researches on applications of (AHP) in suitability evaluation have been done (Mustafa, 2011; Banai-Kashani, 1989; Eastman et al., 1992; Eastman et al., 1993; Xiang & Whitley, 1994). AHP depends on Pairwise Comparison Matrices to assign weights for every factor controlling the suitability analysis. These matrices compare different parameters to each other and give values (weights) according to their relative importance. These values range from 1 to 9, where 1 means that the two parameters being compared have the same impact and 9 reveals that one parameter is particularly more important than the other (Saaty & Vargas, 2001). Finally, the weight of each factor is calculated based on the values given to this factor in comparison to all other factors (Table 5). The land suitability index will be calculated based on ratings of all factors using one of the equations explained later.

Table 5. Pairwise comparison matrix of wheat land suitability (Saaty, 1977).

Parameters	$CaCO_3$	Organic Carbon	pH	Texture	Depth	Drainage	EC	Slope	Altitude	Weights
$CaCO_3$	1	2	3	4	5	6	7	8	9	0.264
Organic carbon	0.500	1	2	3	4	5	6	7	8	0.213
pH	0.333	0.5000	1	2	3	4	5	6	7	0.167
Texture	0.250	0.3333	0.500	1	2	3	4	5	6	0.126
Depth	0.200	0.2500	0.333	0.500	1	2	3	4	5	0.091
Drainage	0.167	0.2000	0.250	0.333	0.500	1	2	3	4	0.062
EC	0.143	0.1667	0.200	0.250	0.333	0.5000	1	2	3	0.039
Slope	0.125	0.1429	0.167	0.200	0.250	0.3333	0.5000	1	2	0.022
Altitude	0.111	0.1250	0.143	0.167	0.200	0.2500	0.3333	0.500	1	0.011

To calculate the final land suitability score for each land unit, one of the suitability indices shall be used. In this study three parametric indices have been used to calculate the final land suitability scores. These indices are Storie, square root (Equations 7 and 8 respectively) (Sys et al., 1991) and Rabia (Equation 9) (Rabia & Terribile, 2013a). In the following paragraphs the equations of the three indices are shown.

- **Storie equation**

$$\mathrm{Si} = \mathrm{A} * \frac{\mathrm{B}}{100} * \frac{C}{100} * \frac{\mathrm{D}}{100} * \ldots\ldots, \qquad (7)$$

where, Si is suitability index, A is the rating value for texture parameter and B, C, D are the rating values for other parameters.

- **Square root equation**

$$\mathrm{Si} = \mathrm{R}_{\min} * \sqrt{\frac{\mathrm{A}}{100} * \frac{\mathrm{B}}{100} * \frac{C}{100} * \ldots\ldots} \qquad (8)$$

where, Si is suitability index, R_{min} is the minimum rating value of the parameters, and A, B, C are the remaining rating values for other parameters

- **Rabia equation**

The proposed method is a parametric approach developed to enhance the land suitability analysis process and to overcome the limitations of classical methods (Rabia and Terribile, 2013a).

$$\mathrm{Si} = \mathrm{W}_{\max} * \sqrt{\frac{\mathrm{A}}{100} * \frac{\mathrm{B}}{100} * \frac{C}{100} * \ldots\ldots} \quad (9)$$

where, Si is suitability index, W_{max} is the rating value of the parameter that has maximum weight and A , B, C are the remaining rating values of other parameters.

Following the procedure proposed by Sys et al. (1991) the suitability ratings will be divided into five classes (S1: highly suitable, S2: moderately suitable, S3: marginally suitable, N1 marginally not suitable and N2: permanently unsuitable). For each suitability class, a range of suitability index is defined (Table 6). If an association of two different classes in the same land unit exists, it will be demonstrated by a slash between the simples of the classes (e.g. “S2/N1” means association of classes S2 and N1). Finally, by assigning a land suitability class or an association of classes for each land unit, we can generate the land suitability map of the study area for wheat growth.

Table 6. Land suitability classes and the corresponding ranges of suitability index.

Suitability Class	Suitability Index (SI)
Class S1: Highly suitable	>75
Class S2: Moderately suitable	50-75
Class S3: Marginally suitable	25-50
Class N1: marginally not suitable	10-25
Class N2: Permanently unsuitable	<10

3.3.3.2. Evaluation of biomass production loss

After generating the land suitability map for wheat production, we can use it as a base map to develop a wheat productivity map. This step involves using wheat production statistical data from literature to assign a wheat productivity rate for each land suitability class. The database of ISTAT was used for this purpose to get rates of wheat productivity in the study area (ISTAT, 2012). Table (7) shows the different wheat productivity rates assigned to different land suitability classes. For the class N2, zero production rate has been assigned as it is permanently unsuitable for wheat production.

Table. 7. Wheat Production rate (Metric Ton $hectare^{-1}$) and the corresponding Land suitability classes (ISTAT, 2012).

Assigned Wheat Production rate	Wheat Production rate (Metric Ton $Hectare^{-1}$)	suitability class
Max production in 5 years	4.2	S1
5yrs max/5yrs average	3.93	S2
5 years average	3.66	S3
Min production in 5 years	3.21	N1
No production	0	N2

Now, for each land unit a wheat production rate was assigned based on the corresponding land suitability class. Later, the wheat productivity map was generated and overlaid on the soil sealing map to evaluate the lost biomass production by soil sealing in Metric Ton per year. The soil sealing map used for this study is the urbanization map of 2011 for the study area. Finally, this productivity map can be used also as a decision supporting system to predict the biomass production lost for future urbanization plans.

RESULTS AND DISCUSSION

4. RESULTS AND DISCUSSION

As suggested before, in previous sections, the work was divided into three main themes. The first one is concerning the detection of the land use and land cover changes during the period between 1954 and 2009. This work was based on old land use and land cover maps and that is why the quality of results is strictly related to the quality of old maps. Therefore, the second theme was a proposal to use the novel approach; GEOBIA technique in classifying the 1954 aerial photographs to generate an enhanced LULC map of the year 1954. Then, the last theme was the evaluation of the impact on soil functions caused by one of the important land use changes. In this theme an evaluation of soil sealing impact on the biomass production loss was conducted as one of the soil functions lost by soil sealing. In the next paragraphs, the results of the three themes will be presented and discussed sequentially.

4.1. Long term detection of land use and land cover change (1954 – 2009)

Although land use and land cover change detection is a mature subject of study now, monitoring the land change is still important for recourses management. This is due to the changing state of food and fiber demands, biodiversity, global climate, and other critical environmental/ecosystem services (Hansen and Loveland, 2012). As a result of the availability of the consecutive data, developing advanced method of processing and the increasing actions for protecting the environment from sever changes, researchers will have to be continuously active in monitoring land use and land cover change. Therefore, this study was conducted to detect the land use and land cover change in Telesina valley and to understand the change trends and motives. By perusal of the four LULC maps of the study area for the years 1954, 1990, 2000 and 2009 which were presented in Figs. 8, 9, 10 and 11, it is clear that the land covers of southern and the far northern parts of the study area are dominated by Forests and Pasture. On the contrary, the middle part of the study area is subjected to different agriculture land uses such as Vineyards, Olive trees plantation, orchids and annual agriculture crops (SOILCONSWEB, 2012). After running the land use and land cover change detection analysis, three maps were generated for land change during the periods 1954-1990, 1990-2000 and 2000-2009. These maps show the actual land change for all of the classes under investigation. Figs. 26, 27 and 28 shows the land change maps during the three periods from 1954 to 2009. The change codes presented in maps' legends are the change codes suggested in Table 1. In view of all three change maps, it is clear that the change code that stands for the largest area representation in the three time periods from 1954 to 2009 is Agriculture Persistence (Pa) (Fichera et al., 2012). In these areas, agriculture land use continued without any change including intensive and extensive agriculture land uses. Forest persistence (Pf) is the second dominant change code in the study area during the three time periods form 1954 to 2009. In this case the forest area remained untouched during the time periods under investigation. Additionally, in the first time period from 1954 to 1990, only thirteen change types have been found while the change types stabilization (St) and degradation (De) didn't appear in this interval. On the other hand, in the second time period from 1990 to 2000, only nine change types appeared in the study area while six change types were absent. The missing change types in this time period are stabilization (St), degradation (De), exceptionality (E), agriculture intensification (Ai), abandonment (A) and agriculture extensive conversion (Ec). This shows that during the time period from 1990 to 2000 there was only slight LULC change as urban intensification (Ui) whilst the rest of the study area were represented by persistence change types such as agriculture persistence (Pa), forest persistence (Pf), persistence (P) and urban persistence (Pu). This is likely to be related to the fact that the compared LULC maps in this case are the corine LULC maps for the years 1990 and 2000 which have exactly the same legends, unlike the other maps which have different legends (EEA, 2000). Finally, in the third time period from 2000 to 2009, all fifteen change types were present with large afforestation (R) and deforestation (D) activities.

Special attention has been given to three important land change types in the study area and will be discussed in more details in the next paragraphs. These land change types were:

- afforestation and deforestation;
- agricultural development;
- urbanization.

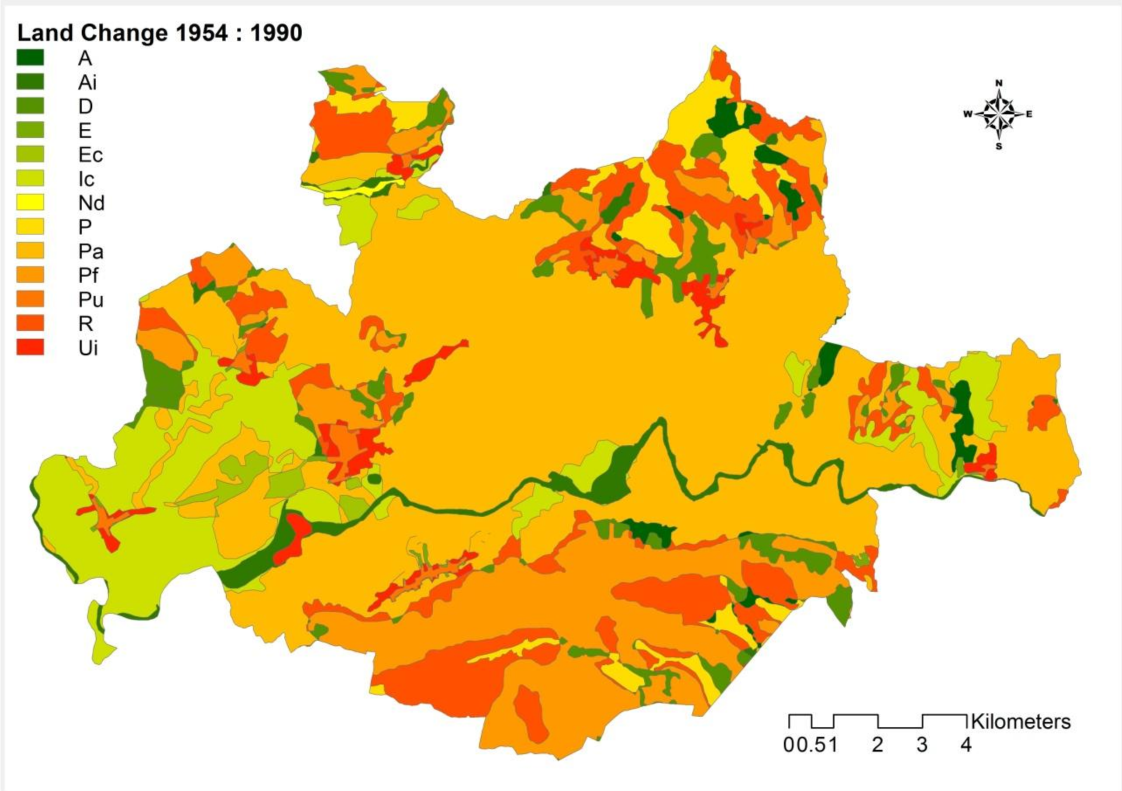

Fig. 26. Land change map during the period 1954 – 1990.

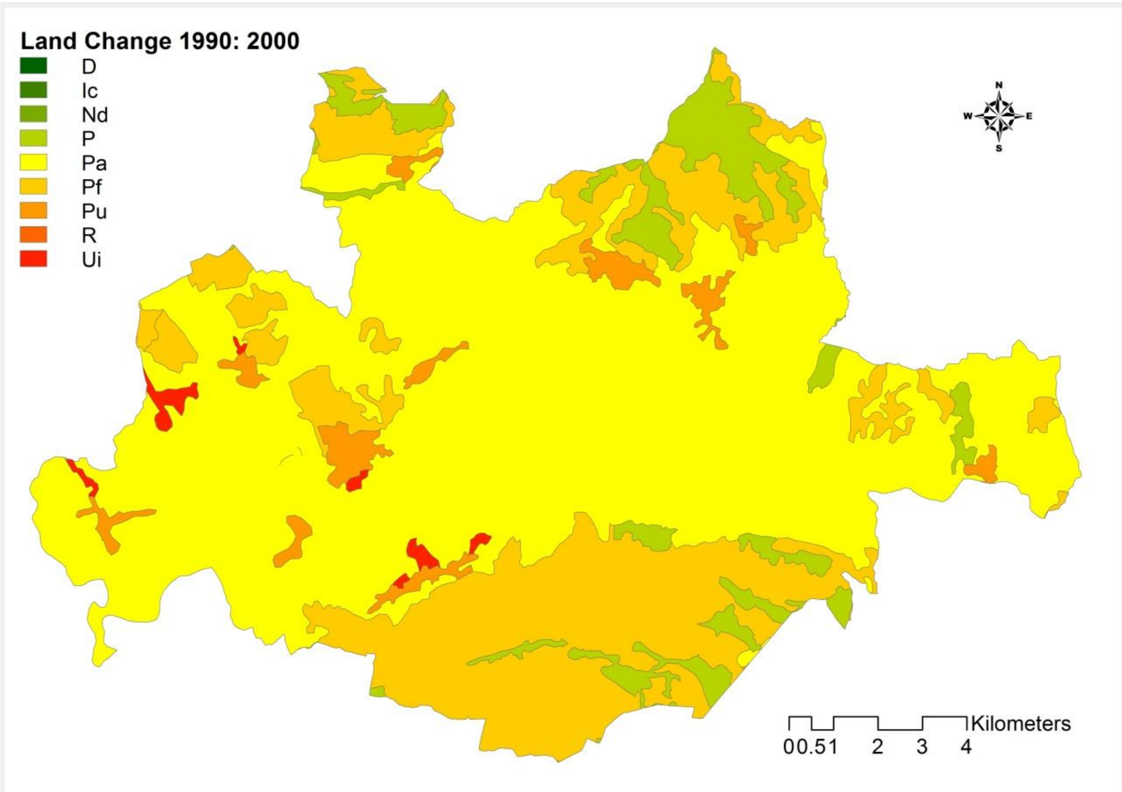

Fig. 27. Land change map during the period 1990 – 2000.

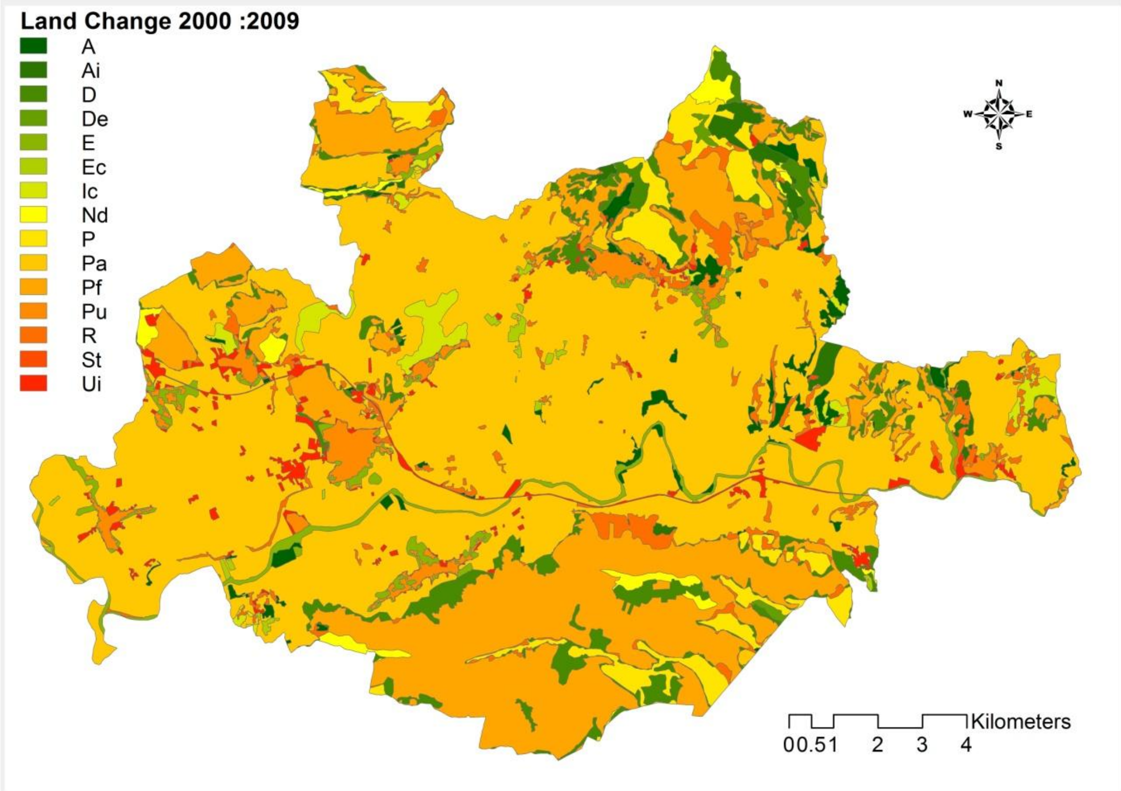

Fig. 28. Land change map during the period 2000 – 2009.

4.1.1. Afforestation and deforestation

Forests and woodland are scattered in the study area but are more close to the borders. Deforestation and afforestation changes during the three time periods are represented spatially in Fig. 29 and by total area in hectares in Fig. 29. Results show that the afforested area was larger than the deforested area during the first time period (1954-1990), where the net afforestation was 43.4 % greater than the initial forest area in 1954 (Piussi & Pettenella, 2000; Falcucci et al., 2007). During the second time period (1990-2000), the afforestation and deforestation were stabilized and there was generally no or little change. A surprising change was found in the last time period (2000-2009) where the deforestation process became larger and the total forest area was reduced by 9.7% (Fig. 30) (Rudel, 1998). Deforestation was clear only in the southern part of the study area while the afforestation process was still taking place in the northern and eastern parts of Telesina valley. Spatial analysis of the deforestation process showed that the deforested areas changed into various land uses. The largest deforested areas were converted to Olive groves, vineyards, pasture, grazing meadows, areas with sparse vegetation, bushes and shrubs (Rudel et al., 2005).

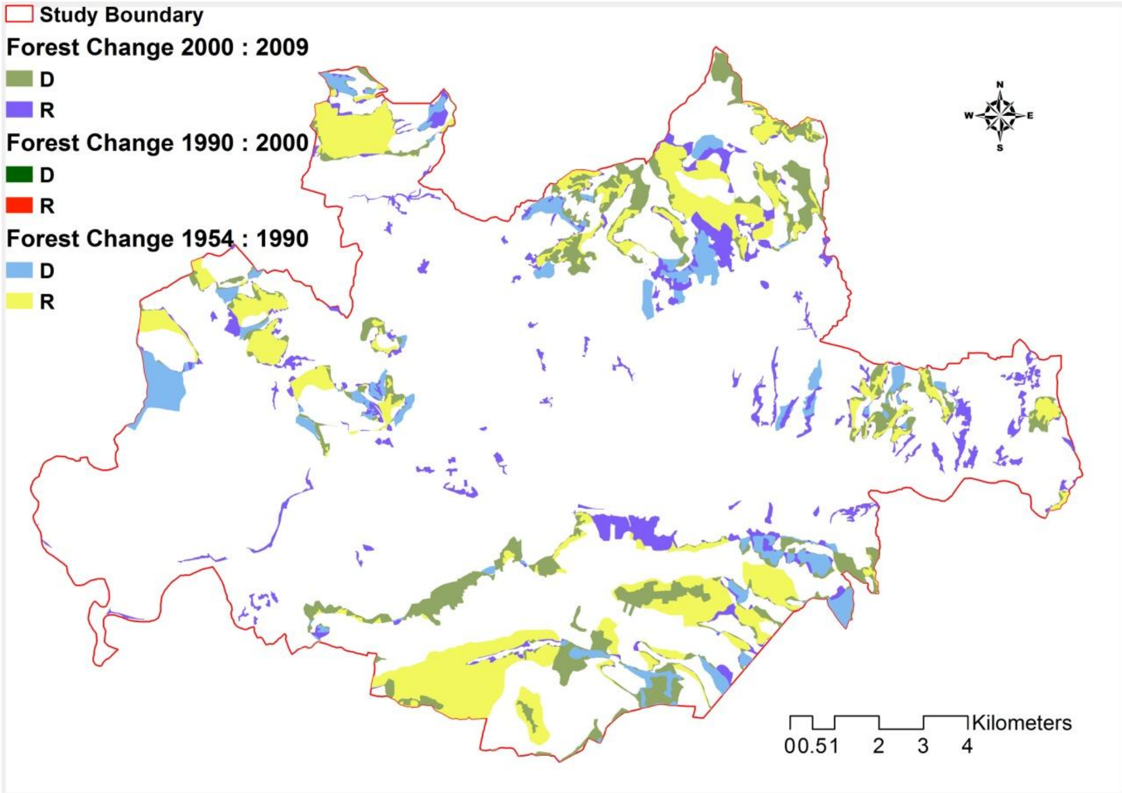

Fig. 29. Map of deforestation and afforestation changes from 1954 to 2009.

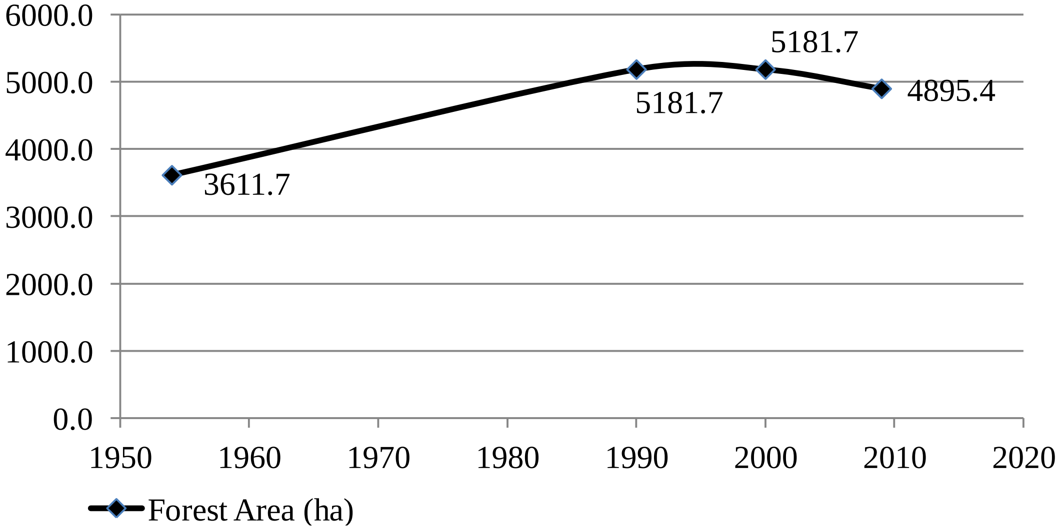

Fig. 30. Forest total area development in hectares from 1954 to 2009.

4.1.2. Agriculture development

Fig. 31 shows the agricultural changes during the three time periods (1954-2009). The results show little agricultural intensification during the last ten years in the northern and eastern part of the study area. Most of the agricultural area remained persistent to any changes while some areas in the northern part of the study area encountered an intensive agricultural change. Moreover, some areas in the centre and southern parts experienced extensive agricultural changes (MacDonald et al., 2000; Falcucci et al., 2007).

Fig. 32 illustrates the total agricultural area in hectares during the three time periods. It shows that the total agricultural area had reduced by 6% during the first period (1954-1990), 1% during the second period (1990-2000) and 3.5% during the third period (2000-2009). Approximately 1200 hectares of agricultural land have been lost during the period from 1954 to 2009. Spatial analysis for the lost agriculture areas revealed that these areas have changed mainly to different land use types such as urban areas (Verzandvoort et al., 2009), pasture, grazing meadows, grasslands, bushes and shrubs.

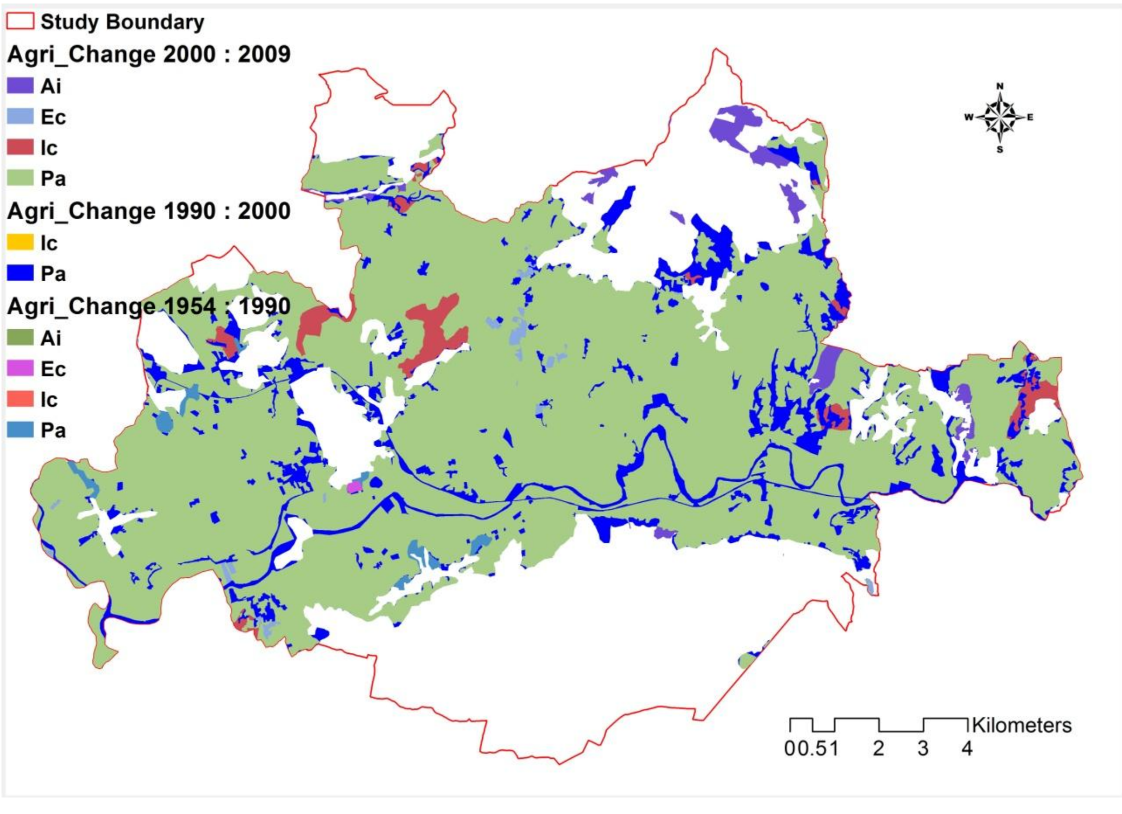

Fig. 31. Map of agriculture changes from 1954 to 2009.

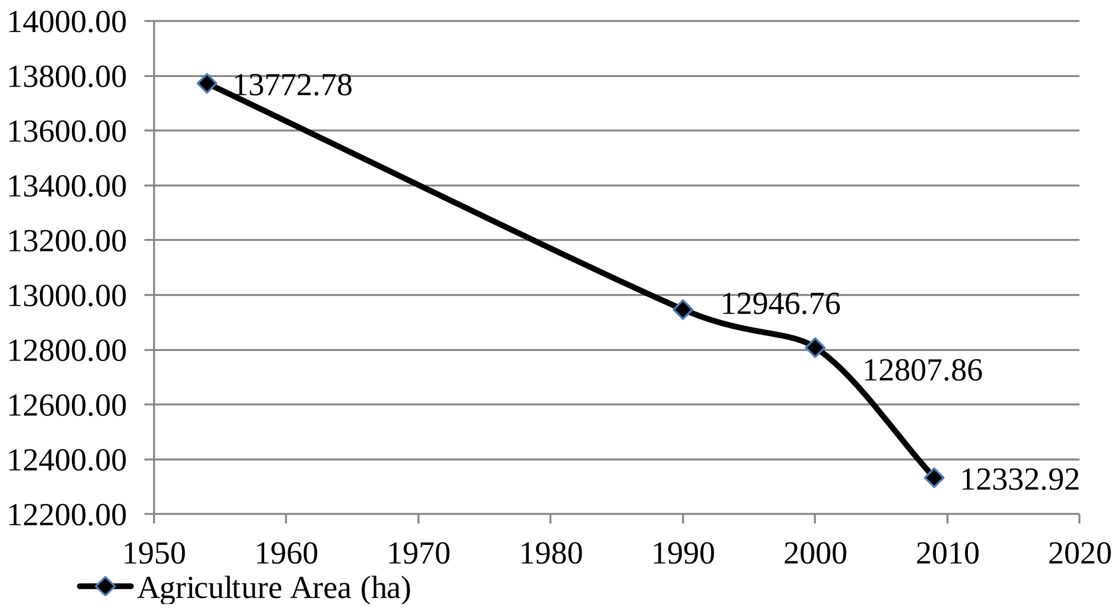

Fig. 32. Total agriculture area development in hectares from 1954 to 2009.

4.1.3. Urbanization

Urbanization is one of the major causes of agricultural land loss (Brook & Davila, 2000; Verzandvoort, et al., 2009). Fig. 33 represents urban change in the study area during the three time periods (1954-2009). Evidence of urbanization can clearly be seen in the middle and southern parts of the study area during the last two decades (Astengo, 1982; Ferrario, 2009). The development includes expansion of old urban areas such as in the southern part and the emergence of new urban areas such as those found in the western part during the second time period (1990-2000). In addition to the emergence of small to medium urban units scattered across the study area, the main urban development during the third time period (2000-2009) was a result of the main road connecting the eastern and western parts of the study area.

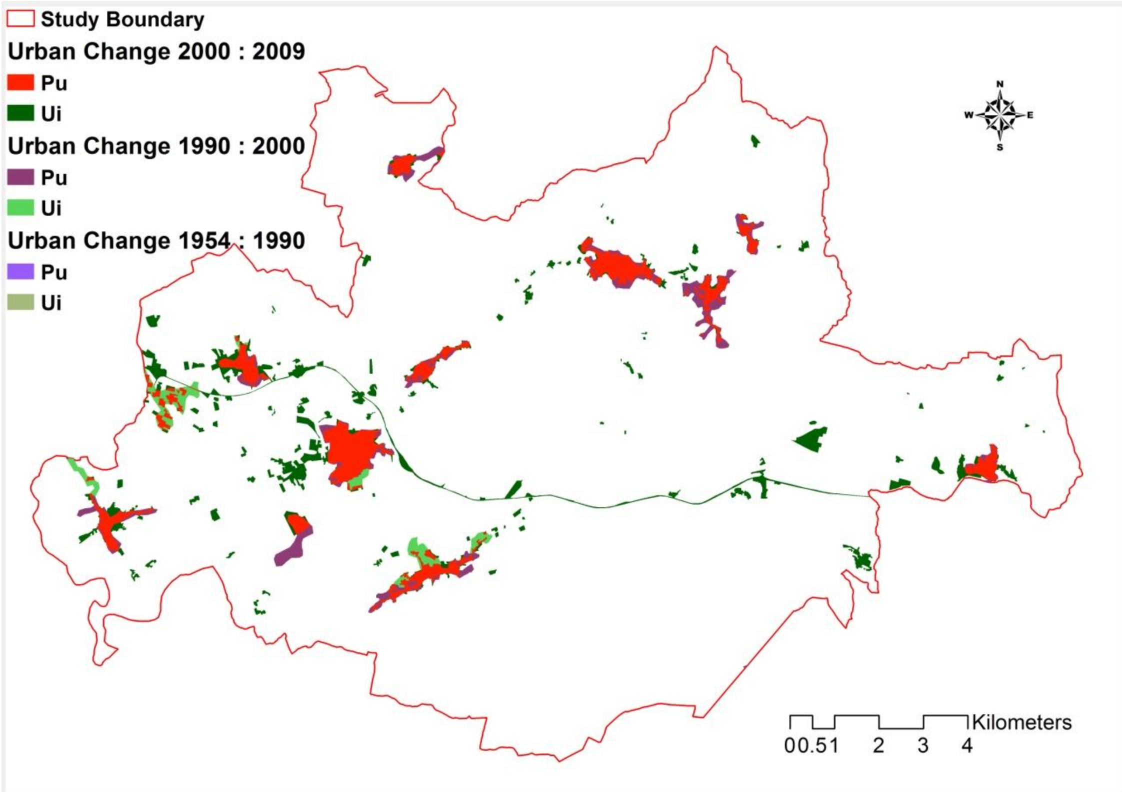

Fig. 33. Map of urbanization change from 1954 to 2009.

Fig. 34 depicts the total growth in urban area in hectares from 1954 to 2009. It shows that the urbanization has continued to grow over the last few decades. The urban area increased more than four times during this time period (1954-2009) (Migliozzi et al., 2010). These data revealed one of the problems occurring in the region, i.e. soil sealing and soil loss due to urbanization (Rabia, 2012b). Spatial analysis for urbanized areas revealed that the urbanized areas were originally different land uses. These urbanized lands had originally diverse land cover and land use such as complex cropping systems, olive groves, fruit orchards, forests and intensive farming (Fichera et al., 2012).

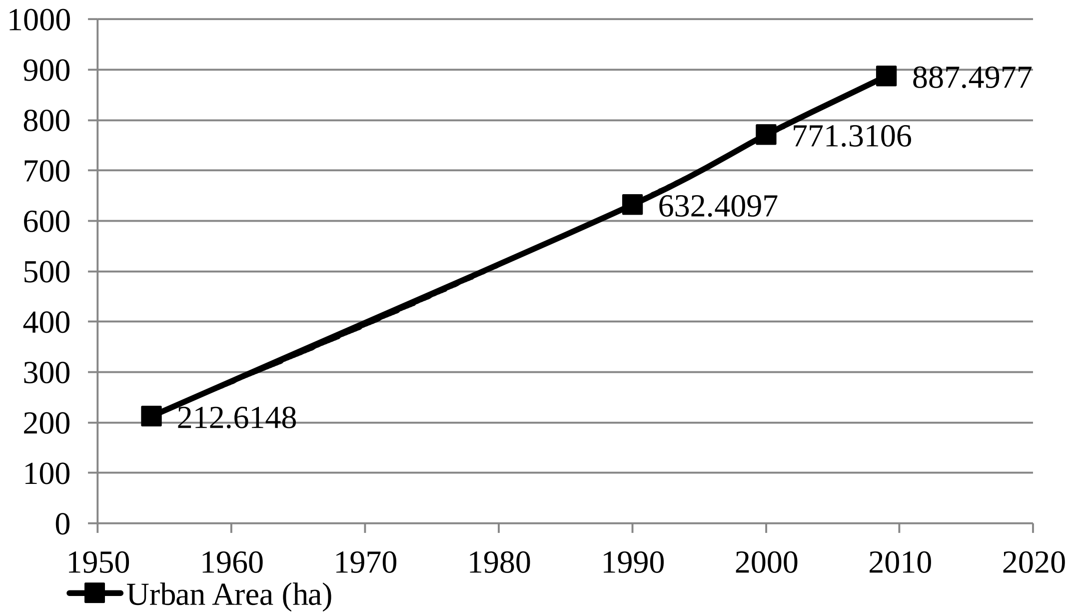

Fig. 34. Total urban area development in hectares from 1954 to 2009.

4.1.4. Analysis of 50 years reciprocal change

Using spatial analysis of the LULC change maps, it was possible to develop a model to shows the interaction between different land uses during the period from 1954 to 2009. Since this work is interested in the development of the urban, agriculture and forest areas, the model was built based on three main compartments to show the main land uses and all other land uses were compiled in one compartment (Fig. 35). The analysis showed that the change was mutual between the different land use and land cover types. As can be seen from the model, 24% of the final forest area in 2009 came from agriculture lands while 21.4% came from other land uses. On the other hand, agriculture land received 2.2% contribution from the forest lands and 3 % from other land uses. The increase in final urban area in 2009 was mainly on agriculture lands as 62.4% of the final urban area came directly from different agriculture land uses while 11.6 and 4.6% came from forests and other land uses respectively (Fichera et al., 2012). Unexpected result was found as the model shows that certain part of the urban area was changed to both forest and agriculture use. This result can be explained as the urban area has been delineated in the 1954 map of LULC in big polygons exaggerating the real area of urban settlements (CNR & Directorate General of Cadastre, 1956-1960).

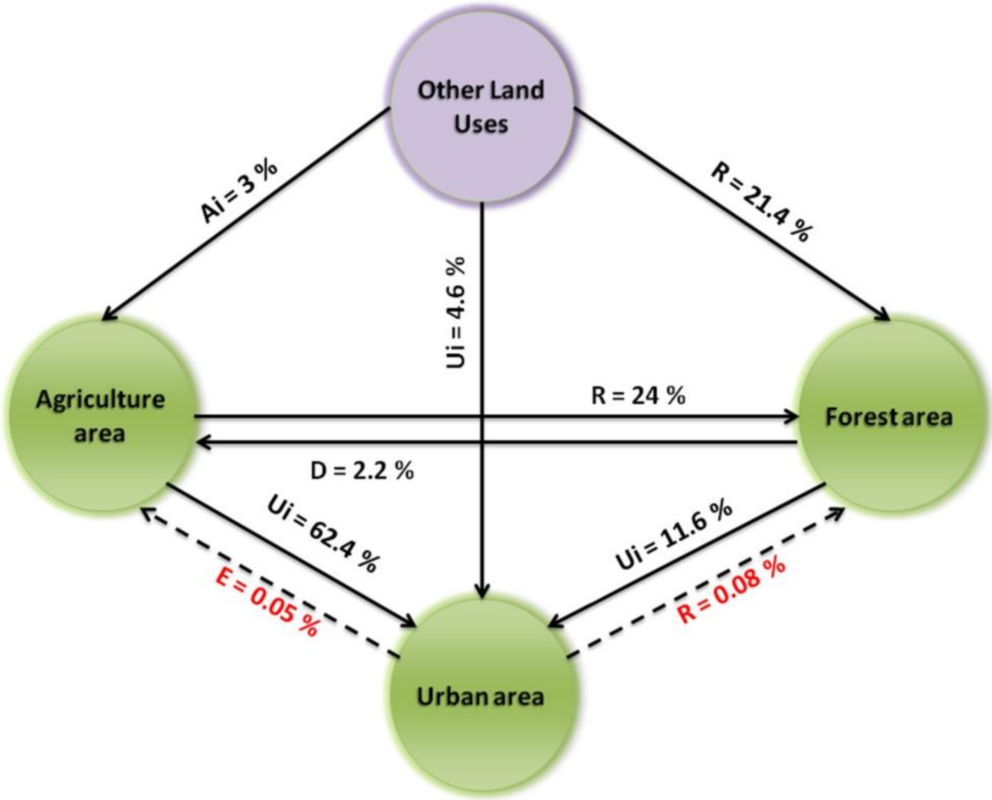

Fig. 35. The reciprocal changes in percentages between different land uses from 1954 to 2009.

4.2. Automatic land use and land cover classification of the 1954 aerial photographs using GEOBIA technique

Since land change detection is highly dependent on the accuracy of the historical input data, improving data accuracy is likely to improve the final results of land change detection (Chapman, 2005; Salmons & Dubenion-Smith, 2005; Pipino et al., 2002). Therefore, the second part of this work was concerned with improving the historical data in order to improve the final land change detection results. As mentioned previously (section 3.3.2), old aerial photograph have been reclassified using a novel image processing technique named GEOBIA in order to enhance the 1954 LULC classification of the study area. The process involves many procedures and steps until the final LULC map is generated. In the following sections, results of the different procedures will be discussed in details.

4.2.1. Orthorectification of aerial photographs

As a first pre-processing step, orthorectification is a very crucial stage in the classification of aerial photographs. By applying RMSE calculation (Equation 1) for GCPs positioning, the accuracy of the orthorectification process of 1954 aerial photographs was verified. The RMSE in all orthophotos never exceeded 1 m. The orthophotos obtained have quite satisfactory rectification results if considering the scale of the original photos. In addition, they are basically in line with the results of other studies, which used aerial photographs of the same year (Rocchini et al., 2006).

4.2.2. Homogenization, clipping and filtering of orthophotos

Homogenization, clipping and filtering are the next stage of orthophotos pre-processing and they were very essential for the classification enhancement. Homogenization process was very important later in the classification procedure as the spectral signal of images was a key tool for the land uses recognition and any deviation in the object spectral signal would lead to misclassification (Gennaretti et al., 2011). As the segmentation and classification algorithms work on all the image area, reducing the image size to the minimum will reduce the processing time and cost. Clipping process was found to be extremely significant to reduce the image processing time to less than half (Erickson et al., 2006). Filtering process was found to be highly effective in enhancing both the visual and spectral signals of the gray scale aerial photographs. Many different filters were tested to check their validity for the classification process. Finally, three filters were chosen as the most suitable for enhancing the gray scale aerial photographs. These filters are ink-out, water and find-edges (Fig. 17). Ink-out filter emphasizes the dark and light pixels, which help in separating the different tone levels in the image. Water filter stretches the spectral signal of the image, which assists in the image spectral homogenization. Lastly, find-edges filter helps in sharpening the edges of objects, which will support the recognition of these objects in the segmentation and classification processes.

Visually overlapping the different filters on the original gray scale image in a Red-Green-Blue composition (RGB) augmented the vision quality of the images and consequently the capabilities of classifiers. Different RGB compositions were examined and the most valuable were selected to be used in the classification. Fig. 36 shows three false color RGB compositions in addition to the original gray scale image. The first RGB composition consists of the three layers i.e., find-edges filter, original image layer and ink-out filter, consecutively (Fig. 36-b). This composition gives a false color image, in which dark pixels such as trees and green cover appear in dark red color. In addition, wet soil, water courses and fields with low agriculture cover appear in middle to dark reddish color. Bare agriculture fields, roads and bare soils appear in light pink or white color. This composition was helpful in distinguishing the green cover such as trees and agriculture fields in addition to single trees such as olive trees. The second RGB composition is made up of the three layers i.e., water filter, original image layer and ink-out filter, consecutively (Fig. 36-c). This composition gives a false color image with a true color impression, in which the object color is close to the object's real color in the environment. Trees and green cover appear in green color, roads and bare soils appear in white color and finally wet soils and water courses appear in degrees of gray color. Lastly, the third RGB composition is made up of the three layers: ink-out filter, water filter and original image layer (Fig. 36-d). This composition gives a false color image in which objects with elevation appear in bright green and non-elevated objects appear in greenish yellow. This composition was helpful to distinguish the elevated objects such as trees and urban building. The 3D impression in this RGB composition is possibly a reason of placing the ink-out filter as a first layer in the composition. However, more work need to be done on this composition to understand this effect.

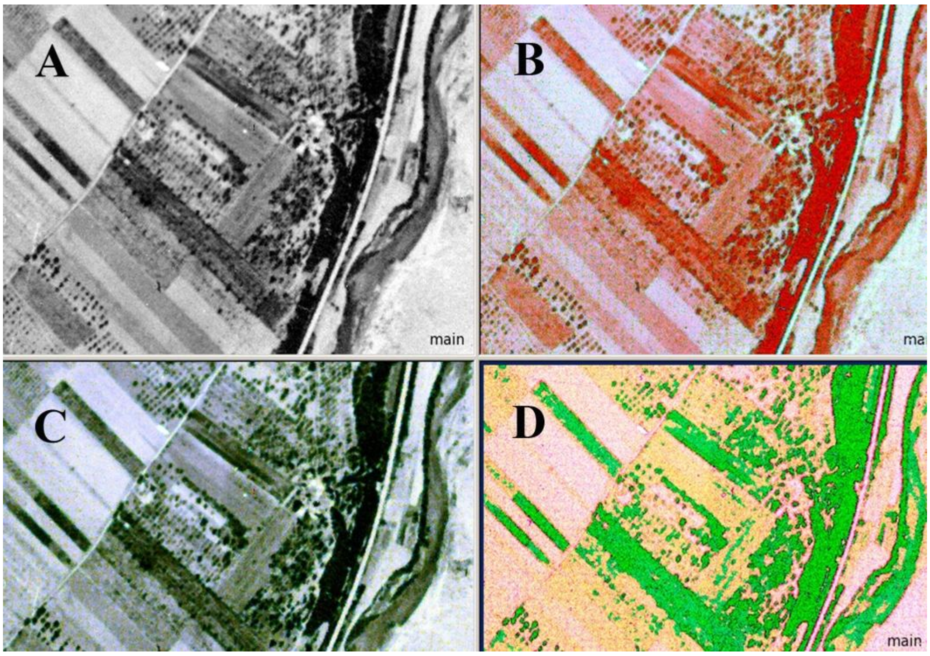

Fig. 36. A comparison between the original aerial photograph and different RGB compositions: a) the original aerial photograph; b) Composition: find-edges filter; original image layer and ink-out filter; c) Composition: water filter; original image layer and ink-out filter; and d) Composition: ink-out filter, Water filter and original image layer.

4.2.3. Semi-automated object based approach for images segmentation

The multi-resolution segmentation algorithm was selected as the main segmentation algorithm through the entire classification process. Fig. 37 shows a comparison test for the four homogeneity criteria (shape, color, smoothness and compactness). A multi-resolution segmentation process with the same scale of 90 was applied four times with different weights for shape and compactness criteria to study the effect of deferent weights on the final segmentation results. The weight of 0.5 means equal magnitude to both the criteria under investigation. For example, if the shape weight is 0.5 means that equal importance has been given to both shape and color criteria. The same is in case of the compactness and smoothness criteria. In Fig. 37-a, multi-resolution segmentation was applied with scale of 90 with 0.5 weight for shape criterion and 0.2 weight for compactness criterion. Fig. 37-b shows the objects generated by a multi-resolution segmentation that has a scale of 90 with 0.2 weight for shape criterion and 0.5 weight for compactness criterion. On the contrary, Fig. 37-c represents the objects that resulted from a multi-resolution segmentation has a scale of 90 with 0.5 weight for shape criterion and 0.8 weight for compactness criterion. Finally, Fig. 37-d demonstrates the objects generated by a multi-resolution segmentation has a scale of 90 with 0.8 weight for shape criterion and 0.5 weight for compactness criterion. In Fig. 37-a, more importance has been given to the smoothness criterion and less to compactness criterion. It is clear from the segmentation results that giving high value to the smoothness criterion created objects close to a square outline as represented with black forms in Fig. 37-a. The "zig zag" effect in the objects (Fig. 37-a) is likely to be a result of the high weight assigned to smoothness, which tries to create objects with smooth borders within the shape criterion (Trimble, 2012). Results obtained when more importance was given to the compactness criterion and less to smoothness criterion (Fig. 37-c) were quite contrary to the above observation. In this case more compact and circular like objects were created and the "zig zag" effect was not as much prominent as in the previous case. This result is important in choosing the suitable weights for compactness and smoothness criteria during the segmentation process. For example, if the targeted objects have circular shapes such as tree crowns or pivot plantations, higher weight should be given to the compactness criterion. In contrast, if the targeted objects have square like shapes such as urban buildings or regular agriculture fields, higher weight should be given to the smoothness criterion. On the other hand, In Fig. 37-b, extra importance has been given to the color criterion (spectral signal) and less to shape criterion. The opposite situation can be seen in Fig. 37-d, where extra importance has been given to the shape criterion and less to color criterion (spectral signal). It is obvious from the segmentation results that giving high value to the color criterion created smaller objects compared to that generated with high value to the shape criterion even when using the same scale parameter value (Figs. 37-b and 37-d). It is apparent that increasing the weight of the shape criterion created objects with better shapes; however, the color homogeneity within the objects is rather low. In addition, the "zig zag" effect was much higher when the weight of the color criterion was high. This can be explained by the fact that the segmentation algorithm in this case tries to assemble too much pixels or small objects with regards to their color homogeneity regardless of the final object shape (Rabia & Terribile, 2013b).

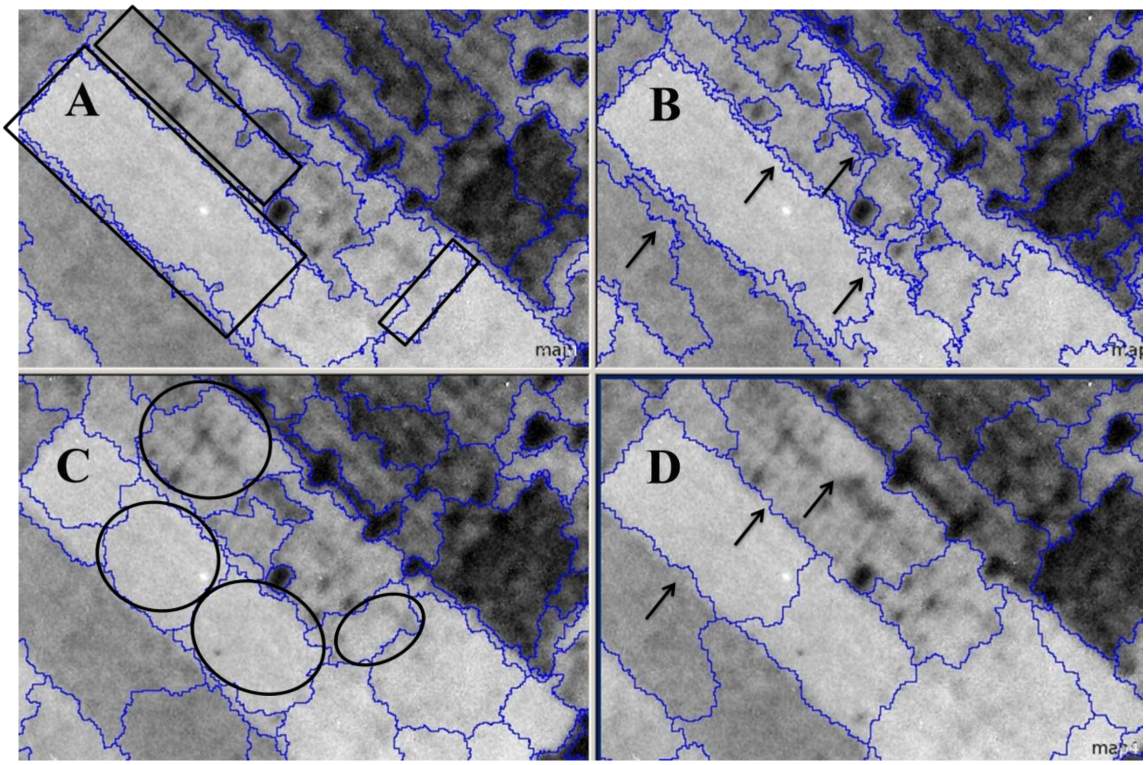

Fig. 37. Comparison between multi-resolution segmentation algorithms with the same value for scale parameter and different weights of shape and compactness: a) shape 0.5 and compactness 0.2; b) shape 0.2 and compactness 0.5; and c) shape 0.5 and compactness 0.8, (D) shape 0.8 and compactness 0.5.

All the potential combinations of segmentation Parameters were tested and the most favorable parameters values were selected. Upper part of Table 8 shows the segmentation parameters values for the different classes. Regarding the scale parameter, a scale of 90 has been chosen as the optimal scale for all the segmentation processes except for the urbanization class, which was 60. Similarly, the weight assigned to the shape criterion was 0.7 in all the segmentation processes except for the urbanization class, which was assigned weight of 0.2. On the other hand, for the compactness criterion, the suitable weight was 0.3 in most of the classes except for the classes Olives, Vineyards, Mixed Olives-Vineyards and urbanization for which the weight 0.5 was more suitable. These parameters values are in part similar to the values used by a study, where the 1954 aerial photographs were used to classify the historical land cover (Gennaretti et al., 2011). Gennaretti et al. (2011) suggested that, the segmentation of the 1954 aerial photographs needed a small scale parameter (40 versus 90 in the case under investigation) and a larger weight for the shape criterion (0.7 similar to the case under investigation). The reason behind this proposal is that the initial grayscale aerial photographs had a low spectral resolution. So, in the object homogeneity criterion calculation, the shape criterion was given more importance with respect to the homogeneity of spectral signature. In the study under investigation the situation is different due to the generated filters and the different RGB compositions that were created. These RGB compositions made it possible to generate larger polygons with a complex shape without losing the association between land cover homogeneity and extracted objects or causing a faulty segmentation.

4.2.4. Orthophotos classification and generation of LULC map

After the segmentation process, the classification phase was carried out. Ten land use and land cover classes were recognized during the classification progression and Table (8) gives an idea about these classes. Successive approach was followed during the classification as the different classes were classified in a sequential order.

Table 8. Legend of land cover classes generated with GEOBIA technique and the corresponding Corine classes.

Class order	Class name	Included CORINE classes
1	Urban	1.1; 1.2; 1.3 and 1.4
2	Water bodies	5.1
3	Tree lines	-
4	Woodland	3.1
5	Pasture	2.3
6	Bare soil	3.3
7	Agriculture fields	2.1 and 2.2.2
8	Olives	2.2.3
9	Vineyards	2.2.1
10	Mixed vine-olives	2.4.2

A simplification of the classification flow chart is displayed in Fig. 38. The flow chart clarifies the order and the concept for each LULC class starting with Urban class until the Vineyards class, which was the last classified land use during the process. Each class has a unique perceptive feature or more in addition to the shared features in between the different classes.

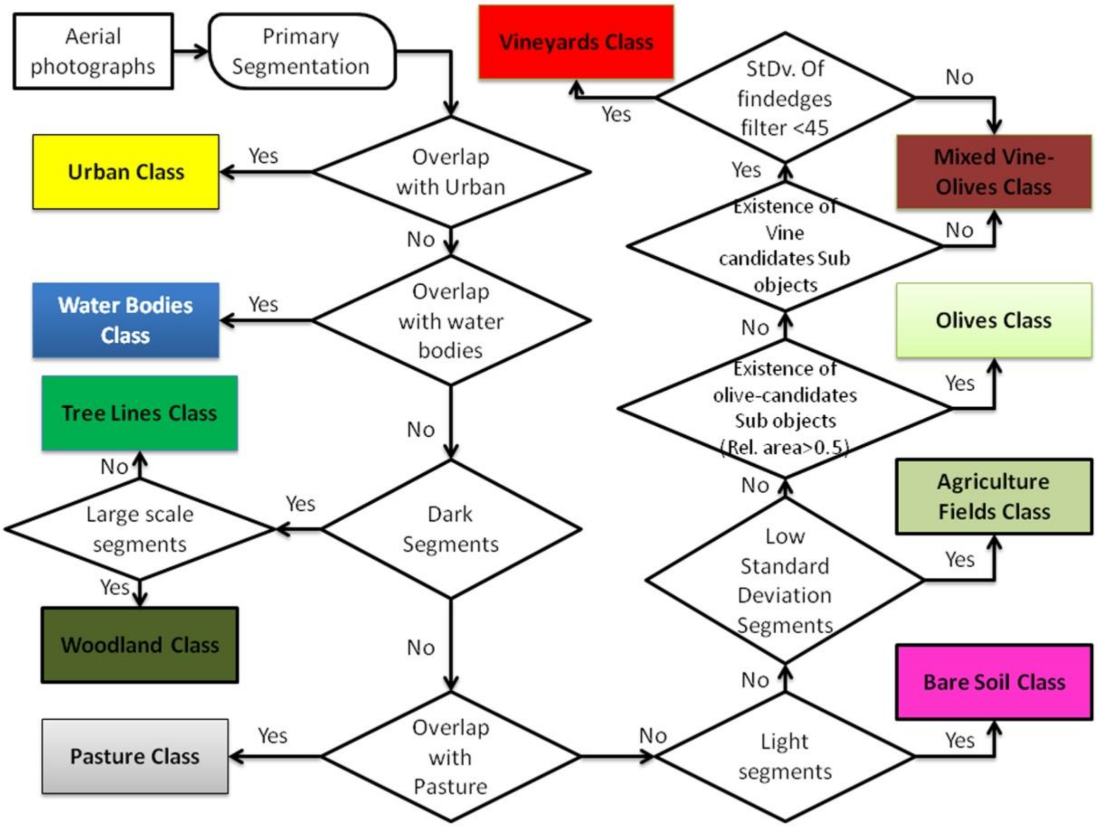

Fig. 38. A simplification flow chart for the classification procedures.

Table (9) shows the different features and their values that were used for the recognition of classes during the classification process. The full registry of the classification process tree and all the algorithms used is found in appendix III. To classify the urbanization class, the LULC map of 1954 (CNR & Directorate General of Cadastre, 1956-1960) was used as a guiding layer to recognize the urban objects. In addition, a brightness threshold of 80 was assigned to exclude object with brightness values less than 80, even if they overlapped with the urban class in the 1954 LULC map. Urban misclassifications were found in the old LULC map of 1954, so this brightness threshold was used to remove the misclassified objects in the new classification. Urbanization class was difficult to classify even with RGB compositions due to the similarity of the features between urban and bare soil objects. River Calore and river Titerno are the main Water Bodies, which flow from east to west in the southern and northern parts of the study area, respectively. However, there is also a small lake called Telese (Lago di Telese) which is close to river Calore. Again, the LULC map of 1954 (CNR & Directorate General of Cadastre, 1956-1960) was used to assist the recognition of the water bodies objects.

To distinguish between the objects of water class and other classes, two features thresholds were used. One of these thresholds was brightness (>=179) and the other one was intensity HSI transformation (>=0.85). The intensity HSI transformation was made of the original layer of aerial photographs and was found to be helpful in the classification of water bodies. This could be explained due to the existence of bright objects surrounding the water bodies (river beds), which usually appear bright because of undeveloped soils and low organic matter content. Tree lines class is an innovative class for this study, where it found that tree lines on borders of agriculture fields or rivers cover a significant part of the study area. This class was found to have a maximum spectral reflectance of 80 of the original aerial photograph layer. Since the tree lines have usually a high contrast to the neighboring objects, this feature was used for its classification. A threshold (<=-340) of contrast to neighbor pixels in the original aerial photograph layer was assigned to the tree line class in order to separate it from other classes. The woodland class was classified after tree lines class. Although the woodland objects have similar spectral features as tree lines objects, they usually have larger extent and different shape index. Contrary to urban objects, woodland objects were given a brightness threshold of 80, to exclude object with brightness more than 80 from woodland class. Moreover, since woodland objects typically have circular shapes, a low threshold (<=0.4) of rectangular fit feature was allocated to classify woodland objects. The two features involved in the classification of pasture objects were spectral reflectance of the original aerial photograph layer (>=120) and the standard deviation value of the find-edges filter (<=48). The standard deviation value of the find-edges filter was used here because pasture objects have uniform patterns and so it will have low standard deviation values for the find-edges filter layer compared to objects of other classes. Regarding the bare soil class, since the conflicting classes such as urbanization and rivers classes are already classified, the recognition of bare soil objects was rather easy seeing that only brightness feature (>=199) was used for bare soil objects classification. Concerning the agriculture fields class, the standard deviation value of the water filter layer (<=37) was used to discriminate it from the other classes such as olives and vineyards. To distinguish between olives and vineyards classes, a sub-level layer was segmented with a smaller scale (5), higher weight to the shape criterion (0.8) and equal compactness and smoothness criteria (0.5). This layer was created in order to delineate single olive trees, which will be used to classify olives class in the upper layer.

Table 9. Different parameters and their values used for the recognition of classes in the classification process.

Parameter \ class		Woodland	Pasture	Bare Soil	Agriculture Fields	Tree Lines	Olives	Vineyards	Mixed Vine-Olives	Urbanization	Water Bodies
Segmentation Parameters	Seg_settings : Scale of Polygons	90	90	90	90	90	90	90	90	60	90
	Seg_settings : Shape Criterion (1- color)	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.7	0.2	0.7
	Seg_settings : Compactness Criterion (1-smoothness)	0.3	0.3	0.3	0.3	0.3	0.5	0.5	0.5	0.5	0.3
Classification Parameters	Brightness	<= 80		>= 199						>= 80	>= 179
	Mean original		>= 120			<= 80	<= 120				
	HSI Transformation Intensity										>= 0.85
	Standard deviation “original layer”							>= 10			
	Standard deviation “water filter”				<= 37						
	Standard deviation “find-edges filter”		<= 48					>= 48			
	Standard deviation “ink-out filter”							>= 59			
	StdDev difference to super-object original (1)							-19:-5			
	Rectangular Fit	<= 0.4									
	Contrast to neighbor pixels original (1)					<= -340					
	Rel. area of sub objects “Olives candidates”						>= 0.5				

A feature calculates the relative area of the candidate sub objects with value of >=0.5 was used to classify olives class. This mains that, if the area of the small candidate sub objects in the lower layer is more than half the area of the big object in the upper layer, this object will be classified as olives class object. As expected, vineyards class was the most difficult to be classified. This is why more features were used in the recognition of vineyards objects. The vineyards object characterized by high standard deviation due to the high contrast in the spectral signal between the vine lines and the soil in between. So, the standard deviation feature in several layers was used to classify the vineyards class such as standard deviation value of original layer (>=10), standard deviation value of find-edges filter (>=48), standard deviation value of ink-out filter (>=59) and standard deviation difference to super-objects of original layer (-19:-5). Finally, the mixed fields of olive trees and vineyards were grouped in one class named mixed vine-olives.

Based on the foregoing step, the entire objects of all aerial photographs were classified in one of the mentioned classes. To generate the final LULC map, the classified tiles were exported to a GIS environment (ArcGIS software; ESRI, 2011) in a polygon shapfile form and then went through mosaicing process to form one polygon layer with all classes (Fig. 39). Looking to the generated LULC map, few mosaicing errors can be seen. These errors could be explained by the low spectral homogeneity between the different aerial photographs, which consequently affect the classification process (Gennaretti et al., 2011). More work need to be done on this area in order to reduce the error percentage.

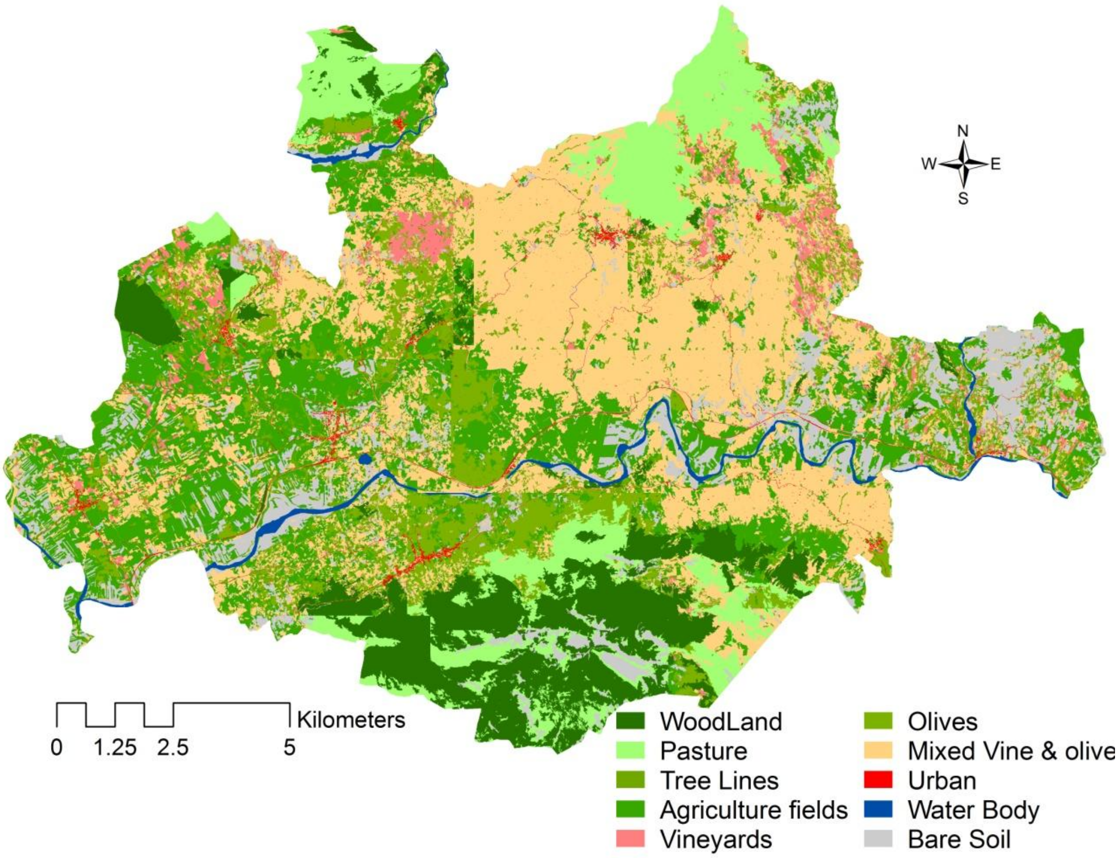

Fig. 39. The LULC map of 1954 generated with GEOBIA technique.

4.2.5. Map accuracy assessment

A classified map remains just a beautiful image until it goes through an accuracy assessment. In the real time LULC classification, usually the map validation is done through a spatial comparison between the classified point on the map and the real class in the validation point in the field. Since this study was to classify old aerial photographs, the real class validation in the field was an inappropriate method. So, stereoscopic view was used in order to validate the classification in the selected points. As proposed (in section 3.3.2.1.6), a number of 292 validation points was generated and validated. Then, the confusion matrix was developed and the different accuracy indices were calculated (Table 10). The calculated overall map accuracy is 77%. Although the overall map accuracy is below the general target of 85% (Thomlinson et al., 1999), several studies discussed classifications with overall accuracies lower than this general target and have a bigger range in the accuracy, with which the individual classes was classified (e.g., Ung et al., 2000; DeGloria et al., 2000). The producer's accuracy states how well the map producer recognized a land cover type on the map from the remote sensing imagery data. Table 10 shows that the highest producer's accuracy was for pasture class (94%) while the lowest was for the vineyards class (44%). Classes such as woodland, bare soil has high producer's accuracy more than 85%. The kappa coefficient (or kappa statistic) (Cohen, 1960), is the most frequently used statistic measure. It reflects the difference between actual agreement and the agreement expected by chance. A kappa of 0 indicates agreement equivalent to chance, whereas a kappa of 1 indicates perfect agreement (Viera & Garret, 2005). Kappa analysis for the results gave a value of 0.73 which means that there is 73% better agreement than by chance alone. This value of kappa represents a moderate to strong agreement (Congalton, 2004).

Table 10. The confusion matrix of the accuracy assessment analysis.

		Classes determined from Aerial photograph stereoscopic view											
Classes determined from GIOBIA classified map	Classes	Woodland	Pasture	Bare Soil	Agriculture Fields	Tree Lines	Olives	Vineyards	Mixed Vine-Olives	Urbanization	Water Bodies	**Totals**	Proportion area (%)	**User's Accuracy (%)**
	Woodland	22	4									26	10.94	85
	Pasture	1	30		1							32	10.10	94
	Bare Soil			17			3					20	10.26	85
	Agriculture Fields		4	4	47	1	12	1	2			71	21.34	66
	Tree Lines				1	12	2		1			16	4.07	75
	Olives	1	2			3	18					24	9.98	75
	Vineyards	1			2	1	3	7	2			16	2.79	44
	Mixed Vine-Olives		1		4	3			57			65	28.13	88
	Urbanization						3			9		12	1.21	75
	Water Bodies			4							6	10	1.17	60
	Totals	25	41	25	55	20	41	8	62	9	6	292		
Producer's Accuracy (%)		88	73	68	85	60	44	88	92	100	100	**Overall Accuracy** = 77 %		

4.2.6. Change detection comparison between old and improved "GIOBIA" LULC classifications of the year 1954

The northern part of the study area was chosen as a pilot area for extensive study for the comparison between the old LULC classification map and the improved GEOBIA classification of LULC for the year 1954. This part of the study area was chosen based of the fact that all LULC classes and also all land change types are represented in it. Also, this area of the map did not experience any of the mosaicing problems, so that it will not affect the results of the comparison. Fig. 40 shows the improved land change detection for agricultural development in total area. It shows that the agricultural area was overestimated in the old LULC map of 1954. The figure demonstrates that the total agricultural area was reduced by 6% during the first period (1954-1990) when considering the original data and only by 3% during the same period when considering the improved data (Jongman, 2004). This result shows that 50% of the detected change using the original data was misclassified compared with the improved classification of aerial photographs. Using the same approach as previously, Fig. 40 shows also a simplified development model for the total agricultural area. The objective here is not to predict or simulate the future land change, but to show the effect of improving historical data on the modeling processes taking into account that LULC change depends on a variety of factors, which can stop or start at any time. It is clear from the results in Fig. 40 that changing or improving any of the data curve points will affect the final predicted values. Following the data curve for the agricultural development using the improved data results, it is evident that the total agricultural area in 2030 will be larger than that obtained using the original data.

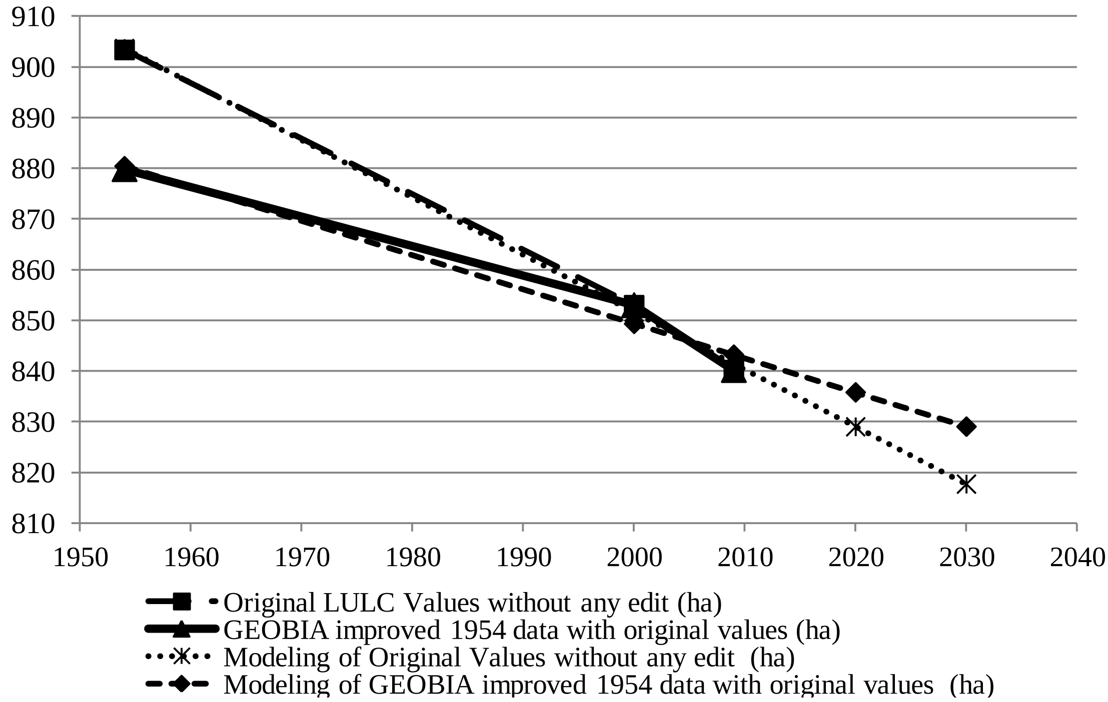

Fig. 40. Modeling of original and improved curves of total agriculture area (ha).

In the case of urban areas, using the GEOBIA technique, the new total urban area has been calculated for the year 1954. Fig. 41 shows the original and improved data curves for the total urban area. The results show that the urban area was underestimated in the old LULC map of 1954. It is clear from Fig. 41 that changing or improving any of the points along the curve will change the curve's trend and shape and consequently will affect the predicted values. This leads to an important finding of this research that modeling results are greatly correlated to the historical input data accuracy, and that changing or improving the data accuracy will improve the final modeling results (Chapman, 2005; Pipino et al., 2002; Salmons & Dubenion-Smith, 2005).

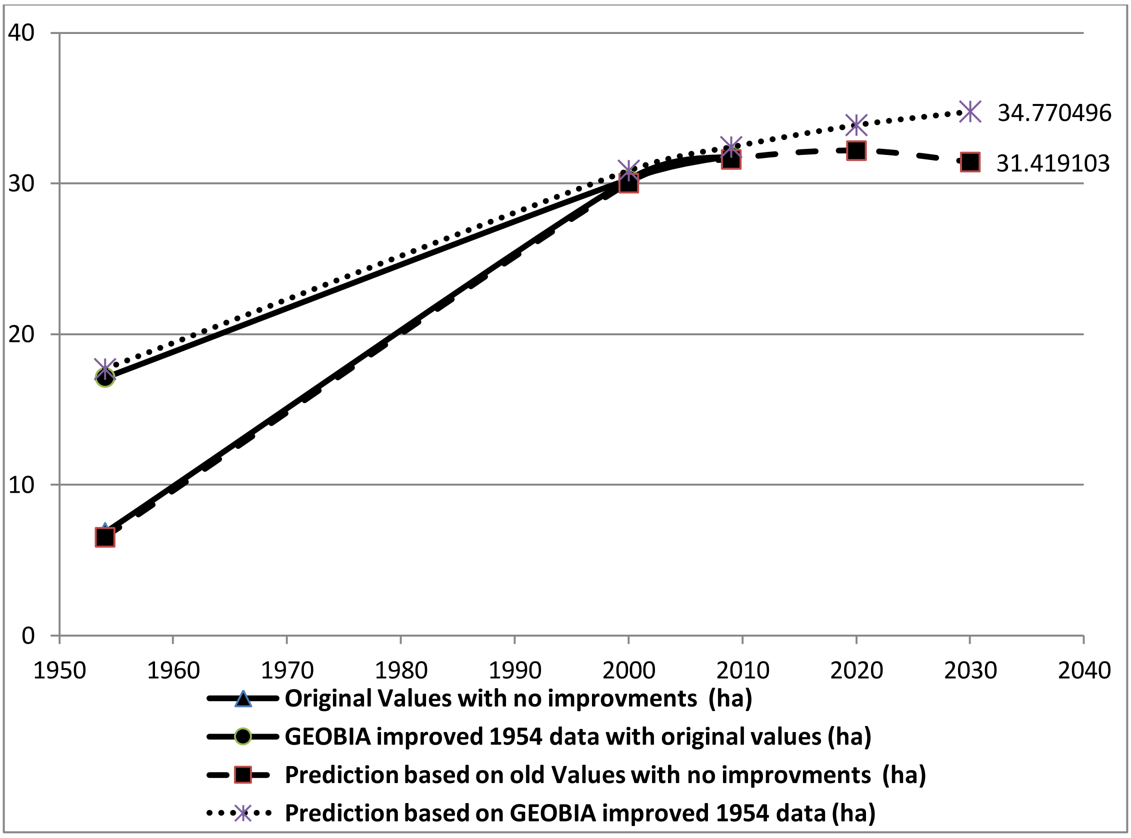

Fig. 41. Comparison of original and improved data of total urban area.

Table 11 shows the total areas in the urban, agriculture and forest classes in both the original and the improved classifications. The table shows that the total urban area was underestimated and the agricultural area was overestimated in the old classification. This reveals that the classification errors may be a result of the poor data quality. In the case of forests, the results show that the values were similar for both the original and improved classifications.

Table 11. Urban, agriculture and forest total area in both original and improved cases.

Classification type	Urban – ha	Agriculture – ha	Forest – ha
Old Classification	6,85	903,33	69,50
GEOBIA Classification	17,12	879,82	69,54

However, when considering the differences spatially (Fig. 42), it becomes clear that there are huge errors in the old classification in case of forest class. Fig. 42 shows that the GEOBIA technique was able to perfectly detect forests and woodlands from aerial photographs while the old classification polygons were wrongly placed in non-forest areas.

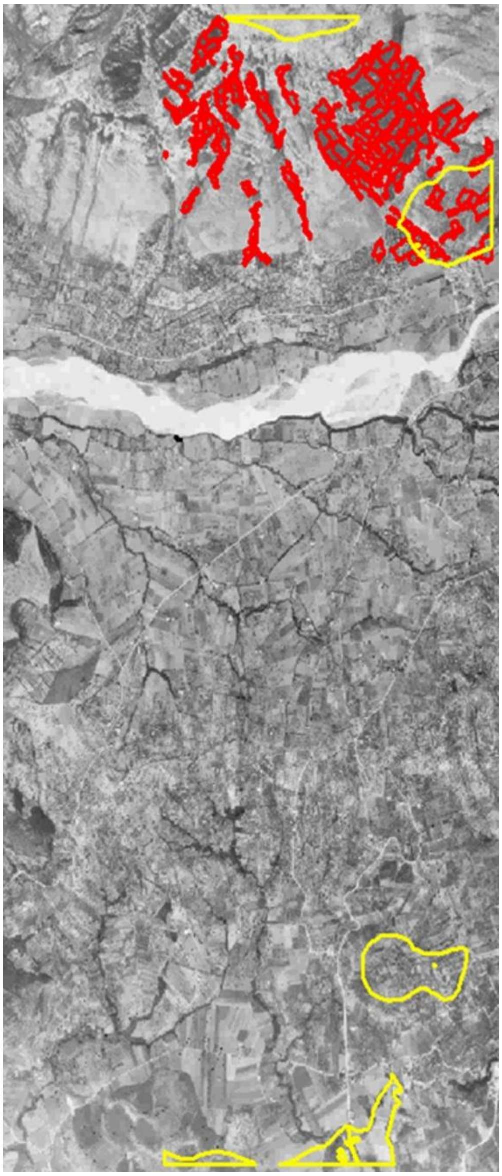

Fig. 42. Spatial distribution of forest polygons for old and GEOBIA classifications (Old classification in yellow and GEOBIA Classification in red).

The reasons behind why the original map was classified incorrectly, in particular in the forest domain, require further investigation. The political or socio-economic motivations behind the classification may have influenced the result. In line with this result, a study was carried out to compare census data versus remote sensing data (APAT, 2005), showed that the inconsistency with cartographic data was apparent. This inconsistency was attributed due to the methodology and aim of production of the two sets of data. In this study, results showed that the data from the Italian National Statistics Institute (ISTAT) show that, on a national level, there was a remarkable decrease in meadowland (-17.2%) and wooded areas (-16.9%), in the period 1990–2000. On the contrary, the remote sensing data from CORINE CLC2000 and CLC1990 showed that, at a national level in Italy, there were a decrease in areas of meadows and natural pastures (Code CLC 3.2.1.) of 2.07%, and a general increase in wooded areas (Code CLC 3.1) of 1.07%.

4.3. Modeling of soil functions loss (biomass production) by soil sealing

The reason behind attempting to improve the old classification of LULC using GEOBIA technique on aerial photographs was to enhance the land change detection, which consequentially will help to advance studying the land change impacts on the environment and this is rather important also for evaluating the effect of soil sealing on soils. Therefore, the next step was to study the effect of urbanization or soil sealing as one of the most important land changes on the soil functions (Wilcke et al., 1998; 1999; Ge et al., 2000; De Kimpe & Morel, 2000; Kaminski & Landsberger, 2000). Biomass production was chosen in this study as one of the lost soil functions by the effect of soil sealing actions. A land suitability analysis for wheat production was done to evaluate the appropriateness of the study area for growing wheat. This was followed by modeling of wheat productivity based on production statistical data of wheat, which was provided by ISTAT (ISTAT, 2012). Finally the productivity map of the study area was developed. In depth presentation of the results will be demonstrated in the next paragraphs.

4.3.1. Spatial distribution of soil properties

Before starting the suitability analysis, a spatial distribution for the soil parameters was done. In order to develop a land suitability index, some criterions need to be prepared typically from soil parameters (Mustafa et al., 2011). Different soil parameters of all the study area land units, which were used for generating soil properties variability maps are present in Appendix IV. These maps were used later to generate the land suitability map for wheat production. The important soil parameters are discussed here beneath.

4.3.1.1. Calcium carbonate ($CaCO_3$)

High concentrations of calcium carbonate ($CaCO_3$) in the soil affect directly and indirectly the plant growth. It reduces the availability of some soil nutrients because of the increase in soil pH (Helyar & Anderson, 1974). That is why it is very important to take into account the $CaCO_3$ concentrations in the soil while evaluating land suitability for agriculture crops. The spatial variability of $CaCO_3$ in soils of the study area is given in Fig. 43. The spatial analysis shows that high concentrations of $CaCO_3$ can be found in correspondence with the actual river flood plain. This can be explained by the high concentrations of $CaCO_3$ in the river water which accumulate in soils of the rivers valleys (Bonfante et al., 2011). Generally speaking, the study area has low to moderate concentrations of $CaCO_3$ except for soils close to rivers beds.

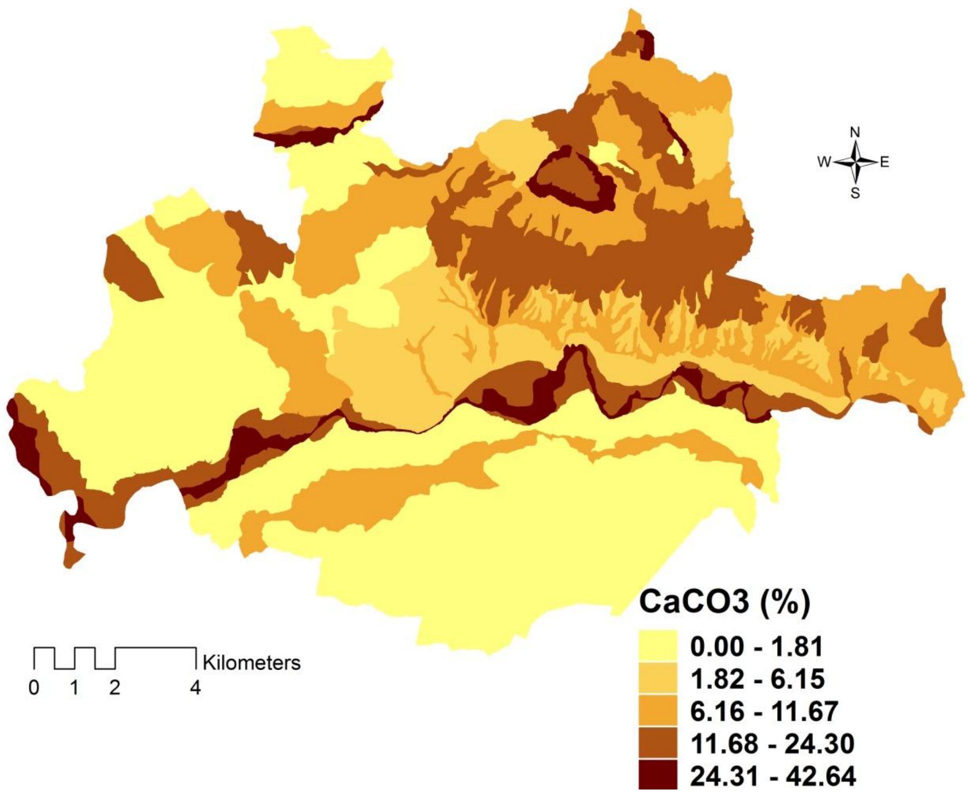

Fig. 43. Spatial variability representation of $CaCO_3$ (%) concentrations in the study area.

4.3.1.2. Soil Organic carbon (OC)

Soil organic carbon (OC) is representation of the soil organic matter (OM) as high concentrations of organic carbon is an indication of high concentrations of organic matter (Jimenez & Garcia, 1992). It helps to improve soil structure and drainage by inducing soil aggregation (Six et al., 2002). Secondly, nutrients and elements can be adsorbed by the organic matter exchange complexes and this may prevent leaching or losing these elements to the ground water and it works as reservoir of plant nutrients. Finally, organic matter is also an important source of nutrients when it decomposes (Six et al., 1999). In the study area, high concentrations of OC exist in southern, northern and northern eastern parts while the rest of the study area has low OC concentrations (Fig. 44). Land units with high OC concentrations generally correspond to woodlands and forests in the study area.

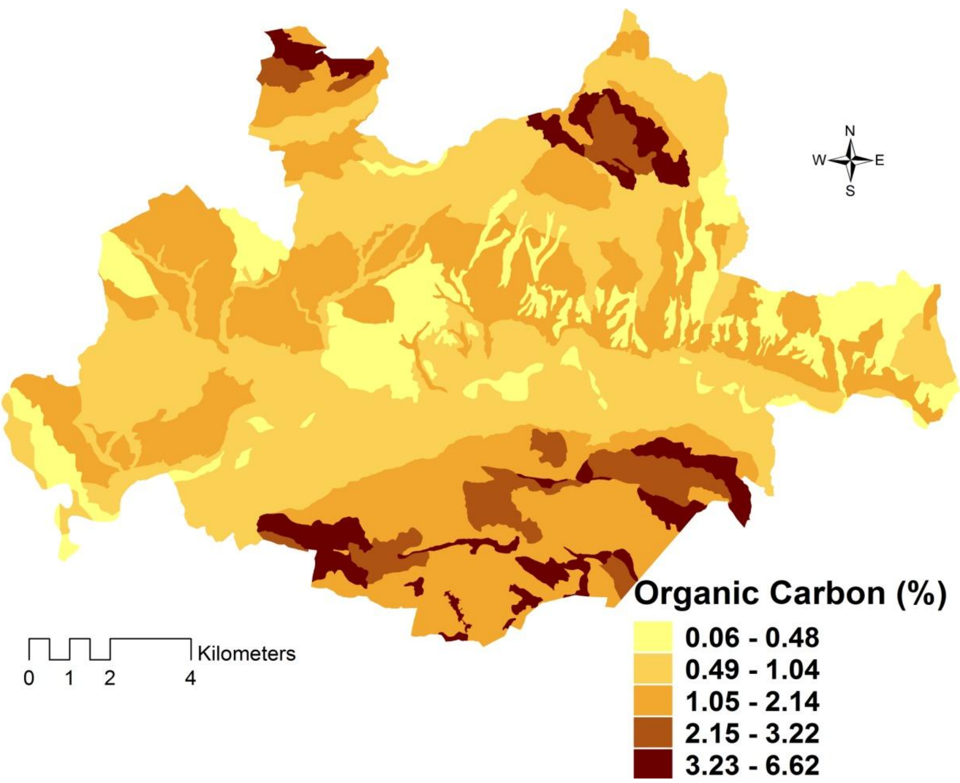

Fig. 44. Spatial variability representation of soil organic carbon (%) concentrations in the study area.

4.3.1.3. Soil reaction (pH)

Soil pH is very important factor in soil suitability evaluation for agriculture development as it affects the solubility and thus the availability of nutrition elements in the soil (Rabia, 2012c). In the study area the maximum pH was 8.6 while the minimum was 6.4 (Fig. 45). The spatial analysis shows that the soil tends to be more sub-alkaline in the Middle Eastern part of the study area while only the Southern part is acidic and the rest of the study area is close to neutral pH.

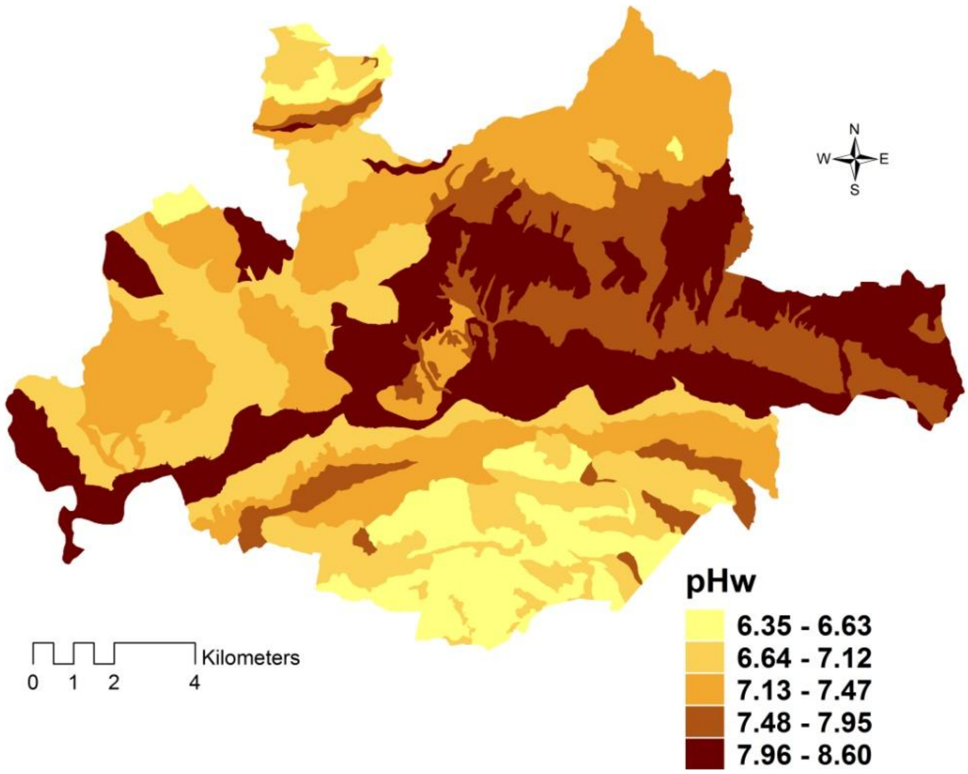

Fig. 45. Spatial variability representation of soil pH_w in the study area.

4.3.1.4. Soil Texture

Texture of the soil is one of the key parameters of soil. Soil texture class designates most of the physical characteristics of the soil (Bardgett, 2005). In the study area almost all texture classes appeared. In Fig. 46, the spatial variability of the soil texture ratings can be found. The ratings are based on wheat's soil texture preference.

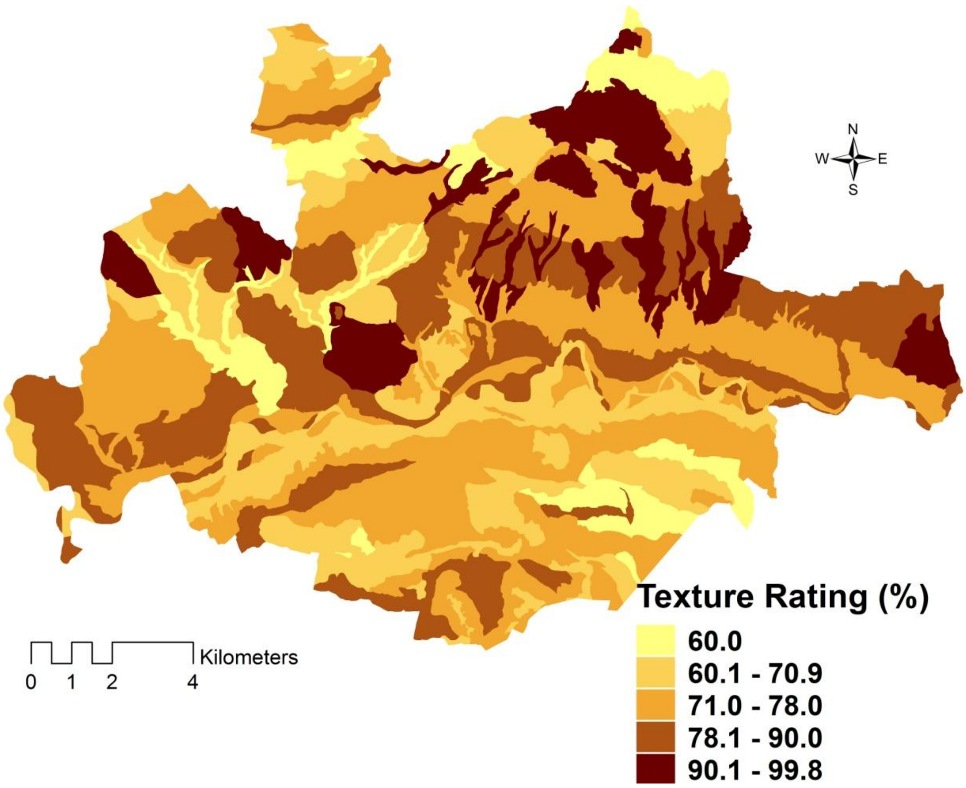

Fig. 46. Spatial variability representation of soil texture ratings in the study area.

4.3.1.5. Maximum soil depth

Soil depth is a sign of the available depth for plant roots. This factor is strongly correlated to the plant under investigation as it determines if the soil is suitable for this plant roots or not. Fig. 47 shows the spatial distribution of the soil maximum profile depth. The soil depth in the study area ranged between 25 cm up to more than 170 cm. The shallow soil depth can be explained usually due to the existence of bedrocks close to the surface (Rabia et al., 2013b).

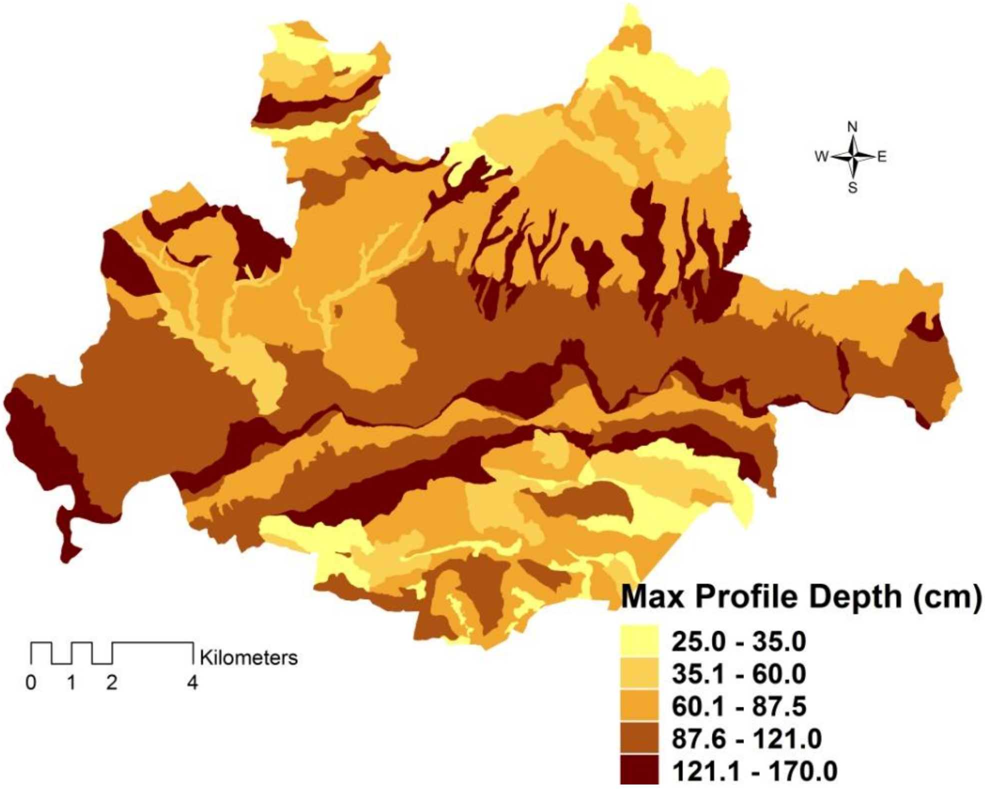

Fig. 47. Spatial variability representation of soil's maximum profile in the study area.

4.3.1.6. Soil Drainage

Soil drainage is a function of many factors such as soil texture, organic matter content, soil depth and ground water level (Bardgett, 2005). Consequently, the soil drainage situation is an important factor affecting the land suitability for agriculture crops (Zhang et al., 2004). In the study area, low drainage class was found in eastern and northern eastern parts of the study area (Fig. 48). These land units are also characterized by shallow profile depth, which may explain the low drainage characteristics.

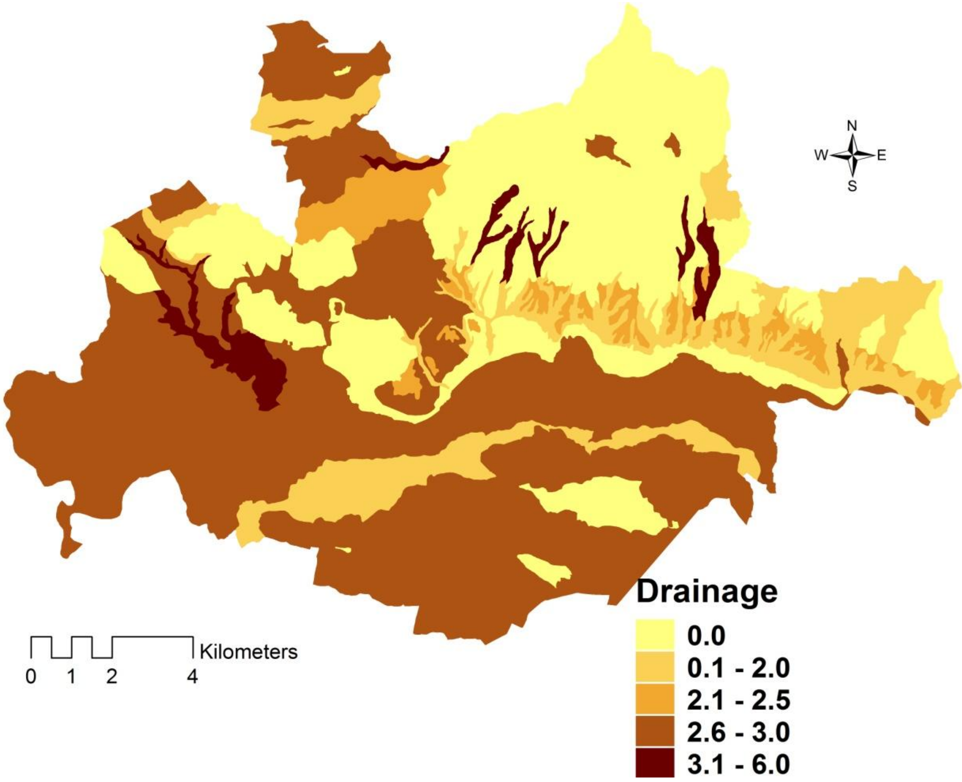

Fig. 48. Spatial variability representation of soil drainage classes in the study area.

4.3.1.7. Soil Electrical conductivity (EC)

Electrical conductivity (EC) indicates the capacity of a substance to conduct electrical current. It is directly linked to the concentration of salts dissolved in the soil water, and consequently to the Total Dissolved Solids (TDS) (Rabia, 2012d). These salts dissolve into negatively and positively charged ions, and both conduct the electricity in the solution. High EC value implies that the soil is salt affected, which consequentially affect plant growth (Moukhtar & El-Hakim, 2004). Spatial variability of the EC values in the study area (Fig. 49) shows that generally most of land units in the study area are salt free except for few land units in the middle of the study area.

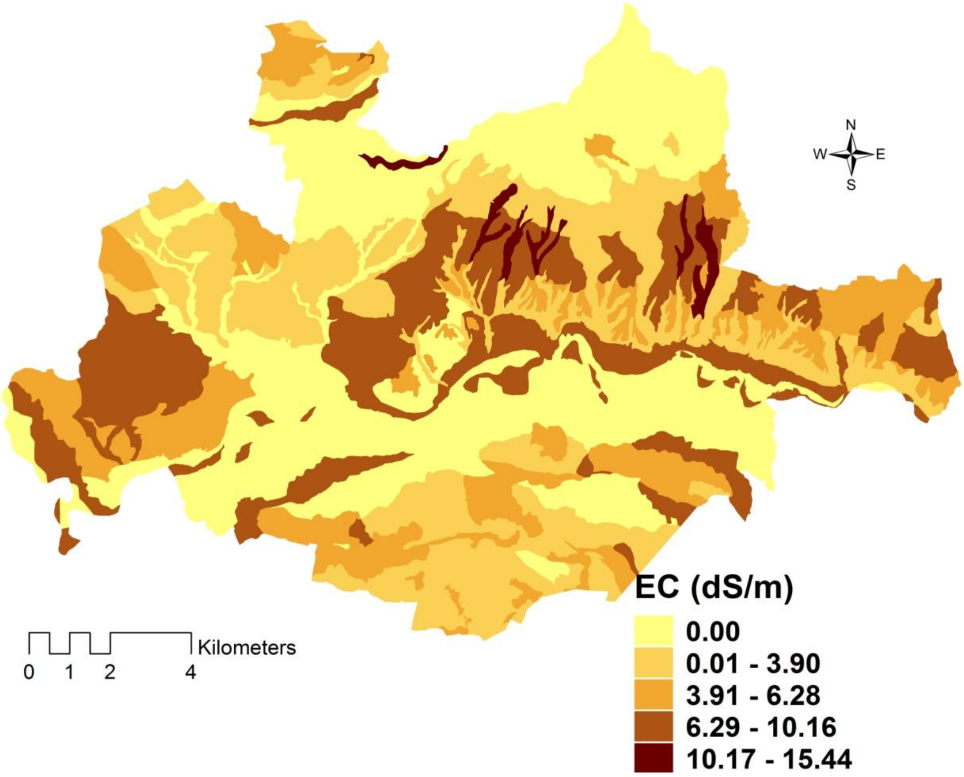

Fig. 49. Spatial variability representation of soil EC (dS m^{-1}) concentrations in the study area.

4.3.1.8. Surface Slope

Slope is a demonstration of the topography of a land unit. Surface slope is one of the key elements for land suitability analysis for agriculture crops. As land units with high slope (more than 30 degrees), is not suitable for agriculture uses (Mokarram et al., 2010). Surface slope in the study area varies between flat surfaces with 0° slope up to very steep surfaces with more than 30° slope (Fig. 50). These land units with steep slopes subsequently are not suitable for wheat production.

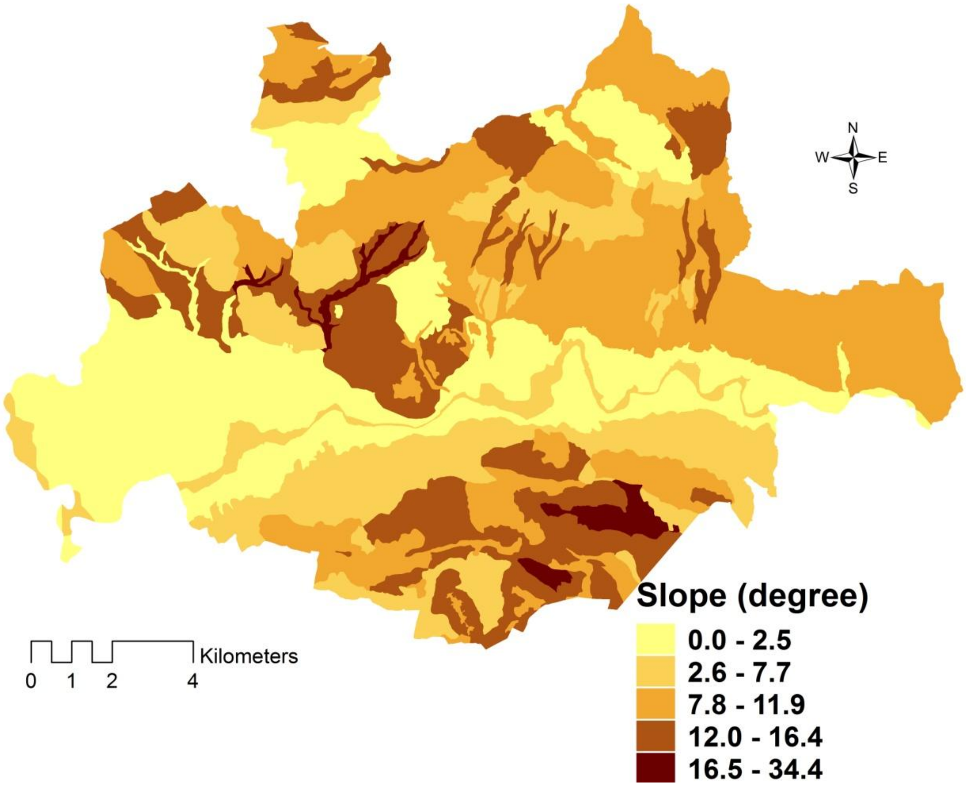

Fig. 50. Spatial variability representation of surface slope in the study area.

4.3.1.9. Altitude

Altitude factor is a depiction for the climatic situation of the land unit. As the altitude will give an idea on the temperature and also wind frequency. This is important since some agriculture crops are not suitable on high altitudes and some others are not suitable on low altitudes due to temperature obstructions (Oram, 1989). In the study area, the altitude ranges between 38 m up to almost 1200 m above sea level (Fig. 51). This huge difference gives an indication of the climatic differences between the land units in low and high altitudes. For wheat plant growth, high altitudes are not preferable. Therefore land units with high altitudes are most likely to be unsuitable for wheat plantation (Cao & Moss, 1989).

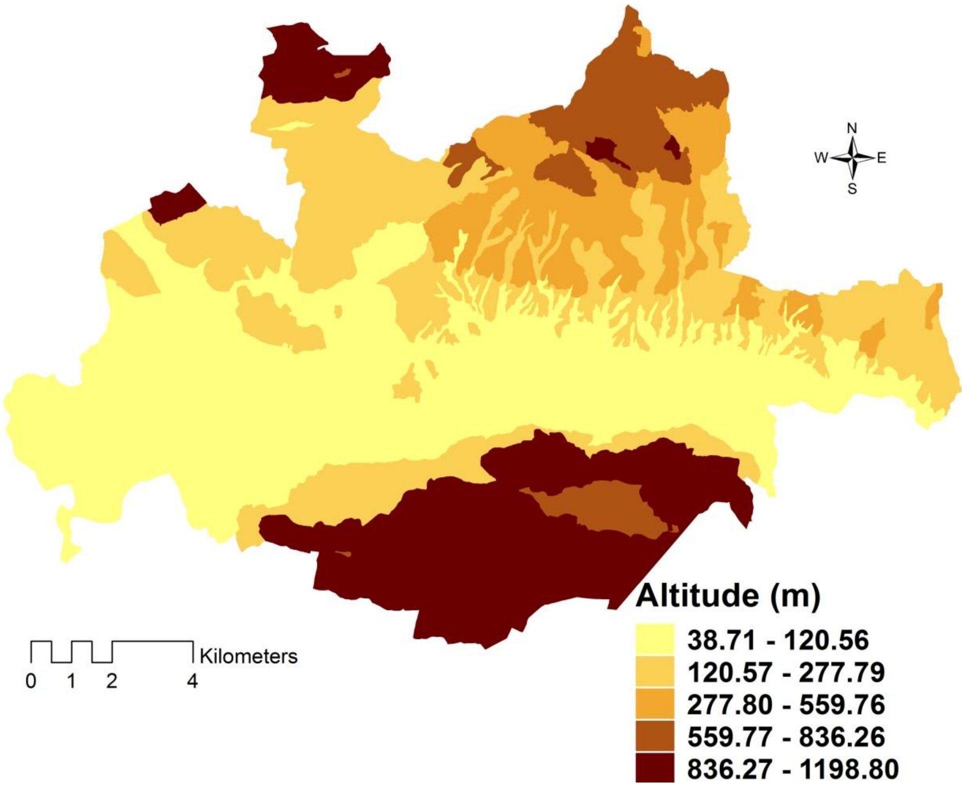

Fig. 51. Spatial variability representation of land units' altitude in the study area.

4.3.2. Land suitability analysis for wheat production

Based on the previously discussed soil parameters, land suitability analysis for wheat production has been conducted. Table 12 shows land suitability index values and the corresponding classes that were obtained by the three parametric equations; Storie, Square root and Rabia (Equations 7, 8 and 9). The table only shows the first 12 land units and the other parts of the table were omitted for ease of data display. The full record of the suitability index values and corresponding classes for all the land units in the study area can be found in Appendix V. In all the land units of the study area, land suitability index was higher in case of Rabia method than the Storie and Square root methods. It was also observed that the suitability index of Square root method was always higher than that of Storie method (Vargahan et al., 2011). Correlation analysis revealed a high correlation between all the three methods (more than 0.95 in all cases).

Regarding land suitability classes, it was clear from results that classes that have been acquired by Rabia method were larger to that of Storie and Square root methods, which had similar classes for the same land unit (e.g. units 1, 2, 3, 4, 5, 9 and 10). The situation was different in units 6 and 7, where the classification results were different in all the three methods. Also, in units 8 and 11 the land suitability classes were the same in both Square root and Rabia methods. In few cases, like in unit 12, the three methods have produced the same land suitability classification although the suitability index is higher in Rabia method than Square root and the later is higher than Storie methods (Khordebin and Landi, 2011).

Table 12. Land suitability index and corresponding class for the three parametric methods (Storie, Square root, Rabia)*.

Unit	Storie Method		Square Root Method		Rabia Method	
	Suitability Index	Suitability class	Suitability Index	Suitability class	Suitability Index	Suitability class
1	13.32	N1	23.09	N1	36.50	S3
2	28.81	S3	41.58	S3	53.68	S2
3	11.10	N1	21.07	N1	33.32	S3
4	29.75	S3	42.25	S3	54.55	S2
5	11.39	N1	21.34	N1	33.75	S3
6	6.53	N2	16.16	N1	25.55	S3
7	7.51	N2	17.33	N1	25.27	S3
8	35.47	S3	53.27	S2	54.91	S2
9	4.69	N2	9.69	N2	19.98	N1
10	14.00	N1	23.67	N1	34.50	S3
11	22.64	N1	36.86	S3	47.59	S3
12	28.63	S3	41.45	S3	49.33	S3

*Only a subset of land units. The full set can be found in Appendix V.

Probably, this can be explained from the observation that in Storie equation the controlling factor, represented with “A” simple in Equation 7, is directly affected by the other factors in the equation as a result of the multiplication process (Sys et al., 1991). While in Square root equation, the limiting factor theory is applied. This limiting factor is the one that has the minimum rating in all factors affecting suitability, represented with “R_{min}” simple in Equation 8, without regarding its weight or impact on the suitability of a certain land use. This may lead, in some cases, that the factor with the minimum rating may also have a minimum weight. This possibly leads to a misleading results indicating unreal situation. On the other hand, in the proposed Equation “Rabia method”, the controlling factor is the one that has highest weight or impact on the land suitability index value, represented by

"W_{max}" simple in Equation 9. In this way, the final suitability index value was based principally on the factor that has the maximum influence on land use suitability but also with regard to the other factors. So, in Rabia equation, the value of suitability index in addition to the suitability class should be more representative of the real situation, which makes this equation superior to the Storie and Square root equations (Rabia & Terribile, 2013a).

Table 13 shows the total area for suitability classes in the three parametric methods. The dominant class with largest area in Storie method is class N2 followed by class N1. While in both Square root and Rabia methods, the leading classes were S3 followed by N2. Conversely, the lowest class area was the association between N1/N2 in both Storie and square root methods and the association between S2/N2 in Rabia method. Results showed that applying Rabia method gave less unsuitable classes and more suitable classes in terms of total area.

Table 13. Total area of land suitability classes for wheat growth using the three parametric methods (Storie, Square root, Rabia).

Suitability Class	Class Area (ha)		
	Storie	Square Root	Rabia
S1	0	0	0
S1/S2	0	0	0
S2	0	803.32	1300.27
S3	2098.66	5563.58	7346.59
S2/S3	0	877.28	2032.03
S2/N1	0	579.12	0
S2/N2	0	0	504.17
S3/N1	2619.79	1597.58	1222.09
S3/N2	1226.00	1004.43	523.71
N1	4981.80	4180.68	2324.84
N2	8699.36	4996.17	4872.17
N1/N2	500.26	523.71	0
Total Area	20125.87	20125.87	20125.87

Figs. 52, 53 and 54 shows land suitability maps of the three parametric methods (Storie, square root and Rabia). It illustrates the spatial distribution of suitability classes over the study area. It can be noticed from the land suitability maps that the northern and southern parts are generally unsuitable for wheat production in all the three parametric methods. This can be attributed to the high altitude in these land units (i.e. as proposed in section 4.3.1.9).

Regarding the land suitability classes of Storie method (Fig. 52), only few land units were suitable for wheat production (i.e. approximately 11% of the study area). This could be due to the fact that Storie equation is just a simple multiplication of all the factors ratings involved in the analysis. This requires that all the factors ratings are above zero or higher to classify the land unit as suitable for wheat production (Mustafa et al., 2011). Since this is not the case in most of the land units in the study area, that is why Storie method gave lower classification in all land units as compared to the other two parametric methods (Ashraf et al., 2010). In case of square root method, more land units (i.e. approximately 36% of the study area) were evaluated as suitable for wheat production (Fig. 53). However, in case of Rabia method, the total area of suitable land units for wheat production was approximately 53% of the study area (Fig. 54). On the other hand, data analysis has stated that the limiting factors for wheat production in the study area are soil organic matter content, Topology and pH (Rezaei et al., 2010; Mustafa et al., 2011)

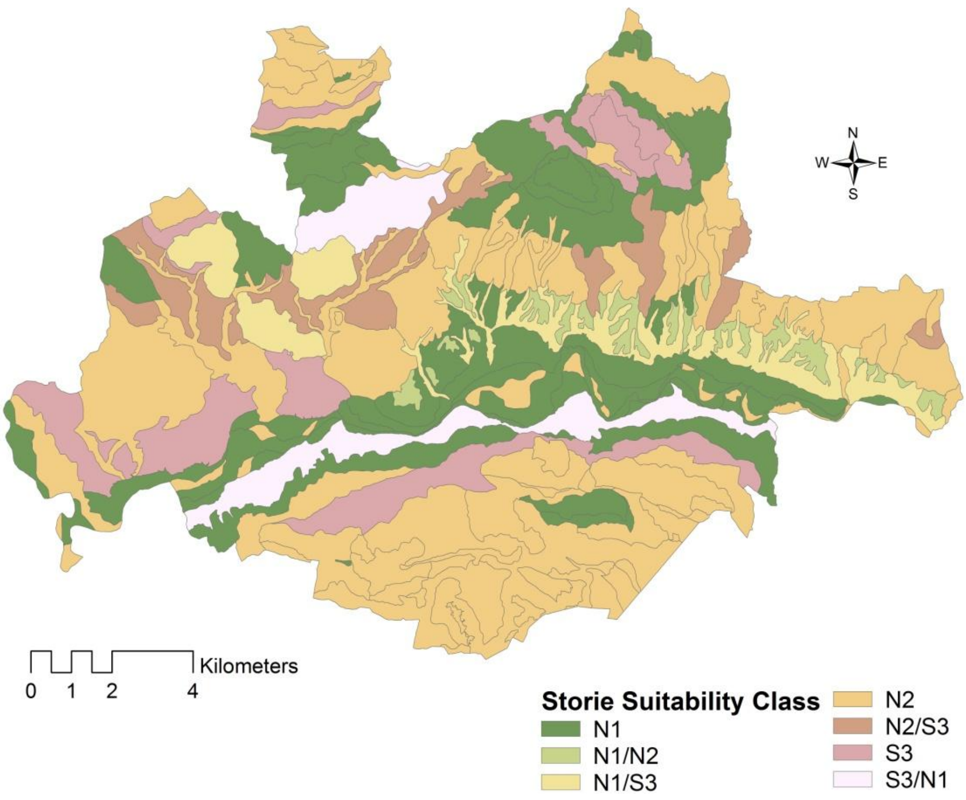

Fig. 52. Land suitability map for wheat production produced by Storie method.

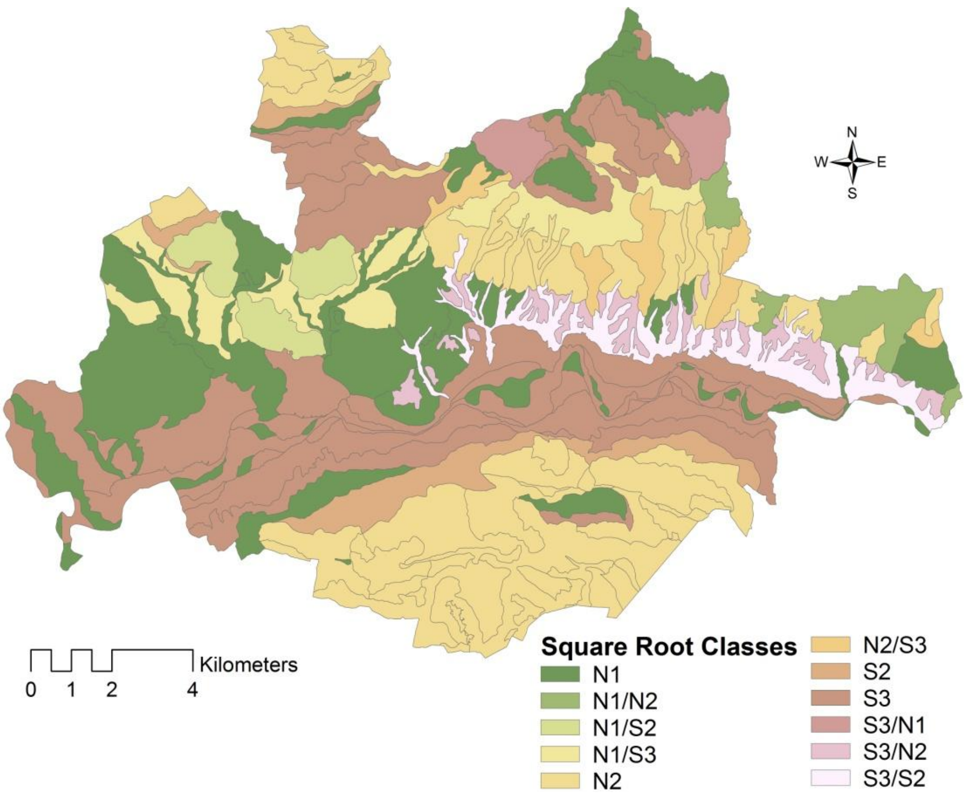

Fig. 53. Land suitability map for wheat production produced by square root method.

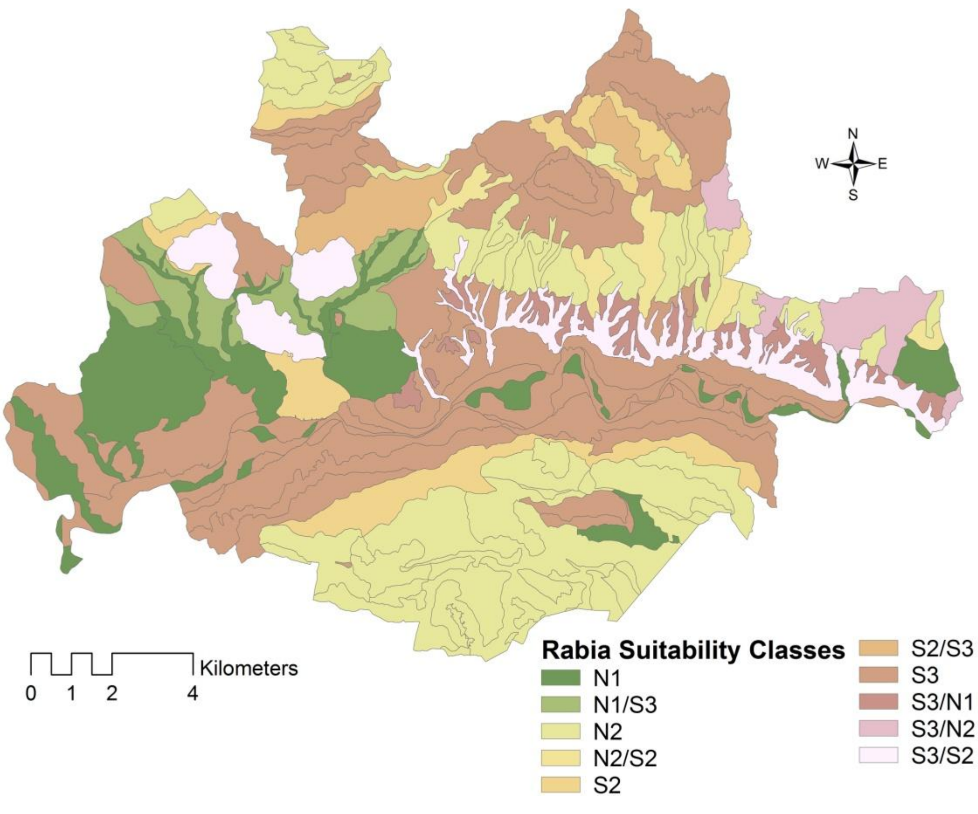

Fig. 54. Land suitability map for wheat production produced by Rabia method.

4.3.3. Evaluation of biomass production loss

Once the land suitability analysis was completed and suitability maps were developed, it was possible to move to the next step, which is modeling the biomass production loss as a soil function lost by soil sealing. As proposed (in section 3.3.3.2), the ISTAT database was used to extract the wheat productivity rates (Table 7), which was used later to generate the wheat productivity map (Fig. 55). In order to facilitate data display, only the results of land suitability analysis based on Rabia method was used to generate final wheat productivity map. Wheat productivity rates in the study area ranged between zero productions (i.e. in case of permanently unsuitable land units) and 3.93 metric tons ha^{-1} (i.e. in case of moderately suitable land units). The spatial analysis shows that the northern and southern parts of the study area give zero productivity of wheat. In these areas the limitation for wheat production is the high altitude, which is an indicator of unfavorable weather conditions (Cao & Moss, 1989). Also there are a few land units in the middle part of the study area with zero production, but in this case, the high soil pH (alkaline) values are the limiting factor for wheat production (Mustafa et al., 2011). Most of the study area gives high potential wheat productivity over of 3 metric tons per hectare except for some land units in the western part of the study area, where the potential wheat productivity is almost 2 metric tons per hectare. The land units in the western part have low wheat productivity since they suffer from high electrical conductivity (EC) and low total carbon content, which reduces the wheat growth rates. In general, it is possible to say that the study area is highly productive in terms of wheat production. So, in case it happened that all the study area has been cultivated with wheat, the total potential wheat production will be 53,323.39 Metric tons per year. For sure, this number is just the expected wheat productivity through the modeling process and it does not represent the real situation in the study area.

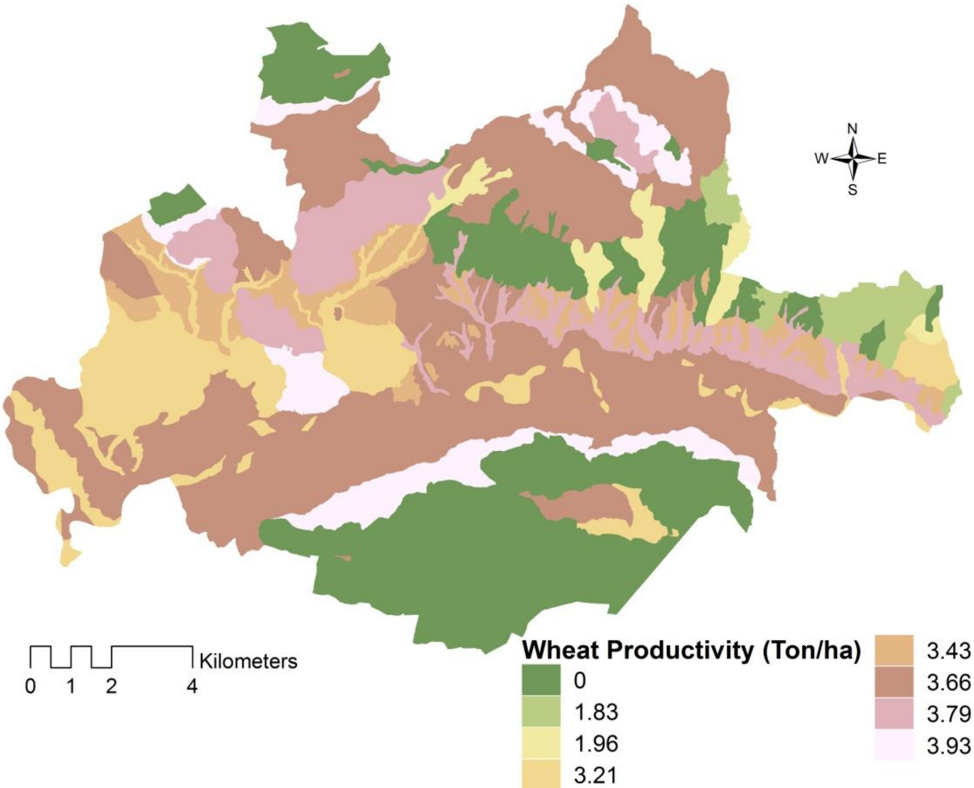

Fig. 55. Wheat productivity map in metric tons per hectare as a biomass production index for the study area.

In order to study the lost biomass production by soil sealing in the study area, the soil sealing maps of 1954, 1990, 2000, 2009 and 2011 was overlaid on the wheat productivity map (Fig. 55) and then intersection processes was done to calculate the lost biomass production by soil sealing over time. A summary of the final results of the lost biomass production and the corresponding sealed soil can be found in Fig. 56. It is clear from the results that biomass production losses increased significantly and progressively over time. The biomass production loss increased more than 7 folds from approximately 790 metric tons in 1954 up to 5797 metric tons in 2011. Regarding the total area sealed by urbanization activities, the area of soil sealing also increased more than 7 folds from 1954 to 2011. This gives an indication about the high correlation (0.99) between the soil sealing inverts and the biomass production decrease with almost equal rate.

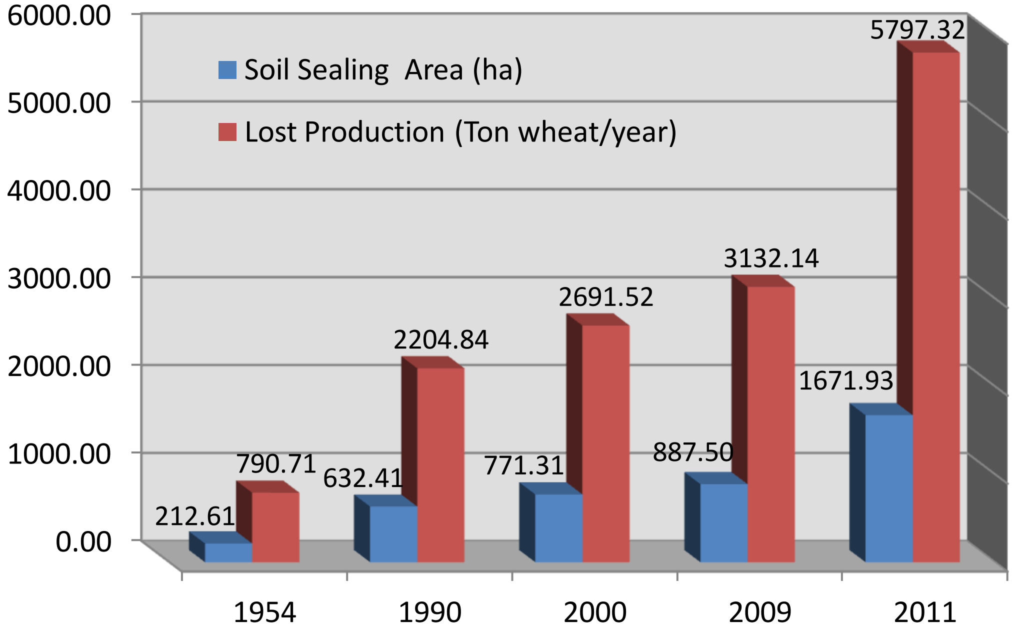

Fig. 56. Total lost biomass production by soil sealing in Telesina Valley (Metric Tons wheat/ year) during the period 1954 to 2011.

Summary and Conclusions

5. Summary and Conclusions

Land use and land cover change analysis is now a mature area of study but it is still important to monitor these changes and their subsequent impacts on ecosystem functions. The rate of Land use and land cover change is much larger than ever recorded previously, with quick changes to ecosystems taking place at local to global scales. The functions of an ecosystem can be significantly impacted by changes in land use and land cover, which in turn critically affect the provision, regulation and supporting services of the ecosystem. Therefore, land use land cover change interventions and strategic planning can contribute to the health and sustainability of an ecosystem and its land use in the future. In order to make appropriate land cover and land use decisions, accurate assessments of change are needed. The health and sustainability of an ecosystem is critically connected to land use and land covers interventions and Strategic planning. Precise estimations of Land use and land cover change are needed in order to identify crucial zones of environmental vulnerability or those which provide valuable ecosystem services. Given that land change detection is greatly dependent on the accuracy of the historical input data, improving historical data accuracy is likely to improve the final land change detection result. In an ecosystem, there is need to establish the quantity and quality of resources and their suitability for a certain range of land uses in order to assure its future productivity and sustainability of biodiversity. Land suitability evaluation is an important process for assessing the value and proficiency of the land and helps in planning for future sustainability of land resources. Accurate assessment methods give better results and consequently facilitate establishment of improved management plans.

Soil presents a large number of functions that are essential for human life. In addition to providing biomass, food and raw materials, soil performs also various services such as being a habitat host and a gene pool. The soil also has the functions of processing, filtering and storage in addition to cultural and social functions. Therefore, the soil plays a key role in regulating natural and socio-economic processes that are necessary for human survival, as the water cycle and climate system. One of the most critical threats to the soils and, in general, the ecosystem, is soil sealing. Soil sealing is the result of new roads, buildings and parking places but also other private and public space, and it involves covering of the soil surface with impermeable materials such as stone and concrete. Urbanization and soil sealing are still growing rapidly, even more than the population growth rate in some cases. Due to this hasty soil sealing process, more fertile soils are being sealed and getting out of the agriculture and food production systems. That is why the soil scientific community as well as the environmental scientists should give more attention to soil losses and try to face this problem.

Based on the foregoing, a study was conducted to evaluation the losses in soil functions due to soil sealing actions. The work was divided into three major objectives. The first objective was to perform long term detection for land use and land cover change for the period from 1954 to 2009 in order to understand the history, rates and trends of the soil sealing in the study area. Then, the second objective was to develop a novel method for automatic LULC classification of the 1954 aerial photographs using geographic object based image analysis (GEOBIA) technique. The reason behind this objective is the assumption that improving the quality of the classification for old land use and land cover maps will improve the final results of the change detection analysis. Consequently, the quantification of the lost biomass production by soil sealing will be improved. Finally, the third objective, was to carry out a modeling of soil function loss by soil sealing to quantify the losses in one of the soil functions i.e., biomass production. The study area was chosen in Telesina Valley (Valle Telesina), located in Benevento in the Campania region of central Italy.

To fulfill the first objective, four maps of land use and land cover (LULC) were obtained for Telesina Valley from the years 1954, 1990, 2000 and 2009. Land use and land cover change analysis was performed using the four maps and finally three change maps were created. Land use changes were defined and classified as the changes in a land use class that occurred in a given area and time. These classes identify the typology of changes by assigning a land use change code to each intersection created by the overlay of successive land use maps, allowing a thematic representation of the spatial distribution of changes. The results showed that, in the first time period from 1954 to 1990, only thirteen change types have been found while the change types stabilization and degradation didn’t appear in this interval.

In contrast, in the second time period from 1990 to 2000, only nine change types appeared in the study area while six change types were absent. The missing change types in this time period are stabilization, degradation, exceptionality, agriculture intensification, abandonment and agriculture extensive conversion. This shows that during the time period from 1990 to 2000 there was only slight LULC change as urban intensification whilst the rest of the study area were represented by persistence change types such as agriculture persistence, forest persistence, persistence and urban persistence. This is likely to be related to the fact that the compared LULC maps in this case are the corine LULC maps for the years 1990 and 2000 which have exactly the same legends, unlike the other maps which have different legends. Finally, in the third time period from 2000 to 2009, all fifteen change types were present with large afforestation and deforestation activities. The study focused on three important land changes types, deforestation, agriculture development and urbanization. The results demonstrated that the forest area has increased in the last fifty years although that the deforestation process was greater than afforestation in the last thirty years. On the contrary, Agriculture area has decreased greatly in the same period. The total agricultural area reduced by 6% during the first period (1954-1990), 1% during the second period (1990-2000) and 3.5% during the third period (2000-2009). Approximately 1200 hectares of agricultural land have been lost during the period from 1954 to 2009.On the other hand; urbanization had a progressive trend during the last five decades. The urban area increased more than four times during this time period (1954-2009). It can be concluded that urbanization in the study area is an ongoing problem that requires active management strategies for controlling the quantity and the direction of the sprawl in the future. These data revealed one of the problems occurring in the region, i.e. soil sealing and soil loss due to urbanization.

Regarding the second objective of the study, using the object-oriented eCognition software, the LULC of the study area for the year 1954 was reclassified using aerial photographs and GEOBIA technique. It was possible to extract land cover data from the aerial photographs using different features such as the tone, brightness, border contrast, roundness and many other features available in the software. Then, the idea was to compare the original 1954 map with the reclassified LULC map to determine whether the reclassified map will improve land change estimates. The results showed that, visually overlapping the different filters on the original gray scale image in a Red-Green-Blue composition (RGB) augmented the vision quality of the images and consequently the capabilities of classifiers. The multi-resolution segmentation algorithm was selected as the main segmentation algorithm through the entire classification process. Regarding the scale parameter, a scale of 90 has been chosen as the optimal scale for all the segmentation processes except for the urbanization class, which was 60. Similarly, the weight assigned to the shape criterion was 0.7 in all the segmentation processes except for the urbanization class, which was assigned weight of 0.2. On the other hand, for the compactness criterion, the suitable weight was 0.3 in most of the classes except for the classes Olives, Vineyards, Mixed Olives-Vineyards and urbanization for which the weight 0.5 was more suitable. Ten land use and land cover classes were recognized during the classification progression which are urban, water bodies, tree lines, woodland, pasture, bare soil, agriculture fields, olives, vineyards and mixed vine-olives. Different features and values were used for the recognition of classes during the classification process. To generate the final LULC map, the classified tiles were exported to a GIS environment in a polygon shapfile form and then went through mosaicing process to form one polygon layer with all classes. The calculated overall map accuracy is 77% with a kappa value of 0.73 which are both within ranges of fair accuracy. The producer’s accuracy states how well the map producer recognized a land cover type on the map from the remote sensing imagery data. Results show that the highest producer’s accuracy was for pasture class (94%) while the lowest was for the vineyards class (44%). Comparing the old and the improved (GEOBIA) maps of LULC shows that, regarding the agricultural area, 50% of the detected change using the original data was misclassified compared with the improved classification of aerial photographs. The results revealed that the urban area was underestimated in the old LULC map of 1954. This leads to an important finding of this research that modeling results are greatly correlated to the historical input data accuracy, and that changing or improving the data accuracy will improve the final modeling results.

The reason behind attempting to improve the old classification of LULC using GEOBIA technique on aerial photographs was to enhance the land change detection, which consequentially will help to advance studying the land change impacts on the environment and this is rather important also for evaluating the effect of soil sealing on soils. Finally, regarding the third study objective, a novel methodology was proposed consists of different sequential stages starting with data collection arriving to a quantification of the biomass production loss by soil sealing. The methodology is mainly based on conducting a land suitability evaluation for wheat production. Then, using the wheat production statistic averages from statistical reports, it is possible to assign a production rate for different suitability classes and generate a land productivity map for wheat. Wheat crop is used here as a standard international land productivity measure and a reference crop for land productivity evaluation. However, any other crop is suitable for the proposed method. Next, using the generated land productivity map along with soil sealing map (i.e. map of urbanization in the study area) it is possible to quantify the lost biomass production due to soil sealing. A new parametric concept “equation” of land suitability evaluation was proposed to improve results of land suitability evaluation. Land suitability assessment for wheat production was conducted in order to compare results of the suggest method with classical parametric methods. Organic matter, CaCO3, pH, Slope, texture, drainage, depth, EC and altitude were recognized as factors affecting land suitability for wheat production in the study area. Comparing results of the three parametric methods (Storie, Square root, Rabia) used showed that the proposed equation gave higher suitability index values than classical methods. Great correlation has been found between results of the three methods. Organic matter, topology and pH were found to be the limiting factors for wheat production in the study area. Generally, the proposed equation may improve land suitability assessment process and gives better realistic results. Results showed that in all the land units in the study area, land suitability index was higher in case of Rabia method. However, correlation analysis exposed a high correlation between all the three methods. This can be explained that, the value of final suitability index of the equation was based principally on the factor that has the maximum influence on land use suitability with regard to the other factors. So, in Rabia equation, the value of suitability index in addition to the suitability class is likely to be more representative of the real situation, which makes this equation superior to the Storie and Square root equations. Regarding the land suitability classes of Storie method, only few land units were suitable for wheat production (i.e. approximately 11% of the study area). In case of square root method, more land units (i.e. approximately 36% of the study area) were evaluated as suitable for wheat production. However, in case of Rabia method, the total area of suitable land units for wheat production was approximately 53% of the study area. It is clear from the results that biomass production losses increased significantly and progressively over time. The biomass production loss increased more than 7 folds from approximately 790 metric tons in 1954 up to 5797 metric tons in 2011. Regarding the total area sealed by urbanization activities, the area of soil sealing also increased more than 7 folds from 1954 to 2011. This gives an indication about the high correlation (0.99) between the soil sealing inverts and the biomass production decrease with almost equal rate.

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APPENDICES

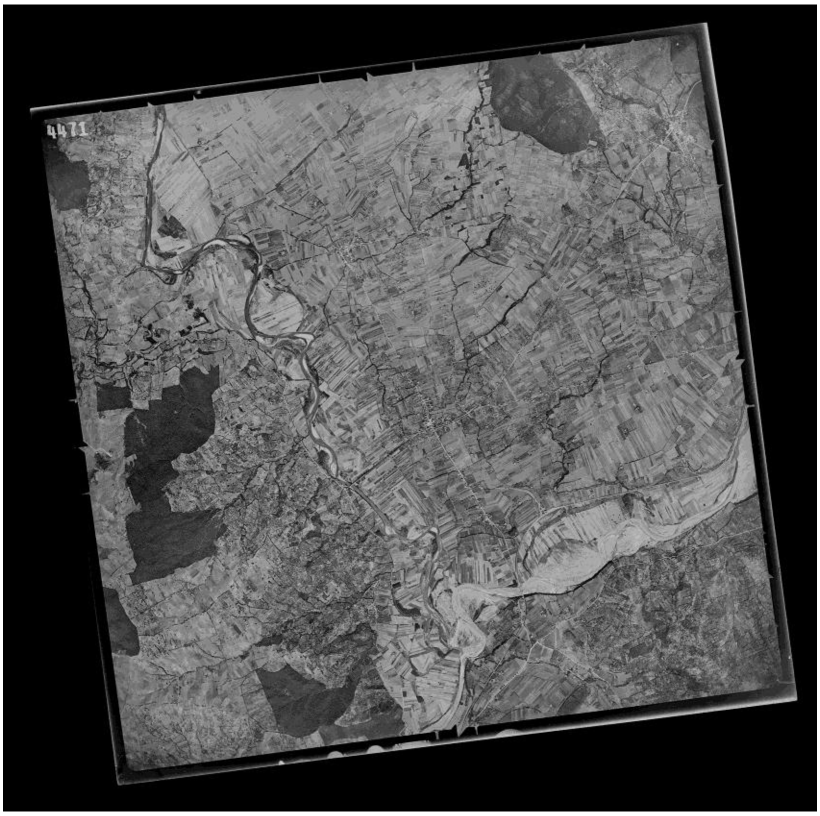
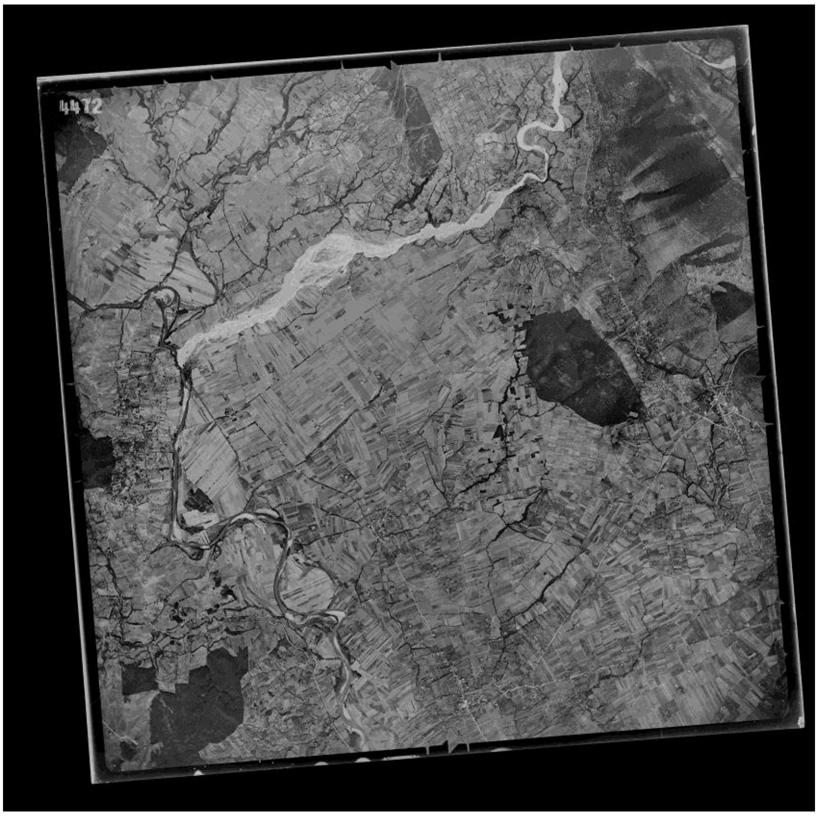
APPENDIX I

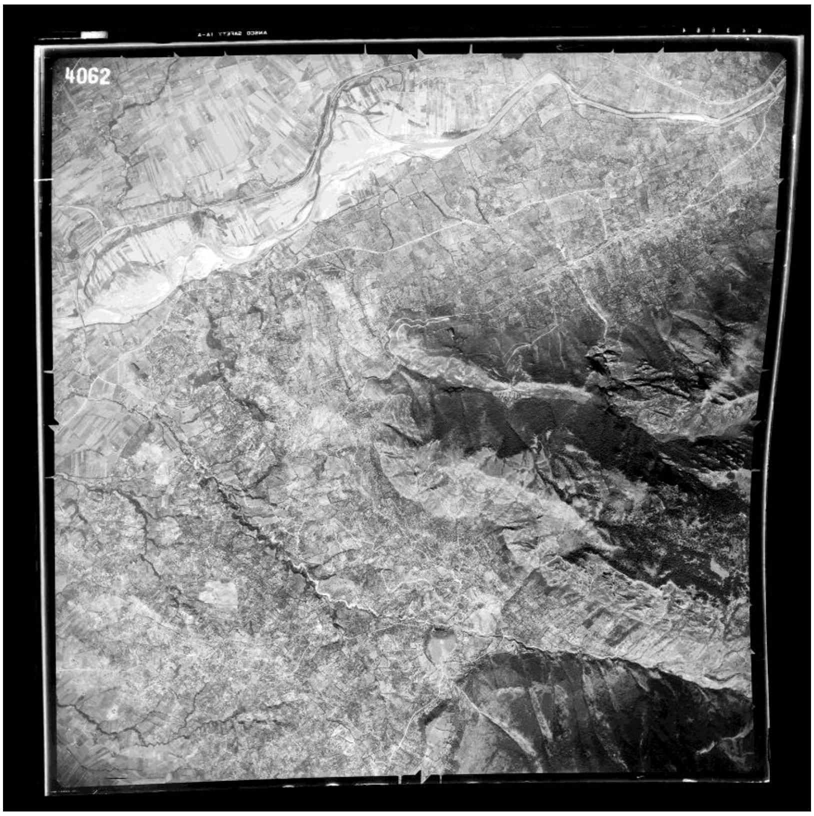
Land systems and sub-systems of study area and the associated soil classes

Land Systems	Land Sub-Systems	Soil Code	Italian Soil Name	USDA Soil Name
Collina preappenninica	Collina preappenninica (CAP)	COC1/SIM1	Associazione dei suoli Colle Calce, Simeone	Typic Ustorthents and Typic Calciustepts
		COC1/SIM1	Associazione dei suoli Colle Calce, Simeone	Typic Ustorthents and Typic Calciustepts
		PTR1/LAR1	Associazione dei suoli Petrara, La Rocca	Typic Calciustolls and Lithic Haplustands
		PTR1/SER1	Associazione dei suoli Petrara, Serrone	Typic Calciustolls and Lthic Haplustepts
		VIV1	Consociazione dei suoli Vigne Vecchie	Vertic Calciustepts
	Glacis d'erosione (GLA)	CAN1	Consociazione dei suoli Candro	Typic Calciustepts
		CAS1/LAM1	Associazione dei suoli Castellone, La Madonnella	Vertic Haplustepts and Typic Ustorthents
		CES1/TOI1	Associazione dei suoli Cese, Torrente Ianare	Typic Ustorthents and Typic Calciustepts
		COD1	Consociazione dei suoli Coste del Duca	Vitrandic Calciustolls
		MAM1	Consociazione dei suoli Masseria Marcatelli	Typic Calciustepts
		MAP1/MAV1	Associazione dei suoli Masseria Puglia, Masseria Venditti	Vitrandic Haplustolls and Typic Calciustolls
		PEN1	Consociazione dei suoli Pennine	Typic Calciustolls
Montagna appenninica	Montagna appenninica (MAP)	CAM1	Consociazione dei suoli Canale di Marco	Typic Haprendolls
		CMP1	Consociazione dei suoli Campo	Typic Melanudands
		CPS1/MOR1	Associazione dei suoli Camposauro, Monte Rosa	Typic Melanudands and Lithic Hapludands
		FAR1	Consociazione dei suoli Farciola	Aquic Eutrudepts
		FOM1	Consociazione dei suoli Fontana Marcolino	Typic Hapludolls
		FOM1/FSS1	Associazione dei suoli Fontana Marcolino, Fosse	Typic Hapludolls and Alfic Hapludands
		LMP1	Consociazione dei suoli Lampazzuoli	Typic Melanudands
		MOR1/SES1	Associazione dei suoli Monte Rosa, Sette Serre	Lithic Hapludands and Typic Hapludands
		MOR2	Consociazione dei suoli Monte Rosa, molto ripidi	Lithic Hapludands
		SAZ1	Consociazione dei suoli Sazzarana	Alfic Hapludands
		SEG1	Consociazione dei suoli Serra La Giumenta	Vitrandic Hapludolls
		SER1/ZEP1	Associazione dei suoli Serrone, Zeppetella	Lithic Haplustepts and Typic Calciustepts
		SES1	Consociazione dei suoli Sette Serre	Typic Hapludands
		TOR1	Consociazione dei suoli Torre di Rienzo	Typic Hapludands

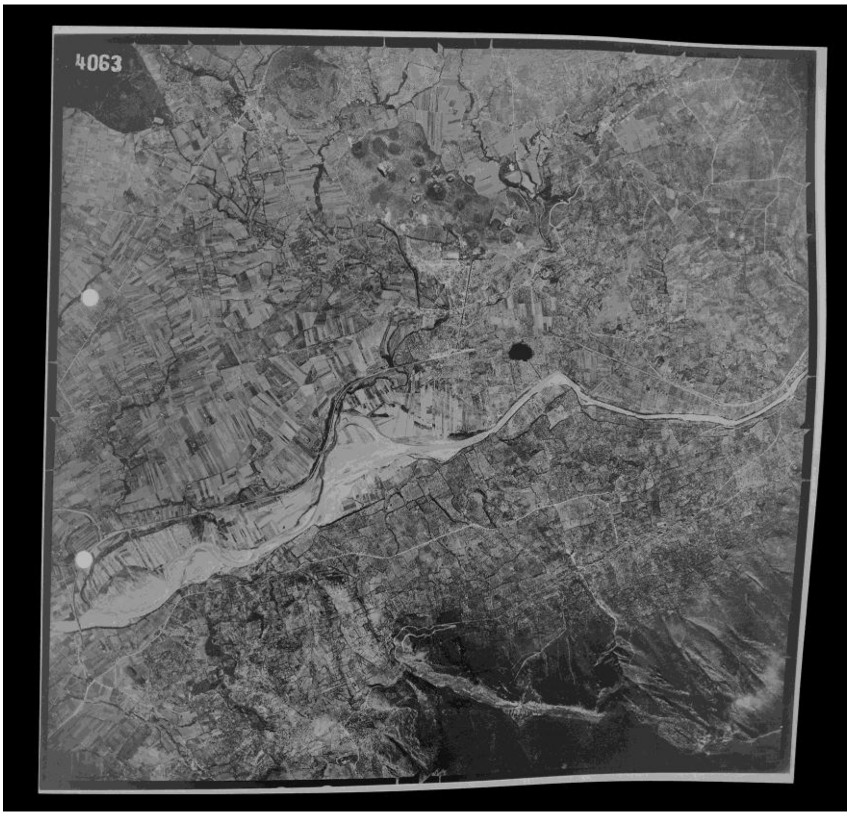
		VAO1	Consociazione dei suoli Valle Oscura	Typic Hapludands
Pianura intermontana	Superfici di aggradazione a genesi complessa (AGG)	ADD1	Consociazione dei suoli Addone	Humic Ustivitrands
		CAP1	Consociazione dei suoli Campo del Pero	Typic Ustivitrands
		LAT1	Consociazione dei suoli Lago di Telese	Typic Calciustolls
		MAG1	Consociazione dei suoli Masseria la Grotta	Vitrandic Haplustolls
		MAG1/PET1	Associazione dei suoli Masseria la Grotta, Pera Tonda	Vitrandic Haplustolls and Humic Haplustands
		PEL1	Consociazione dei suoli Pezza del Lago	Typic Vitraquands
		PET1	Consociazione dei suoli Pera Tonda	Humic Haplustands
		SPE1	Consociazione dei suoli Sperazzo	Humic Ustivitrands
	Pianura alluvionale (PAL)	CAL1	Consociazione dei suoli Calore	Typic Ustifluvents
		POC1	Consociazione dei suoli Ponte Cavallo	Fluventic Haplustepts
		SLR1	Consociazione dei suoli Sotto la Ripa	Fluventic Haplustepts
		TIT1	Consociazione dei suoli Titerno	Typic Ustifluvents
	Fascia di raccordo alluvio-colluviale (RAC)	CER1	Consociazione dei suoli Cerzillo	Alfic Haplustands
		CRU1/IMP1	Associazione dei suoli Crugliano, Impiano	Vitrandic Haplustalfs and Typic Calciustepts
		PEZ1	Consociazione dei suoli Pezzalonga	Alfic Udivitrands
		SOL1	Consociazione dei suoli Solopaca	Typic Haplustands
	Terrazzi alluvionali antichi (TET)	BOC1	Consociazione dei suoli Bosco Caldaia	Typic Calciustepts
		CDA1/MON1	Associazione dei suoli Codacchio, Monaci	Typic Haplustepts and Typic Haplustepts
		LAC1/TOV1	Associazione dei suoli La Cerasa, Toppo Verciunni	Typic Haplustolls and Typic Ustorthents
		PAO1	Consociazione dei suoli Padulo dell'Oro	Vitrandic Calciustolls
		TAS1	Consociazione dei suoli Taverna Starze	Typic Calciustolls

APPENDIX II
Aerial photographs of the study area

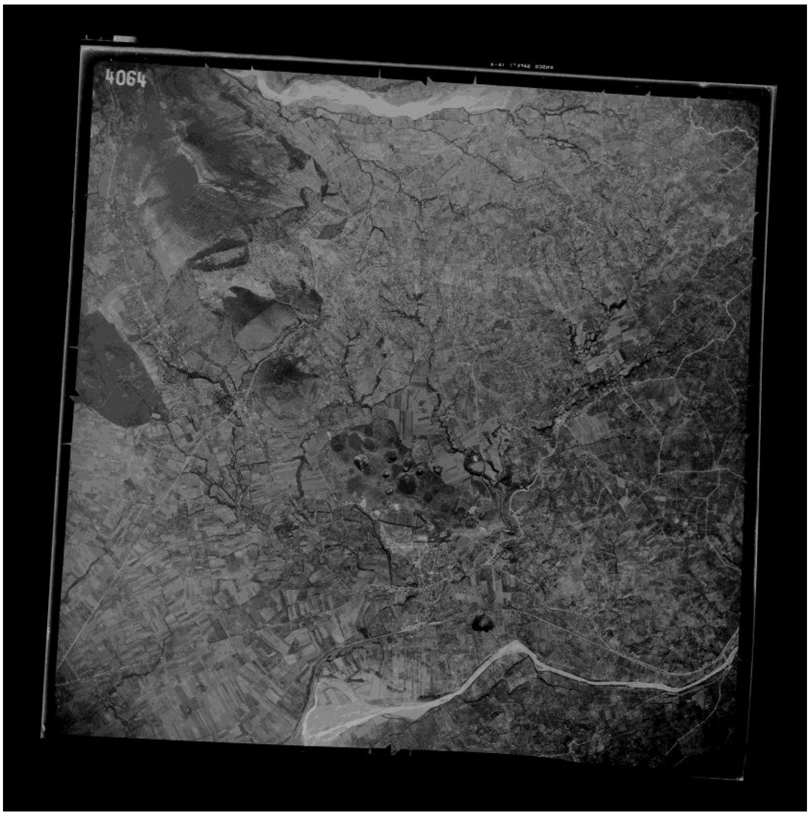
Photo ID	Aerial Photograph
Flight line 116 – Photo No. 4471	
Flight line 116 – Photo No. 4472	



Flight line 117_A – Photo No. 4062



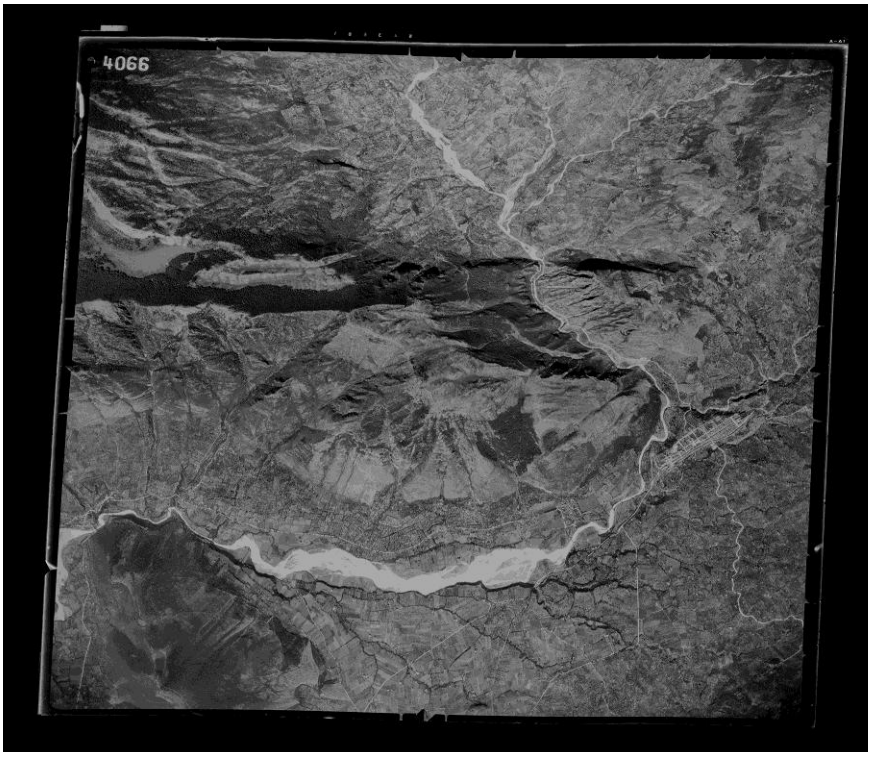
Flight line 117_A – Photo No. 4063



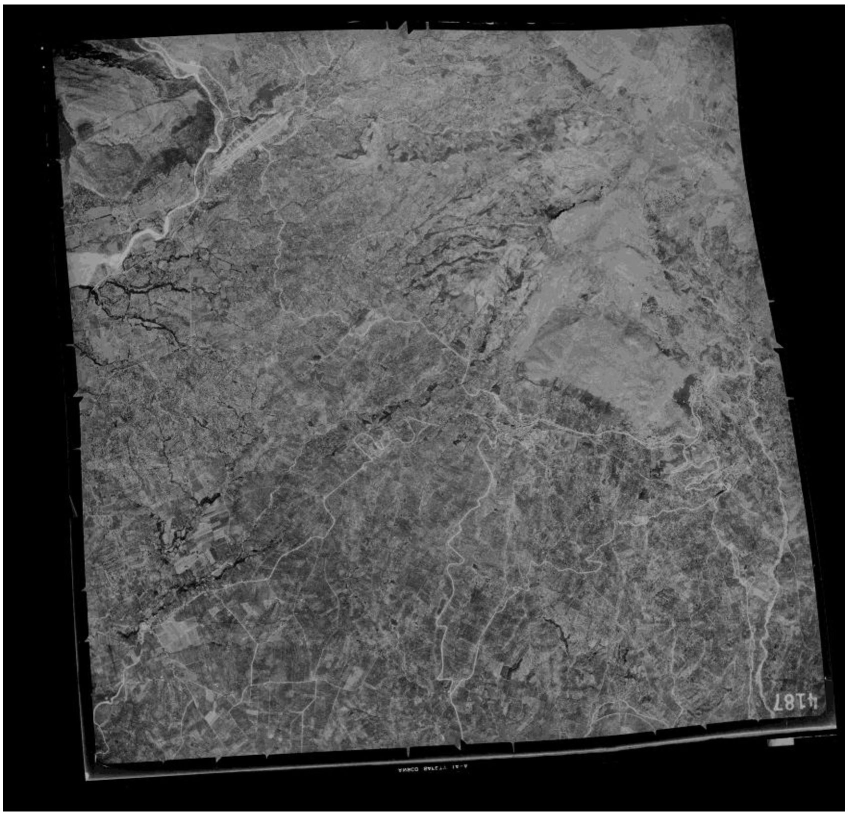
Flight line 117_A – Photo No. 4064

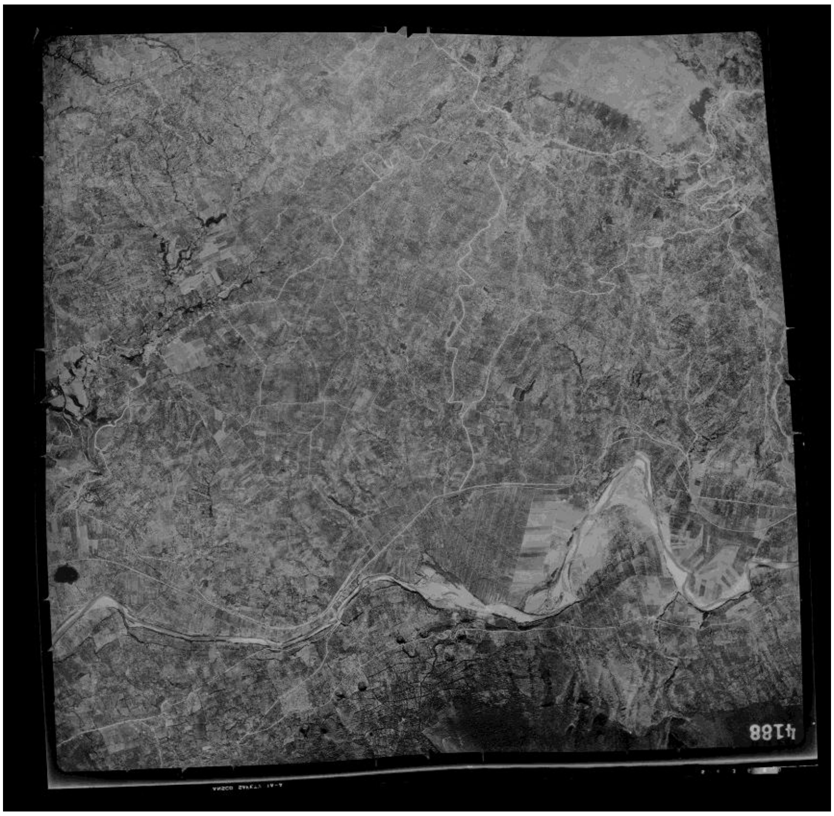
Flight line 117_A – Photo No. 4065

Flight line 117_A – Photo No. 4066

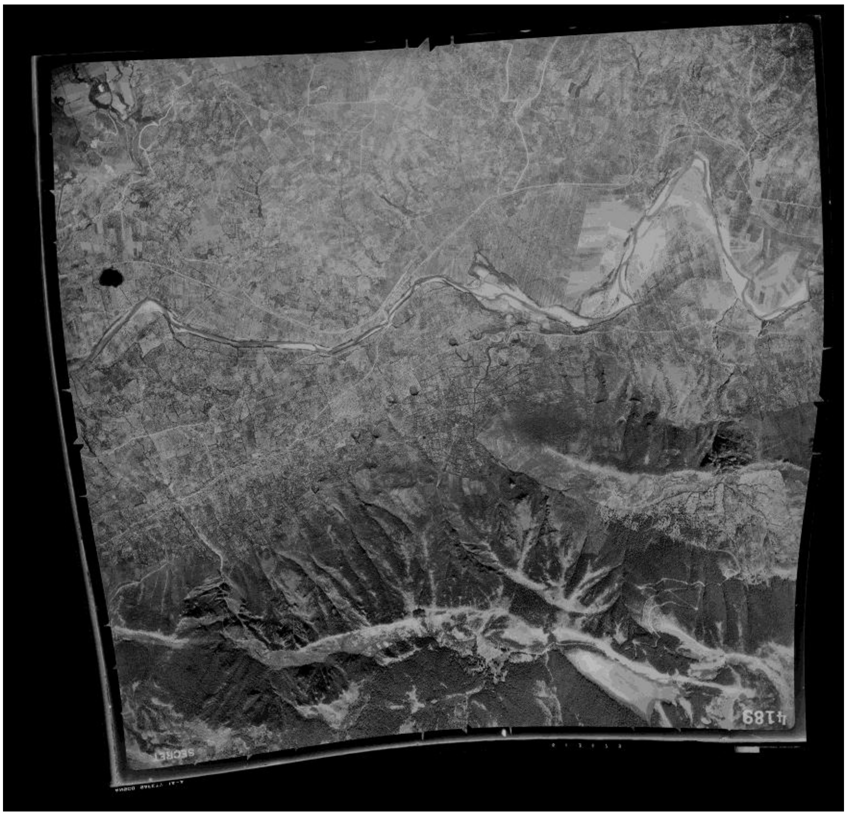


Flight line 118 – Photo No. 4187

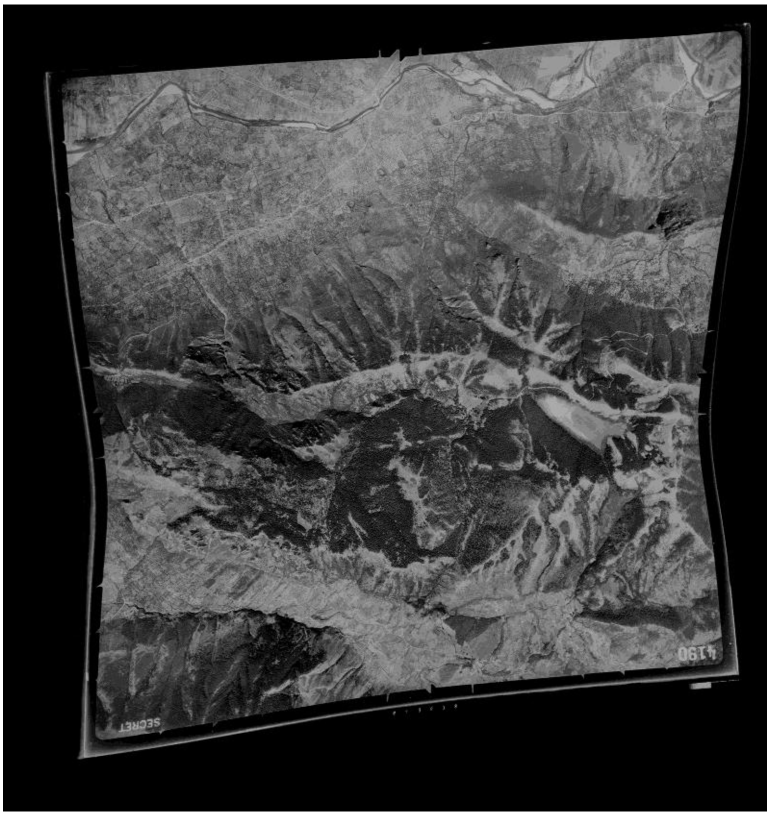




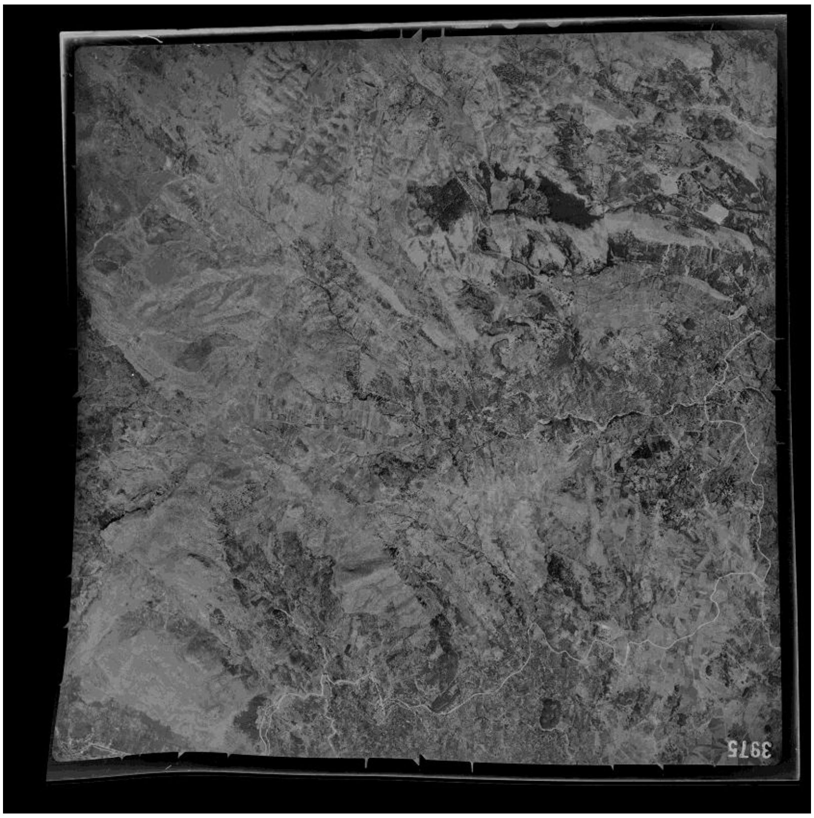
Flight line 118 – Photo No. 4188



Flight line 118 – Photo No. 4189

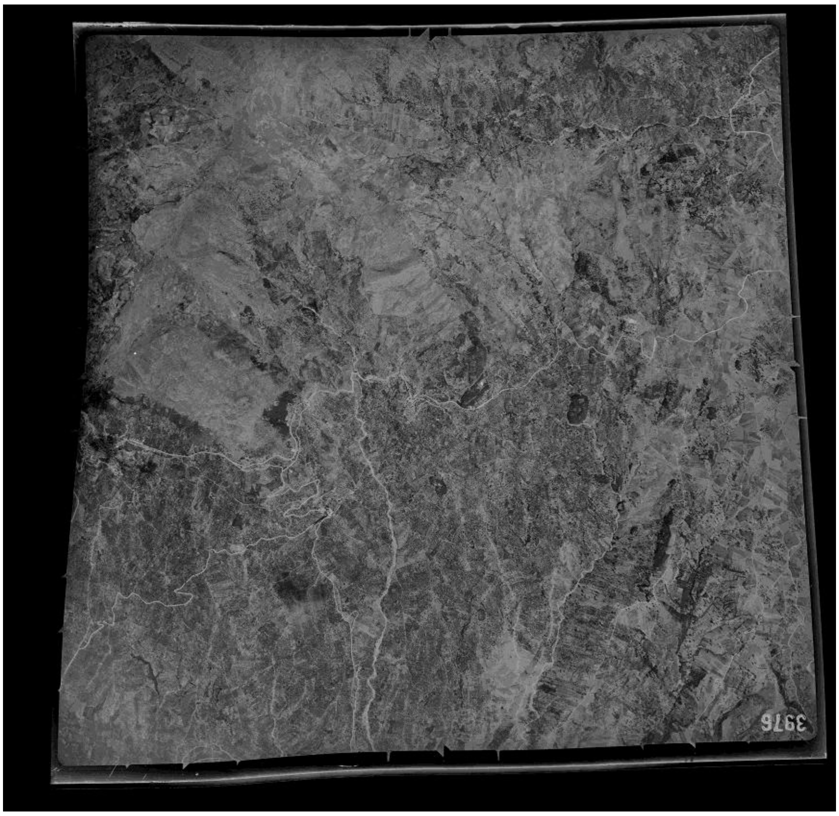


Flight line 118 – Photo No. 4190

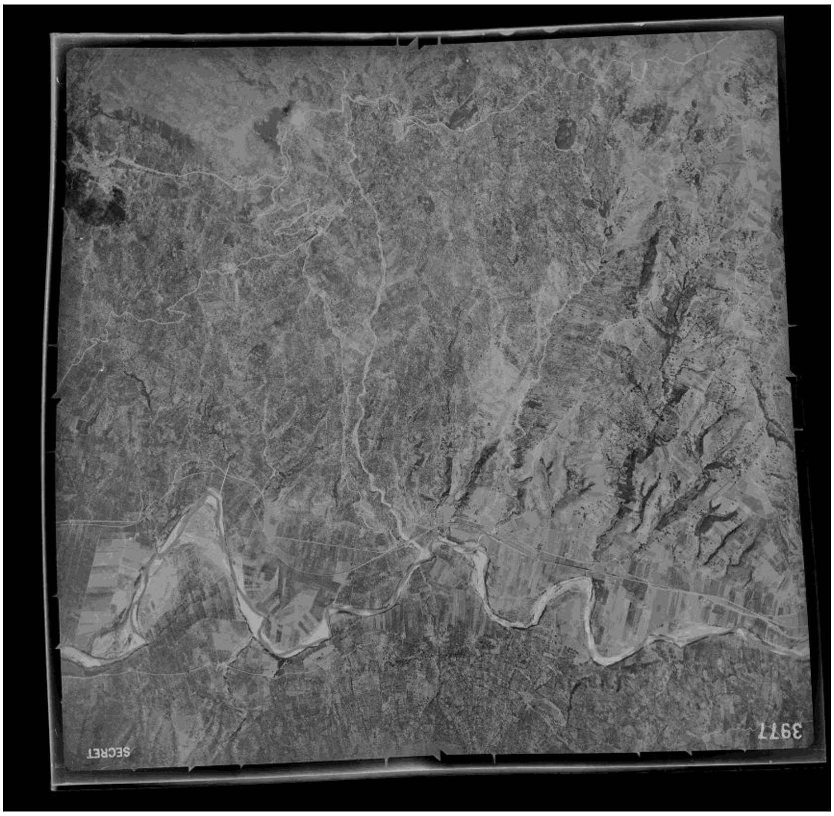


Flight line 119 – Photo No. 3975

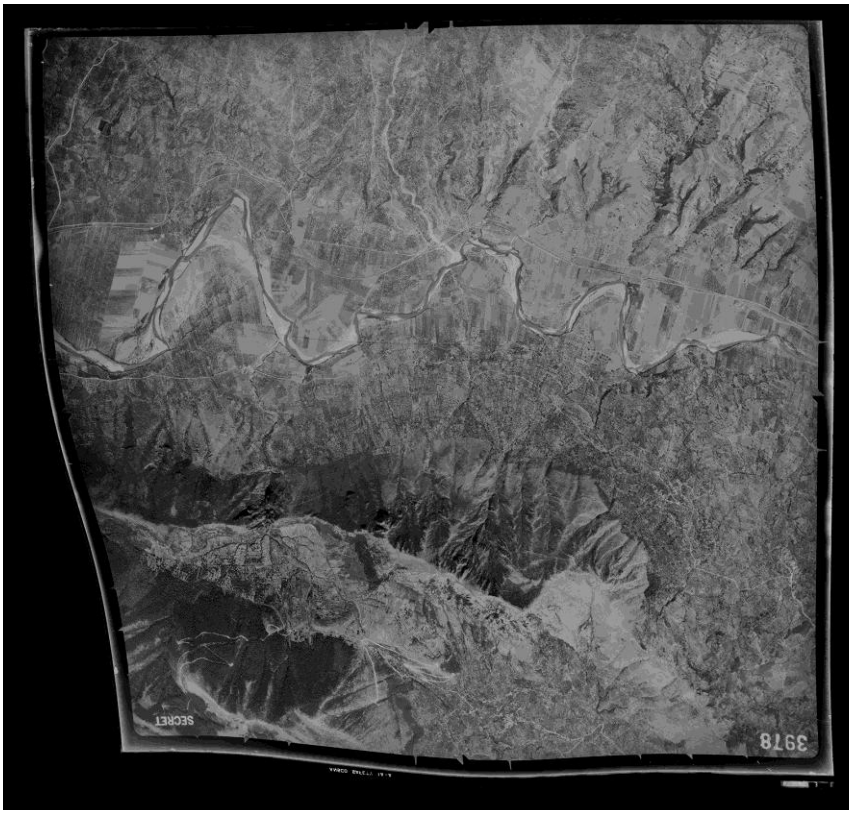
Flight line 119 – Photo No. 3976



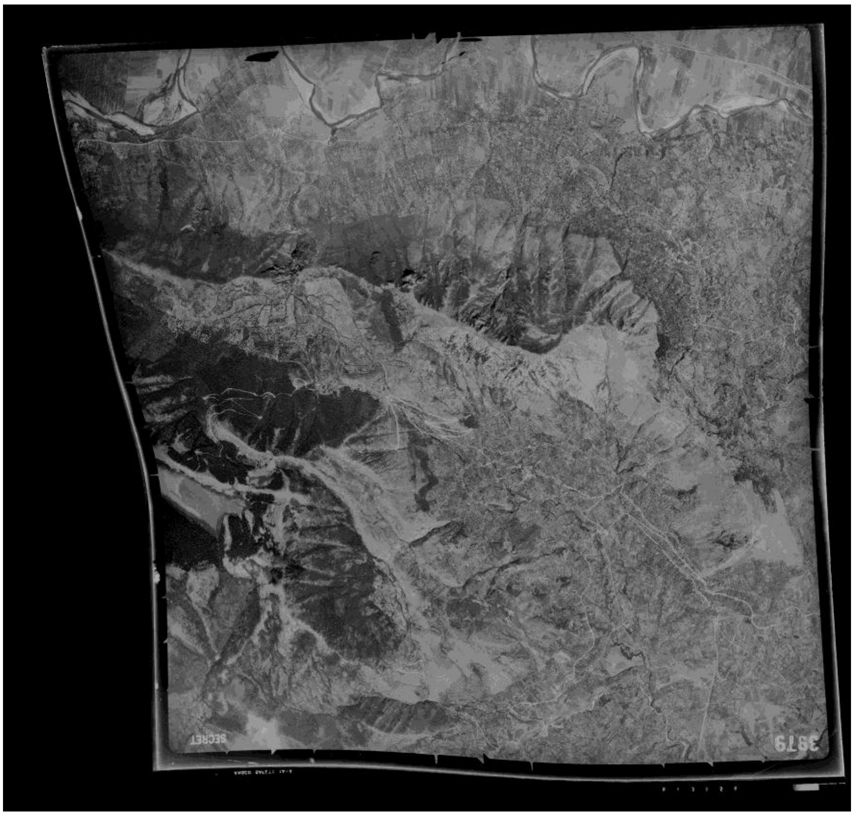
Flight line 119 – Photo No. 3977



Flight line 119 – Photo No. 3978



Flight line 119 – Photo No. 3979



Flight line 120 – Photo No. 4213

APPENDIX III
Process tree and the algorithms used in the GEOBIA classification

Classes:

- **0_Bare_Soil**
- **0_InBoundary**
  - and (min)
    - [0-35]: Width
    - Threshold: Border to 4_Roods > 0 Pxl
    - Threshold: Density <= 1.5
    - Threshold: Rel. border to 4_Roods >= 0.41
- 0_Temp_Classes
- **black**
  - and (min)
    - [0-87]: Brightness
- Classification
- **Dark_gray**
- **Gray**
- **Olives_candidates**
- **TreeLine_Candidate**
  - and (min)
    - [0-80]: Mean original
    - Threshold: Contrast to neighbor pixels original (1) <= -340
- **vineyard candidate**
  - and (min)
    - [-19--5]: StdDev diff. to super-object original (1)
- **White**
  - and (min)
    - and (*)
      - [194-255]: Brightness
      - Threshold: Mean water > 30
- **1_WoodLand**
- **2_Pasture**
- **3_TreeLines**
  - and (min)
    - Standard nearest neighbor (generated)
- **4_Roods**
  - and (min)
    - Standard nearest neighbor (generated)
- **5_river**
- **6_Urbans**
  - and (min)
    - Standard nearest neighbor (generated)
- **7_Mixed_Vine_olive**
  - and (min)
    - Standard nearest neighbor (generated)
- **8_Olives**
  - and (min)
    - Standard nearest neighbor (generated)
- **9_Agric_fields**
  - and (min)
    - Standard nearest neighbor (generated)
- **22_Vine_**

and (min)
Standard nearest neighbor (generated)

Process: Main:

do

Preprocessing&Urbans

chessboard segmentation: on main : chess board: 99999 creating 'Class_Level'

chessboard segmentation: on main with Num. of overlap: Studyarea = 1 at Class_Level: chess board: 99999

assign class: with Num. of overlap: Studyarea = 1 at Class_Level: 0_InBoundary

assign class: on main 0_InBoundary with Num. of overlap: urbans = 1 at Class_Level: 6_Urbans

multiresolution segmentation: on main 6_Urbans at Class_Level: 60 [shape:0.2 compct.:0.5]

Refine_Urbans

assign class: 6_Urbans with Brightness <= 80 at Class_Level: 0_InBoundary

Rivers

chessboard segmentation: on main 0_InBoundary at Class_Level: chess board: 99999

assign class: 0_InBoundary with Num. of overlap: Rivers = 1 at Class_Level: 5_river

multiresolution segmentation: 0_InBoundary at Class_Level: 50 [shape:0.7 compct.:0.3]

assign class: on main White with HSI Transformation Intensity(R=original,G=original,B=original) >= 0.85 and Width >= 90 Pxl at New Level60spec: 5_river

find enclosed by class: on main 0_InBoundary, 6_Urbans at Class_level: enclosed by 5_river: 5_river +

Refine rivers

multiresolution segmentation: on main 0_InBoundary at Class_Level: 90 [shape:0.7 compct.:0.3]

spectral difference segmentation: on main 0_InBoundary at Class_Level: spectral difference 10

assign class: on main 0_InBoundary with Brightness >= 179 and Rel. border to 5_river >= 0.4 at Class_Level: 5_river

merge region: on main 5_river at Class_Level: merge region

assign class: 5_river with Area <= 260210 Pxl at Class_Level: 0_InBoundary

Woodlands

classification: on main 0_InBoundary at Class_Level: black

merge region: on main black at Class_Level: merge region

assign class: on main black with Area <= 260500 Pxl at Class_Level: 0_InBoundary

assign class: on main black with Rectangular Fit <= 0.4 at Class_Level: 0_InBoundary

assign class: black at Class_Level: 1_WoodLand

Tree Lines

classification: on main 0_InBoundary at Class_Level: TreeLine_Candidate
merge region: on main TreeLine_Candidate at Class_Level: merge region
assign class: on main TreeLine_Candidate with Area <= 5000 Pxl at Class_Level: 0_InBoundary
assign class: on main TreeLine_Candidate at Class_Level: 3_TreeLines

Bare Soil

assign class: on main 0_InBoundary with Brightness >= 199 at Class_Level: 0_Bare_Soil

Classi_agri_fields

assign class: on main 0_InBoundary with Standard deviation water <= 37 at Class_Level: 9_Agric_fields
find enclosed by class: on main 0_Bare_Soil, 0_InBoundary with Area <= 5000 Pxl at Class_Level: enclosed by 9_Agric_fields: 9_Agric_fields +
merge region: on main 9_Agric_fields at Class_Level: merge region
assign class: on main 9_Agric_fields with Area <= 5000 Pxl at Class_Level: 0_InBoundary

Vineyard & Olives

multiresolution segmentation: on main 0_InBoundary at Class_Level: 40 [shape:0.5 compct.:0.5] creating 'New Level20'
assign class: on main with Existence of super objects 0_InBoundary (1) = 1 at New Level20: 0_InBoundary
multiresolution segmentation: on main 0_InBoundary at New Level20: 20 [shape:0.8 compct.:0.5]
multiresolution segmentation: on main 0_InBoundary at New Level20: 5 [shape:0.8 compct.:0.5]
assign class: on main 0_InBoundary with Mean original <= 120 at New Level20: Dark_gray
assign class: on main Dark_gray with Area >= 500 Pxl at New Level20: 0_InBoundary
classification: on main Dark_gray, Gray at New Level20: Olives_candidates
assign class: on main 0_InBoundary with Rel. area of sub objects Olives_candidates (1) >= 0.5 at Class_Level: 8_Olives
classification: on main 0_InBoundary at New Level20: vineyard candidate
merge region: on main vineyard candidate at New Level20: merge region
assign class: on main vineyard candidate with Area < 5000 Pxl at New Level20: 0_InBoundary
multiresolution segmentation: on main vineyard candidate at New Level20: 90 [shape:0.6 compct.:0.5]
assign class: vineyard candidate with Standard deviation original <= 10 at New Level20: 0_InBoundary
assign class: vineyard candidate with Standard deviation inkout <= 59 at New Level20: Gray
multiresolution segmentation: on main 0_InBoundary at Class_Level: 90 [shape:0.7 compct.:0.5]
assign class: 0_InBoundary with Existence of sub objects vineyard candidate (1) = 1 at Class_Level: 22_Vine_
merge region: 22_Vine_ at Class_Level: merge region
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 22_Vine_: 22_Vine_ +

merge region: 22_Vine_ at Class_Level: merge region
assign class: 22_Vine_ with Area < 5000 Pxl at Class_Level: 0_InBoundary

finall_refinments

do
assign class: 0_InBoundary with Existence of sub objects Olives_candidates (1) = 1 and Rel. border to 8_Olives >= 0.15 at Class_Level: 8_Olives
merge region: 8_Olives at Class_Level: merge region
assign class: 0_InBoundary at Class_Level: 7_Mixed_Vine_olive
merge region: 7_Mixed_Vine_olive at Class_Level: merge region
assign class: 7_Mixed_Vine_olive with Area <= 5000 Pxl at Class_Level: 0_InBoundary
assign class: 22_Vine_ with Standard deviation findedges <= 45 at Class_Level: 7_Mixed_Vine_olive
merge region: 7_Mixed_Vine_olive at Class_Level: merge region
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 5_river: 5_river +
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 1_WoodLand: 1_WoodLand +
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 3_TreeLines: 3_TreeLines +
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 0_Bare_Soil: 0_Bare_Soil +
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 9_Agric_fields: 9_Agric_fields +
find enclosed by class: 0_InBoundary, 8_Olives, 22_Vine_ at Class_Level: enclosed by 7_Mixed_Vine_olive: 7_Mixed_Vine_olive +
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 8_Olives: 8_Olives +
find enclosed by class: 0_InBoundary at Class_Level: enclosed by 22_Vine_: 22_Vine_ +
merge region: 6_Urbans at Class_Level: merge region
merge region: 5_river at Class_Level: merge region
merge region: 1_WoodLand at Class_Level: merge region
merge region: 3_TreeLines at Class_Level: merge region
merge region: 0_Bare_Soil at Class_Level: merge region
merge region: 8_Olives at Class_Level: merge region
merge region: 22_Vine_ at Class_Level: merge region
merge region: 7_Mixed_Vine_olive at Class_Level: merge region
find enclosed by class: 0_InBoundary, 7_Mixed_Vine_olive, 8_Olives, 22_Vine_ with Area <= 10000 Pxl at Class_Level: enclosed by 9_Agric_fields: 9_Agric_fields +
merge region: 9_Agric_fields at Class_Level: merge region
assign class: 0_InBoundary with Rel. border to 9_Agric_fields >= 0 at Class_Level: 9_Agric_fields
assign class: 0_Bare_Soil, 8_Olives, 22_Vine_ with Rel. border to 9_Agric_fields >= 0.2 and Area <= 6000 Pxl at Class_Level: 9_Agric_fields
merge region: 9_Agric_fields at Class_Level: merge region

assign class: 0_Bare_Soil, 9_Agric_fields with Area <= 8000 Pxl and Rel. border to 8_Olives >= 0.2 at Class_Level: 8_Olives
merge region: 8_Olives at Class_Level: merge region
assign class: 0_InBoundary with Rel. border to 7_Mixed_Vine_olive > 0 at Class_Level: 7_Mixed_Vine_olive
merge region: 7_Mixed_Vine_olive at Class_Level: merge region
assign class: 0_InBoundary with Rel. border to 0_Bare_Soil > 0 at Class_Level: 0_Bare_Soil
merge region: 0_Bare_Soil at Class_Level: merge region
assign class: 0_InBoundary with Rel. border to 22_Vine_ > 0 at Class_Level: 22_Vine_
merge region: 22_Vine_ at Class_Level: merge region
find enclosed by class: 8_Olives with Area <= 8000 Pxl at Class_Level: enclosed by 0_Bare_Soil: 0_Bare_Soil +
find enclosed by class: 8_Olives with Area <= 8000 Pxl at Class_Level: enclosed by 22_Vine_: 22_Vine_ +
assign class: 8_Olives with Area <= 8000 Pxl and Rel. border to 7_Mixed_Vine_olive > 0 at Class_Level: 7_Mixed_Vine_olive
merge region: 0_Bare_Soil at Class_Level: merge region
merge region: 22_Vine_ at Class_Level: merge region
merge region: 7_Mixed_Vine_olive at Class_Level: merge region

APPENDIX IV

Analysis of soil samples of the study area

Profile No.	Unit ID	pHw	Organic Carbon	Total Carbon	EC	Max Profile depth	Texture rating	Stoniness	Drainage	Slope	Altitude
6	LAC1	8.26	0.89	5.22	4.62	120.00	85.00	0.00	3.00	12.08	132.07
7	POC1	8.19	0.83	17.48	0.00	120.00	74.00	0.00	3.00	1.03	54.72
8	CDA1	7.24	0.08	7.07	0.00	116.00	68.75	0.00	2.00	14.99	154.50
9	SIM1	7.23	0.61	6.19	0.00	140.00	94.00	0.00	3.00	5.49	236.85
17	BOC1	7.40	0.56	5.89	0.00	105.00	68.75	0.00	3.00	13.78	71.00
18	LAT1	7.22	0.76	11.20	0.00	121.00	84.25	0.00	3.00	2.36	52.84
24	TIT1	7.30	0.58	28.40	0.00	25.00	75.00	0.00	1.00	0.91	174.79
30	MAG1	7.08	0.79	0.00	0.00	50.00	60.00	0.00	3.00	31.37	99.77
32	IMP1	7.10	0.61	0.60	0.00	20.00	75.00	0.00	3.00	1.63	68.62
33	PET1	7.07	1.49	0.00	4.89	115.00	81.80	0.00	3.00	0.64	70.02
34	SLR1	8.34	0.47	18.09	7.54	130.00	82.75	0.00	3.00	0.00	40.47
35	CAL1	8.26	0.62	27.42	0.00	141.00	68.55	0.00	3.00	3.82	38.71
36	AIC1	8.04	0.94	34.20	4.45	51.00	87.55	0.00	3.00	7.46	223.69
37	SPE1	7.28	0.54	0.00	7.85	100.00	78.00	0.00	3.00	1.74	75.43
41	ACS1	7.86	0.71	2.35	6.37	140.00	83.75	0.00	3.00	12.73	249.32
44	LCH1	8.02	0.38	34.76	6.44	100.00	88.00	0.00	4.00	12.40	146.00
45	PEL1	6.93	0.93	1.81	0.00	60.00	60.00	1.00	6.00	0.64	54.28
47	ADD1	6.81	1.39	0.00	0.00	80.00	60.00	0.00	3.00	0.84	186.81
50	COD1	7.77	0.51	16.45	5.57	120.00	90.70	0.00	3.00	3.66	140.88
52	COD1	8.19	0.06	3.18	8.43	120.00	80.00	0.00	3.00	0.57	155.58
53	PTR1	8.20	1.69	36.72	7.85	30.00	100.00	0.00	3.00	5.33	237.40
55	COC1	7.30	1.47	7.90	0.00	25.00	60.00	0.00	2.00	15.56	191.20
56	CAP1	6.82	0.85	0.10	0.00	110.00	68.05	0.00	3.00	1.30	204.14
58	CER1	7.95	0.91	8.23	10.16	103.00	90.00	0.00	2.00	5.94	145.41
59	CRU1	7.14	1.26	0.53	0.00	116.00	65.70	0.00	3.00	2.92	77.00
64	PEZ1	7.17	0.95	0.16	0.00	100.00	75.00	0.00	3.00	6.14	109.55
66	SOL1	7.28	1.76	10.59	0.00	130.00	75.00	0.00	2.00	7.46	204.17
67	CAS1	7.60	0.28	5.35	3.73	100.00	97.00	0.00	4.00	9.06	352.79
68	CES1	8.51	0.50	19.80	7.80	140.00	99.50	0.00	0.00	12.56	220.91
69	CHI1	7.72	0.53	17.67	25.55	140.00	88.00	0.00	5.00	9.93	260.51
70	CAN1	8.45	0.30	20.80	15.44	130.00	95.00	0.00	4.00	12.75	233.92
72	TAS1	8.03	0.68	5.26	7.41	110.00	81.35	0.00	0.00	2.54	84.73
73	MON1	8.05	0.12	0.16	10.40	124.00	81.60	0.00	3.00	3.69	130.96
75	LMP1	6.54	1.38	0.00	3.27	120.00	85.91	0.00	3.00	5.94	1075.60
77	CPS1	6.53	8.42	0.00	4.52	40.00	80.00	3.00	3.00	9.68	1195.96
78	MOR1	7.58	4.83	0.00	7.30	30.00	60.00	0.00	3.00	6.67	1198.80
79	SES1	6.35	1.42	0.00	2.72	75.00	73.07	0.00	3.00	15.10	1155.03
83	LAM1	8.70	0.65	8.54	7.73	46.00	80.00	0.00	0.00	14.80	202.78
84	PTR1	8.03	0.47	12.39	7.22	130.00	83.75	0.00	0.00	1.43	165.70
85	MAP1	8.38	0.75	11.67	8.29	105.00	92.00	0.00	0.00	8.90	202.04
87	PEN1	8.60	1.23	17.06	8.33	75.00	88.00	0.00	0.00	9.37	386.71

89	PAO1	8.33	1.22	14.44	9.08	130.00	97.50	0.00	0.00	5.94	189.71
91	MAM1	7.83	0.36	30.31	2.61	100.00	97.00	0.00	0.00	5.19	167.33
95	MAM1	8.42	0.40	6.15	6.98	85.00	95.59	0.00	0.00	16.37	120.56
96	VIV1	8.13	0.48	24.30	6.28	170.00	95.00	0.00	0.00	10.26	159.77
98	TOI1	7.19	0.61	19.85	0.00	130.00	100.00	0.00	0.00	9.52	238.31
100	LAR1	6.90	1.79	0.82	0.00	45.00	80.00	0.00	0.00	14.04	210.67
101	TOR1	6.81	1.76	0.74	0.00	35.00	60.00	0.00	0.00	27.81	836.26
103	VAO1	6.63	1.89	0.00	0.00	100.00	87.20	0.00	0.00	24.81	683.01
104	SAZ1	6.75	1.15	0.05	0.00	120.00	60.00	0.00	0.00	15.64	669.35
106	ZEP1	7.20	0.39	5.84	0.00	90.00	70.33	7.00	0.00	14.58	561.40
107	SER1	7.27	1.49	5.84	0.00	30.00	62.00	7.00	0.00	11.09	558.11
108	FAR1	7.40	0.55	7.70	0.00	32.00	60.00	0.00	0.00	11.58	774.38
109	SEG1	7.35	1.67	17.81	0.00	80.00	95.00	0.00	0.00	8.77	814.20
111	FSS1	7.17	1.56	0.00	0.00	105.00	94.00	0.00	0.00	2.50	631.74
112	CAM1	7.32	2.14	42.64	0.00	70.00	72.50	2.00	0.00	10.14	511.26
113	FOM1	7.30	4.89	15.55	0.00	60.00	92.50	0.00	0.00	1.87	603.63
114	TOV1	7.35	1.36	18.04	0.00	121.00	64.67	0.00	0.00	8.74	103.71
115	CMP1	7.03	6.12	0.00	0.00	103.00	84.60	1.00	0.00	34.40	1142.25

APPENDIX V

Suitability index values and corresponding classes for all the study area land units

Unit No.	Land Unit ID	**Storie** Suitability Class	**Square Root** Suitability Class	**Rabia** Suitability Class
0	FAR1	N2	N1	S3
1	SES1	N2	N2	N2
2	CPS1/MOR1	N2	N2	N2
3	CAM1	N1	S3	S3
4	SEG1	N1	N1	S3
5	SES1	N2	N2	N2
6	FAR1	N2	N1	S3
7	MOR1/SES1	N2	N2	N2
8	MOR2	N2	N2	N2
9	MOR1/SES1	N2	N2	N2
10	SAZ1	N1	N1	S3
11	SEG1	N1	N1	S3
12	SOL1	S3	S2	S2
13	SEG1	N1	N1	S3
14	CER1	N2	N1	S3
15	FOM1	S3	S3	S2
16	FOM1/FSS1	S3	S3	S2/S3
17	TIT1	N1	S3	S3
18	SER1/ZEP1	N1	S3/N1	S3
19	CAM1	N1	S3	S3
20	ADD1	N1	S3	S3
21	FOM1	S3	S3	S2
22	SER1/ZEP1	N1	S3/N1	S3
23	POC1	N1	S3	S3
24	CAP1	N1	S3	S3
25	SES1	N2	N2	N2
26	FAR1	N2	N1	S3
27	MOR1/SES1	N2	N2	N2
28	CAM1	N1	S3	S3
29	SEG1	N1	N1	S3
30	CAN1	N2	N2	N2

31	COC1/SIM1	S3/N1	S3	S2/S3
32	PTR1/SER1	N1	N1/S3	S3
33	FOM1	S3	S3	S2
34	CES1/TOI1	N2/S3	N2/S3	N2/S2
35	CAP1	N1	S3	S3
36	CAS1/LAM1	N2	N1/N2	S3/N2
37	COC1/SIM1	S3/N1	S3	S2/S3
38	CES1/TOI1	N2/S3	N2/S3	N2/S2
39	SES1	N2	N2	N2
40	CAN1	N2	N2	N2
41	PEN1	N2	N2	N2
42	CAN1	N2	N2	N2
43	PEN1	N2	N2	N2
44	SOL1	S3	S2	S2
45	PEN1	N2	N2	N2
46	VIV1	N1	N1	S3
47	PTR1/LAR1	N1/S3	N1/S2	S3/S2
48	CAN1	N2	N2	N2
49	CAN1	N2	N2	N2
50	CES1/TOI1	N2/S3	N2/S3	N2/S2
51	CAN1	N2	N2	N2
52	PEN1	N2	N2	N2
53	MAG1/PET1	N2/S3	N1/S3	N1/S3
54	PEN1	N2	N2	N2
55	MAG1	N2	N1	N1
56	MAG1/PET1	N2/S3	N1/S3	N1/S3
57	MAG1/PET1	N2/S3	N1/S3	N1/S3
58	MAG1/PET1	N2/S3	N1/S3	N1/S3
59	PEN1	N2	N2	N2
60	LAC1/TOV1	N1/S3	S3/S2	S3/S2
61	VIV1	N1	N1	S3
62	PTR1/LAR1	N1/S3	N1/S2	S3/S2
63	PEN1	N2	N2	N2

64	PEN1	N2	N2	N2
65	PEL1	N2	N1	N1
66	CES1/TOI1	N2/S3	N2/S3	N2/S2
67	PEN1	N2	N2	N2
68	COD1	N2	N1	S3
69	SOL1	S3	S2	S2
70	MAG1/PET1	N2/S3	N1/S3	N1/S3
71	MAG1/PET1	N2/S3	N1/S3	N1/S3
72	MAG1/PET1	N2/S3	N1/S3	N1/S3
73	MAG1/PET1	N2/S3	N1/S3	N1/S3
74	MAG1	N2	N1	N1
75	CDA1/MON1	N1/N2	S3/N2	S3/N1
76	CDA1/MON1	N1/N2	S3/N2	S3/N1
77	PAO1	N1	N1	S3
78	MAG1/PET1	N2/S3	N1/S3	N1/S3
79	CAS1/LAM1	N2	N1/N2	S3/N2
80	MAG1/PET1	N2/S3	N1/S3	N1/S3
81	PAO1	N1	N1	S3
82	PEN1	N2	N2	N2
83	PAO1	N1	N1	S3
84	CDA1/MON1	N1/N2	S3/N2	S3/N1
85	CDA1/MON1	N1/N2	S3/N2	S3/N1
86	CDA1/MON1	N1/N2	S3/N2	S3/N1
87	PAO1	N1	N1	S3
88	PEN1	N2	N2	N2
89	CDA1/MON1	N1/N2	S3/N2	S3/N1
90	PAO1	N1	N1	S3
91	CAS1/LAM1	N2	N1/N2	S3/N2
92	CDA1/MON1	N1/N2	S3/N2	S3/N1
93	PTR1/LAR1	N1/S3	N1/S2	S3/S2
94	CDA1/MON1	N1/N2	S3/N2	S3/N1
95	PEN1	N2	N2	N2
96	SPE1	N2	N1	N1

97	CDA1/MON1	N1/N2	S3/N2	S3/N1
98	MAG1/PET1	N2/S3	N1/S3	N1/S3
99	CDA1/MON1	N1/N2	S3/N2	S3/N1
100	CDA1/MON1	N1/N2	S3/N2	S3/N1
101	BOC1	N1	N1	S3
102	MAM1	N2	N1	N1
103	COD1	N2	N1	S3
104	CDA1/MON1	N1/N2	S3/N2	S3/N1
105	CES1/TOI1	N2/S3	N2/S3	N2/S2
106	CDA1/MON1	N1/N2	S3/N2	S3/N1
107	CDA1/MON1	N1/N2	S3/N2	S3/N1
108	TAS1	N1	S3	S3
109	PEN1	N2	N2	N2
110	LAC1/TOV1	N1/S3	S3/S2	S3/S2
111	LAC1/TOV1	N1/S3	S3/S2	S3/S2
112	CDA1/MON1	N1/N2	S3/N2	S3/N1
113	CDA1/MON1	N1/N2	S3/N2	S3/N1
114	CDA1/MON1	N1/N2	S3/N2	S3/N1
115	MAP1/MAV1	N2	N1	N1
116	CDA1/MON1	N1/N2	S3/N2	S3/N1
117	LAC1/TOV1	N1/S3	S3/S2	S3/S2
118	CAL1	N1	S3	S3
119	POC1	N1	S3	S3
120	SLR1	N2	N1	N1
121	LAT1	S3	S3	S2
122	SLR1	N2	N1	N1
123	CDA1/MON1	N1/N2	S3/N2	S3/N1
124	POC1	N1	S3	S3
125	POC1	N1	S3	S3
126	SLR1	N2	N1	N1
127	BOC1	N1	N1	S3
128	CDA1/MON1	N1/N2	S3/N2	S3/N1
129	CDA1/MON1	N1/N2	S3/N2	S3/N1

130	SLR1	N2	N1	N1
131	POC1	N1	S3	S3
132	CDA1/MON1	N1/N2	S3/N2	S3/N1
133	PET1	S3	S3	S3
134	SLR1	N2	N1	N1
135	SLR1	N2	N1	N1
136	POC1	N1	S3	S3
137	PET1	S3	S3	S3
138	POC1	N1	S3	S3
139	CRU1/IMP1	S3/N1	S3	S3
140	CAS1/LAM1	N2	N1/N2	S3/N2
141	POC1	N1	S3	S3
142	CDA1/MON1	N1/N2	S3/N2	S3/N1
143	SLR1	N2	N1	N1
144	SLR1	N2	N1	N1
145	POC1	N1	S3	S3
146	SLR1	N2	N1	N1
147	POC1	N1	S3	S3
148	POC1	N1	S3	S3
149	CAL1	N1	S3	S3
150	POC1	N1	S3	S3
151	SLR1	N2	N1	N1
152	SLR1	N2	N1	N1
153	POC1	N1	S3	S3
154	POC1	N1	S3	S3
155	PEZ1	N1	S3	S3
156	POC1	N1	S3	S3
157	SLR1	N2	N1	N1
158	SLR1	N2	N1	N1
159	PEZ1	N1	S3	S3
160	SLR1	N2	N1	N1
161	PEZ1	N1	S3	S3
162	PET1	S3	S3	S3

163	SOL1	S3	S2	S2
164	MOR1/SES1	N2	N2	N2
165	PET1	S3	S3	S3
166	MOR2	N2	N2	N2
167	POC1	N1	S3	S3
168	SES1	N2	N2	N2
169	POC1	N1	S3	S3
170	SLR1	N2	N1	N1
171	MOR1/SES1	N2	N2	N2
172	SLR1	N2	N1	N1
173	CER1	N2	N1	S3
174	MOR2	N2	N2	N2
175	MOR1/SES1	N2	N2	N2
176	POC1	N1	S3	S3
177	CPS1/MOR1	N2	N2	N2
178	SES1	N2	N2	N2
179	TOR1	N2	N2	N1
180	SAZ1	N1	N1	S3
181	VAO1	N1	S3	S3
182	SES1	N2	N2	N2
183	MOR2	N2	N2	N2
184	CAL1	N1	S3	S3
185	CPS1/MOR1	N2	N2	N2
186	SLR1	N2	N1	N1
187	CPS1/MOR1	N2	N2	N2
188	TOR1	N2	N2	N1
189	MOR2	N2	N2	N2
190	MOR1/SES1	N2	N2	N2
191	MOR1/SES1	N2	N2	N2
192	SLR1	N2	N1	N1
193	CPS1/MOR1	N2	N2	N2
194	SES1	N2	N2	N2
195	CPS1/MOR1	N2	N2	N2

196	MOR2	N2	N2	N2
197	SAZ1	N1	N1	S3
198	LMP1	N2	N2	N2
199	MOR1/SES1	N2	N2	N2
200	CMP1	N2	N2	N2
201	SES1	N2	N2	N2
202	SES1	N2	N2	N2
203	CPS1/MOR1	N2	N2	N2
204	CPS1/MOR1	N2	N2	N2
205	CPS1/MOR1	N2	N2	N2
206	CPS1/MOR1	N2	N2	N2
207	CPS1/MOR1	N2	N2	N2