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Thesis Topic:

A First Complete Benchmarking of the New Chinese 30 m resolution Global Land Cover Dataset (GLC30) and Regional Land Coverage Datasets in Italy

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Dedicate

I'd like to thank my family who support me all my life. Give to me light steps in all my life.
I kindly thank my mom, the one who always support me with her payers, for her teaching me from the first step on my life until now; god bless her to me.
To my dad, who always been there for me, support me in every step I had taken on my life. Says always to me" I trust in you, you can do more", Thank you dad.
To my sisters Heba, Nahla and Hind, my life flowers. Thank you for your entire support and kindness god blesses them all to me.

Abstract

The production of thematic maps using an image classification is one of the most common applications of remote sensing; such as the production of Land Use and Land cover maps which derived from photo-interpretation of satellite images and Aerial photos. Considerable research has been directed at the various components of the mapping process, including the assessment of accuracy, which is the focused subject of the Thesis.

As the result of the "Global Land Cover Mapping at Finer Resolution" project led by National Geomatics Center of China, the first 30-meters resolution Open Global Land Cover Dataset (named GlobeLand30) have been produced for the years 2000 and 2010. This important dataset is free, open and downloaded through Website:
http://www.globallandcover.com:6677/InfoServer/GLC/DownLoad.aspx?No=0.

The objective of the current study is the assessment of the thematic accuracy of these data on the Italian area by means of a benchmarking with the more detailed land cover open datasets available for many Italian regions. These datasets are independent each other and provided with different thematic classification and resolutions.

The accuracy assessment is based on the cell-by-cell comparison between Italian regional maps and the GlobeLand30 in order to obtain the confusion matrix and all its derived agreement statistics (overall accuracy, producer's and user's accuracy, allocation and quantity disagreement, etc.), which help to understand the Classification Quality.

The Thesis presents the Methodology and Procedures for assessing open GlobeLand30. The analysis has been performed in 8 regions across Italy by taking advantage of GRASS, an open-source GIS which offers advanced features for geospatial data processing and analysis. The results of the assessment was very good. This has proven that the combination of open data and open source software provides us a new way for spatial analyses and geographical applications.

Keywords: Remote sensing; Classification; Benchmarking; Accuracy assessment.

Sommario

La produzione di carte tematiche mediante tecniche di classificazione d'immagine rappresenta una delle applicazioni più comuni del telerilevamento; un tipico esempio in questo senso è la realizzazione di carte di copertura e uso del suolo a partire da fotointerpretazione di immagini satellitari o aeree. Tra i numerosi studi di ricerca condotti in tale ambito notevole importanza riveste la valutazione dell'accuratezza del processo di classificazione, tema sul quale è incentrato il presente lavoro.

Nell'ambito del progetto "Global Land Cover Mapping at Finer Resolution" guidato dal National Geomatics Center of China, è stato prodotto, per gli anni 2000 e 2010, il primo dataset globale di copertura del suolo con risoluzione 30 metri (chiamato GlobeLand30); questo importante dataset è gratuito, aperto e scaricabile tramite il sito web:
http://www.globallandcover.com:6677/InfoServer/GLC/DownLoad.aspx?No=0.

L'obiettivo del presente studio è la valutazione dell'accuratezza tematica dei dati GlobeLand30 sul territorio italiano attraverso un'analisi comparativa con le più dettagliate carte di copertura del suolo rese disponibili come "open data" da varie regioni italiane; tali dataset sono indipendenti tra loro e caratterizzati da classificazione tematica e risoluzioni diverse.

La stima dell'accuratezza è stata condotta tramite una procedura che, attraverso un confronto cella per cella tra le carte regionali e la GlobeLand30, ha permesso di calcolare la matrice di confusione e derivare da essa una serie di statistiche (accuratezza globale, accuratezza del produttore, accuratezza dell'utente, grado di discordanza tematica e spaziale etc.) in grado di descrivere la qualità della classificazione.

La tesi presenta la metodologia e le procedure adottate per la valutazione di GlobeLand30. Le analisi, condotte in 8 regioni italiane con risultati molto soddisfacenti, sono state eseguite mediante GRASS, GIS open-source che offre funzionalità avanzate per l'elaborazione e l'analisi di dati geospaziali. Lo studio dimostra come la combinazione di open data e software open source possa fornire una nuova possibilità nello svolgimento di analisi spaziali e nello sviluppo di applicazioni geografiche.

Parole Chiave: Telerilevamento; Classificazione: Analisi Comparativa; Valutazione dell'accuratezza.

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CHAPTER 1

1 INTRODUCTION

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Land cover, and human and natural alteration of land cover, play a major role in global-scale patterns of the climate and biogeochemistry of the earth system. Terrestrial ecosystems exert considerable control on the planet's biogeochemical cycles, which in turn significantly influence the climate system through the radiative properties of greenhouse gases and reactive species. Further, variations in topography, albedo, and vegetation cover, and other physical characteristics of the land surface influence surface-atmosphere fluxes of sensible heat, latent heat, and momentum, which in turn influence weather and climate (Sellers et al., 1997)[i]. Reliable information on the state of our planet's land cover is thus needed on a regular basis if we are to understand the balance between global land cover patterns, climate, and changes occurring in either of these. Despite the significance of land cover as an environmental variable, our knowledge of land cover and its dynamics is poor. Understanding the significance of land cover and predicting the effects of land cover change is particularly limited by the paucity of accurate land cover data.

Land-cover data are some of the most important variables in all nine societal benefit areas that the Global Earth Observation System (Herold et al. 2008)[ii]. Until recently, land-cover data sets used within models of global climate and biogeochemistry were derived from pre-existing maps and atlases. The most commonly used data sets were compiled by Olson and Watts (1982)[iii], Matthews (1983)[iv], and Wilson and Henderson-Sellers (1985)[v]. While these (and other) data sources provided the best available source of information regarding the distribution of global land cover at the time, several limitations are inherent in their use. For example, global land cover is intrinsically dynamic.

Therefore, the source data upon which these maps were compiled is now out of date in many areas. Further, each of these data sets utilize different spatial scales and classification schemes, which are generally different from those required by contemporary models. As a result, confusion regarding how the reference class units are translated to the classification system and scale used by a model can lead to errors in the final product. For example, floristic and climatically based classifications, while not inherently compatible, may need to be combined and reclassified to generate physiognomic cover types (Townshend, Justice, Li, Gurney, & MacManus, 1991)[vi].

Finally, conventional land cover data sets such as those mentioned above often provide maps of potential vegetation inferred from climatic variables such as temperature and precipitation. In many regions, especially where humans have dramatically modified the landscape, the true vegetation type or land cover can deviate significantly from the potential vegetation.

1.1 GLOBAL LAND COVER FROM SPACE

More recently, remote sensing has been used as a basis for mapping global land cover, large volumes of high-quality global remotely-sensed data have become available, provided by such orbiting instruments as SPOT-Vegetation (CNES, 2000)[vii], MODIS (Justice et al., 1998)[viii], and MERIS (ESA, 2004)[ix]. These imagers provide near-daily multispectral imaging of the Earth's land surface at resolutions ranging from 250 to 1000 m. Their frequent coverage provides a higher probability of observing the surface without interference from clouds, thus allowing the construction of global datasets in which nearly all points on the Earth's land surface have been imaged on multiple occasions. This, in turn, opens the door for global science data products derived from multispectral and multi-temporal measurements.

Among these science data products is global land cover, typically presented as a digital thematic map in raster format with pixels in the range of 500-1000 m. Thus far, six types of global land-cover maps derived from remotely sensed data are freely available:

1. The 1 km International Geosphere-Biosphere Programme Data and Information System Cover (IGBP-DISCover) map was produced from monthly normalized difference vegetation index (NDVI) composites derived from 1992 to 1993 National Oceanic and Atmospheric Administration (NOAA) Advanced Very High Resolution Radiometer (AVHRR) data (Loveland et al. 2000)[x]. An unsupervised classification method was used to produce this map.
2. The 1 km University of Maryland (UMD) land-cover map was produced with the same data set as mentioned above (Hansen et al. 2000)[xi]. A supervised classification tree method was used to produce this map.
3. The 1 km Global Land Cover 2000 (GLC2000) map was produced from monthly NDVI data derived from 1999 to 2000 Satellite Pour l'Observation de la Terre (SPOT) vegetation data (Bartholome and Belward 2005)[xii]. It was produced by people working separately, in parallel, on 19 different regions of the world using various types of algorithms.
4. 500 m Moderate Resolution Imaging Spectrometer (MODIS) land-cover maps are now being generated annually with MODIS data (Friedl et al. 2002, 2010)[xiii]. Recently, a supervised classification tree algorithm has been used to produce these maps.
5. 300 m GlobCover land-cover maps were produced with bimonthly Medium Revolution Imaging Spectrometer (MERIS) data mosaics derived from the Environmental Satellite (ENVISAT) for 2005 and 2009 (Arino et al. 2008; Bontemps et al. 2010)[xiv]. They were produced with an automatic multi stage classification procedure using spectral–temporal and phonological information with an unsupervised classification method.
6. The 1 km MODIS land-cover map was derived from the MODIS 1 km monthly product led by Japan through international collaboration (Tateishi et al. 2011)[xv]. A combination of supervised classification and single-class extraction algorithms was used to make this map.

The classification schemes used by the three US global land cover products (IGBPDISCover, UMD, MODIS) used the IGBP classification system with 17 categories of cover types, whereas the two European products (GLC2000, GlobCover) used a 22 category classification scheme that was developed for similar purposes by the IGBP system in order to meet global modelling purposes. This has come about through a standard class definition and aggregation system developed by the Food and Agriculture Organization (FAO) (Di Gregorio 2005)[xvi].

1.2 CHALLENGES TO VALIDATION

In many applications, remotely-sensed global land cover maps are simply ingested without concern for their quality or accuracy. The rationale for this action is often that conventional sources of land cover information are so generalized that anything is an improvement. Another factor leading to unquestioned use is that other uncertainties may have a greater effect on the modeled outcome than errors in land cover information. In either case, land cover maps are being used without an appreciation of their inherent uncertainties, which may be large. It is clear that users of land cover information can improve their products and predictions by having some knowledge of the error structure of the land cover data in use. Moreover, global land cover maps differ significantly, depending on the quality of the input data and the classification algorithm used to produce them, as well as the spatial resolution and legend (Townshend, et al., 1991)[xvii]. Given this variation, the choice of a particular map may substantially affect user's outputs. All land-cover products were generated by computer classification algorithms of different types but on a per-pixel basis.

The term validation as a suite of techniques for determining the quality of a particular map. The techniques include assessing the accuracy of a given map based on observations such as overall accuracy, errors of omission and commission by land cover class, errors analyzed by region, and fuzzy accuracy (probability of class membership), all of which may be estimated by statistical sampling. Although the validation techniques we will describe rely heavily on probability sampling designs for collecting validation data, information obtained without a proper statistical sample design will often be useful in understanding the basic error structure of the map. Such information includes spatially-distributed confidence values provided by classification algorithms, as well as systematic qualitative examinations of the map and comparisons (both qualitative and quantitative) with other maps and data sources.

The overall accuracy (OA) of the IGBP DISCover map was 66.9% (Scepan 1999)[xviii], and the GLC2000 map was 68.6% (Mayaux et al. 2006)[xix]. Cross-validated OA (using training data) for the MODIS product was 78.3% (Friedl et al. 2002) and 77.9% for GlobCover based on 2186 random samples of homogeneous land covers (Arino et al. 2008). Through international collaboration, Tateishi et al. (2011) made use of reference map data from over 180 countries. They developed their own classification scheme with 20 classes. Using a validation data set of 600 points, they reported an OA of 76.5%.

In spite of these validation assessments, some third-party researchers have found considerably lower accuracies in different parts of the world when verifying the various global land-cover products (Gong 2009a; Fritz, See, and Rembold 2010)[xx]. Using 400 field survey points to assess the MODIS land-cover product, Sedano, Gong, and Ferrao (2005)[xxi] found greater than 50% error in the Mozambique Miombo ecosystem over an area of approximately 100,000 km^2. Using over 2000 field samples collected in Siberia covering approximately 1 million km^2, Frey and Smith (2007)[xxii] found that the OAs for the IGBP DisCover and MODIS global land-cover products were 22% and 11%, respectively. From a global comparison of the IGBP DISCover, UMD, MODIS, and GLC2000 data products, it was found that relatively consistent results can be found only over the snow and ice fields of Greenland, the desert areas in Africa, and the rain-forests of the Amazon Basin, areas occupying 26% of the global land surface (MaCallum et al. 2006)[xxiii]. From seven selected 500 km × 500 km comparison areas, in Africa, Asia, Australia, Europe, North America, Russia, and South America, the consistencies among these four global land-cover products for all but South America were below 20%. Using 250 Fluxnet sites, Gong (2009a) found that the OAs of the first three global land-cover maps produced with the IGBP classification system were below 42%. Previous research found that accuracies for different land-cover categories varied greatly, with evergreen broadleaf forest and desert areas best classified, but heterogeneous land-cover areas poorly classified (Jung et al. 2006; Herold et al. 2008)[xxiv].

It seems that so far only the evergreen broadleaf and the snow and ice cover classes have been reliably mapped with certainty. Mixed trees, deciduous broadleaf trees, shrub, and herbaceous land covers are the most confused classes (Herold et al. 2008; Sterling and Ducharne 2008)[xxv]. A spatial consistency check revealed that tropical forest, barren, and snow and ice cover classes are mapped homogeneously, but many transitional zones have low classification accuracies where finer resolution data are called for (Herold et al. 2008; Tchuente, Roujean, and de Jong 2011)[xxvi]. It was believed that improving the mapping of heterogeneous landscapes is the most significant challenge for improving global land cover mapping. Future efforts based on finer resolution data may provide improvements' (Herold et al. 2008). However, this does not come without significant costs for data, local knowledge, and detailed field data.

Current trends in land-cover classification have shifted from a single general purpose classification to individual class information extraction for human settlements (Imhoff 1997; Lu et al. 2008; Schneider et al. 2010; Wang et al. 2010)[xxvii], agricultural lands (Ramankutty and Foley 1998, 1999; Thenkabail et al. 2009)[xxviii], wetlands (Niu et al. 2009; et al. 2010; Gong et al. 2010), lakes (Sheng, Shah, and Smith 2008)[xxix], wild-land fires (Pu et al. 2007; Chuvieco, Giglio, and Justice 2008)[xxx], and quantification of vegetation cover fractions (DeFries, TownShend, and Hansen 1999; Hansen, DeFries, and Townshend 2002; Clinton et al. 2009)[xxxi]. In addition, classification algorithms have increased from simple statistical classifiers like the widely used maximum likelihood classifier (MLC), to classification trees (such as the seminal CART and C4.5) to more computationally demanding machine learning classifiers such as support vector machines (SVM) and ensemble classifiers such as Random Forest (RF), and other bagged or boosted classifiers (Witten and Frank 2005)[xxxii].

Due to the improvement of computational efficiency, it is now easier to employ and compare results from a number of different classifiers in a mapping task (e.g. Carreiras, Preira, and Shima bukuro 2006; Clinton et al. 2009)[xxxiii]. In the meantime, more and more ancillary information and remotely sensed data from different sources are being used in land-cover classification (e.g. Aksoy et al. 2009)[xxxiv]. From a global perspective, data provided for browsing purposes in virtual globes, particularly Google Earth, have proved useful for their geometric precision and large volumes of high spatial resolution data available at better than 1 m level (Yu and Gong 2012)[xxxv].

In summary, existing global land-cover maps derived from remote sensing were all based on time series of coarser resolution satellite data. The time series is usually for a specific year. Recent advances in data acquisition, data accessibility, and high-performance computing make it possible to use finer spatial resolution data for global land-cover mapping.

In particular, as more Landsat-level data are made freely accessible, it is natural to consider adopting such medium resolution data for global land-cover mapping purposes. Although it is still hard to collect medium resolution data for the entire globe in a consistent season or a year, it is possible to use such data in multiple years to cover the entire globe. Townshend et al. (2012) reported their efforts in mapping global forest cover and monitoring forest changes using Landsat data. They found that atmospheric interference, terrain effects, selecting data from the appropriate season in a year, and training sample selection are particularly challenging.

Despite these difficulties, globally consistent land-cover data from medium resolution satellite sensors that are an order of magnitude finer than weather satellite sensors have never been produced, but they are badly needed for many reasons. First, land process models at regional and global scales need better surface cover fraction data that coarser resolution data cannot provide. Second, although land-cover data at the medium resolution exist, in many developed countries, their classification schemes vary widely making them hard to crosswalk for cross-regional studies such as water resources management in international river basins, conservation of wildlife and biodiversity, and carbon sequestration planning through afforestation. This requires a global land-cover map with a consistent land-cover classification scheme. Third, many developing countries in Africa and Asia do not have land-cover data at this scale. A global land-cover map can fill this gap.

1.3 FINER RESOLUTION OBSERVATION AND MONITORING OF GLOBAL LAND COVER WITH 30 M RESOLUTION[1]

The first efforts in mapping global land cover with 30 m resolution Landsat Thematic Mapper (TM) and Enhanced TM plus (ETM+) data. This was carried out under Finer Resolution Observation and Monitoring of Global Land Cover (FROM-GLC) project. The long-term goal in FROM-GLC is to develop a multiple stage approach to mapping global land cover so that the results can better meet the needs of land process modelling and other application needs mentioned earlier that global Landover maps produced with coarser resolution data failed to meet. The FROM-GLC project should also be easily cross walkable to existing global land-cover classification schemes.

The first step maps broad land-cover categories based on spectral data only. It is meant to serve as a benchmark for future improvements when spatial and temporal and other ancillary features are combined. As Landsat-like data are being made more frequently available, optimal dates for data selection and multi-seasonal data in the same year cannot be used in the future.

1.3.1 Data pre-processing and Image classification procedure

A total of 8929 Landsat TM/ETM+ scenes were collected from various sources (Figures 1 and 2). A total of 2181 scenes were collected from the Global Land Cover Facility (GLCF) at the UMD, 6229 scenes were collected from United States Geological Survey (USGS) Earth Resources Observation and Science (EROS) data center, and an additional 519 scenes were collected from the Satellite Ground Station of China. About 74% of the imagery was acquired after 2006, while images available before 2006 were used as substitutes for places where no suitable imagery could be found after 2006 at the time of the project initiation.

[1] Peng Gong , Jie Wang , Le Yu , Yongchao Zhao , Yuanyuan Zhao , Lu Liang , Zhenguo Niu , Xiaomeng Huang , Haohuan Fu , Shuang Liu , Congcong Li , Xueyan Li , Wei Fu , Caixia Liu , Yue Xu , Xiaoyi Wang , Qu Cheng , Luanyun Hu , Wenbo Yao , Han Zhang , Peng Zhu , Ziying Zhao , Haiying Zhang , Yaomin Zheng , Luyan Ji , Yawen Zhang , Han Chen , An Yan , Jianhong Guo , Liang Yu , Lei Wang , Xiaojun Liu , Tingting Shi , Menghua Zhu , Yanlei Chen , Guangwen Yang , Ping Tang , Bing Xu , Chandra Giri , Nicholas Clinton , Zhiliang Zhu , Jin Chen & Jun Chen (2013) Finer resolution observation and monitoring of global land cover: first mapping results with Landsat TM and ETM+ data, International Journal of Remote Sensing, 34:7, 2607-2654, http://dx.doi.org/10.1080/01431161.2012.748992

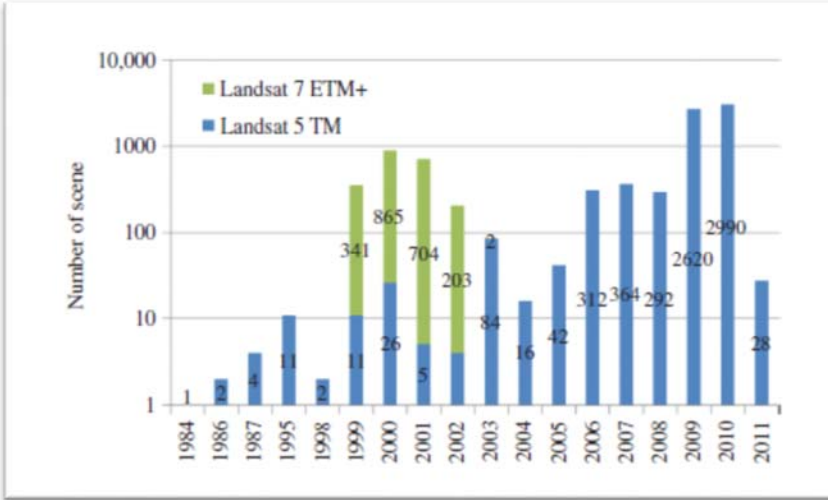

Figure 1: The temporal distribution of Landsat scenes used in the study (N=8929)

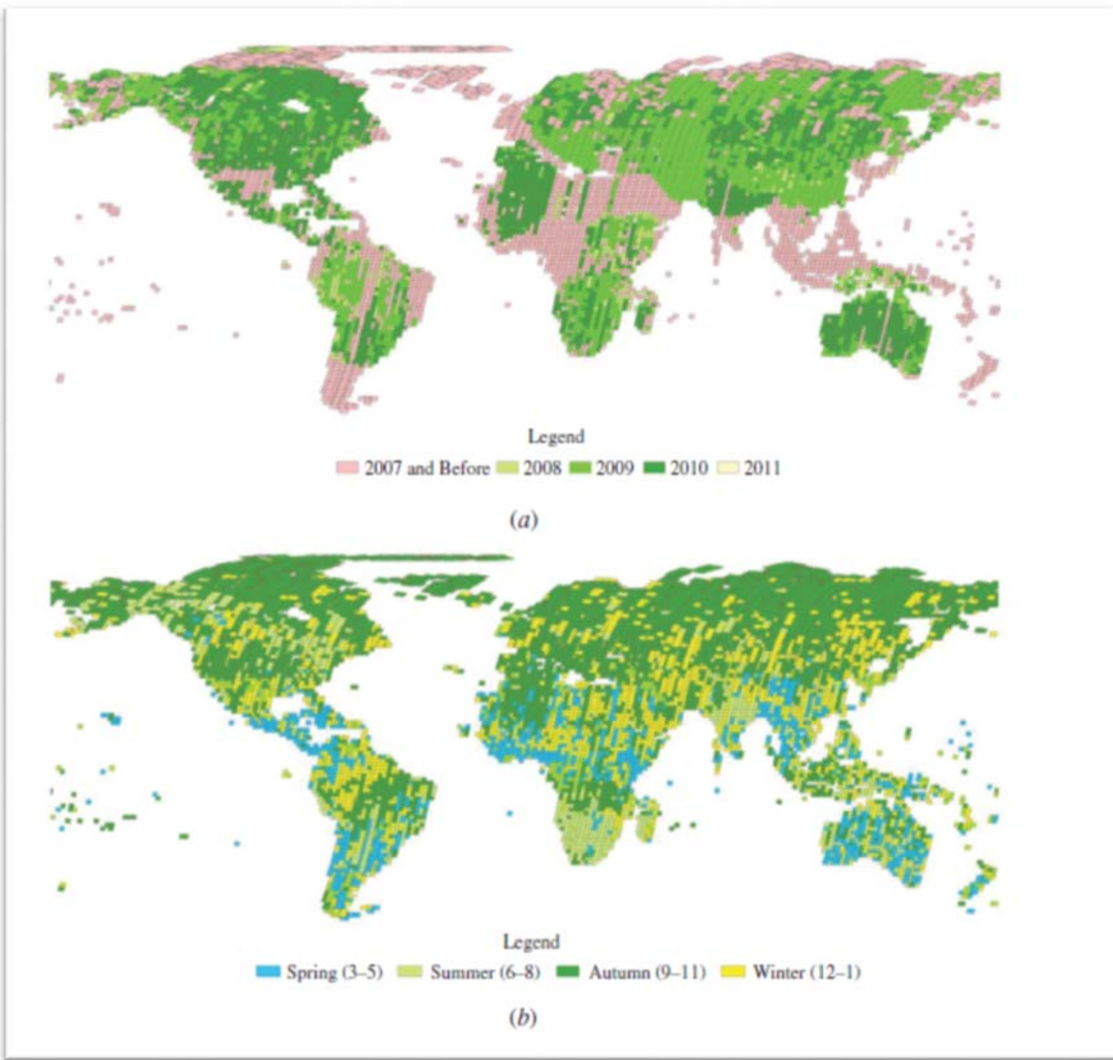

Figure 2: Temporal distribution of Landsat scenes used in this study. Annual distributions (a) and seasonal distribution (b) of scenes.

Only 18 scenes acquired before 1998 were used. As a result, approximately three quarters of the imagery is circa 2010 and one quarter is circa 2000. Most of the scenes except those covering China were processed to level L1T (orthorectified), while 161 scenes at higher latitudes were processed to level L1G (non-orthorectified, Figure 3). Only geometrical correction was applied to the images covering China. Since the non-orthorectified images were mainly taken over relatively flat areas, terrain effects were considered negligible where orthorectified imagery was unavailable. A total of 40 scenes were randomly selected to evaluate the geometric discrepancy against Google Earth images. In each scene, 10 ground control points were selected from typical locations to calculate a root mean square error (RMSE). Only one scene in Russia near the Arctic had an RMSE of 2.76 pixels. The remaining RMSEs were below 1.43 pixels. On average, the RMSE was 1.01 pixels, indicating an acceptable geometric agreement between the Landsat images and Google Earth images.

Figure 3: Processing level distributions. Levels L1T (brown) and L1G (blue).

Except those images from the GLCF that were already radiometrically corrected to reduce atmospheric and topographic effects, all remaining L1T images from USGS were radiometrically corrected using software (Figure 4).

The overall work flow of the global land-cover classification is shown in Figure 5. It involves data pre-processing, training, and test sample collection, image classification on a scene-by-scene basis using local training samples from spatio-temporal neighborhood scenes, and finally accuracy assessment.

The radiometric processing was done automatically using the Global Mapper (GM) software package developed by chines that enables image processing coupled with Google Earth image display and visualization. This processing includes atmospheric correction and topographic correction. The final product is images of reflectance with the atmospheric and topographic effects substantially reduced. After automatic processing, manual checking was carried out to ensure correction quality. Scenes with a poor quality correction were re-processed with manually selected parameter sets.

Atmospheric correction was done with an enhanced version of the Fast Line-of-Sight Atmospheric Analysis of Spectral Hyper-cubes (FLAASH) algorithm (Alder-Golden et al. 1999)[xxxvi] implemented in the GM. Parameter setup was automatically generated based on the acquisition time and location information from the imagery and ancillary data.

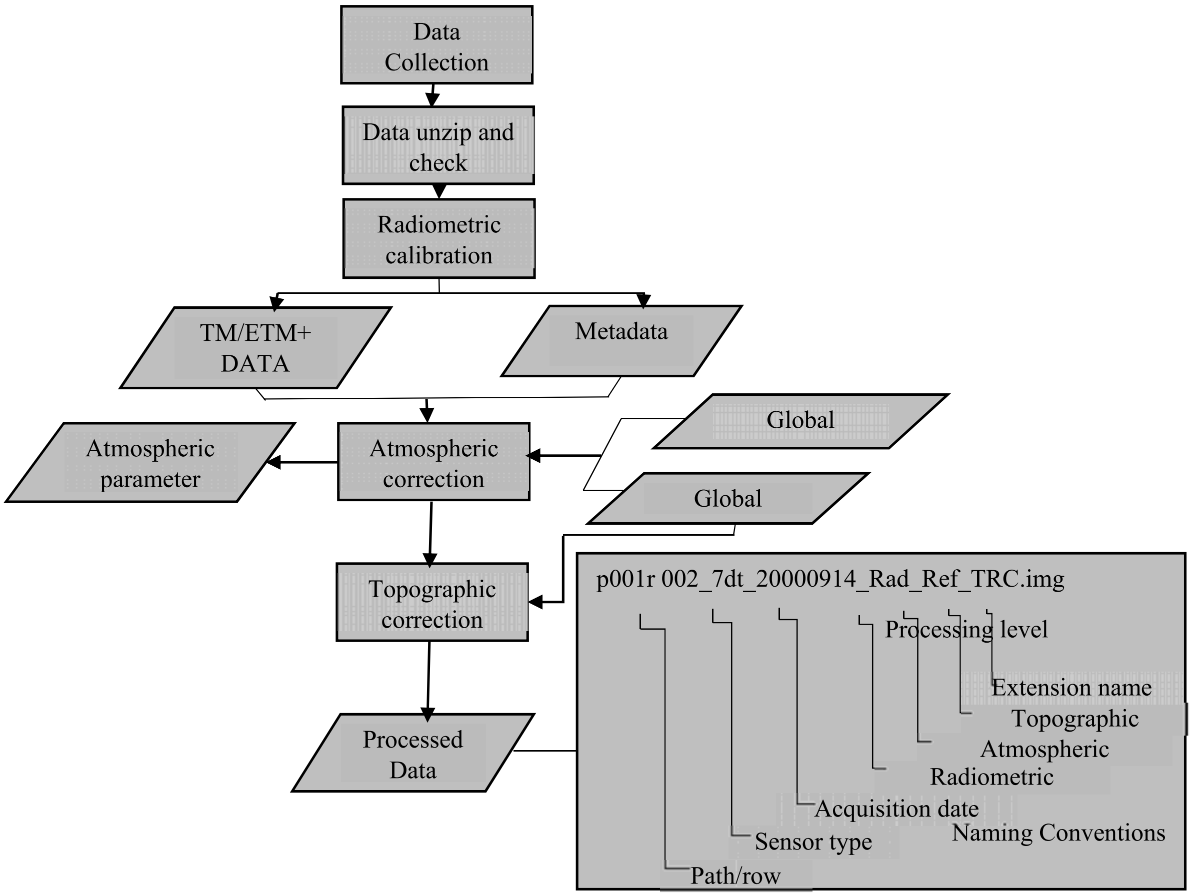

Figure 4: Radiometric processing of Landsat TM and ETM+ scenes

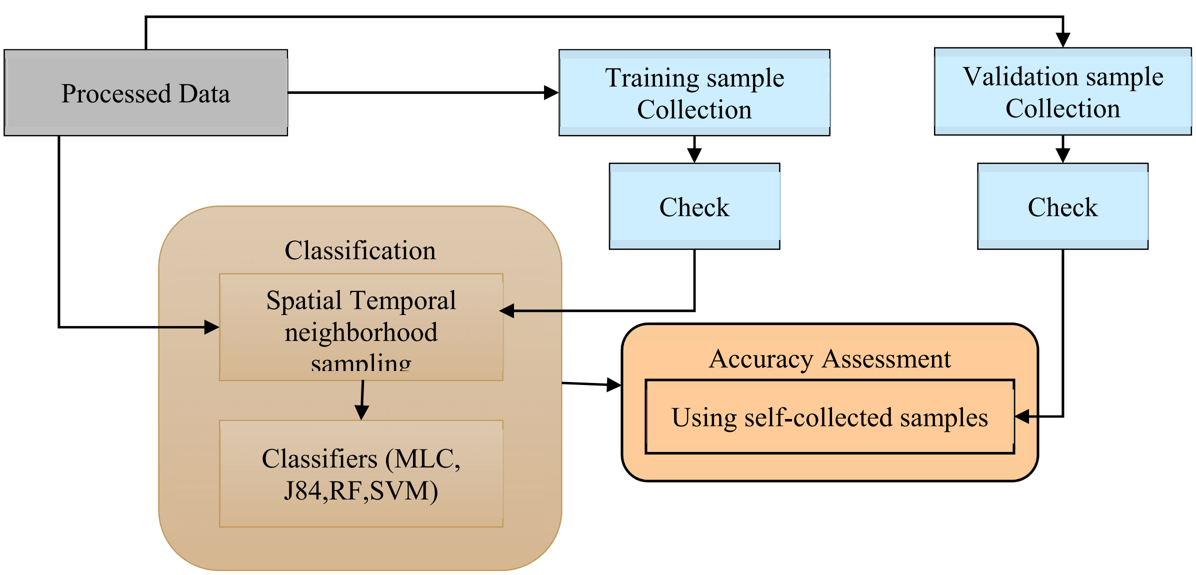

Figure 5: Classification Workflow

For example, the elevation information was obtained from the Geospatial Image Pyramid (GIP) of the global digital elevation model (DEM) data (recognizable by Google Earth and Environment for Visualizing Images (ENVI)). Aerosol data are inferred from the location information of each scene and DEM data. The GM FLAASH module also contains an automatic processing and optimization mechanism. When it detects over-correction of the imagery, indicated by a large quantity of 0 values, it automatically adjusts the water vapour and aerosol parameters, feeding the optimized parameters back into the atmospheric correction. After the atmospheric correction, the optimized parameters are recycled for use by the topographic correction procedure.

The topographic correction is based on the TopoRadCor procedure in GM. TopoRadCor takes the output from the atmospheric correction and uses the 90 m DEM from the GIP as input. The solar incidence angle is computed based on the DEM and the location and local time information for each pixel. The topographic correction can reduce the distortion over higher latitudes and complex terrain. TopoRadCor automatically adjusts to surface cover type, resulting in a well-characterized surface structure that overcomes over-correction effects

Although many processed scenes have been collected, by the time of training and test sample collection, there were still 656,889 km^2 of terrestrial land areas (excluding Antarctica and Greenland) not covered. These areas were mostly distributed within the Arctic region. Canada, the USA, Russia, and Norway (Svalbard) were among the top four countries with the largest un-mapped areas. Among the 8929 scenes used in this project, 192 scenes were sampled twice by different interpreters due to overlap in separate national and continental mapping task assignments. A total of 1007 scenes (including those 192 scenes mentioned above) share the same Path/Row collected at different times. Training samples were collected on all these images resulting in higher sample density over those overlap areas.

Four types of classifiers were experienced: the traditional MLC, a simple J4.8 decision tree classifier (an improved version of C4.5), support vector machine (SVM) classifier, and RF classifier (Bradski 2000; Hall et al. 2009; Chang and Lin 2011)[xxxvii]. The MLC was used as a reference for its popularity, computational simplicity, and robustness. Recently, The SVM classifier has been widely reported as an outstanding classifier in remote sensing (Huang, Davis, and Townshend 2002; Liu, Kelly, and Gong 2006)[xxxviii]. The RF classifier was tested due to its reported performance in the machine learning community (Bauer and Kohavi 1999; Caruna and Niculescu-Mizil 2006)[xxxix].

Representative sample collection is the most time-consuming and labor-intensive process in the global land-cover mapping effort. Limited by human power, we could not collect as many training samples as we would have liked for each class in every scene. We used samples collected in neighboring scenes to augment training samples. Training samples collected from any particular scene were pooled with samples from a certain number of neighboring scenes and were used to train a classifier for that particular scene. This is not usually needed in training sample collection when mapping areas are smaller in size but is considered to be a necessary alternative for global mapping.

The selection rule is set to be 30 neighboring scenes that meet the spatial and temporal criteria. The search for spatial neighbor images is limited within each of the Eco regions as defined by the World Wildlife Fund (Olson et al. 2001)[xl]. Temporal neighbor images are based on the acquisition date of images. At first, image acquisition time is ± 30 days from the current image. If 30 neighborhood scenes cannot be found, the time is relaxed to ±60 days. If 30 neighborhood scenes are still not available, the time is further relaxed to ± 90 days. If still 30 neighborhood scenes cannot be found, use what is available. All bands except the thermal band of the TM or ETM+ images were used in the classification.

1.3.2 Classification System Design

Existing global land-cover maps were produced for different purposes from different types of data with different types of algorithms. Some were developed by different groups of creators. Their classification schemes and implementations are also inconsistent. As a result, a thorough comparison of different land-cover maps is challenging if not impossible. Even so, some efforts have been made to crosswalk and compare these results (Herold et al. 2008; Tateishi et al. 2011).

Based on the analysis of existing classification systems, we found that there are major limitations to using a composite class type that combines vegetation trait, structure, and life-form information in a fixed manner. Taking the IGBP, GLC2000, and GLOBCover classification systems as examples, although the three systems differ in some details, they have high consistency as well. All vegetation categories contain life form, canopy closure, and height specifications, but different thresholds within a category. The IGBP system specifies that woody vegetation under 2 m height is classified as shrubs whereas the height limit was increased to 3 m in the GLC2000 and 5 m in the GlobCover classification systems.

Similarly, the canopy closure in different vegetation classes varied among the classification systems. Most land-cover classification systems do not include the distinction between C3 and C4 photosynthetic types but they are needed for land surface process models (DeFries et al. 1995; Dai et al. 2003)[xli]. However, such information is hard to obtain from remotely sensed data. Additional data sources or bio-geographical modelling results are often considered for obtaining such information (Stirling and Ducharne 2008)[xlii].

In GLC design, it was chosen to build a system separating the trait, life form, and structural information into distinct layers, retaining the original quantitative structural information as much as possible. Traits, life form, and structural data were treated as basic building blocks towards the construction of a complete classification system. These building blocks called end-components. There are a total of 10 land-cover types and eight life form or PFT classes. Canopy closure and heights can be preserved in unclassified form in their original quantities. As the nominal cover-type end-component from canopy closure and height end-components that can be quantitatively characterized were de-coupled.

Any land-cover class can resolve in a new classification system that contains those quantitative end-components. In fact, different types of end-components should be derived from different sources of data or by different types of algorithms. For example, the canopy closure can be derived by applying linear unmixing or regression techniques (Gong, Miller, and Spanner 1994; Roberts et al. 1998; Hansen, DeFries, and Townshend 2002)[xliii] to the spectral data, whereas vegetation height information can be obtained from other sources of data such as stereo pairs of images (Gong 2002)[xliv], interferometry of synthetic aperture radar (SAR) data (Neumann, Ferro-Famil, and Reigber 2010)[xlv], or the use of lidar data (Lefsky 2010; Hall et al. 2011; Simard et al. 2011)[xlvi].

Based on the end-component analysis and the potential of only six bands of spectral data from TM and ETM+ imagery, the determination of the cover-type end-component at this initial stage of global land-cover mapping were targeted. In addition, some life form categories spectrally were included separable from the TM data such as broadleaved and coniferous trees (at level 2). The resultant classification scheme, with a two-level hierarchy involving only the cover-type end-component, is listed in Table 1.

Level 1	Level 2	LCC label	Group	LCC level	LCC code	Description	Translation notes
10 Croplands						This type of land has clear traits of intensive human activity. It varies a lot from bare field, seeding, crop growing to harvesting. It can be easily identified if edges or textures are visible with sufficiently large land parcels. Fruit trees are classified into forests. Bare field is classified into bare land. Pasture could be transitional from croplands to natural grasslands.	
	11 Rice fields	Irrigated graminoid crops(s)	A11	A4XXXXC1D 3-S0308	11388-S0308	Land for rice cultivation.	
	12 Greenhouse farming					Land with plastic foam or grass roof protection with distinguishing spectral properties.	Hard to define 'Greenhouse framing' with LCCS
	13 Other croplands	Herbaceous crop(s)// Shrub crop(s)	A11//A11	A3//A2	10025//10013	This category includes arable and tillage land.	
20 Forest						Trees observable in the landscape from the images. Forest has a distinct canopy texture on TM images.	
	21 Broadleaf forests	Broadleaved closed to open trees	A12	A3A20B2XXD1	21495	Usually higher reflectivity than conifer species in the near infrared (NIR) spectral band. Shaded and sunlit sides less contrast.	LCCS limits tree cover percentage classification to >15%, limits tree height classification to >3 m
	22 Needleleaf forests	Needleleaved closed to open trees	A12	A3A20B2XXD1	21498	Lower reflectivity than broadleaf trees in the NIR band.	LCCS limits tree cover percentage classification to >15%, limits tree height classification to >3 m

(Continued)

Level 1	Level 2	LCC label	Group	LCC level	LCC code	Description	Translation notes
	23 Mixed forests	Broadleaved Closed to open trees/ Needleleaved closed to open trees	A12	A3A20B2XX D1/A3A20B2 XXD1	21495/21498	Neither coniferous nor broadleaf trees dominate in a mixed forest stand.	LCCS limits tree cover percentage classification to >15%, limits tree height classification to >3 m
	24 Orchards	Tree Crop(s) Cover: Orchard(s)	A11	A1-W8	10001-W8	Parcels planted with fruit trees or shrubs: single or mixed fruit species, fruit trees associated with permanently grassed surfaces.	
30 Grasslands	31 Pastures	Herbaceous closed to open vegetation	A12	A6A10	20033	Grasslands for grazing.	LCCS limits herbaceous cover percentage classification to >15%
	32 Other grasslands	Herbaceous closed to open vegetation	A12	A6A10	20033	Natural grasslands identifiable.	LCCS limits herbaceous cover percentage classification to >15%
40 Shurblands		Closed to open shrubland (thicket)	A12	A4A20B3	21450	Shrub cover identifiable in the image. Has a texture finer than tree canopies but coarser than grasslands.	LCCS defines shrubland's height between 5 and 0.3 m, and cover percentage classification to >15%
50 Wetlands		Natural and semi-natural aquatic or regularly flooded vegetation	A24	A24	0007	Although wetland is defined in the RAMSAR convention to maximize wetland areas, we intend to include only marshland with distinctively high reflectivity in the NIR band. Low relief areas with perched bogs, playas, and patholes may also be included depending on the season of image acquisition time. Forested wetland is not included here as it cannot be well identified from TM images.	

	51 Marshland	Closed to open herbaceous vegetation/ closed to open lichens/ mosses	A24	A2A20/A7A20	42155/42260	Aquatic and hydrophytic herbaceous plants observable from the image as non-water cover.	LCCS limits vegetation cover to >15%
	52 Mudflats	Bare land/// river	B16///B28	A5///A1-A4	6005///8001-1	Generally unvegetated expanses of mud, sand or rock lying between high and low water lines.	
60 Waterbodies		Natural waterbodies/ artificial waterbodies	B28/B27	A1/A1	8001/7001	All inland waterbodies with >3 pixels in width or 8 pixel × 8 pixel (6 ha) in area. Patches of fish ponds are included in this category. Spectral characteristics vary widely and the waterbody change in area with season.	
	61 Lake	Natural waterbodies (standing)	B28	A1-A5	8001-5	Natural waterbodies.	
	62 Reservoir/ Pond	Artificial waterbodies	B27	A1-A5	7001-5	Dammed waterbodies.	
	63 River	Natural waterbodies (flowing)	B28	A1-A4	8001-1	Natural or artificial water-courses serving as water drainage channels. Minimum width for inclusion 3 pixels.	
	64 Ocean	Natural waterbodies: salinity	B28	A1B1-V2/ A1B1-V3/ A1B1-V4// A1B1-V5	8002-V2/8002-V3/8002-V4//8002-V5	Salinity water.	
70 Tundra		Closed to open lichens/mosses	A12	A7A20	21465	Located at high mountains above tree line and high latitude regions with low height vegetation. The growing season is between 1 and 2 months.	
	71 Shrub and Brush Tundra (=40 Shrublands)					Dominated by low shrubs with grasses, lichens, and mosses at the background.	

(*Continued*)

Level 1	Level 2	LCC label	Group	LCC level	LCC code	Description	Translation notes
	72 Herbaceous Tundra	Herbaceous closed to open vegetation //closed to open lichens/mosses	A11//A12	A2A20//A7A20	21453//21465	Dominated by various sedges, grasses, forbs, lichens, and mosses, all of which lack woody stems.	
80 Impervious		Artificial surfaces and associated area(s)	B15	A1/A2	5001/5004	Primarily based on artificial cover such as asphalts, concrete, sand and stone, bricks, glasses, and other cover materials.	
	81 Impervious-high albedo					Impervious road cover with high albedo materials (e.g. concrete, cement).	Hard to define 'Impervious-high albedo' with LCCS.
	82 Impervious-low albedo					Impervious roof tops covered by low albedo materials (e.g. asphalts, black shingles).	Hard to define 'Impervious-high albedo' with LCCS.
90 Barren Land						Vegetation is hardly observable but dominated by exposed soil, sand, gravel, and rock backgrounds.	
	91 Dry salt flats	Bare soil and/or unconsolidated material(s) with salt flats	B16	A5B13	6020	Dry salt flats occurring on the flat floored bottoms of interior desert basins.	
	92 Sandy areas	Loose and shifting sands	B16	A6	6006	Sandy areas are composed primarily of dunes accumulations of sand transported by wind.	
	93 Bare exposed rock	Gravels, stones and/or boulders/ bare rock(s)	B16	A3–A8/A3–A7	6002-2/6002-1	Gravel land and bare rocks.	
	94 Bare herbaceous croplands	Bare soil and/or other unconsolidated material(s)/// herbaceous croplands	B16///A11	A5///A3	6005///10025	Just harvested, fallow land and all other types of land not covered by vegetation such as lake bottoms in dry season.	

	95 Dry lake/river bottoms	Bare soil and/or other unconsolidated material(s)	B16///B28	A5/// A1–A5 A5/// A1–A4	6005///8001-5 6005///8001-4	Other types of land not covered by vegetation such as lake/river bottoms in dry season.
	96 Other barren lands	Bare soil and/or other unconsolidated material(s)	B16	A5	6005	All other types of land not covered by vegetation.
100 Snow and ice						Distributed in the polar areas and high mountains.
	101 Snow	Perennial snow/seasonal snow	B28	A2B1/A2B2	8006/8007	Lands under perennial or non-perennial snow over.
	102 Ice	Perennial ice/seasonal ice	B28	A3B1/A3B2	8009/2010	Lands under perennial or non-perennial ice over.
999 Cloud		N/A	N/A	N/A	N/A	

Note: LCCS, land-cover classification system (Di Gregorio 2005).

Table 1: Land Cover Classification Classes

In this scheme, the use of the land use concept was avoided as much as possible. For example, only land covered by crops is included as cropland. Harvested agricultural land and grazed grassland with traces of cultivation are listed under barren land in consideration of their land-cover function.

Similarly, there are areas that are seasonally varying. For example, lakes in arid areas can look like barren land during the dry season but like water bodies during the wet season. Lakes in tropical and subtropical areas may exhibit totally different cover types ranging from bare land, vegetation, to water surfaces due to large fluctuation of water levels (e.g. Poyang Lake, the largest freshwater lake in China, Dronova, Wang, and Gong 2011)[xlvii]. In training sample selection from the Landsat TM/ETM+ imagery, a 'what you see is what you get' principle was followed to prevent subjective inference of image information from apparent land use.

Based on these considerations, the urban class was not included as it is a compound class reflecting land use. Wetland is a class that encompasses a large number of geomorphological sub-categories such as marine, estuarine, riverine, lacustrine, and palustrine wetlands (Cowardin et al. 1977)[xlviii]. Temporally, they can be divided into permanent, seasonal, and intermittent. Spectrally, they vary among water, barren land, and vegetation. Vegetated marsh lands are probably the only spectrally unique wetland category that can be discerned from TM and ETM+ imagery. In addition, marshland is one of the most productive wetlands and is biologically significant for conservation reasons.

At level 2, an inundated marsh-land with emergent vegetation is included as a wetland class. In addition, wet muddy bare land such as a wet lake bottom or a wet silt land at coastal areas that are spectrally unique is chosen as a second wetland class. At level 1, marshland is merged into grassland but wet muddy bare land is merged into bare land in consideration of their land-cover function. Forested wetlands and other wetlands are not specifically treated as individual classes and they will be extracted using special algorithms and additional data types such as surface hydrology, terrain, and SAR data in the future.

CHAPTER 2

2 ACCURACY ASSESSMENT[2]

2.1 INTRODUCTION

The main objective of accuracy assessment is to derive a quantitative description of the accuracy of the global land cover map. This is a nontrivial task, and it must recognized that there is no one universal "best" method of accuracy assessment, but rather a suite of methods of varying value and applicability for any given map and purpose. The selection of an approach for map accuracy assessment should recognize both the limits of the data (*e.g.,* impacts of mixed pixels) and purpose of the accuracy assessment (*e.g.,* the different accuracy requirements of diverse user communities or the needs of map producers in evaluating mapping methods *etc*.). The basis of accuracy assessment is simply the comparison of the class labelling derived from an image classifier against some ground reference data set. It can, however, be a distinctly challenging analysis and one that is often undertaken poorly by the geosciences and remote sensing community.

Accuracy assessment has evolved considerably history of remote sensing. The issue is, however, complex, partly because of the great diversity of motivations and objectives in accuracy assessment as well as a set of difficulties that are widely encountered. For example, interest may focus on the accuracy of the classification as a whole or on just a sub-set of the classes mapped, and then also from the User's and Producer's perspectives depending on the importance of different types of errors. There may also be variations relating to issues such as the cost of different errors which should be integrated into the analysis. Consequently, there is no single universally accepted approach to accuracy assessment but a variety of approaches that may be used to meet the varied objectives that are encountered in remote sensing research. There are however, some general issues that are common to accuracy assessment. Indeed, two broad types of accuracy assessment are popular within remote sensing related research.

First, non-site specific accuracy which involves an evaluation of the similarity of the predicted and actual land cover representations in terms of the areal extent of classes in the mapped region. The focus of this type of accuracy assessment is, therefore, on the quantity or coverage of the land cover classes within the region. While this can sometimes be a useful approach to accuracy assessment it is insensitive to the geographical distribution of the classes in the region mapped. Thus, a classified image which contained the classes in correct proportions but in incorrect locations would be deemed perfect. This limitation to the non-site specific approach to accuracy assessment often renders it unsuitable for use in validation programs and so it is used relatively infrequently.

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[2] Alan H. Strahler, Luigi Boschetti, Giles M. Foody, Mark A. Friedl , Matthew C. Hansen, Martin Herold, Philippe Mayaux, Jeffrey T. Morisette , Stephen V. Stehman and Curtis E. Woodcock (2006) Global Land Cover Validation: Recommendations for Evaluation and Accuracy Assessment Of Global Land Cover Maps,GOFC-GOLD,,Report No.25.

Instead, the second type of approach to accuracy assessment, based on site-specific measures, is more widely used. Site-specific accuracy assessment involves the comparison of the predicted and actual class labels for a set of specific locations within the region classified. Thus, for example, for a typical remote sensing scenario, the actual and predicted class label information for a sample of pixels drawn from the region mapped are compared. This comparison is typically based upon the cross-tabulation of the actual and predicted class labels. This latter cross-tabulation provides the error or confusion matrix which should provide a wealth of information to summarize the quality of the classification. Indeed the confusion matrix may be used to derive a suite of quantitative measures to express classification accuracy, on both an overall and per-class basis. Site specific accuracy assessment is extremely popular in remote sensing and there is a large literature that promotes it as a 'best practice'.

2.2 ISSUES AND CONSTRAINTS OF CONCERN

There are many issues to be considered in an accuracy assessment (*e.g.,* Congalton and Green, 1999; Foody, 2002)[xlix], but the following are of particular concern:

1. It is effectively impossible to produce a land cover map that is completely accurate and satisfies the needs of all (Brown *et al.,* 1999)[l]. The different viewpoints and components of classification accuracy also act to ensure that there is no single all-purpose universal measure of accuracy. The purpose of the map should, therefore, be considered in its production and assessment. In most mapping applications and map evaluations, interest is focused on overall map accuracy. It may, however, be more appropriate in some circumstances to focus on other features (Lark, 1995; Boschetti *et al.,* 2004)[li]. This has important implications to the evaluation of map accuracy. Commonly, a relatively subjectively defined target of greater than 85 percent overall accuracy with reasonably equal accuracy across the classes is specified, but this need not be appropriate for all maps or applications.
2. To avoid bias, a sample of pixels independent of that used to train a classification should be used in the accuracy assessment (Swain, 1978; Hammond and Verbyla, 1996)[lii]. The sample design used to acquire the testing set of samples used to evaluate classification accuracy is of fundamental importance and must be considered when undertaking an accuracy assessment and interpreting the accuracy metrics derived (Stehman and Czaplewski, 1998; Stehman, 1995, 1999*a*)[liii].
3. Since the accuracy assessment is based on a sample of cases, confidence intervals should ideally accompany the metrics of accuracy contained in an accuracy statement (Rosenfield *et al.,* 1982; Thomas and Allcock, 1984)[liv].
4. The nature of the techniques used to map land cover from the remotely sensed imagery has important implications. For example, with some classifiers it is relatively easy to derive a measure of the uncertainty of the class allocation made for each pixel (*e.g.,* maximum likelihood classification), while with others the ability to derive an uncertainty metric is limited (*e.g.,* parallelepiped classification).

5. The use of site-specific approaches to accuracy assessment based on the confusion matrix requires accurate registration of the map and ground data sets. Some degree of tolerance to misallocation can be integrated into accuracy assessment (Hagen, 2003)[lv], although most assessments assume implicitly that the data sets are perfectly registered. The importance of misregistration as a source of nonthematic error in the confusion matrix is most apparent in regions where the land cover mosaic is fragmented (Estes *et al.,* 1999; Loveland *et al.,* 1999)[lvi].
6. For conventional (hard) classifications, in which each image pixel is allocated to a single class, it is assumed that the pixels are pure (*i.e.,* each pixel represents an area that comprises homogeneous cover of a single land cover class). Any hard class allocation made for a mixed pixel will, to some extent, be erroneous, and alternative approaches to accuracy assessment (*e.g.,* Gopal and Woodcock, 1994; Foody, 1996; Shalan *et al.,* 2004)[lvii] should be adopted if the proportion of mixed pixels is large. In general, the proportion of mixed pixels increases with a coarsening of the spatial resolution of the imagery.
7. Errors are commonly treated as being of equal magnitude. If some errors are more damaging than others, it may be possible to weight their effect in the assessment of classification accuracy (*e.g.,* Foody *et al.,* 1996; Naesset, 1996*a*; Stehman, 1999*b*; Smits *et al.,* 1999)[lviii].
8. The ground or reference data may contain error and thus misclassification does not always indicate a mistake in the classification used to derive the map. In reality, therefore, the assessment of maps commonly undertaken is one of agreement or correspondence with the ground data rather than strictly of thematic accuracy. In some instances, it may be useful to include some measure of confidence in the ground data used (Scepan, 1999; Estes *et al.,* 1999).
9. The pixel is the basic spatial unit of the analysis. Maps could be produced using other spatial units. For example, the minimum mapping unit could be set at a size larger than the image pixel size. The use of large units may help in reducing the effect of spatial misregistration problems. With soft/fuzzy classifications and with super-resolution mapping, where the aim is to map at a scale finer than the source data, the problems of spatial misregistration in conventional approaches to accuracy assessment are likely to be large.
10. The same set of class definitions/protocols should be used in the image classification as in the ground data; that is, the class labels used in both data sets should have the same meaning. Approaches to explore and accommodate differences in the meaning of class labels may be useful if the classes have been defined differently in the data sets (Comber *et al.,* 2004)[lix]. If different classification schemes have been used, it is still possible to evaluate the level of agreement between a map and the ground data using a cross-tabulation of class labels (*e.g.,* Finn, 1993)[lx].
11. The confusion matrix should be presented as well as the summary metrics of accuracy derived from it. To avoid problems associated with normalization (Stehman, 2004*a*)[lxi], the raw matrix should be provided and the sample design used in its generation specified.

2.3 Basic Approach

The basis of the suggested approach to accuracy assessment is the confusion or error matrix. This matrix provides a cross tabulation of the class label predicted by the image classification analysis against that observed in the ground data for the test sites (Figure 6). The confusion matrix provides a great wealth of information on a classification. It may, for example, be used to provide overall and per-class summary metrics of land cover classification accuracy (Congalton, 1991; Congalton and Green, 1999; Foody, 2002)[lxii] as well as to refine areal estimates (*e.g.,* Prisley and Smith, 1987; Hay, 1988; Jupp, 1989) or aspects of the classification analysis in order to meet specific user requirements (Lark, 1995; Smits *et al.,* 1999). Moreover, the confusion matrix is relatively easy to interpret and is familiar to both the map user and producer communities.

GROUND TRUTH (REFERENCE)

CLASSIFICATION	A	B	C	D	
A	f_{AA}	f_{AB}	f_{AC}	f_{AD}	f_{A+}
B	f_{BA}	f_{BB}	f_{BC}	f_{BD}	f_{B+}
C	f_{CA}	f_{CB}	f_{CC}	f_{CD}	f_{C+}
D	f_{DA}	f_{DB}	f_{DC}	f_{DD}	f_{D+}
	f_{+A}	f_{+B}	f_{+C}	f_{+D}	n

Figure 6: Layout of a typical confusion or error matrix.

The use of the confusion matrix in accuracy assessment applications is based on a number of important assumptions. In particular, it is assumed that each pixel can be allocated to a single class in both the ground and map data sets, and that these two data sets have the same spatial resolution and are perfectly registered. All of these assumptions are often not satisfied in remote sensing. In some instances, deviation from the assumed condition is relatively unimportant (*e.g.,* if testing pixels are drawn from very large homogenous regions of the classes then the impact of mis-registration of the data sets is unlikely to have a major impact on accuracy assessment) but in other situations they may lead to significant error and misinterpretation (*e.g.,* if the land cover mosaic is very fragmented and mixed pixels are common).

Interpretation of the confusion matrix also requires consideration of the sample design used to acquire the testing set. Since the testing set is a sample, its relationship to the population (the map) is important. Confusion matrices and associated metrics of accuracy derived from a land cover map using simple random or stratified random sampling may, for example, differ markedly if there are interclass differences in the accuracy of classification. Ideally a probability sample design should be used (Stehman, 1999*a*).

Map accuracy may be assessed using a variety of units (*e.g.,* pixels, blocks of pixels or polygons such as land parcels). For the purposes of our study the accuracy assessment is based on pixels. Given that the pixel is the smallest spatial unit, assessing map accuracy on a per-pixel basis is somewhat ambitious. A coarser minimum mapping unit may be more appropriate, but pixel-based assessment is common and, providing its limitations are realized, can be useful. Given that there is a trade-off between accuracy and spatial resolution, with aggregation acting to reduce mis-registration errors, knowledge of the relationship between accuracy and resolution may help in the specification of an appropriate cell size for a map (Carmel, 2004)[lxiii].

2.4 THEMATIC ACCURACY

For global land cover maps, accuracy assessment aims to provide an index of how closely the derived class allocations depicted in the thematic land cover map represent reality. In essence, the summary metrics of accuracy provide a measure of the degree of correctness in the class allocations in the map. Attention is, therefore, focused on thematic accuracy. The confusion matrix is well suited to this task (Figure 6). The cases that lie on the main diagonal of the matrix represent those correctly allocated, while those in the off-diagonal elements represent errors. Two types of thematic error, omission and commission, are possible and both may be readily derived from a confusion matrix (Congalton and Green, 1999). An error of omission occurs when a case belonging to a class is not allocated to that class by the classification. Such a case has been erroneously allocated to another class, which suffers an error of commission.

A major problem in the use of the confusion matrix and associated accuracy metrics, however, is that it may contain nonthematic error. In particular, error due to mis-registration of the data sets is commonly included (Canters, 1997; Pontius, 2000; Powell *et al.,* 2004). It is important to be aware of this source of error, as the error due to mis-registration may be larger than the thematic error actually present in the map. Sometimes it may be appropriate to spatially adjust locations of testing sites to account for known mis-registration effects (Husak *et al.,* 1999) or to attempt to directly include some tolerance to spatial mis-registration effects into the accuracy assessment (Hagen, 2003).

2.4.1 Measures of Accuracy

A variety of measures of overall and per-class accuracy can be derived from the confusion matrix. Metrics of overall accuracy provide an indication of the quality of the entire land cover map. For overall accuracy, attention is focused on the main diagonal of the confusion matrix (Congalton 2009)[lxiv].

$$\boldsymbol{OA} = \frac{\sum \boldsymbol{f_{ii}}}{\boldsymbol{n}} \qquad (i=A,B,C,D)$$

Equation 1*: Overall Accuracy.*

Sometimes interest is focused on the accuracy with which a particular land cover class is represented. Metrics to describe per-class accuracy can be readily derived from the confusion matrix. Clearly, this may be approached from two perspectives, depending on whether the data in the confusion matrix are read vertically or horizontally (Story and Congalton, 1986)[lxv].

If attention is focused on the accuracy of the map as a predictive device, concern is with errors of commission. In this situation what is generally termed user's accuracy, UA, may be derived, which is based on the ratio of correctly allocated cases of a class relative to the total number of testing cases allocated to that class(Congalton 2009)[lxvi].

$$\boldsymbol{UA_i} = \frac{f_{ii}}{f_{i+}} \quad \text{(i=A,B,C,D)}$$

***Equation 2**: User Accuracy.*

$$\boldsymbol{CE_i} = 1 - UA_i \text{ (i=A,B,C,D)}$$

***Equation 3:** Commission Error.*

The resulting metric provides an indication of the probability that a pixel allocated to a particular land cover class actually represents that class on the ground. Reading the matrix in the alternative way, from the map producer's perspective, the focus is on errors of omission. What is generally termed producer's accuracy, PA, may be derived from the ratio of cases correctly allocated to a class to the total number of cases of that class in the testing set (Congalton 2009).

$$\boldsymbol{PA_i} = \frac{\boldsymbol{f_{ii}}}{\boldsymbol{f_{+i}}} \quad \textit{(i=A,B,C,D)}$$

***Equation 4:** Producer Accuracy.*

$$\boldsymbol{OE_i} = 1 - PA_i \textit{ (i=A,B,C,D)}$$

***Equation 5:** Omission Error.*

Many summary metrics may be derived from a confusion matrix to express accuracy. The two most widely used measures of land cover map accuracy are the percentage of correctly allocated cases and the kappa coefficient of agreement (Trodd, 1995)[lxvii]. These give a guide to the overall quality of the map. Cohen's (1960)[lxviii] Kappa, introduced to remote sensing in the early 1980s (Congalton & Mead, 1983; Congalton et al., 1983)[lxix], in particular, Congalton and Green (2009, p. 105) state that 'Kappa analysis has become a standard component of most every accuracy assessment (Congalton et al. 1983, Rosenfield and Fitzaptrick- Linz 1986, Hudson and Ramm 1987, Congalton 1991)[lxx] and is considered a required component of most image analysis software packages that include accuracy assessment procedures'. Indeed, Kappa is published frequently and has been incorporated into many software packages (Visser and de Nijs 2006, Erdas Inc. 2008, Eastman 2009)[lxxi].

Kappa is the proportion of agreement after chance agreement is removed (Rosenfield and Fitzpatrick-Lins, 1986). From the error matrix, Kappa calculated as following:

$$\boldsymbol{k} = \frac{\frac{1}{n}\sum f_{ii} - \frac{1}{n^2}\sum f_{i+}f_{+i}}{1 - \frac{1}{n^2}\sum f_{i+}f_{+i}}$$

$$\boldsymbol{k_i} = \frac{\frac{f_{ii}}{n} - \left(\frac{f_{i+}}{n} * \frac{f_{+i}}{n}\right)}{\frac{1}{2}\left(\frac{f_{i+}}{n} + \frac{f_{+i}}{n}\right) - \left(\frac{f_{i+}}{n} * \frac{f_{+i}}{n}\right)} \; (i = A, B, C, D)$$

Equation 6: *Kappa Standard.*

The value of Kappa is between 1 and –1, the higher the value, the stronger the agreement. Although the kappa coefficient has been widely promoted for accuracy assessment (*e.g.,* Congalton *et al.,* 1983; Smits *et al.,* 1999), there are sufficient concerns with its use (*e.g.,* Foody, 1992; Ma and Redmond, 1995; Stehman and Czaplewski, 1998; Turk, 2002) that it cannot be recommended as general measure of map accuracy. Foody (2008)[lxxii]. exposed some of the conceptual problems with the standard Kappa, the arguments used to promote the use of the kappa coefficient are fundamentally flawed **First**, chance agreement is of no particular concern to classification accuracy assessment; it does not matter if a pixel is allocated correctly by chance or design. Thus, chance correction is unnecessary. Even if chance correction was desired the standard method to calculate the agreement due to chance is inappropriate for the typical remote sensing scenario and alternatives that are not dependent on the confusion matrix's row marginal may be used.

Critically, however, chance correction is unnecessary and the derived coefficient just a downward scaled version of overall accuracy. **Second**, although only a minor and possibly pedantic issue, the kappa coefficient does not actually use all of the matrix's elements directly but rather only its marginal values. **Third**, the existence of popular scales for the evaluation of kappa may be useful but these scales are necessarily arbitrary and not of universal applicability. **Fourth and finally**, the kappa coefficient is not unique in relation to comparisons. In order to rigorously compare two accuracy values all that is normally required are appropriate estimates of the accuracy and the variance of the accuracy for each classification. Pontius (2000)[lxxiii] also recommends replace these indices with a more useful and simpler approach that focuses on two components of disagreement between maps in terms of the quantity and spatial allocation of the categories.

Allocation disagreement (AD) can be considered as difference between classified data and reference data due to incorrect spatial location of pixels on the classification. Allocation disagreement is always an even number of pixels because allocation disagreement always occurs in pairs of misallocated pixels.

$$\boldsymbol{AD_i} = 2 * min\left(\frac{f_{+i}}{n} - \frac{f_{ii}}{n}, \frac{f_{i+}}{n} - \frac{f_{ii}}{n}\right) \qquad i = (A, B, C, D)$$

$$\boldsymbol{AD} = \frac{\sum AD_i}{2} \qquad i = (A, B, C, D)$$

Equation 7: *Allocation Disagreement.*

Quantity disagreement (QD) is defined as the difference between the reference data and classified data based upon mismatch of class proportion.

$$\boldsymbol{QD_i} = \left|\frac{f_{+i}}{n} - \frac{f_{i+}}{n}\right| \qquad i = (A, B, C, D)$$

$$\boldsymbol{QD} = \frac{\sum QD_i}{2} \qquad\qquad i = (A, B, C, D)$$

***Equation 8**: Quantity Disagreement*

The total disagreemnet is the sum of the Quantity diasagreement and Allocation disagreemnet (Pontius and Millones 2011).

Other metrics of overall and per-class accuracy can be derived from a confusion matrix (*e.g.*, Foody, 1992; Finn, 1993; Ma and Redmond, 1995; Naesset, 1996*b*; Stehman, 1997*a*)[lxxiv]. Each metric focuses on different aspects of accuracy and may vary in utility between map users. Since it is impossible to anticipate the needs of all users, the confusion matrix itself should be provided so that the user may derive a specific measure of interest. To maintain flexibility, the raw and not a normalized matrix should be provided (Stehman, 2004*a*).

Values of acceptable classification accuracy presented in literature differ considerably. Pringle et al. (2009) consider accuracy over 70 % as adequate, whereas Foody (2002) recommends values over 85 %. Landis and Koch (1977)[lxxv] proposed categories for assessment of the classification performance measured by Kappa value as poor (<0.41), moderate (0.41-0.61), good (0.61-0.81), and excellent (>0.81).

CHAPTER 3

3 BENCHMARKING CONDUCTED HEREIN BETWEEN GLC30 AND ITALIAN REGIONAL LAND COVER DATASET

The benchmarking conducted herein uses accuracy assessment techniques based on map comparison (Stehman 2006)[lxxvi]. Map comparison is a complex process as documented in Hargrove et al. (2006)[lxxvii] and Liu et al. (2007)[lxxviii] and is used - also in validation maps produced with different image analysis techniques (Kuzera and Pontius 2008)[lxxix] that is the ultimate objective of this study. Several comparison measures have been reviewed by Liu et al. (2007).

Map validation includes both assessing the accuracy and robustness of the product. The accuracy assessment based on agreement measure alone fails to take into account spatial patterns (Foody 2007; Pontius 2000, 2002; Chen et al. 2005, 2006; Mc Callum et al. 2006)[lxxx]. For this reason additional measures had been introduced in literature taking into account the location of map categories (Pontius 2000, Hagen 2002)[lxxxi] as well as spatial patterns (White 2006)[lxxxii]. Multiple resolution comparison methods can also be used to measure agreement at multiple scales (Kuzera and Pontius 2008, Pontius 2002, Pontius and Suedmeyer 2004, Pontius and Connors 2009, Pontius and Cheuk 2006)[lxxxiii].

3.1 METHODOLOGY

3.1.1 Study Area

Italy, officially the Italian Republic, is a unitary parliamentary republic in Southern Europe. To the north, Italy borders France, Switzerland, Austria, and Slovenia, and is approximately delimited by the Alpine watershed, enclosing the Po Valley and the Venetian Plain. To the south, it consists of the entirety of the Italian Peninsula and the two biggest Mediterranean islands of Sicily and Sardinia.

Italian territory also includes the islands of Pantelleria, 60 km (37 mi) east of the Tunisian coast and 100 km (62 mi) southwest of Sicily, and Lampedusa, at about 113 km (70 mi) from Tunisia and at 176 km (109 mi) from Sicily, in addition to many other smaller islands. Italy covers an area of 301,338 km^2 (116,347 sq. mi) and has a largely temperate climate. Italy is subdivided into 20 regions as shown in Table 2 & Figure 7.

Region	Capital	Area(Km^2)	Area sq. mi
Abruzzo	L'Aquila	10,763	4,156
Aosta Valley	Aosta	3,263	1,260
Puglia	Bari	19,358	7,474
Basilicata	Potenza	9,995	3,859
Calabria	Catanzaro	15,080	5,822
Campania	Naples	13,590	5,247

Emilia-Romagna	Bologna	22,446	8,666
Friuli-Venezia Giulia	Trieste	7,858	3,034
Lazio	Rome	17,236	6,655
Liguria	Genoa	5,422	2,093
Lombardy	Milan	23,844	9,206
Marche	Ancona	9,366	3,616
Molise	Campobasso	4,438	3,616
Piedmont	Turin	4,438	1,713
Sardinia	Cagliari	24,090	9,301
Sicily	Palermo	25,711	9,927
Tuscany	Florence	22,993	8,878
Trentino-Alto Adige	Trento	13,607	5,254
Umbria	Perugia	8,456	3,265
Veneto	Perugia	18,399	7,104

Table 2: [3]Italy Regions.

Figure 7: Italy Regions.

[3] Data are available from http://en.wikipedia.org/wiki/Italy.

3.1.2 Italian Land cover Data Collection

Figure 8 shows the regional Italian land cover data that were collected from Regional Geoportal.

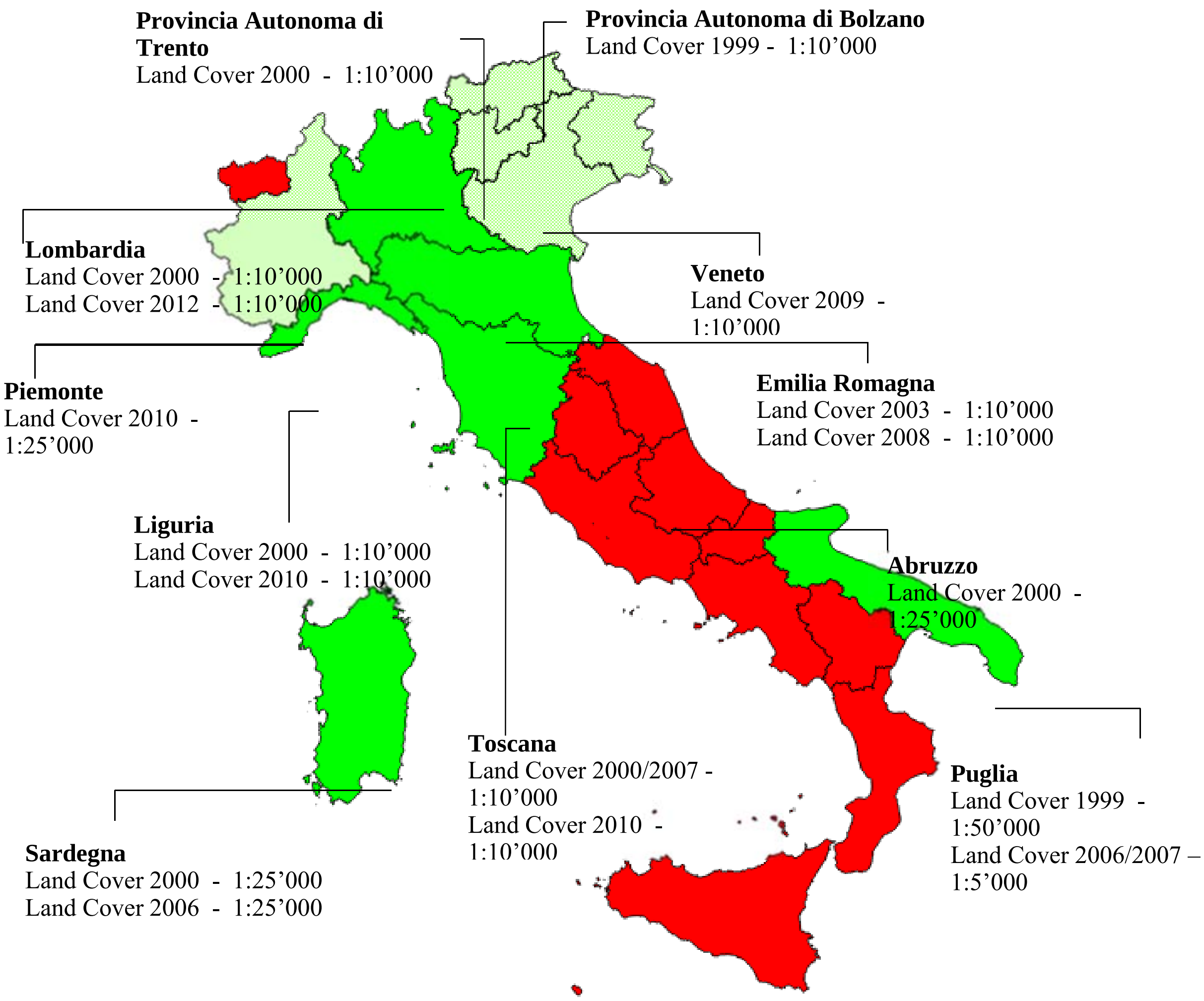


Figure 8: Italian Land cover Data Collection.

3.1.3 Data Processing

Data processing was carried out by using the software open-source GRASS GIS 6.4.1 (Neteler et al. 2012)[lxxxiv]. First, The Italian land cover datasets are available in ESRI Shape file format, the conversion from vector to raster is performed by taking into account different resolution values and different methods such as Raster 30m with central method, 5m with central method and 30m with prevalence method as shown in Figure 9.

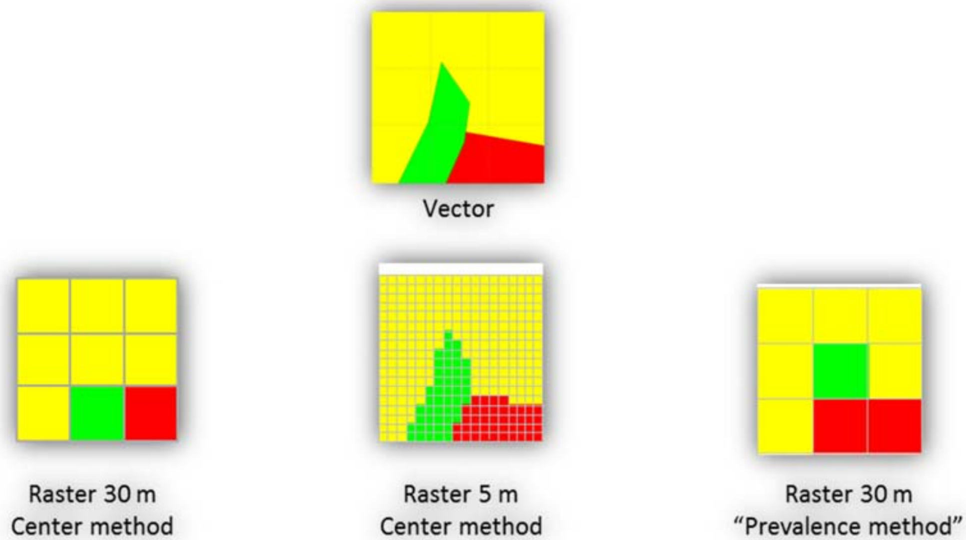


Figure 9: Rasterization with different resolution and different methods.

The rasterization performed through GRASS GIS module *v.to.rast*. *v.to.rast* module is based on the center method which attributes to a cell the value of the polygon that occupies its center. In this study also another popular approach, the prevalence method, was considered; this algorithm attributes to a cell the value of the polygon spatially prevalent in the whole cell.

As prevalence method is not directly available in GRASS GIS rasterization algorithm, a new 30 m resolution raster map based on it was calculated taking advantage of *r.resamp.stats*, GRASS GIS module able to resample a raster map layer to a coarser grid using different aggregation methods (average, median, variance, mode, etc.). In the study, 5 m resolution was the input raster layer and the mode was the selected aggregation method.

Second, the other important phase of Data processing was relative to the different thematic classification of the land cover maps. The Italian land cover dataset are mostly based on a fourth level hierarchical CORINE nomenclature. To allow the comparison procedure, a reclassification of the raster maps were carried out to obtain a first level CORINE legend , furthermore a reclassification was performed taking into account the four Sub-classes of category 3, the legend is listed in Table 3.

CORINE LEGEND	
1. Artificial cover	
2. Cropland	
3. Forest and semi natural areas	31. Forest
	32. Scrub and/or herbaceous vegetation associations
	33. Beaches, dunes, sands, bare rocks, sparsely vegetated areas
	335. Glaciers and perpetual snow
4. Wetland	
5. Open Water	

Table 3:CORINE land Cover Legend

On other hand, the Global land cover (GLC) is available in raster format in different tiles, Therefore a "patching" procedure is required sometimes to obtain the area corresponding to the Italian regional land cover (Ex. Figure 10). The patching is performed through GRASS GIS module *r.patch, r.patch* allows to build a new raster map the size and resolution of the current region by assigning known data values from input raster maps to the cells in this region. This is done by filling in "no data" cells, those that do not yet contain data, contain NULL data, or, optionally contain 0 data, with the data from the first input map. Once this is done the remaining holes are filled in by the next input map, and so on.

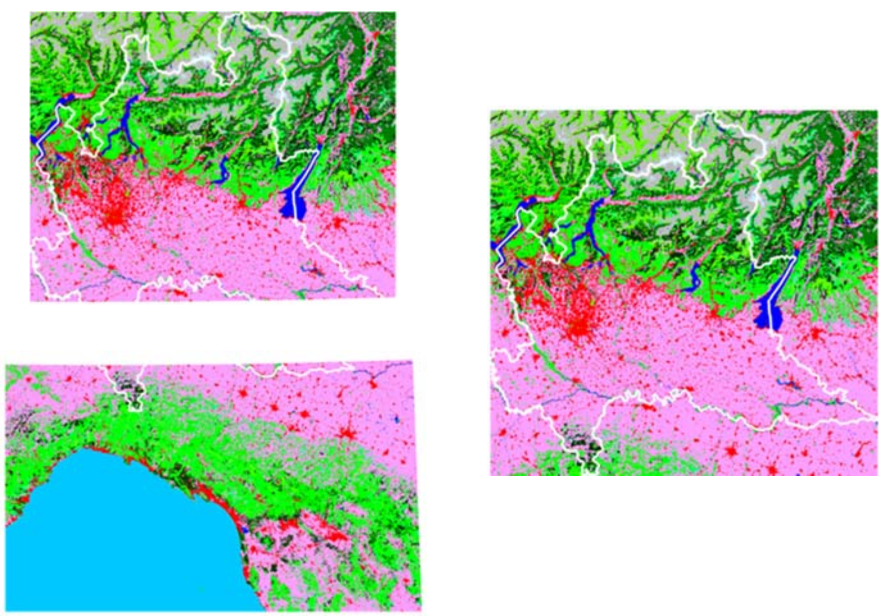


Figure 10: Patching different tiles.

The Global land cover dataset legend is based on eleven Land cover categories listed in Table 4. To allow the comparison procedure, a reclassification of the raster maps were carried out to obtain a first level CORINE legend, furthermore a reclassification was performed taking into account the four Sub-classes of category 3. Table 5 list the GLC legend correspond to CORINE legend.

GLC LEGEND
10. Cropland
25. Mixed Forester
26. Broadleaf Forester
27. Coniferous Forester
30. Grass
40. Shrub
50. Wetland
60. Water
80. Artificial Cover
90. Bare Cover
100. Permanent ice of Snow

Table 4: GLC Legend.

CORINE LEGEND	GLC LEGEND
1 Artificial surfaces	80. Artificial cover
2 Croplands	10. Croplands
4. Wetlands	50. Wetlands
5. Open water	60. Water
31. Forests	25. Mixed forest 26. Broadleaf forest 27. Coniferous forest
32. Scrub and/or herbaceous vegetation associations	30. Grass 40. Shrub
330. Beaches, dunes, sands, bare rocks, sparsely vegetated areas	90. Bare land
335. Glaciers and perpetual snow	100. Permanent ice or snow

Table 5: GLC Legend Corresponding to CORINE Legend.

The overall workflow of the study is shown in Figure 11

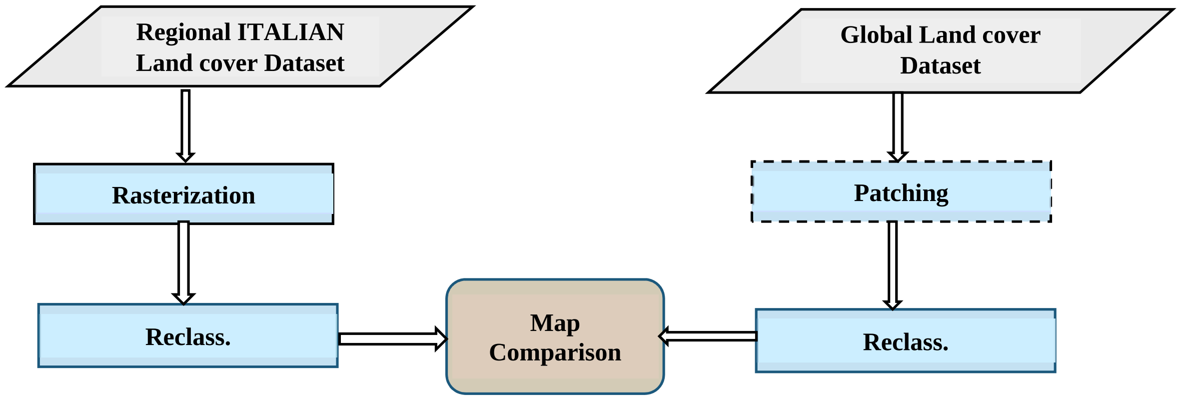


Figure 11: Data Processing work flow.

3.1.4 Agreement Measures

The overall agreement measures are based on cell-by-cell comparison between Italian regional map (REFERANCE MAP) and GLC (CLASSIFIED MAP) and provide a general assessment of consistency between two maps (Pontius et al. 2004). This study uses the recommended User's and Producer's accuracy, Overall accuracy, Kappa, Commission Error and Omission Error. However those metrics do not quantify the quantity and the location error (Pontius 2000, 2002). For this reason we have used the Allocation Disagreement and Quantity Disagreement to compare allocation and quantity of pixels for the two land cover of maps. The two measures are recommended as the most important components to directly assess differences between maps (Pontius et al. 2004, Pontius et al. 2007, Pontius and Millones 2008).

The error matrix and some of the mentioned statistics were calculated taking advantage of GRASS GIS *r.kappa* module. *r.kappa* tabulates the error matrix of classification result by crossing classified map layer with respect to reference map layer. Both overall *kappa* (accompanied by its *variance*) and conditional *kappa* values are calculated. Also percent of commission and omission error, total correct classified result by pixel counts, total area in pixel counts and percentage of overall correctly classified pixels are tabulated. This analysis program respects the current geographic region and mask settings.

Land cover maps are sometimes used for area estimation of a land cover class by simply adding the area of the polygons labelled as belonging to that class. This approach is rather naïve and can lead to a serious bias if the mapping scale is not detailed enough or the thematic accuracy is not very high (Gallego et al, 1999)[lxxxv]. By comparing different land cover maps, part of the disagreement can be attributed to the fact that the images were taken on different dates, part can be due to the scale effect and part to different thematic accuracy levels.

Another part of the disagreement may be due to a different interpretation of the nomenclature or to photo-interpretation errors, but it is difficult to know the impact of each source of disagreement without a suitable ground survey.

Trying to resolve the impact of each source of disagreement, statistical analysis of the differences between the two maps can be applied, by taking into account to eliminate the part of disagreement due to the co-location tolerance we need to eliminate a buffer around the polygons border.

Corresponds to that the location accuracy of GLC is 70 m, we eliminate a buffer 70 m wide on each side of the GLC polygons border for each class then recalculate the Agreement statistics. The calculation of buffer is performed taking advantage of GRASS module *r.mapcalc, r.mapcalc* performs arithmetic on raster map layers. New raster map layers can be created which are arithmetic expressions involving existing raster map layers, integer or floating point constants, and functions.

3.2 FIRST CASE STUDY: LOMBARDY REGION

Lombardy is one of the 20 regions of Italy (Figure 12)[4], the capital is Milan. Lombardy is bordered by Switzerend and by Italian regions of Trentino-Alto and Veneto (east), Emilia-Romagna (south), and piedmont (west). Three distinct natural zones can be fairly easily distinguished in the Lombardy region: Mountains, Hills and Plains. The great Lombard lakes, all of glacial origin lie in this zone. From west to east these are Lake Maggiore, Lake Lugano (shared with Switzerland), Lake Como, Lake Iseo, Lake Idro, then Lake Garda, the largest in Italy. Figure 13, shows the overall workflow for Lombardy region.

Figure 12: Lombardy Region.

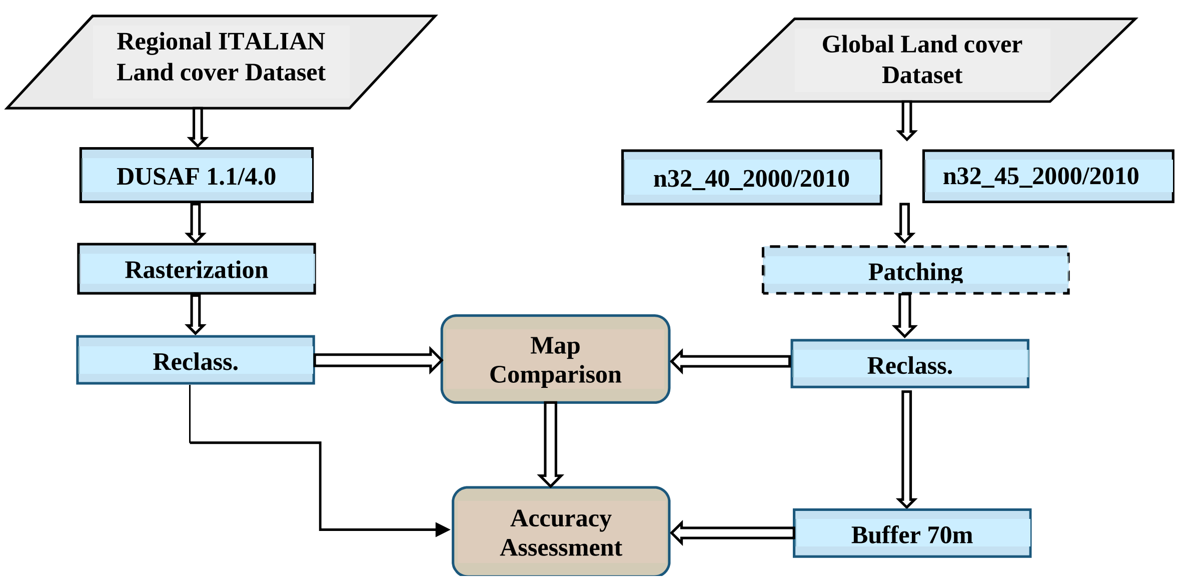


Figure 13: Overall Workflow of Lombardy region.

[4] http://en.wikipedia.org/wiki/Lombardy

3.2.1 DUSAF Land Cover Database

DUSAF, Italian acronym for "Use Categories of Agricultural and Forest Soils", is a land cover database created in 2000-2001 within a project promoted and funded by Regione Lombardia (Bonomi et al.2012)[lxxxvi] and carried out by the Regional Authority for Services to Agriculture and Forests (ERSAF) with the cooperation of the Lombardy Regional Agency for the Protection of the Environment (ARPA).

The database[5] is composed by two vector maps at 1:10'000 information scale: a polygonal layer representing the land use and cover, and a linear layer representing hedges and rows. The DUSAF legend adopts the Corine Land Cover (CLC) nomenclature for the first three levels (Bossard et al. 2000)[lxxxvii]; two additional levels allow to identify characteristic features of Lombardia region.

Five releases of the database are currently available (Table 6):

- **DUSAF 1.0** was obtained from the photointerpretation of aerial photos taken in 1998-1999. The original map was not conform to CLC nomenclature: for this reason a second version, named **DUSAF 1.1**[6] was obtained through a reclassification procedure;;
- **DUSAF 2.0** was obtained from photointerpretation of aerial photos acquired at different dates (2005, 2006, and 2007). Starting from this release, data are always integrated with regional databases information;
- **DUSAF 2.1** was derived by photointerpretation of aerial photos taken in 2007 on the whole region;
- **DUSAF 3.0**[7] was based on aerial photos acquired in 2009 and is currently available for only a part of Lombardia territory (Brescia, Sondrio, Cremona, Milano and Monza e Brianza provinces);
- **DUSAF 4.0** [8]was obtained from aerial photos taken in 2012.

[5] The Database were downloaded from Geoportal of Lombardy region http://www.cartografia.regione.lombardia.it/geoportale
[6] Metadata: http://www.cartografia.regione.lombardia.it/geoportale/DiscoveryServlet?command=viewdetails&uuid=%7bB121D1AE-C2FA-B826-FA58-EFA86BE15E7E%7d
[7] Metadata: http://www.cartografia.regione.lombardia.it/geoportale/DiscoveryServlet?command=viewdetails&uuid=%7b2A584127-C937-BF3C-2987-456CC5F2C0AA%7d
[8] Metadata: http://www.cartografia.regione.lombardia.it/geoportale/DiscoveryServlet?command=viewdetails&uuid=%7b3EC071B1-5189-9F69-B5C5-0879ED03375A%7d

	DUSAF 1.1	DUSAF 2.0	DUSAF 2.1	DUSAF 3.0	DUSAF 4.0
YEAR	1999 - 2000	2005 - 2007	2007	2009	2012
SCALE	1:10'000	1:10'000	1:10'000	1:10'000	1:10'000
REF SYS	WGS84/UTM32N	WGS84/UTM32N	WGS84/UTM32N	WGS84/UTM32N	WGS84/UTM32N
LEGEND	CORINE	CORINE	CORINE	CORINE	CORINE
SOURCE	Aerial photos	Aerial photos and regional databases	Aerial photos and regional databases	Aerial photos and regional databases	Aerial photos and regional databases
EXTENT	whole region	whole region	whole region	BS, MI, MB, SO, CR	whole region

Table 6: DUSAF Database

3.2.2 Data Processing

Due to the availability of GLC for both years 2000 and 2010, a First comparison has been done between **GLC2000** and Land cover map of Lombardy region named **DUSAF1.1**. A second comparison has been done between **GLC2010** and Land cover map of Lombardy region, since there is two releases of DUSAF land cover are candidates for the comparison with the GLC relative to year 2010:

- **DUSAF 3.0** is based on aerial photos acquired in 2009 and is currently available for only a part of Lombardy territory.

- **DUSAF 4.0** is obtained from aerial photos taken in 2012 and covers the whole region.

A comparison between DUSAF 3.0 – DUSAF 4.0 has been done to see the differences between both maps, as a result the observed agreement was about 98.9%. Since there are no significant differences between the two maps, the **DUSAF 4.0** is chosen for the comparison procedure due to the fact of missing parts in DUSAF 3.0.

The Data processing procedure for both comparisons is as following, Firstly, the DUSAF vector map was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two DUSAF raster maps at different cell sizes, respectively 30 m and 5 m, were calculated. While the former corresponds to the GLC resolution, the latter is selected to take into account the greater level of detail of the DUSAF map.

Also another popular approach, the prevalence method, was considered, a new 30 m resolution raster map based on it was calculated taking advantage of GRASS GIS module *r.resamp.stats*, 5 m resolution was the input raster layer and the mode was the selected aggregation method. On the other hand, GLC was available in two different tile, therefore a patching procedure was needed to obtain the area corresponding to Lombardy region.

The second important phase of data processing was relative to the different thematic classification of the two land cover maps. To allow the comparison procedure, a reclassification of DUSAF raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3.

3.2.2.1 GLC2000-DUSAF1.1

Figure 14 & 15 gives a visual overview of both reclassified Land cover maps (DUSAF1.1, GLC2000).

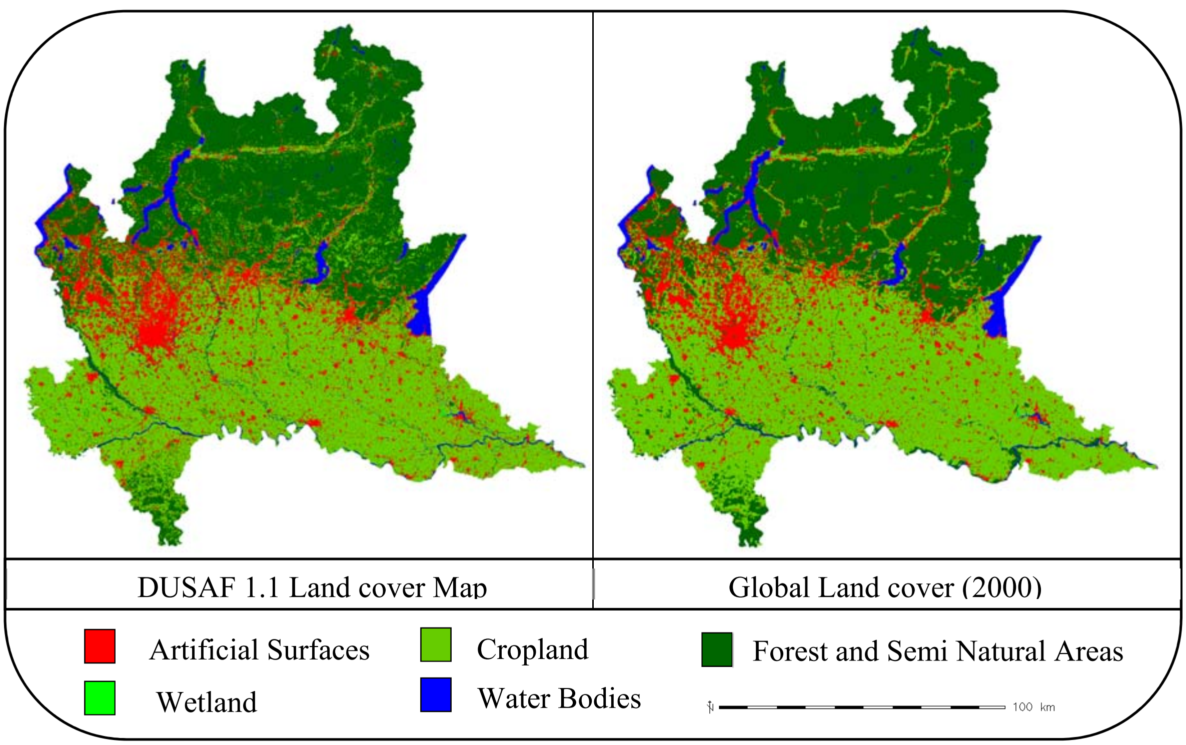


Figure 14: Visual Overview of Both Reclassified DUSAF1.1 and GLC2000 (1st Classification).

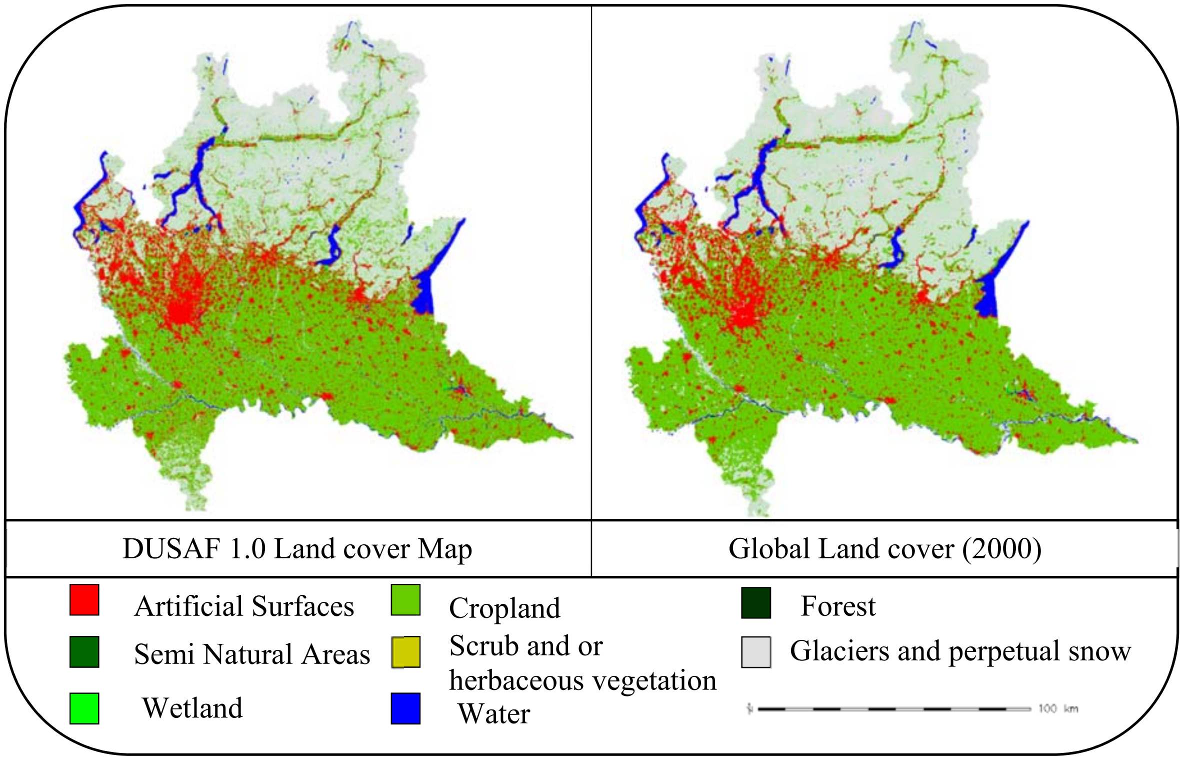


Figure 15: Visual Overview of Both Reclassified DUSAF1.1 and GLC2000 (2nd Classification).

3.2.2.2 GLC2010-DUSAF4.0

Figure 16 & 17 gives a visual overview of both reclassified Land cover maps (DUSAF4.0, GLC2010).

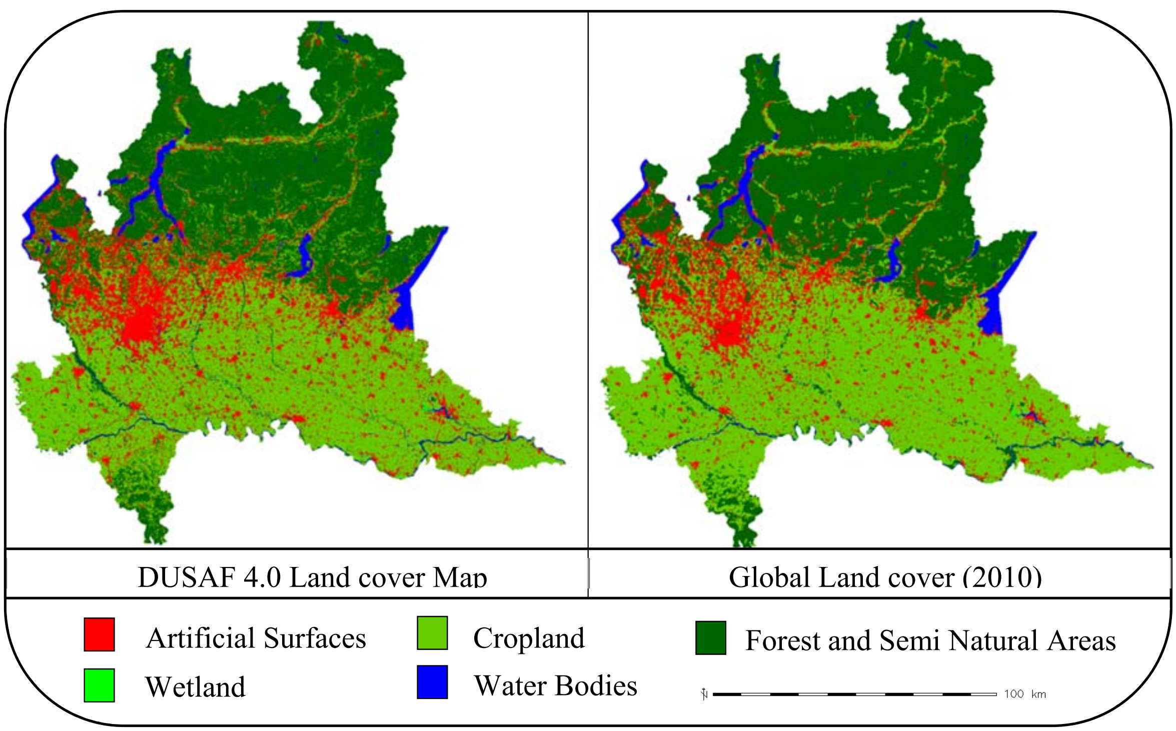


Figure 16: Visual Overview of Both Reclassified DUSAF4.0 and GLC2010 (1st Classification).

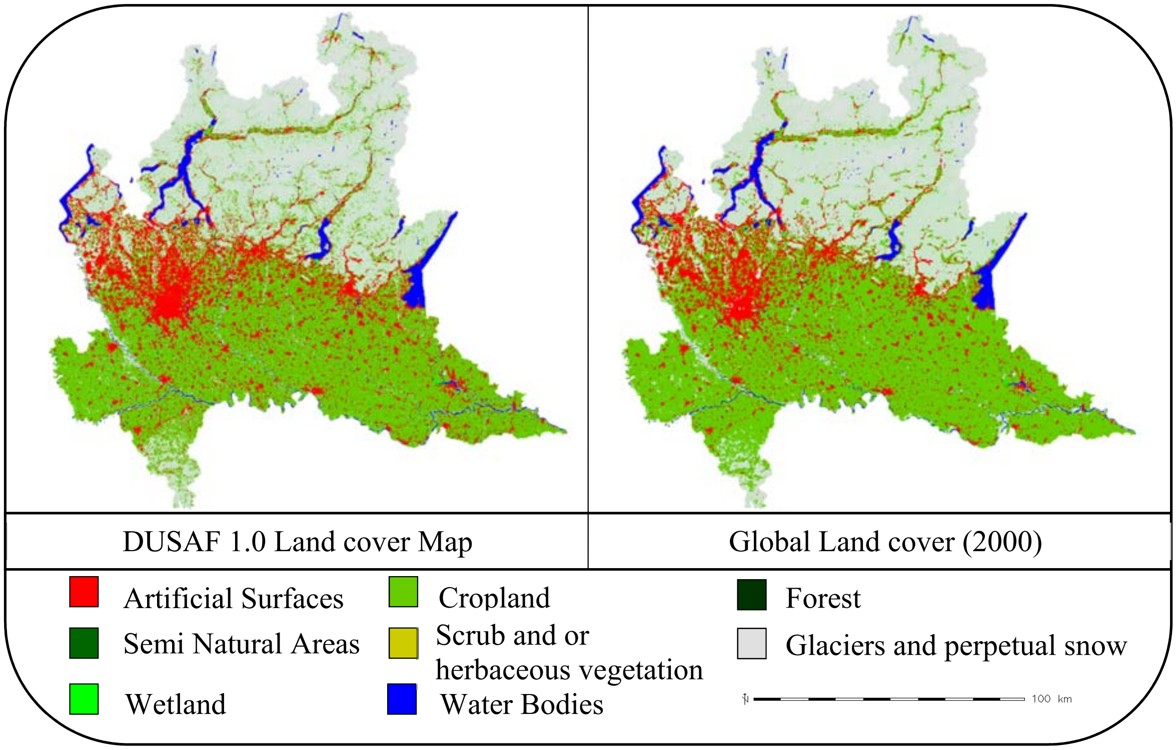


Figure 17: Visual Overview of Both Reclassified DUSAF4.0 and GLC2010 (2^{nd} Classification).

3.2.3 Accuracy Assessment

In a pixel based assessment, the accuracy assessment was derived from a comparison pixel by pixel between Reclassified DUSAF Land cover map (REFERENCE MAP) and GLC (CLASSIFIED MAP). In thematic mapping from remotely sensed data, the term accuracy is used typically to express the degree of 'correctness' of a classification. A thematic map derived with a classification may be considered accurate if it provides an unbiased representation of the land cover of the region it portrays. In essence, therefore, classification accuracy is typically taken to mean the degree to which the derived image classification agrees with reality or conforms to the 'truth' (Campbell, 1996; Janssen & vander Wel, 1994; Maling, 1989; Smits et al., 1999).

3.2.3.1 GLC2000- DUSAF1.1

Table 7 list the Confusion matrices and agreement measures corresponding to the first comparison that have been done between DUSAF1.1 and GLC2000, with first reclassification method (Case1) which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH DUSAF1.1

CLASSIFIED GLC2000	1	2	3	4	5	sum	UA	CE
1	2314534	413525	149311	451	14371	2892192	80.03%	19.97%
2	923590	10687700	855310	11657	68793	12547050	85.18%	14.82%
3	107383	952466	9142071	6336	34488	10242744	89.25%	10.75%
4	366	2867	2347	12771	2277	20628	61.91%	38.09%
5	8702	15791	36748	3666	753103	818010	92.07%	7.93%
sum	3354575	12072349	10185787	34881	873032	26520624		
PA	69.00%	88.53%	89.75%	36.61%	86.26%			
OE	31.00%	11.47%	10.25%	63.39%	13.74%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	86.39%	0.781	11.61%	2.00%

CASE B (5 m resoulation):

GROUND TRUTH DUSAF1.1

CLASSIFIED GLC2000	1	2	3	4	5	sum	UA	CE
1	83173920	14994685	5409661	16238	524003	104118507	79.88%	20.12%
2	33358558	384593515	30823798	420071	2496441	451692383	85.15%	14.85%
3	3889373	34334271	329031858	227734	1255200	368738436	89.23%	10.77%
4	13259	104014	84600	458730	81920	742523	61.78%	38.22%
5	320644	581477	1339950	132702	27072535	29447308	91.94%	8.06%
sum	120755754	434607962	366689867	1255475	31430099	954739157		
PA	68.88%	88.49%	89.73%	36.54%	86.14%			
OE	31.12%	11.51%	10.27%	63.46%	13.86%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	86.34%	0.780	11.66%	2.00%

CASE C (resampled 30 m resolution):

GROUND TRUTH DUSAF1.1

CLASSIFIED GLC2000	1	2	3	4	5	sum	UA	CE
1	2319794	410904	146648	459	14672	2892477	80.20%	19.80%
2	910598	10722530	840032	11761	70472	12555393	85.40%	14.60%
3	106753	956861	9151502	6406	34366	10255888	89.23%	10.77%
4	363	2867	2318	12841	2254	20643	62.21%	37.79%
5	8760	15769	36771	3717	758001	823018	92.10%	7.90%
sum	3346268	12108931	10177271	35184	879765	26547419		
PA	69.32%	88.55%	89.92%	36.50%	86.16%			
OE	30.68%	11.45%	10.08%	63.50%	13.84%			

GENERAL AGREEMENT MEASURES

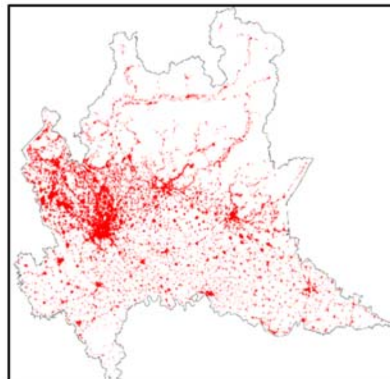
	OA	*K*	*AD*	*QD*
30 m res	86.50%	0.783	11.52%	1.98%

Table 7: First Reclassification Method (Case 1) - Error matrix and Agreement measures for Different Input data Resolution between GLC2000 and DUSAF 1.1.

The agreement measures are most similar with different input data resolution, the kappa values are high identify with high overall accuracy. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

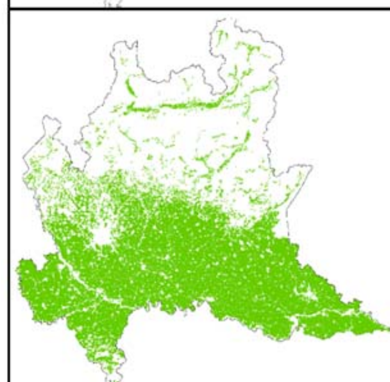
- **Artificial surfaced category**

	5 m	*30 m*	*30 m res*
UA	79.88%	80.03%	80.20%
PA	68.88%	69.00%	69.32%
K	0.705	0.707	0.710
AD	4.39%	4.36%	4.31%
QD	1.74%	1.74%	1.71%



- **Cropland**

	5 m	*30 m*	*30 m res*
UA	85.15%	85.18%	85.40%
PA	88.49%	88.53%	88.55%
K	0.753	0.754	0.756
AD	10.48%	10.44%	10.44%
QD	1.79%	1.79%	1.68%

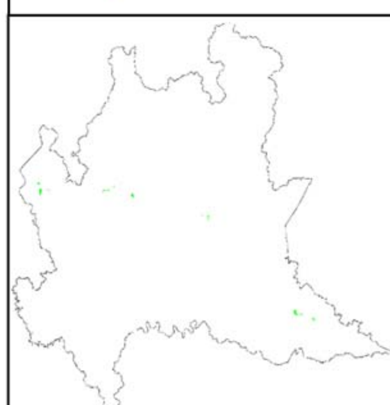


- **Forest and Semi Natural area Category**

	5 m	*30 m*	*30 m res*
UA	89.23%	89.25%	89.23%
PA	89.73%	89.75%	89.92%
K	0.829	0.829	0.831
AD	7.89%	7.87%	7.73%
QD	0.21%	0.21%	0.30%

- **Wetland**

	5 m	*30 m*	*30 m res*
UA	89.23%	89.25%	89.23%
PA	89.73%	89.75%	89.92%
K	0.829	0.829	0.831
AD	7.89%	7.87%	7.73%
QD	0.21%	0.21%	0.30%



- **Open Water Category**

	5 m	*30 m*	*30 m res*
UA	91.94%	92.07%	92.10%
PA	86.14%	86.26%	86.16%
K	0.886	0.887	0.887
AD	0.50%	0.49%	0.49%
QD	0.21%	0.21%	0.21%

Table 8 list the general agreement measures corresponding to the first comparison that have been done between DUSAF1.1 and GLC2000, with second reclassification method (Case2) which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

***[9]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	77.18%	0.673	17.97%	4.85%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*	*PERPETUAL SNOW / GLACIERS*
UA*	74.76%	32.11%	70.41%	24.27%
PA*	81.12%	32.25%	42.82%	72.72%
K*	0.703	0.276	0.505	0.359
AD*	9.20%	8.50%	2.62%	0.26%
QD*	2.07%	0.03%	2.85%	0.96%

Table 8: Second Classification Method (Case2); Agreement measures with 30 m input data resolution Between Reclassified Maps GLC2000 and DUSAF1.1.

Comparing the results of the two different classification method, the general agreement measures shows that the overall accuracy decreased by 8%, this explain the increase in both values of Allocation and Quantity disagreement. Among the sub classes, Forest are classified with the best accuracies (74.76% for the User's accuracy and 81.12% for the Producer's accuracy). This followed by Shrub/Grass, Beaches, Rocks, Sparsely vegetated area and Permanent snow are poorly classified with less accuracies.

To eliminate the part of disagreement according to co-location tolerance, Firstly; a buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy (Figure 18).

[9] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

Secondly; recalculation of the agreement statistics, here the usual terms “confusion matrix” and “commission and omission errors” are substituted by “disagreement matrix” and “commission and omission disagreement” to stress the fact that two different land cover are compared. Table 9 list the General agreement measures.

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	90.83%	0.8462	7.10%	2.07%
30 m	90.53%	0.8421	7.40%	2.07%
30 m res	90.64%	0.8440	7.33%	2.03%

Table 9: General Agreement measures after eliminating the Buffer between reclassified GLC2000 and DUSAF1.1.

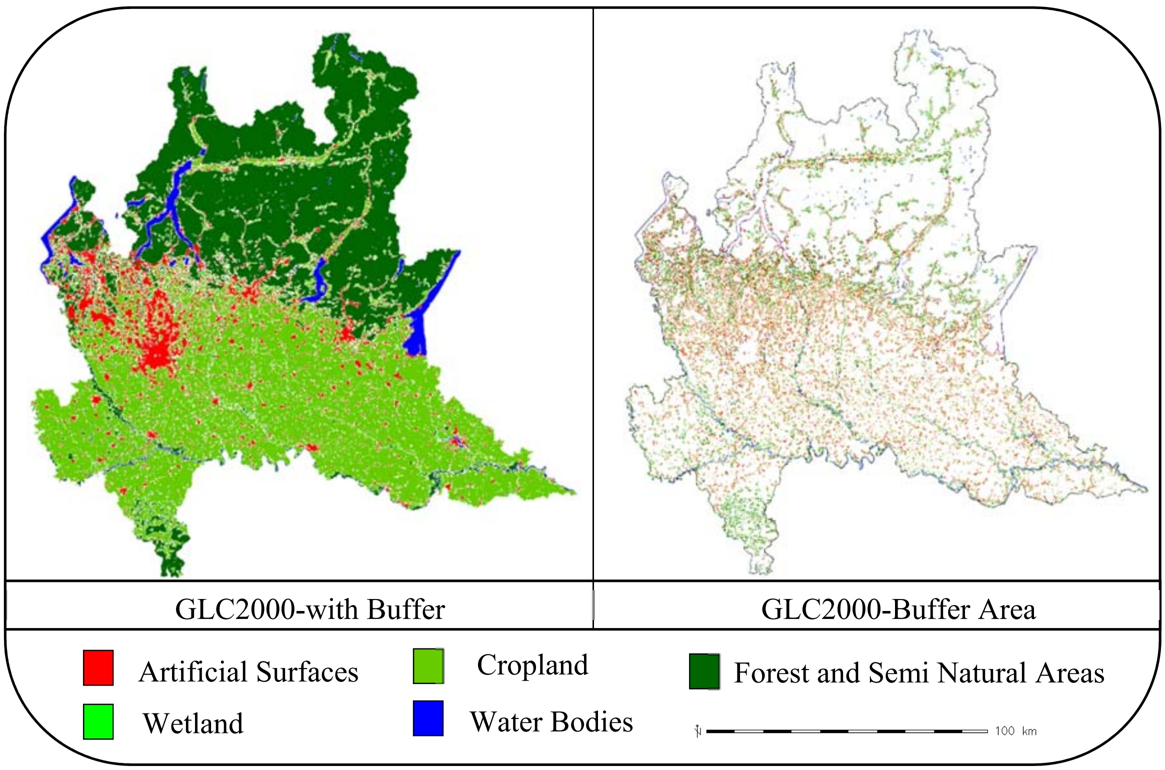


Figure 18: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Lombardy2000 Case).

Corresponding to the first comparison between DUSAF1.1 and GLC2000, with first reclassification method, the comparison between the general agreement measures with and without buffer gives an idea about the part of disagreement that can be attributed to the co-location inaccuracy. The percentage of the cells that have been removed was about 14.44% with 61.85% overall accuracy. Moreover, the comparison shows the increasing of the overall accuracy and standard Kappa, which explains the decreasing in Allocation and Quantity disagreement. Table 10 reports commission and omission disagreement with and without buffer corresponding to 30 m resolution.

	Commission Error		Omission Error	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	19.93%	10.68%	31.00%	27.63%
2. Cropland	14.83%	10.32%	11.47%	8.39%
3. Forest and semi Natural areas	10.75%	8.80%	10.25%	6.41%
4. Wetland	38.09%	28.94%	63.39%	59.73%
5. Water Surfaces	7.93%	1.26%	13.47%	7.83%

Table 10: GLC2000-DUSAF1.1, Commission and Omission disagreement by pixel (%).

Furthermore with second reclassification method (Case2), the cells that have been removed was about 18.81 % with 56.27 % overall accuracy (Figure19). Table 11 list the general agreement measures with buffer.

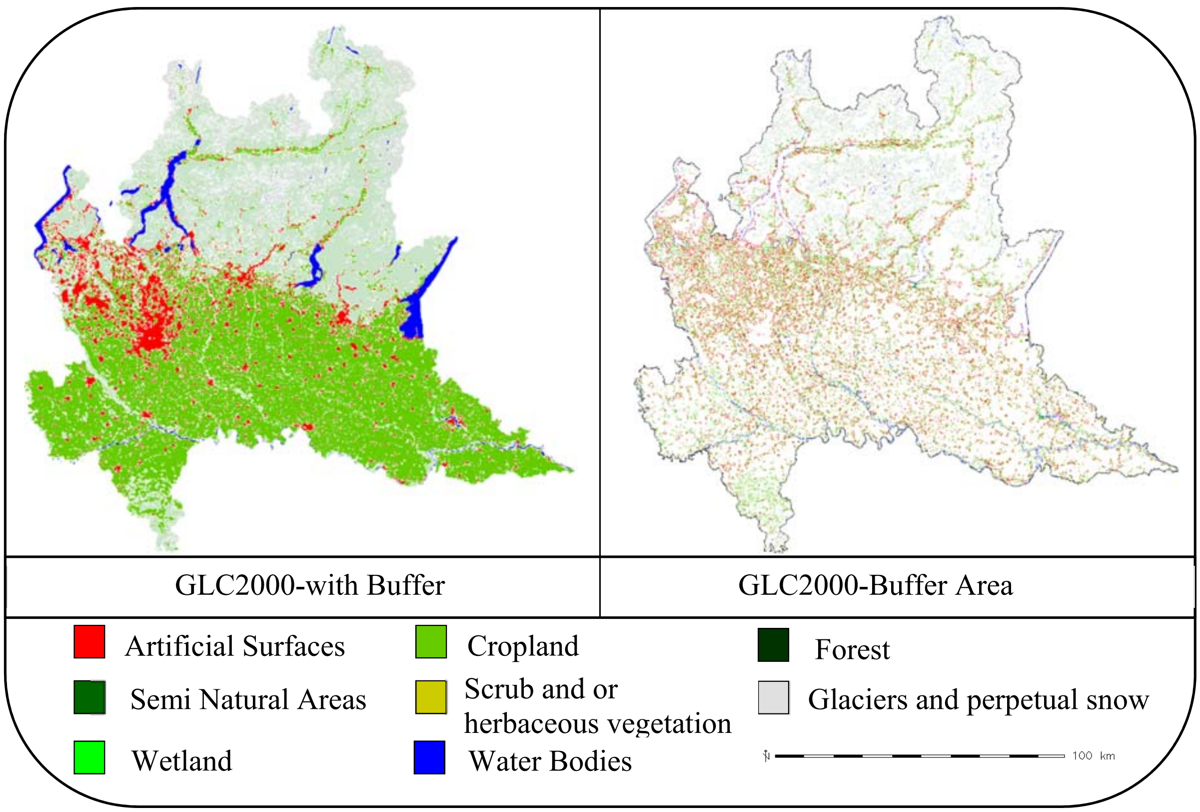


Figure 19: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Lombardy2000 Case).

***[10]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	82.03%	0.7319	12.82%	5.15%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*	*PERPETUAL SNOW / GLACIERS*
UA*	77.53%	34.29%	74.03%	26.83%
PA*	86.99%	32.79%	43.94%	75.60%
K*	0.7574	0.2939	0.5276	0.3922
AD*	6.33%	7.52%	2.09%	0.21%
QD*	2.97%	0.26%	2.75%	0.79%

Table 11: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer between reclassified GLC2000 and DUSAF1.1.

3.2.3.2 GLC2010- DUSAF4.0

Table 12 list the Confusion matrices and agreement measures corresponding to the comparison that have been done between DUSAF4.0 and GLC2010, with first reclassification method (Case1) which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH DUSAF4.0

CLASSIFIED GLC2010

	1	**2**	**3**	**4**	**5**	sum	**UA**	**CE**
1	2572746	351863	151332	404	16738	3093083	83.18%	16.82%
2	1140325	10293005	934361	13032	78265	12458988	82.62%	17.38%
3	132990	746873	9224882	8021	36115	10148881	90.90%	9.10%
4	431	2558	8895	13241	8345	33470	39.56%	60.44%
5	5868	7567	20294	2759	749925	786413	95.36%	4.64%
sum	3852360	11401866	10339764	37457	889388	26520835		
PA	66.78%	90.27%	89.22%	35.35%	84.32%			
OE	33.22%	9.73%	10.78%	64.65%	15.68%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	86.17%	0.781	9.84%	3.99%

[10] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

CASE B (5 m resoulation):

GROUND TRUTH DUSAF4.0

CLASSIFIED GLC2010

	1	2	3	4	5	sum	UA	CE
1	92457387	12787375	5479750	14591	612201	111351304	83.03%	16.97%
2	41159279	370404223	33653462	467567	2840898	448525429	82.58%	17.42%
3	4811464	26919178	332022006	289293	1316215	365358156	90.88%	9.12%
4	15312	93137	319887	476452	300359	1205147	39.53%	60.47%
5	222371	287792	753558	100683	26946098	28310502	95.18%	4.82%
sum	138665813	410491705	372228663	1348586	32015771	954750538		
PA	66.68%	90.23%	89.20%	35.33%	84.17%			
OE	33.32%	9.77%	10.80%	64.67%	15.83%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	86.13%	0.780	9.89%	3.98%

CASE C (resampled 30 m resolution):

GROUND TRUTH DUSAF4.0

CLASSIFIED GLC2010

	1	2	3	4	5	sum	UA	CE
1	2578437	348901	148508	404	17154	3093404	83.35%	16.65%
2	1129141	10325569	919732	13166	80292	12467900	82.82%	17.18%
3	132200	749926	9235301	8109	36091	10161627	90.88%	9.12%
4	429	2567	9041	13316	8400	33753	39.45%	60.55%
5	5910	7503	20038	2786	754693	790930	95.42%	4.58%
sum	3846117	11434466	10332620	37781	896630	26547614		
PA	67.04%	90.30%	89.38%	35.25%	84.17%			
OE	32.96%	9.70%	10.62%	64.75%	15.83%			

GENERAL AGREEMENT MEASURES

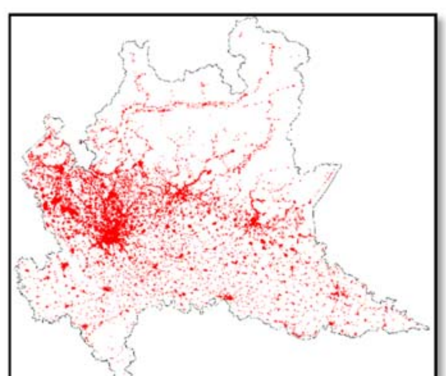
	OA	*K*	*AD*	*QD*
30 m res	86.29%	0.783	9.82%	3.89%

Table 12: First Reclassification Method (Case 1) - Error matrix and Agreement measures for Different Input data Resolution between GLC2010 and DUSAF 4.0.

The agreement measures are most similar with different input data resolution, the kappa values are high identify with high overall accuracy. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

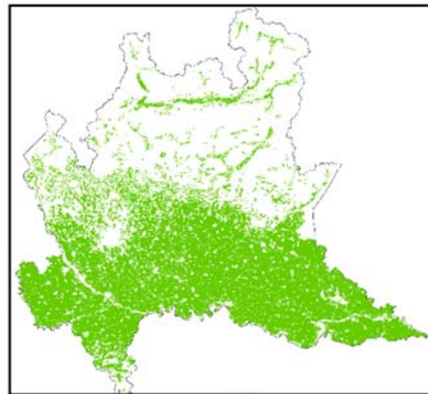
- **Artificial surfaced category**

	5 m	*30 m*	*30 m res*
UA	83.03%	83.18%	83.35%
PA	66.68%	66.78%	67.04%
K	0.701	0.702	0.705
AD	3.96%	3.92%	3.88%
QD	2.86%	2.86%	2.84%



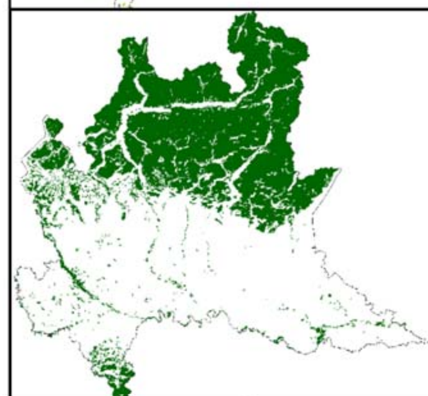
- **Cropland**

	5 m	*30 m*	*30 m res*
UA	82.58%	82.62%	82.82%
PA	90.23%	90.27%	90.30%
K	0.750	0.751	0.753
AD	8.40%	8.36%	8.35%
QD	3.98%	3.99%	3.89%



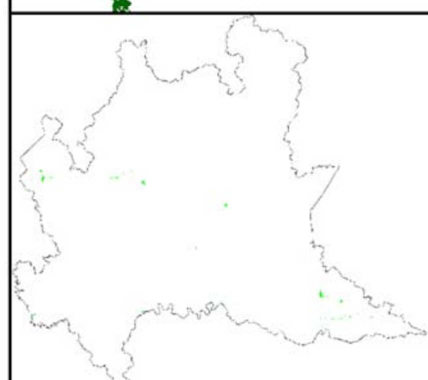
- **Forest and Semi Natural area Category**

	5 m	*30 m*	*30 m res*
UA	90.88%	90.90%	90.88%
PA	89.20%	89.22%	89.38%
K	0.838	0.838	0.839
AD	6.98%	6.97%	6.98%
QD	0.72%	0.72%	0.64%



- **Wetland**

	5 m	*30 m*	*30 m res*
UA	39.53%	39.56%	39.45%
PA	35.33%	35.35%	35.25%
K	0.372	0.373	0.371
AD	0.15%	0.15%	0.15%
QD	0.02%	0.02%	0.02%



- **Open Water Category**

	5 m	*30 m*	*30 m res*
UA	95.18%	95.36%	95.42%
PA	84.17%	84.32%	84.17%
K	0.890	0.892	0.891
AD	0.29%	0.28%	0.27%
QD	0.39%	0.39%	0.40%

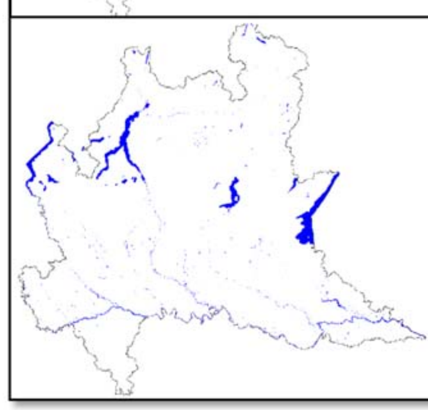


Table 13 list the general agreement measures corresponding to the comparison that have been done between DUSAF4.0 and GLC2010, with second reclassification method (Case2) which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

***[11]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	77.18%	0.673	17.97%	4.85%

	FOREST	***SHRUB/GRASS***	***BEACHES,ROCKS,SPARSELY VEGETATED AREAS…***	***PERPETUAL SNOW / GLACIERS***
UA*	80.11%	47.31%	79.55%	89.40%
PA*	79.43%	43.98%	79.70%	81.77%
K*	0.733	0.416	0.780	0.854
AD*	9.62%	6.92%	2.92%	0.07%
QD*	0.21%	0.50%	0.01%	0.03%

Table 13: Second Classification Method (Case2); Agreement measures with 30 m input data resolution between reclassified Maps GLC2010 and DUSAF4.0.

Comparing the results of the two different classification method, the general agreement measures shows that the overall accuracy decreased by 9%, this explain the increase in both values of Allocation and Quantity disagreement. Among the sub classes, Permanent snow are classified with the best accuracies (89.40% for the User's accuracy and 81.77% for the Producer's accuracy). Further, Forest are classified with the high accuracies (80.11% for the User's accuracy and 79.43% for the Producer's accuracy). This followed by Shrub/Grass, Beaches, Rocks, and Sparsely vegetated area are poorly classified with less accuracies.

To eliminate the part of disagreement according to co-location tolerance, Figure 20, shows a buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy. Table 14 presents the recalculation of the agreement statistics.

[11] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

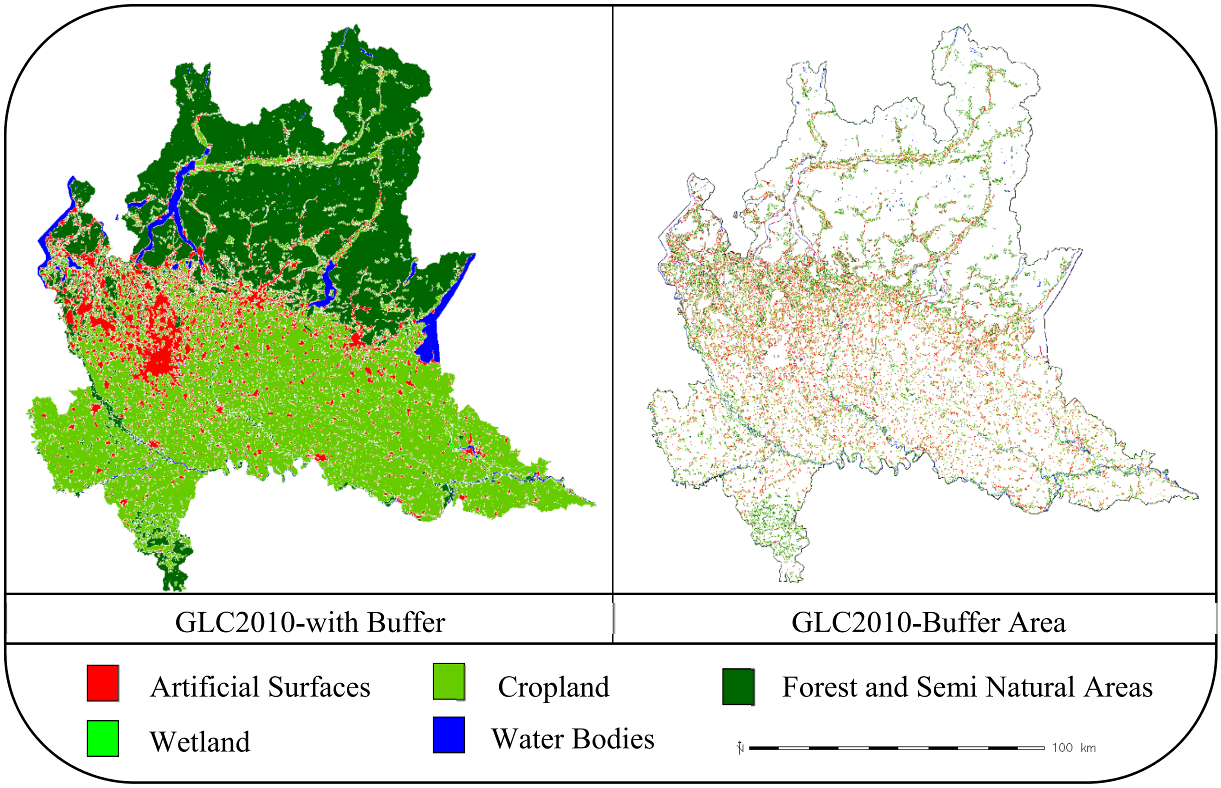


Figure 20: First Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Lombardy2012 Case).

Due to that there is no significantly difference in the results by using different data input resolution. 30 m and 5 m input data resolution have been chosen for the Comparison between land cover maps.

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	90.29%	0.8407	6.26%	3.06%
30 m	90.29%	0.8407	6.60%	3.10%

Table 14: General Agreement measures after eliminating the buffer between reclassified maps GLC2010 and DUSAF4.0.

Corresponding to the comparison between DUSAF4.0 and GLC2010, with first reclassification method, the comparison between the general agreement measures with and without buffer gives an idea about the part of disagreement that can be attributed to the co-location inaccuracy. The percentage of the cells that have been removed was about 14.49% with 61.86% overall accuracy. Moreover, the comparison shows the increasing of the overall accuracy and standard Kappa, which explains the decreasing in Allocation and Quantity disagreement. Table 15 reports commission and omission disagreement with and without buffer corresponding to 30 m resolution. The results shows the decreasing in commission and omission error after applying the buffer.

	Commission Error		Omission Error	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
Artificial cover	16.82%	8.10%	33.22%	30.86%
Cropland	17.38%	13.63%	9.73%	6.77%
Forest and semi Natural areas	9.10%	7.21%	10.87%	6.95%
Wetland	60.44%	44.26%	64.65%	59.90%
Water Surfaces	4.64%	0.26%	9.06%	9.06%

Table 15: GLC2000-DUSAF4.0, Commission and Omission disagreement by pixel (%)

Furthermore with second reclassification method (Case2), the cells that have been removed was about 18.98 % with 57.72 % overall accuracy (Figure 21). Table 16 list the general agreement measures with buffer.

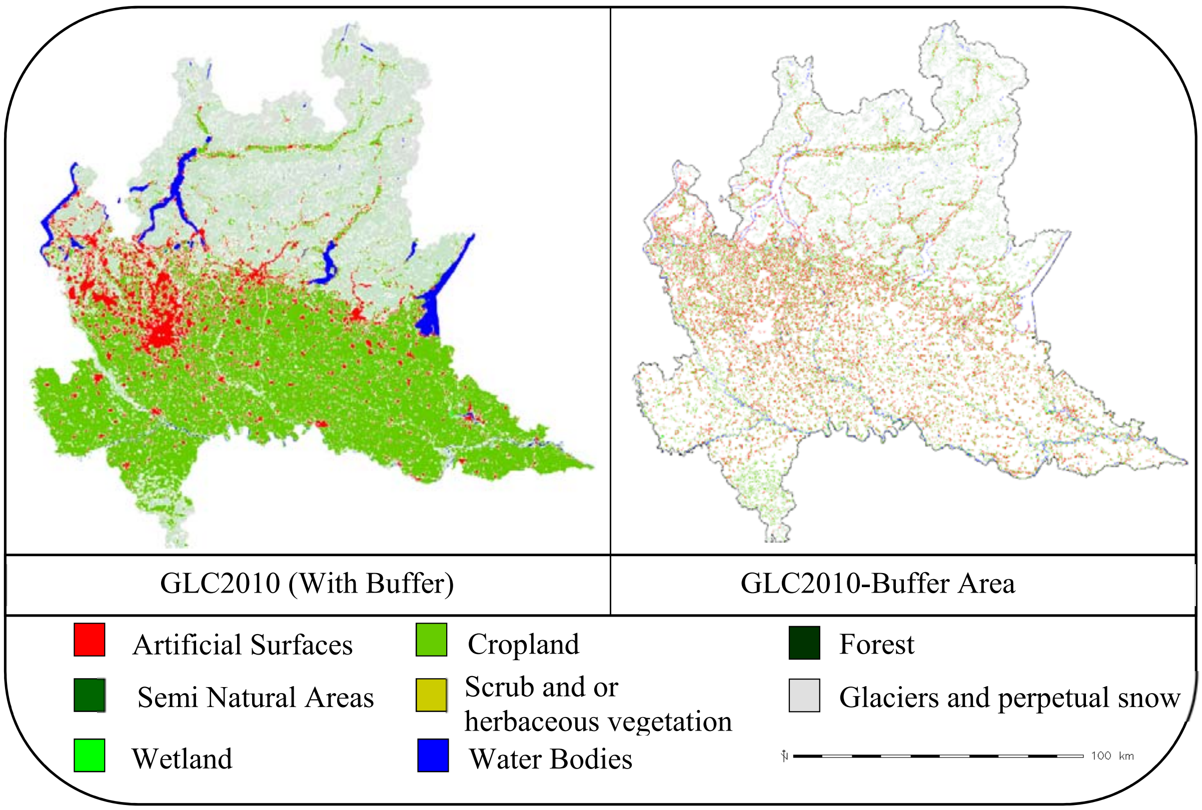


Figure 21: Second Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Lombardy2012 Case).

***[12]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	85.06%	0.7827	10.74%	4.19%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*	*PERPETUAL SNOW / GLACIERS*
UA*	83.79%	53.34%	83.60%	96.60%
PA*	85.54%	45.62%	84.73%	87.50%
K*	0.7979	0.4591	0.8286	0.9180
AD*	6.89%	5.23%	2.30%	0.02%
QD*	0.50%	0.95%	0.10%	0.03%

Table 16: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer.

3.2.4 Lombardy Case Study Conclusion

In summary, the general agreement measures is fundamental to understand the overall differences between the maps. The results of the analysis shows that eliminating the buffer around GLC polygon border gives better results with higher overall accuracies and higher standard kappa which means decreasing in the Allocation and Quantity disagreement. For both types of assessment, UA was significantly correlated with the kappa value and negatively with both disagreement measures whereas PA was only correlated to AD. AD and QD were significantly correlated, in all cases AD values is higher than QD. In addition the analysis of the results shows that among the classes the Permanent snow was poorly classified in GLC2000 compared with GLC2010.

[12] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.3 Second Case study: Liguria region

Liguria is a coastal region of north-western Italy, where Genoa is the capital (Figure 22)[13]. Liguria is bordered by France to the west, Piedmont to the north, and Emilia-Romagna and Tuscany to the east. It lies on the Ligurian Sea. The narrow strip of land is bordered by the sea, the Alps and the Apennines Mountains. Figure 23, shows the overall workflow for Liguria region.

Figure 22: Liguria Region.

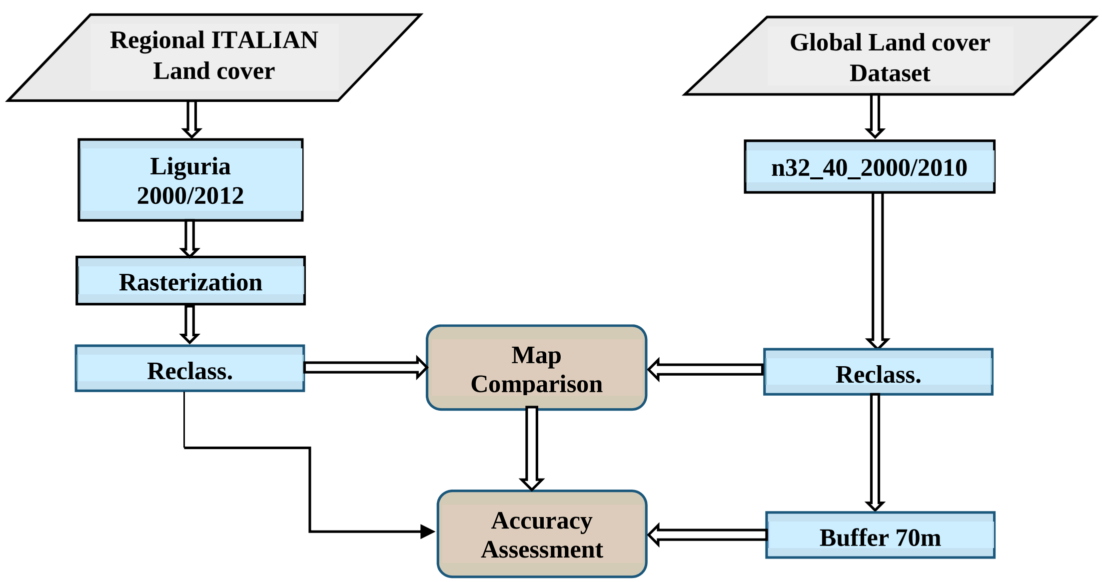


Figure 23: Overall workflow of Liguria Region.

[13] http://en.wikipedia.org/wiki/Liguria

3.3.1 Liguria land cover layer

Currently there is three release for Liguria land cover layers are available[14] (Table 17).

	LIGURIA	LIGURIA	LIGURIA
YEAR	2000	2009	2012
SCALE	1:25'000	1:10'000	1:10'000
REF SYS	WGS84/UTM32N	WGS84/UTM32N	WGS84/UTM32N
LEGEND	No CORINE	CORINE	CORINE
SOURCE	Aerial photos	QuickBird 2003-2007; EROS-B 2009; Landsat 2006; Orthophotos IT2000	Update of 2009 land cover (in particular urban-woody areas and hydrography). Orthophotos AGEA 2010 and World View2 2012 for La Spezia province
EXTENT	whole region	whole region	whole region

Table 17: Liguria Land cover layers.

- **Liguria 2000**[15] was obtained from the photo interpretation and Aerial shots in B/W or color scale of 1:25'000. The legend wasn't adopted by the Corine Land Cover (CLC) nomenclature.
- **Liguria 2009**[16] was obtained by Region of Liguria, they provided the materials that used as auxiliary data for the realization of the Land Use map are the following:

  ✓ **Raster Data:**
  - High-resolution QuickBird satellite orthoimagery (acquisition period 2003-2007);
  - Orthophoto Mosaic IT2000;
  - Regional technical map at a scale of 1:10,000 and 1:25,000 for regional cartography;
  - Multitemporal Landsat imagery for the year 2006;
  - Multitemporal Landsat imagery for the year 2006;
  - Orthoimagery high-resolution satellite EROS B (acquisition period 2009) – Liguria West.

[14] The data were downloaded from http://cartodownloadpubb.regione.liguria.it/webpubb/RichiestaDownload.aspx?CodiceCatalogo=1415
[15] Metadata: http://geoportale.regione.liguria.it/geoportal/catalog/search/resource/details.page?uuid=r_liguri:D.39.2012-1221
[16] Metadata: http://geoportale.regione.liguria.it/geoportal/catalog/search/resource/details.page?uuid=r_liguri:D.1415.2012-12-21. DATASIEL S.p.A. Codice di identificazione gara (CIG) : 0226921D1E. Bando di Gara per la realizzazione della Carta di Uso del Suolo del territorio della Regione Liguria in scala 1:10.000.

- ✓ **Aerial Data:**
  - Forest map (2006);
  - Areas covered by fire (acquisition period 1996-2005);
  - Regional Land Use 2000;
  - Buildings derived from the CTR Dimensional Vector sc. 1:5’000;
  - Administrative Boundaries.
- ✓ **Point Data:**
  - Tourist accommodation facilities in 1:5’000 (updated to 2008);
  - Gardens in scale 1:5’000 (updated to 2008);
  - Leisure Complex in scale 1:5’000 (updated to 2006).

- **Liguria 2012**[17] was obtained starting from the Land Use Map 2009 scale 1:10’000, that have been updated some fundamental levels of information subject to more abrupt changes. The images used for photo interpretation are, for the whole region, the orthophoto of AGEA 2010 in the compositions of the true color and near infrared. Only the province of La Spezia were also used the ortho satellite images of 2012, in the compositions of the true color and near-infrared acquired by the satellite Word view2.

The legend for both of Liguria 2009 and 2012 was adopts by Corine Land Cover (CLC) nomenclature.

3.3.2 Data Processing

The First Comparison has been done between **GLC2000** and Land cover map of **Liguria region year 2000**. The second comparison has been done between **GLC2010** and since there was two available layers 2009 and 2012, Land cover map of **Liguria region year 2012** has been chosen for the comparison by cause of that it was updated from Liguria 2009 and used images for photo interpretation in year 2010.

The Data processing procedure for both comparisons is as following, Firstly, the Liguria vector layer was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Ligure raster maps at different cell sizes, respectively 30 m and 5 m, were calculated. While the former corresponds to the GLC resolution, the latter is selected to take into account the greater level of detail of the Liguria layer. Also another popular approach, the prevalence method, was considered, a new 30 m resolution raster map based on it was calculated taking advantage of GRASS GIS module *r.resamp.stats*, 5 m resolution was the input raster layer and the mode was the selected aggregation method.

The second important phase of data processing was relative to the different thematic classification of the two land cover maps. To allow the comparison procedure, a reclassification of Liguria raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module.

[17] Metadata: http://www.regione.liguria.it/opendata/dati-cartografici/item/36002-uso-del-suolo-sc-1-10000-ed-2012.html

Due to the differences in coastline between the two maps and to reduce the error around the Coastline, a new class (255) was added in order to calculate the common difference area between the two maps. The calculation has been done taking advantage of GRASS GIS module *r.mapcalc*. Moreover, the patching procedure was needed to add the difference pixels with respect to one to another to both maps. The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3.

3.3.2.1 GLC2000-Liguria2000

Figure 24 & 25 gives a visual overview for both reclassified Land Cover maps (GLC2000, Liguria2000).

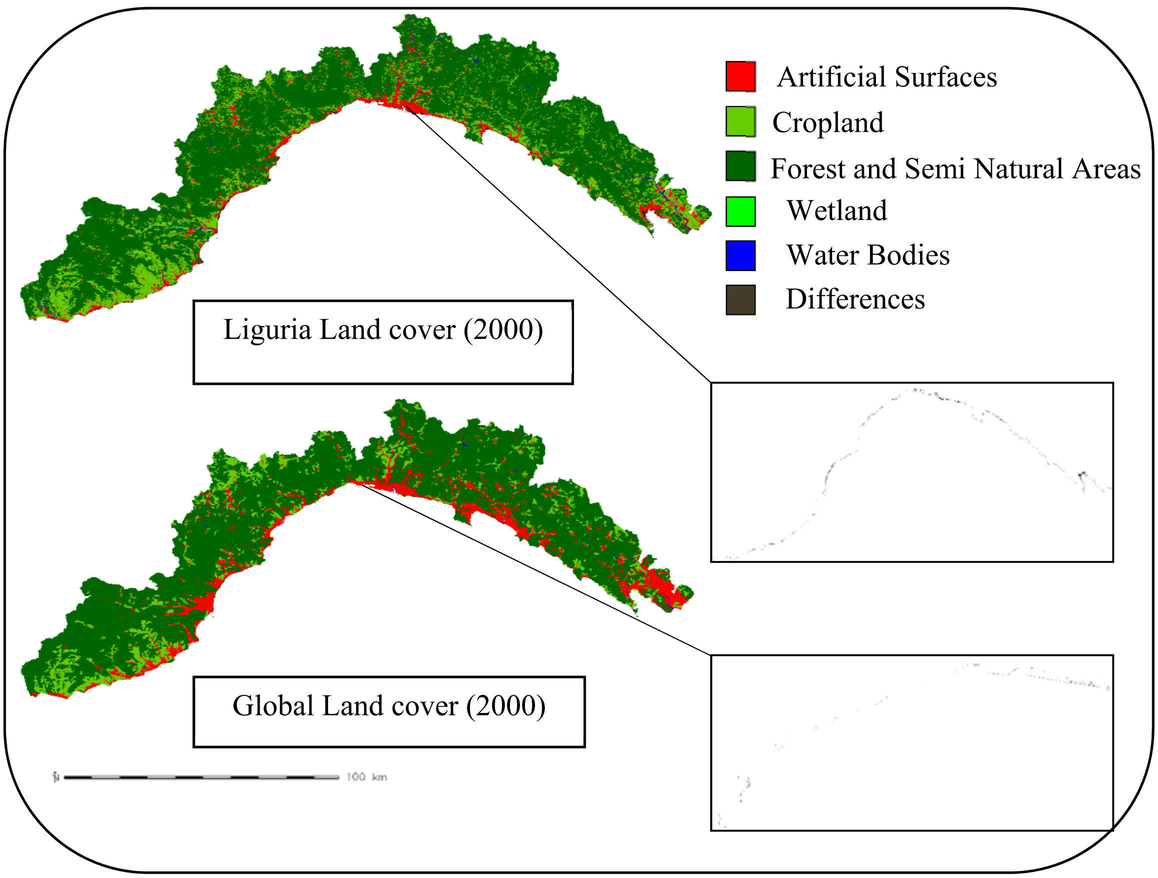


Figure 24: Visual Overview of Both Reclassified Liguria 2000 and GLC2000 (1st Classification).

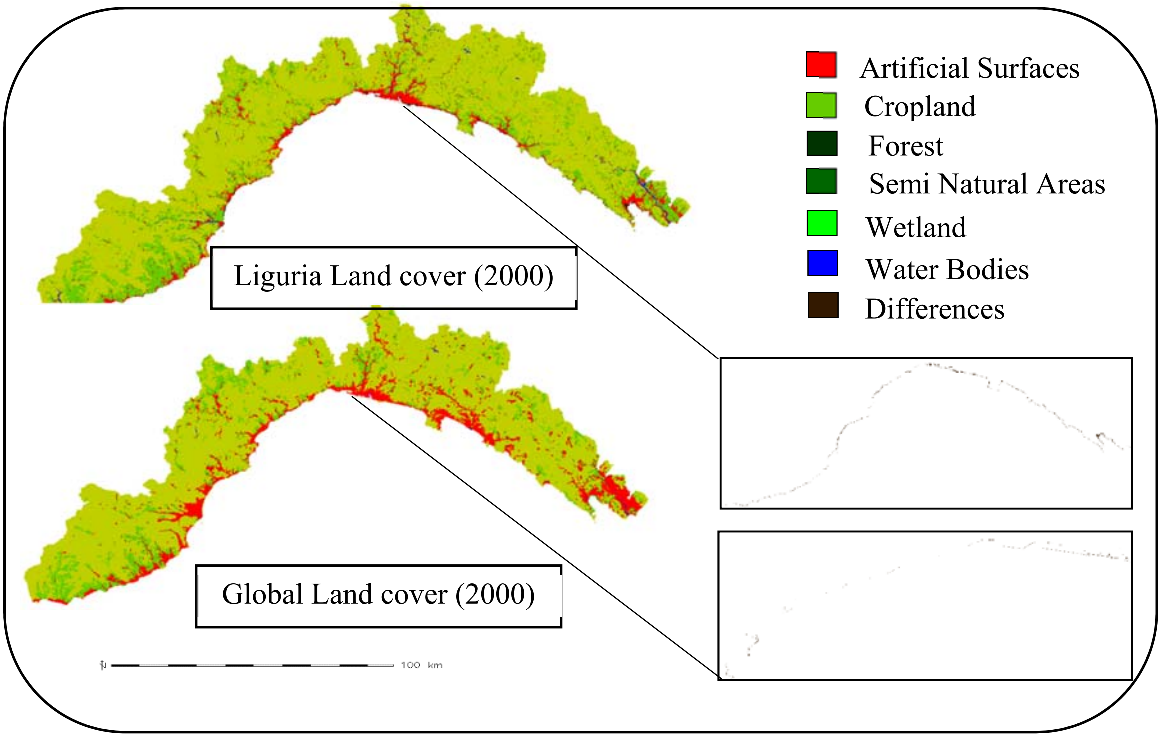


Figure 25: Visual Overview of Both Reclassified Liguria 2000 and GLC2000 (2nd Classification).

3.3.2.2 GLC2010-Liguria2012

Figure 26 & 27 gives a visual overview for both reclassified Land Cover maps (GLC2010, Liguria2012).

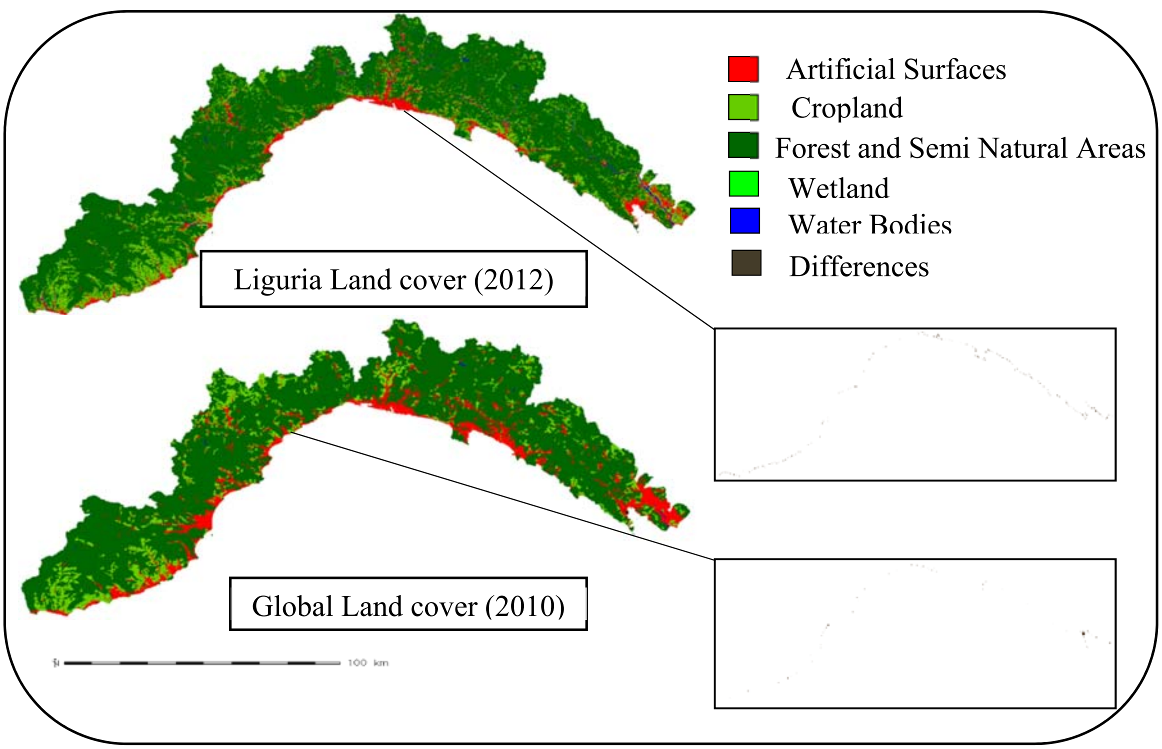


Figure 26: Visual Overview of Both Reclassified Liguria 2012 and GLC2010 (1st Classification).

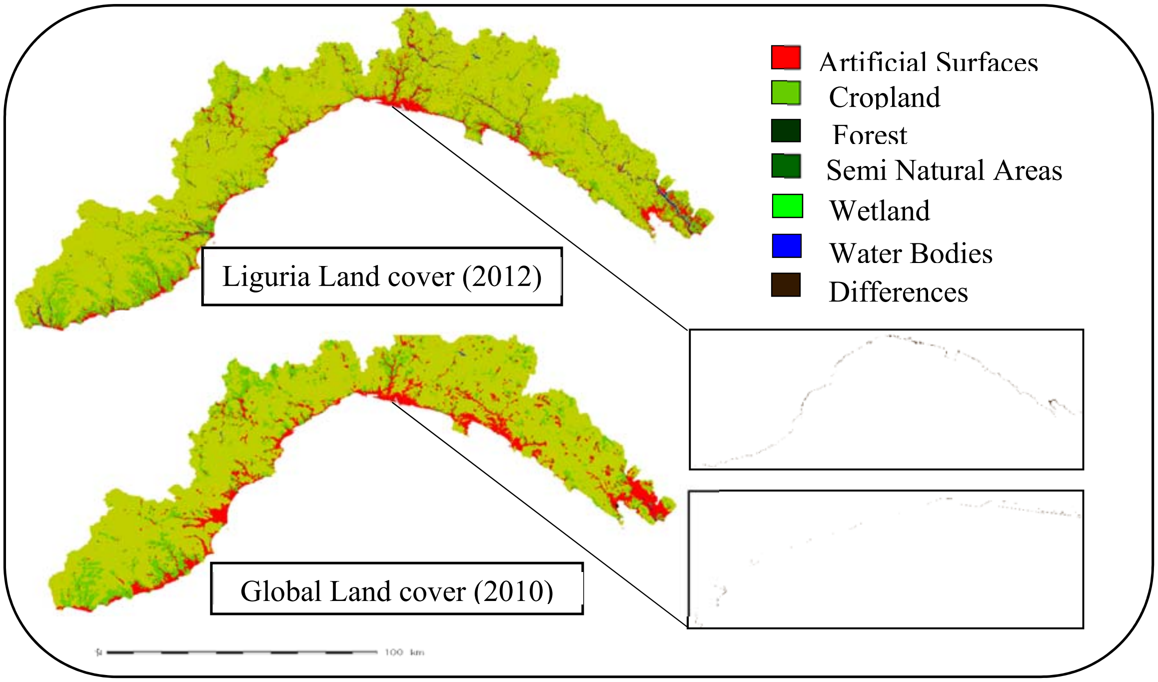


Figure 27: Visual Overview of Both Reclassified Liguria 2012 and GLC2010 (2nd Classification).

3.3.3 Accuracy Assessment

In a pixel based assessment, the accuracy assessment was derived from a comparison pixel by pixel between Reclassified Liguria Land cover map (REFERENCE MAP) and GLC (CLASSIFIED MAP).

3.3.3.1 GLC2000 and Liguria 2000

The confusion matrices and the agreement measures are represented in Table 18, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED		1	2	3	4	5	255	sum	UA	CE
	1	265034	278369	96601	288	12254	11320	663866	39.92%	60.08%
	2	39799	438933	240161	1	3280	991	723165	60.70%	39.30%
	3	37765	408664	4185073	226	6155	14932	4652815	89.95%	10.05%
	4	830	14	67	0	745	2302	3958	0.00%	100.00%
	5	582	159	924	115	4082	1215	7077	57.68%	42.32%
	255	912	10	324	0	4	0	1250	0.00%	100.00%
	sum	344922	1126149	4523150	630	26520	30760	6052131		
	PA	76.84%	38.98%	92.53%	0.00%	15.39%	0.00%			
	OE	23.16%	61.02%	7.47%	100.00%	84.61%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	80.85%	0.5176	11.68%	7.47%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	9530529	10018952	3487301	10379	442611	409473	23899245	39.88%	60.12%
2	1434453	15786130	8658781	29	117883	36297	26033573	60.64%	39.36%
3	1367634	14732436	150634929	8329	222826	536384	167502538	89.93%	10.07%
4	29895	632	2676	0	26680	82585	142468	0.00%	100.00%
5	21276	5976	33487	4110	146724	43457	255030	57.53%	42.47%
255	33976	485	12671	0	153	0	47285	0.00%	100.00%
sum	12417763	40544611	162829845	22847	956877	1108196	217880139		
PA	76.75%	38.94%	92.51%	0.00%	15.33%	0.00%			
OE	23.25%	61.06%	7.49%	100.00%	84.67%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	80.82%	0.5169	11.71%	7.47%

CASE C (resampled 30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	268521	278403	97323	284	12109	7498	664138	40.43%	59.57%
2	40266	440730	239138	1	3248	532	723915	60.88%	39.12%
3	38548	410941	4192579	231	6075	12464	4660838	89.95%	10.05%
4	1316	16	106	0	771	1776	3985	0.00%	100.00%
5	761	161	954	115	4126	1027	7144	57.75%	42.25%
255	2078	28	888	0	7	0	3001	0.00%	100.00%
sum	351490	1130279	4530988	631	26336	23297	6063021		
PA	76.40%	38.99%	92.53%	0.00%	15.67%	0.00%			
OE	23.60%	61.01%	7.47%	100.00%	84.33%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m res.	80.91%	0.5192	11.73%	7.35%

Table 18: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2000 and Liguria2000.

The agreement measures are most similar with different input data resolution, the kappa values are low identify with low overall accuracy due to the fact that Liguria2000 layer was not CORINE based. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

- **Artificial surfaced category**

	5 m	*30 m*	*30 m res*
UA	39.88%	39.92%	40.43%
PA	76.75%	76.84%	76.40%
K	0.4863	0.4870	0.4901
AD	2.65%	2.64%	2.74%
QD	5.27%	5.27%	5.16%

- **Cropland**

	5 m	*30 m*	*30 m res*
UA	60.64%	60.70%	60.88%
PA	38.94%	38.98%	38.99%
K	0.3847	0.3852	0.3860
AD	9.41%	9.39%	9.34%
QD	6.66%	6.66%	6.70%

- **Forest and Semi Natural area Category**

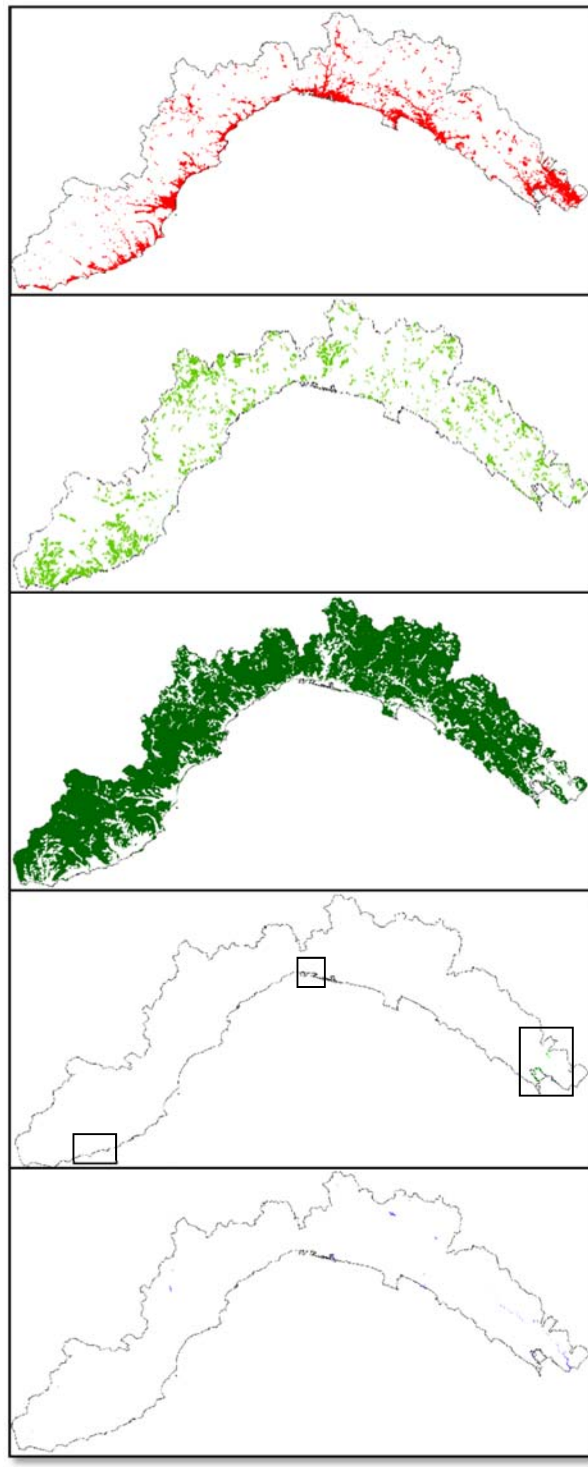
	5 m	*30 m*	*30 m res*
UA	89.93%	89.95%	89.95%
PA	92.51%	92.53%	92.53%
K	0.6366	0.6372	0.6375
AD	11.19%	11.17%	11.16%
QD	2.14%	2.14%	2.14%

- **Wetland**

	5 m	*30 m*	*30 m res*
UA	0.00%	0.00%	0.00%
PA	0.00%	0.00%	0.00%
K	-0.0002	-0.0002	-0.0002
AD	0.02%	0.02%	0.02%
QD	0.05%	0.05%	0.06%

- **Open Water Category**

	5 m	*30 m*	*30 m res*
UA	91.94%	92.07%	92.10%
PA	86.14%	86.26%	86.16%
K	0.886	0.887	0.887
AD	0.50%	0.49%	0.49%
QD	0.21%	0.21%	0.21%



Among the classes, Open Water Category and Forest and semi Natural areas are classified with the best accuracies with different input data resolution. This followed by Cropland, Wetland and Artificial cover are classified with less accuracies.

Corresponding to the second reclassification method (Case2), Table 19 represent the Agreement measures between the compared maps GLC2000 and Liguria2000.

***[18]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	70.60%	0.4885	20.26%	9.14%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	86.17%	43.79%	11.14%
PA*	83.87%	55.86%	19.35%
K*	0.6086	0.4176	0.1305
AD*	16.83%	9.91%	1.57%
QD*	1.67%	3.10%	0.72%

Table 19: Second Classification Method (Case2); Agreement measures between compared maps GLC2000 and Liguria 2000 with 30 m input data resolution.

A buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy (Figure 28) to eliminate the part of disagreement according to co-location tolerance. The agreement measures are recalculated (Table 20), here the usual terms “confusion matrix” and “commission and omission errors” are substituted by “disagreement matrix” and “commission and omission disagreement” to stress the fact that two different land cover are compared.

[18] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

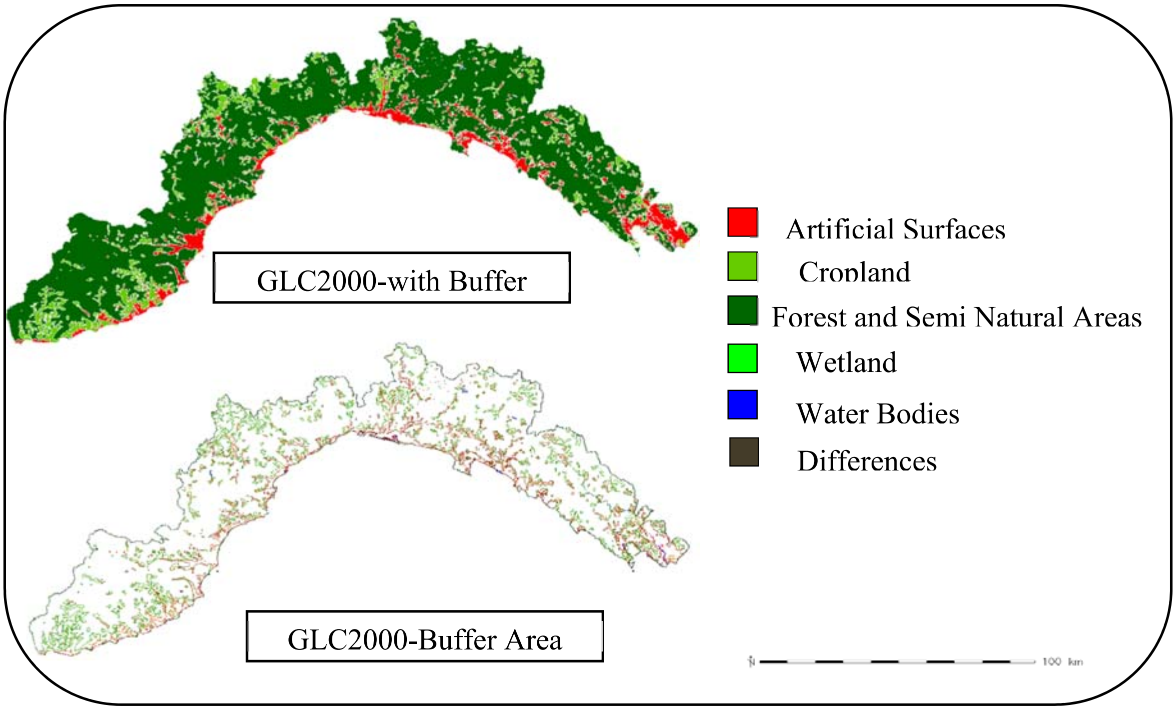


Figure 28: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Liguria2000 Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	85.98%	0.5665	6.82%	7.19%
30 m	85.47%	0.5643	7.31%	7.22%

Table 20: General Agreement Measures between Reclassified GLC2000 and Liguria2000 after the Elimination of a Buffer.

Eliminating the part of the disagreement that can attribute to the co-location inaccuracy gives us better results, higher overall accuracy and Standard Kappa and decreasing in Allocation and Quantity disagreement values. The percentage of the cells that have been eliminated were about 13.73 % with 51.83% overall accuracy. Table 21 represent the Commotion and Omission Disagreement by pixel%.

	Commission Error		**Omission Error**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	60.08%	57.12%	23.16%	18.15%
2. Cropland	39.30%	34.06%	61.02%	62.72%
3. Forest and semi Natural areas	10.05%	8.12%	7.47%	4.25%
4. Wetland	100.00%	100.00%	100.00%	100.00%
5. Water Surfaces	42.32%	19.04%	84.61%	92.74%

Table 21: GLC2000-Liguria2000, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the cells that have been removed was about 20.74 % with 48.15 % overall accuracy (Figure 29). Table 22, list the general agreement measures with buffer.

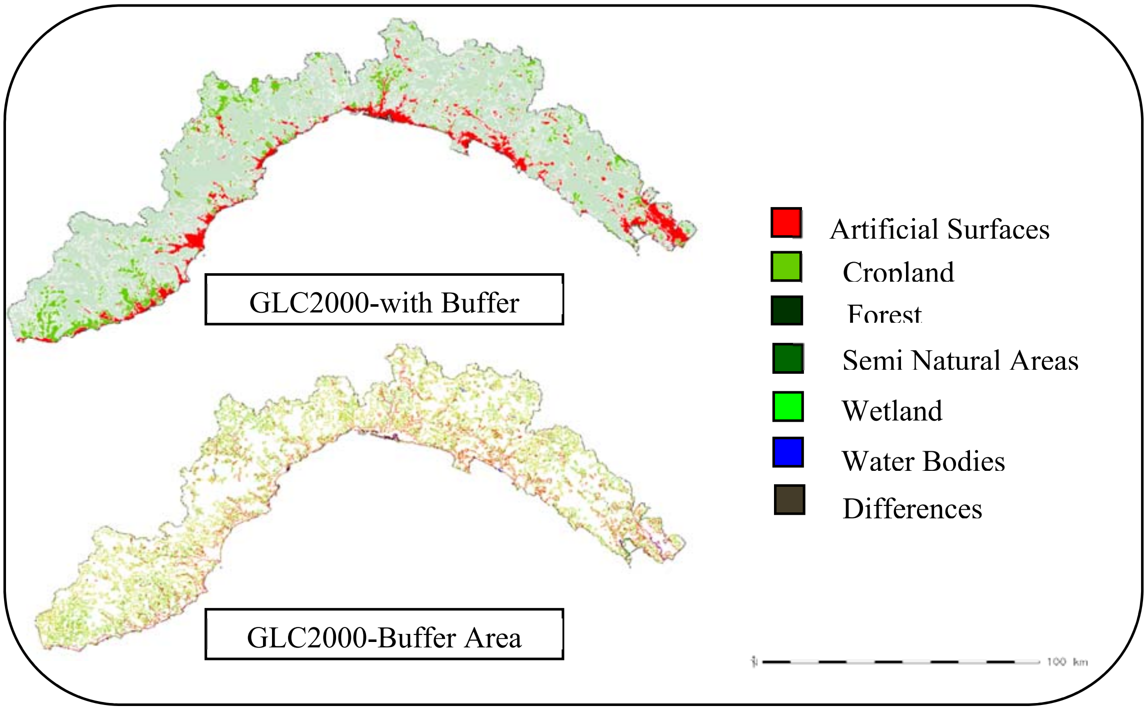


Figure 29: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Liguria2000 Case).

***[19]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	76.38%	0.5486	10.72%	6.89%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	89.03%	49.15%	11.31%
PA*	88.85%	58.04%	19.95%
K*	0.6698	0.4706	0.1348
AD*	14.58%	9.03%	1.38%
QD*	0.13%	1.95%	0.66%

Table 22: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer between reclassified GLC2000 and Liguria2000.

[19] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.3.3.2 GLC2010-Liguria2012

Table 23 list the Confusion matrices and agreement measures corresponding to the comparison that have been done between Liguria2012 and GLC2010, with first reclassification method (Case1) which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	279432	251423	104646	0	20974	4937	661412	42.25%	57.75%
2	51176	372790	307270	18	9320	3294	743868	50.12%	49.88%
3	43612	272225	4282752	55	18339	4841	4621824	92.66%	7.34%
4	434	149	168	0	122	383	1256	0.00%	100.00%
5	470	76	1170	0	3934	14	5664	69.46%	30.54%
255	5273	14	607	0	207	0	6101	0.00%	100.00%
sum	380397	896677	4696613	73	52896	13469	6040125		
PA	73.46%	41.57%	91.19%	0.00%	7.44%	0.00%			
OE	26.54%	58.43%	8.81%	100.00%	92.56%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	81.77%	0.5200	13.56%	4.67%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	10050927	9043792	3781590	0	754890	179873	23811072	42.21%	57.79%
2	1845460	13408540	11070943	619	334608	118867	26779037	50.07%	49.93%
3	1577557	9825218	154144295	2060	661003	175380	166385513	92.64%	7.36%
4	15793	5275	6175	0	4309	13664	45216	0.00%	100.00%
5	17326	2565	42993	0	140496	490	203870	68.91%	31.09%
255	191502	663	24177	0	7329	0	223671	0.00%	100.00%
sum	13698565	32286053	169070173	2679	1902635	488274	217448379		
PA	73.37%	41.53%	91.17%	0.00%	7.38%	0.00%			
OE	26.63%	58.47%	8.83%	100.00%	92.62%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	81.74%	0.5193	13.59%	4.67%

CASE C (resampled 30 m resoulation):

GROUND TRUTH

CLASSIFIED

	1	2	3	4	5	255	sum	UA	CE
1	279176	253910	105154	0	20601	2858	661699	42.19%	57.81%
2	50105	376561	307263	17	9046	1707	744699	50.57%	49.43%
3	41413	274567	4292872	56	17892	3209	4630009	92.72%	7.28%
4	460	147	222	0	121	306	1256	0.00%	100.00%
5	475	73	1189	0	3969	13	5719	69.40%	30.60%
255	7457	33	1949	0	220	0	9659	0.00%	100.00%
sum	379086	905291	4708649	73	51849	8093	6053041		
PA	73.64%	41.60%	91.17%	0.00%	7.65%	0.00%			
OE	26.36%	58.40%	8.83%	100.00%	92.35%	100.00%			

GENERAL AGREEMENT MEASURES

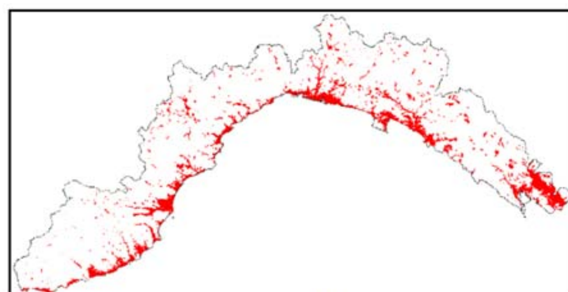
	OA	*K*	*AD*	*QD*
30 m res.	80.82%	0.5112	13.47%	4.71%

Table 23: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2010 and Liguria2012.

The agreement measures are most similar with different input data resolution. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

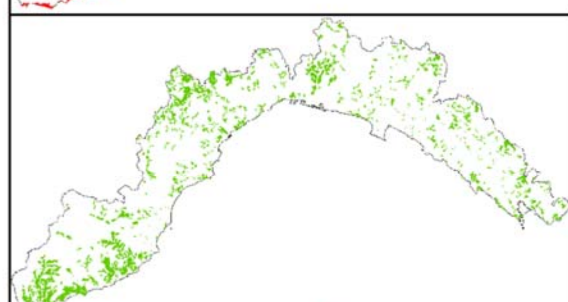
- **Artificial surfaced category**

	5 m	*30 m*	*30 m res*
UA	42.21%	42.25%	42.19%
PA	73.37%	73.46%	73.64%
K	0.4956	0.4961	0.4964
AD	3.35%	3.34%	3.30%
QD	4.65%	4.65%	4.67%



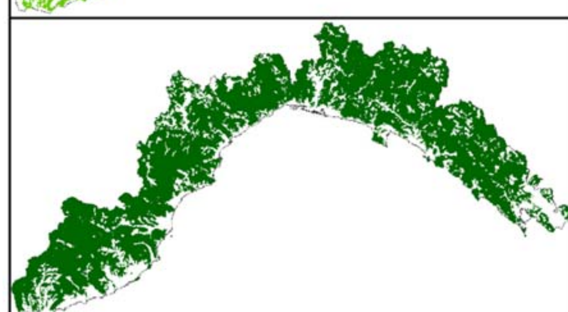
- **Cropland**

	5 m	*30 m*	*30 m res*
UA	50.07	50.12	50.57
PA	41.53	41.57	41.60
K	0.3690	0.3696	0.3716
AD	12.30	12.29	12.16
QD	2.53	2.53	2.65



- **Forest and Semi Natural area Category**

	5 m	*30 m*	*30 m res*
UA	92.64%	92.66%	92.72%
PA	91.17%	91.19%	91.17%
K	0.6459	0.6467	0.6474
AD	11.26%	11.23%	11.14%
QD	1.23%	1.24%	1.30%

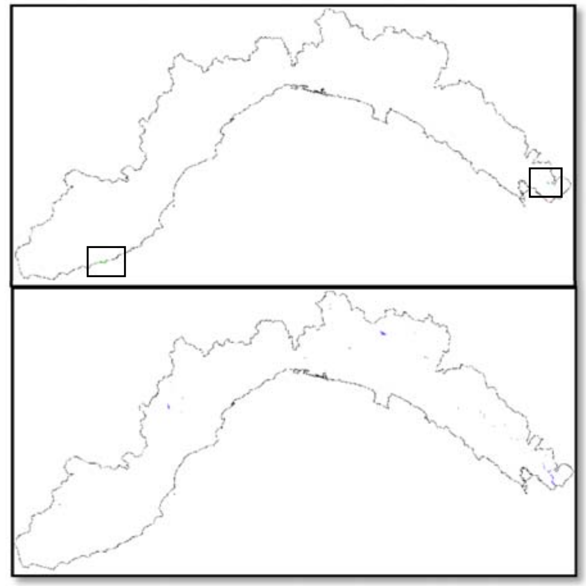


- **Wetland**

	5 m	*30 m*	*30 m res*
UA	0.00%	0.00%	0.00%
PA	0.00%	0.00%	0.00%
K	-0.00002	-0.00002	-0.00002
AD	0.00%	0.00%	0.00%
QD	0.02%	0.02%	0.02%

- **Open Water Category**

	5 m	*30 m*	*30 m res*
UA	68.91%	69.46%	69.40%
PA	7.38%	7.44%	7.65%
K	0.1319	0.1329	0.1364
AD	0.06%	0.06%	0.06%
QD	0.78%	0.78%	0.76%



Forest and semi Natural areas are classified with the best accuracies with different input data resolution. This followed by Cropland, Wetland, Artificial cover and Open Water Category are classified with less accuracies.

Corresponding to the second reclassification method (Case2), Table 24 represent the Agreement measures between the compared maps GLC2010 and Liguria2012.

***[20]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	69.78%	0.4723	23.66%	6.56%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	87.37%	41.75%	7.83%
PA*	83.06%	47.42%	8.68%
K*	0.6104	0.3572	0.0672
AD*	15.26%	13.36%	2.81%
QD*	3.13%	1.72%	0.17%

Table 24: Second Classification Method (Case2); Agreement measures between reclassified maps GLC2010 and Liguria 2012 with 30 m input data resolution.

A buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy (Figure 30) to eliminate the part of disagreement according to co-location tolerance. Table 20 represent the agreement measures.

[20] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

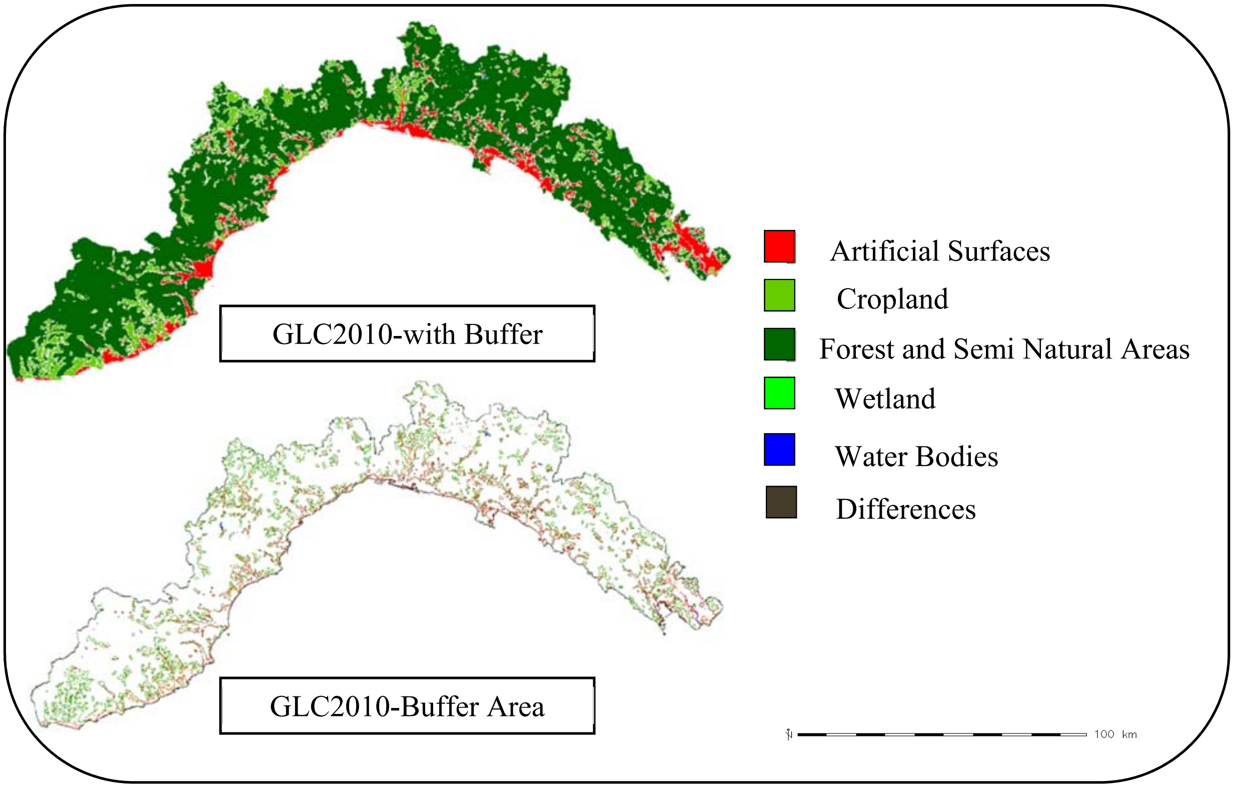


Figure 30: First Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Liguria2012 Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	86.77%	0.5735	9.02%	4.21%
30 m	86.27%	0.5707	9.61%	4.12%

Table 25: General Agreement Measures between Reclassified GLC2010 and Liguria2012 after the Elimination of a Buffer.

Eliminating the part of the disagreement that can attribute to the co-location inaccuracy gives us better results, higher overall accuracy and Standard Kappa which explains the decreasing in Allocation and Quantity disagreement values. The percentage of the cells that have been eliminated were about 13.74 % with 53.12% overall accuracy. Table 26 represent the Commotion and Omission Disagreement by pixel%.

	Commission Error		**Omission Error**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	57.75%	52.40 %	26.54%	21.92 %
2. Cropland	49.88%	44.35 %	58.43 %	59.57 %
3. Forest and semi Natural areas	7.34%	6.00 %	8.81 %	5.30 %
4. Wetland	100.00%	100.00 %	100.00 %	100.00%
5. Water Surfaces	30.54%	2.43 %	92.56 %	96.90 %

Table 26: GLC2000-Liguria2000, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the cells that have been removed was about 20.53 % with 49.06 % overall accuracy (Figure 31). Table 27 list the general agreement measures with buffer.

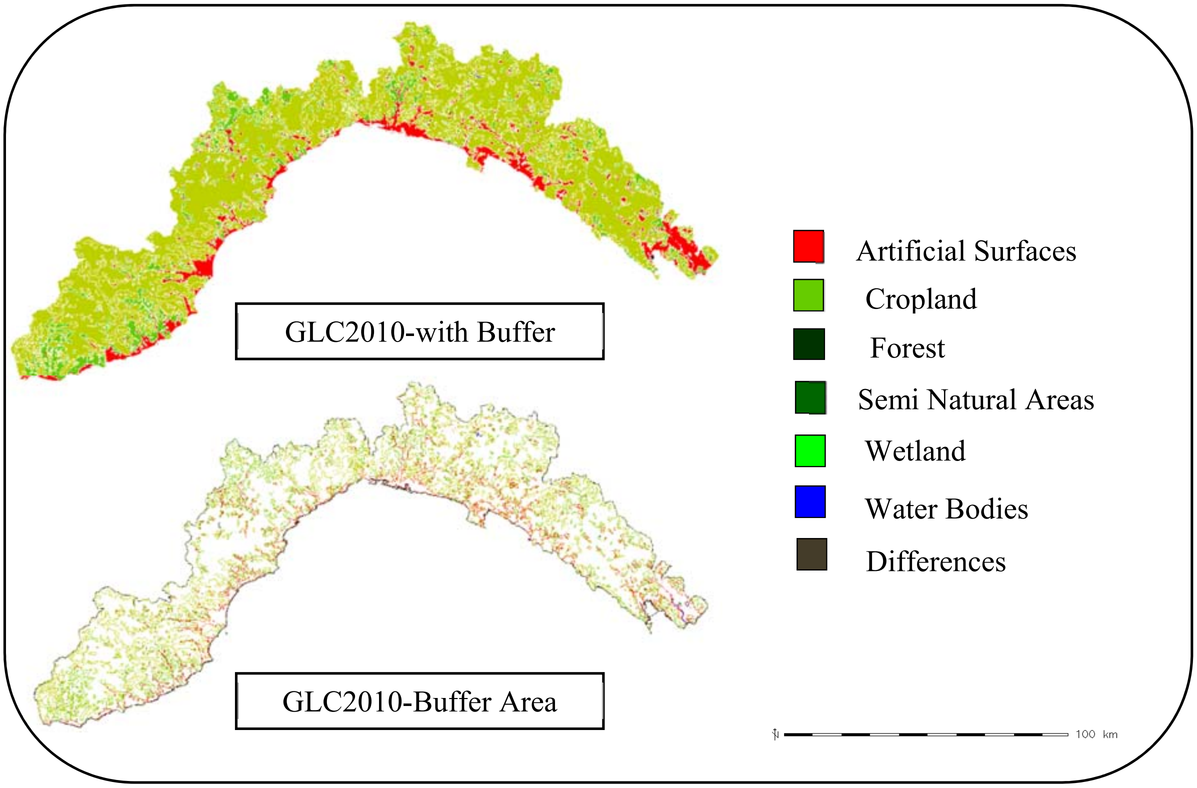


Figure 31: Second Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Liguria2012 Case).

***[21]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	75.08%	0.5365	20.15%	4.77%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	89.48%	45.76%	7.85%
PA*	88.14%	48.66%	8.32%
K*	0.6698	0.4706	0.1348
AD*	13.84%	12.44%	2.69%
QD*	1.00%	0.77%	0.09%

Table 27: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer between reclassified maps GLC2010 and Liguria2012.

[21] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.3.4 Liguria Case Study Conclusion

The analysis shows that the best agreement results occur after eliminating the buffer around GLC polygons border, while there is ambiguities in the results of Liguria2000 due to the interpretation of the legend as the layer was not CORINE based. The Kappa values are law at both reclassification methods in both years despite the high overall accuracy. The Quantity disagreement is stable for both assessment as long as the high value of the Allocation disagreement. In both assessment, Forest are classified with the best accuracies compared with the other classes.

3.4 THIRD CASE STUDY: TRENTINO-ALTO ADIGE REGION

Trentino-Alto Adige is an autonomous region in Northern Italy (Figure 33)[22]. Since the 1970s most legislative and administrative competencies have been transferred to the two autonomous provinces which make up the region: Trentino and South Tyrol. The region is bordered by Tyrol (Austria) to the north-east and north, by Graubünden Switzerland to the north-west, and by the Italian regions of Lombardy to the west and Veneto to the south and south-east. It covers 13,607 km^2. It is extremely mountainous, covering a large part of the Dolomites and the Southern Alps. The region is composed of two provinces, Trentino in the south and South Tyrol in the north.

Trentino has an area of 6,207 km^2, most of it mountainous land and covered by vast forests (50% of the territory). Its capital is the town of Trento. South Tyrol has an area of 7,400 km^2, all of it mountainous land and covered by vast forests. Its capital the city of Bolzano.

Figure 32: Trentino-Alto Adige Region.

3.4.1 Trentino-Alto Adige Land cover data collection

3.4.1.1 Prov. Autonomous Trento

Trento2000 land cover layer [23] is obtained based on update of orthophotos IT 2000 (September/Octber2000) scale 1:10'000. It's provided by Planning Services and Landscape Conservation carried by Telespazio Company.

[22] http://en.wikipedia.org/wiki/Trentino-Alto_Adige/S%C3%BCdtirol

[23] Metadata: http://www.territorio.provincia.tn.it/portal/server.pt/gateway/PTARGS_0_18720_2521_862_0_43/http%3B/172.20.3.95%3B8380/geoportlet/showSingleMetadata.jsp?uuid=p_tn%3AUso%20del%20Suolo%20Reale%20Urbanistica%20(ed.%2008%2F2003)&id=1513&currTab=simple

3.4.1.2 Prov. Autonomous Bolzano

Bolzano1999 land cover layer[24] is provided by Provincia di Bolzano. The Land use map of the Autonomous Province of Bolzano in scale 1: 10'000, based on the classification scheme and according to the methodological approach of CORINE project.

3.4.2 Data Processing

3.4.2.1 Prov. Autonomous Trento

Figure 34, shows the overall work flow for Trento province. The Comparison has been done between **GLC2000** and Land cover map of **Trento2000**. The Data processing procedure have been done as following: Firstly the Trento vector layer was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Trento raster maps at different cell sizes, respectively 30 m and 5 m, were calculated. While the former corresponds to the GLC resolution, the latter is selected to take into account the greater level of detail of the Trento layer.

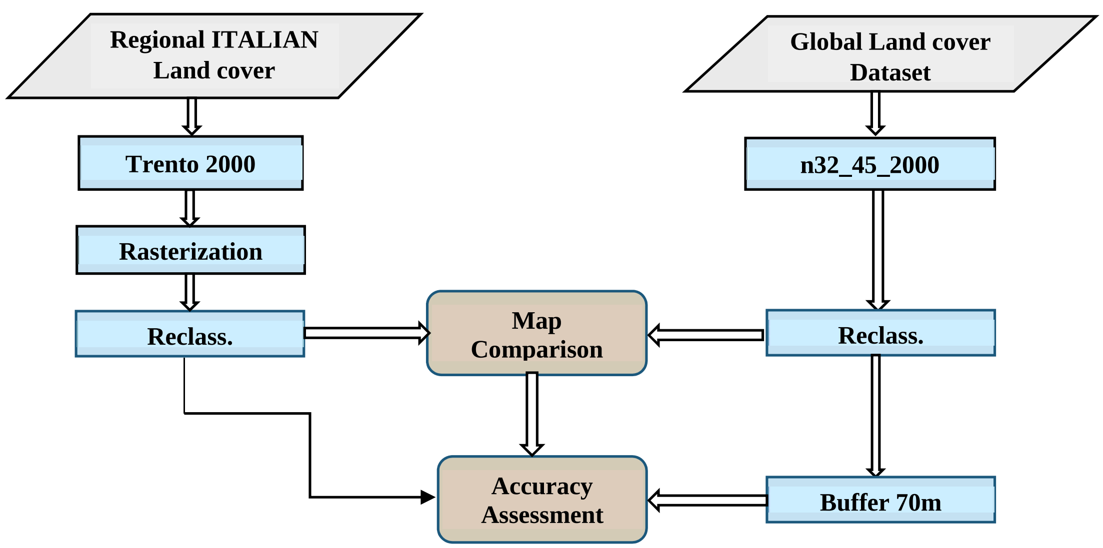


Figure 33: Overall Workflow for Trento Province.

The second important phase of data processing was relative to the different thematic classification of the two land cover maps. To allow the comparison procedure, a reclassification of Trento raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3.

[24] Downloaded from: http://gis.provinz.bz.it/Infokatalog/searchList.faces?ids=1183,1184

Figure 35 & 36 gives a visual overview of both reclassified Land cover maps (Trento2000, GLC2000).

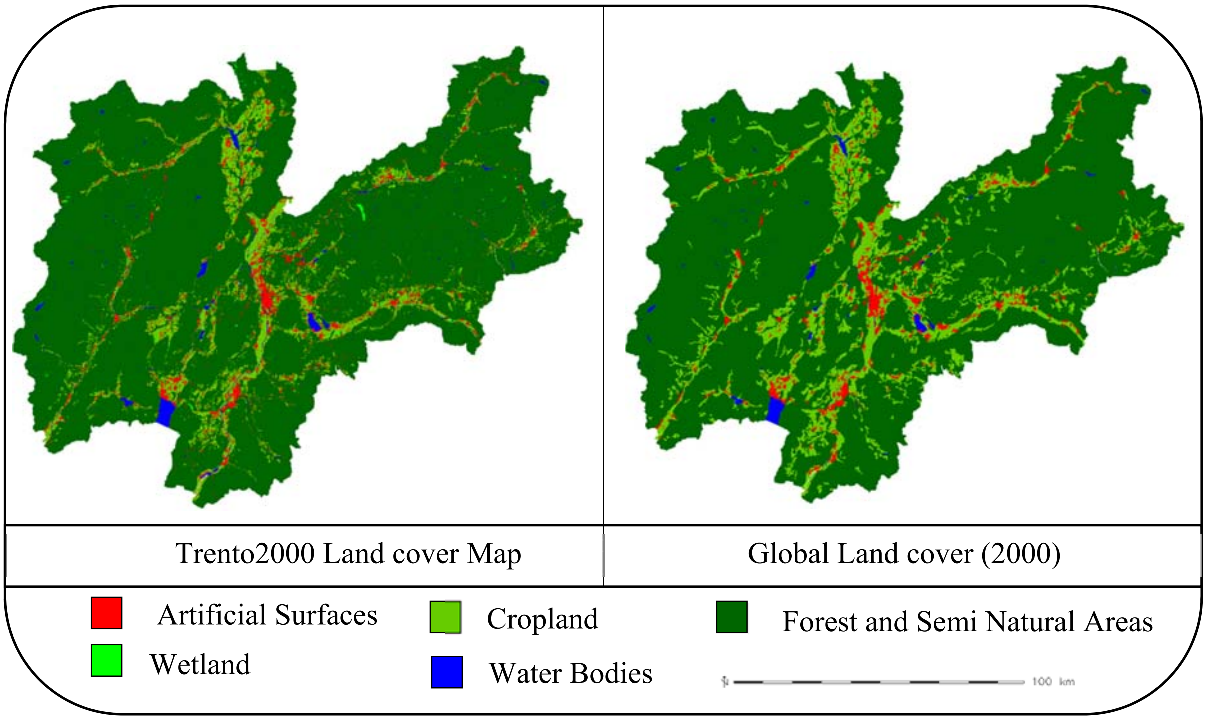


Figure 34: Visual Overview of Both Reclassified Trento2000 and GLC2000 (1st Classification).

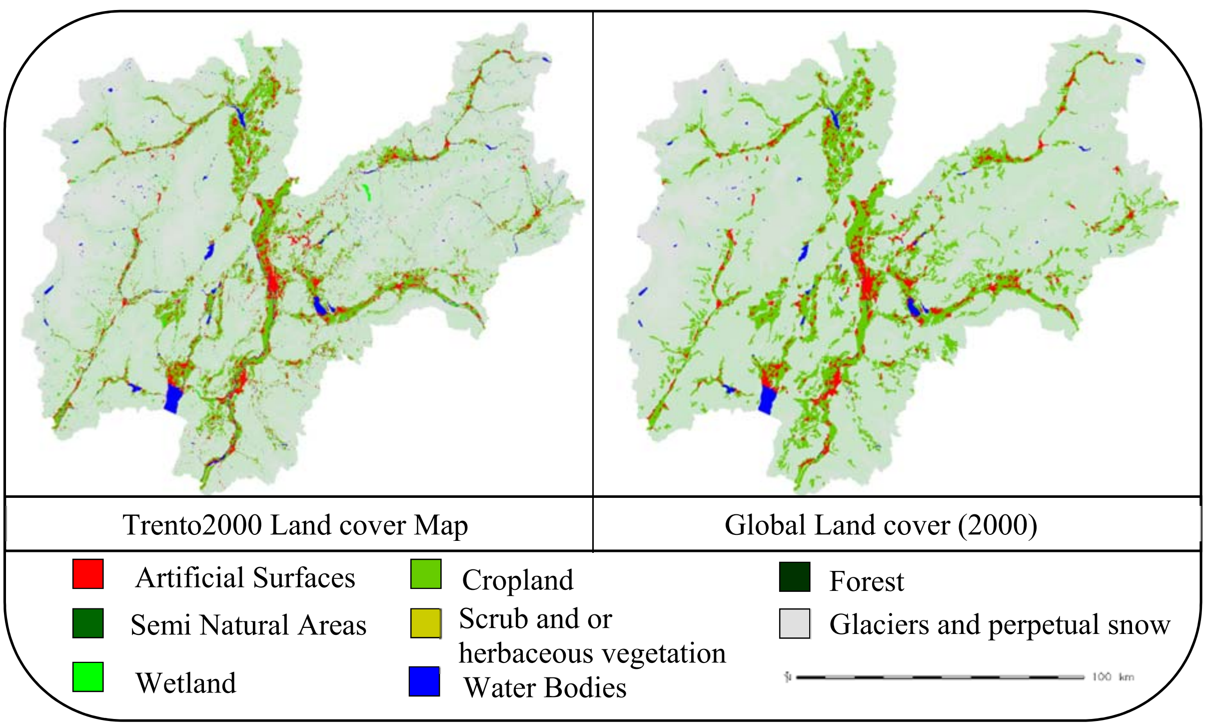


Figure 35: Visual Overview of Both Reclassified Trento2000 and GLC2000 (2nd Classification).

3.4.2.2 Prov. Autonomous Bolzano

Figure 37, shows the overall work flow for Bolzano province. The Comparison has been done between **GLC2000** and Land cover map of **Bolzano1999.** GLC2000 was available in two different tiles, therefore patching procedure was needed to obtain the area corresponding to Bolzano province. Furthermore the two tiles were in two different reference system, consequently converting the raster map between different projection procedures was needed, and it has been done taking advantage of GRASS GIS *r.proj* module. *r.proj* converts a map to a new geographic projection. It reads a map from a different location, projects it and write it out to the current location. The projected data is resampled with nearest neighbor method, which performs a nearest neighbor assignment. It is primarily used for land use classification, since it will not change the values of the data cells.

On other hand, the Bolzano vector layer was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Bolzano raster maps at different cell sizes, respectively 30 m and 5 m, were calculated. While the former corresponds to the GLC resolution, the latter is selected to take into account the greater level of detail of the Bolzano layer.

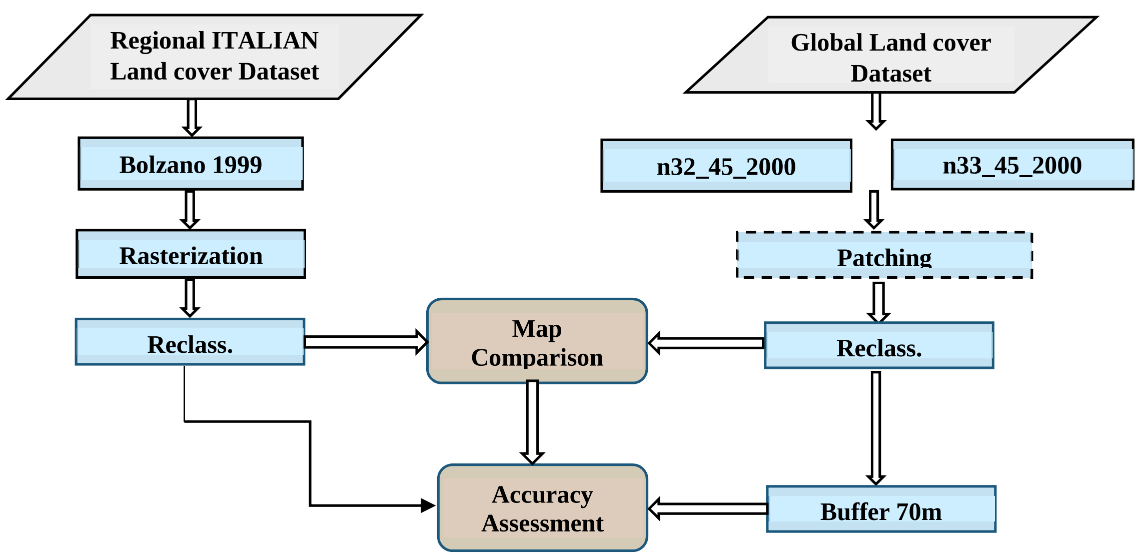


Figure 36: Overall Workflow of Bolzano Province.

Secondly, to allow the comparison procedure, a reclassification of Bolzano raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3.

Figure 38 & 39 gives a visual overview of both reclassified Land cover maps (Bolzano1999, GLC2000).

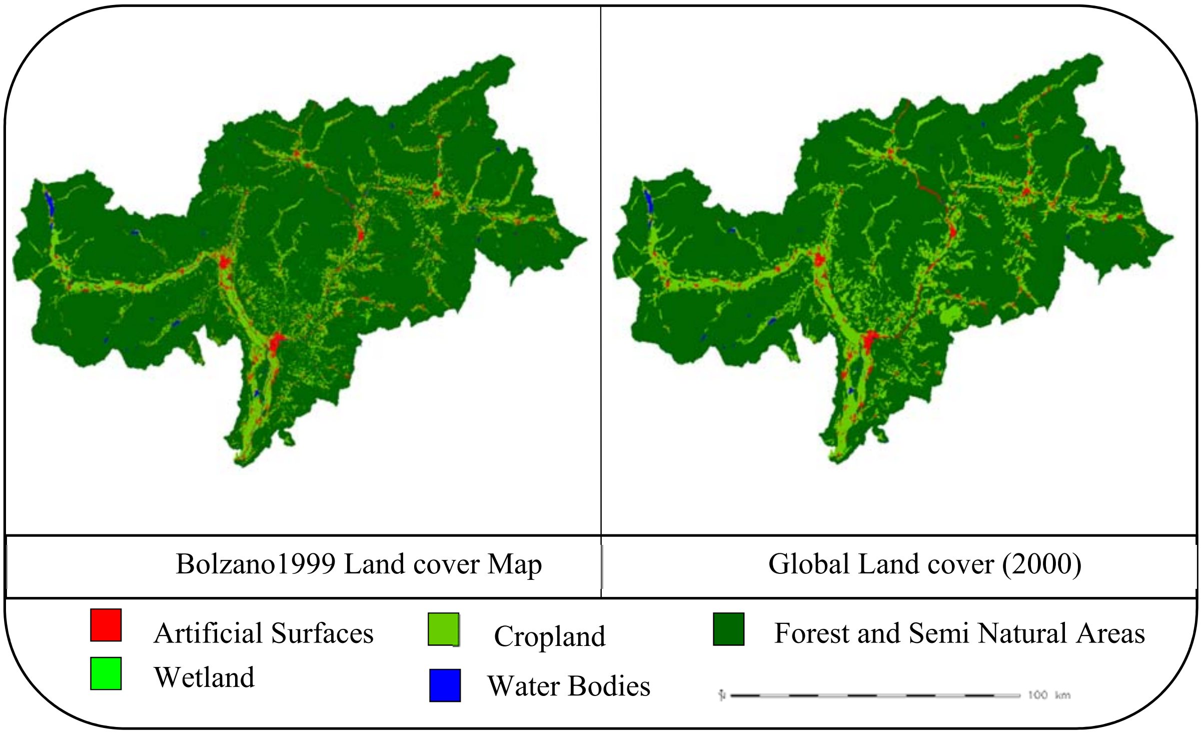


Figure 37: Visual Overview of Both Reclassified Bolzano1999 and GLC2000 (1st Classification).

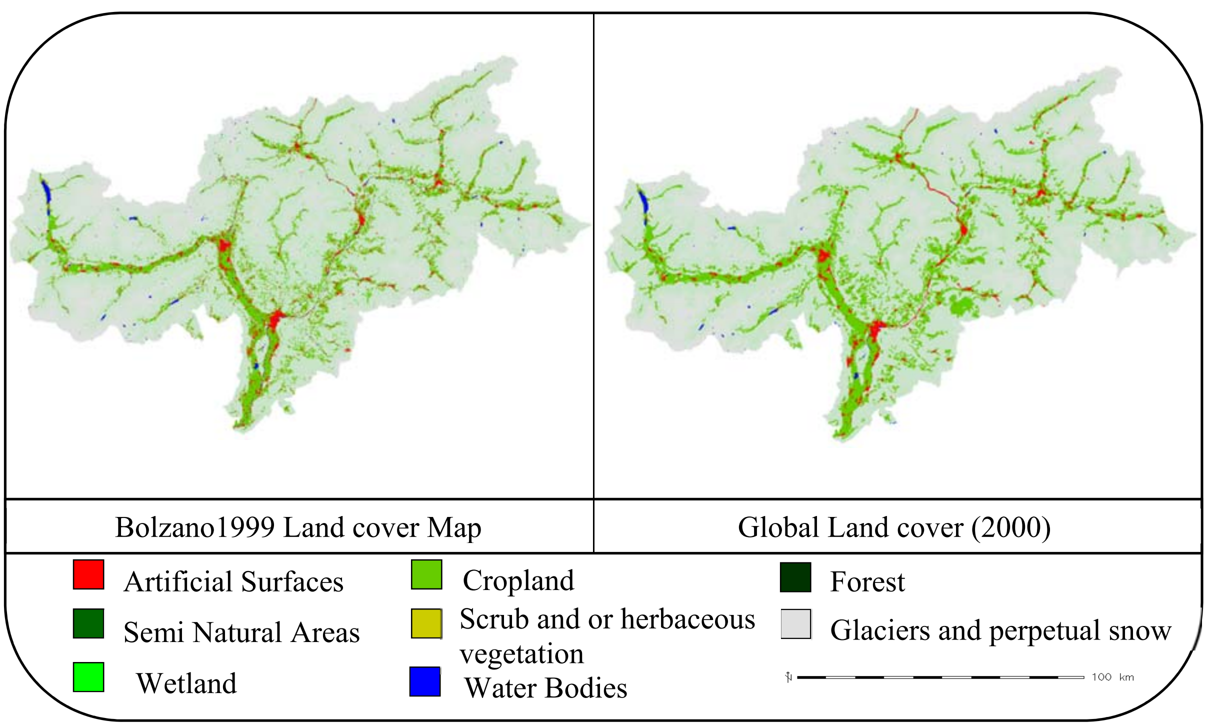


Figure 38: Visual Overview of Both Reclassified Bolzano1999 and GLC2000 (2nd Classification).

3.4.3 Accuracy assessment

3.4.3.1 Prov. Autonomous Trento

The confusion matrices and the agreement measures are represented in Table 28, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	sum	UA	CE
1	126400	48532	22814	109	4252	202107	62.54%	37.46%
2	66953	538345	334055	5352	16776	961481	55.99%	44.01%
3	28056	61868	5627676	9699	22505	5749804	97.88%	2.12%
4	0	0	248	118	0	366	32.24%	67.76%
5	661	664	4777	70	43819	49991	87.65%	12.35%
sum	222070	649409	5989570	15348	87352	6963749		
PA	56.92%	82.90%	93.96%	0.77%	50.16%			
OE	43.08%	17.10%	6.04%	99.23%	49.84%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	90.99%	0.6735	4.53%	4.48%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	sum	UA	CE
1	4538360	1754203	827065	3894	152076	7275598	62.38%	37.62%
2	2420517	19347841	12047855	191662	605141	34613016	55.90%	44.10%
3	1015410	2252695	202561768	349137	812635	206991645	97.86%	2.14%
4	3	0	8932	4241	0	13176	32.19%	67.81%
5	24291	23754	173148	2434	1576067	1799694	87.57%	12.43%
sum	7998581	23378493	215618768	551368	3145919	250693129		
PA	56.74%	82.76%	93.94%	0.77%	50.10%			
OE	43.26%	17.24%	6.06%	99.23%	49.90%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	90.96%	0.6724	4.56%	4.48%

Table 28: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2000 and Trento2000.

The results shows that the agreement measures are most similar with different input data resolution, the kappa values are high identify with high overall accuracy which explains the low values of Allocation and Quantity disagreement with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

- **Artificial surfaced category**

	5 m	*30 m*
UA	62.38%	62.54%
PA	56.74%	56.92%
K	0.5815	0.5833
AD	2.18%	2.17%
QD	0.29%	0.29%

- **Cropland**

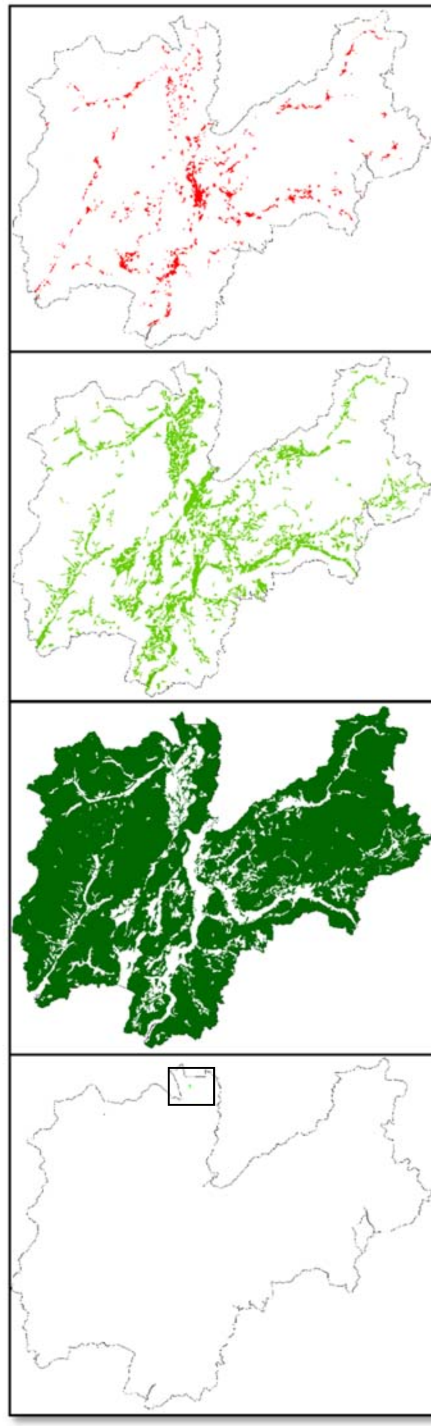
	5 m	*30 m*
UA	55.90%	55.99%
PA	82.76%	82.90%
K	0.6256	0.6268
AD	3.22%	3.19%
QD	4.48%	4.48%

- **Forest and Semi Natural area Category**

	5 m	*30 m*
UA	97.86%	97.88%
PA	93.94%	93.96%
K	0.7372	0.7382
AD	3.53%	3.51%
QD	3.44%	3.44%

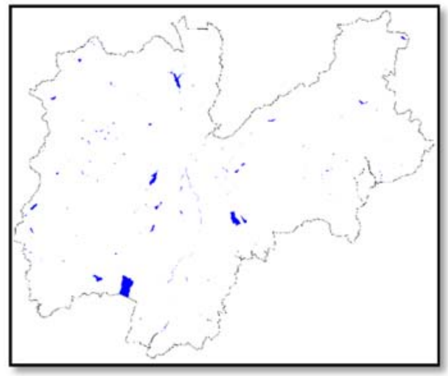
- **Wetland**

	5 m	*30 m*
UA	32.19%	32.24%
PA	0.77%	0.77%
K	0.0149	0.0149
AD	0.01%	0.01%
QD	0.21%	0.22%



➢ Open Water Category

	5 m	*30 m*
UA	87.57%	87.65%
PA	50.10%	50.16%
K	0.6340	0.6348
AD	0.18%	0.18%
QD	0.54%	0.54%



The results shows that both Forest and semi Natural Areas and Open water category are classified with the best accuracies compared with Artificial cover, Cropland and wetland which have less accuracies.

Table 29 list the agreement measures between the compared maps GLC2000 and Trento2000 Corresponds to the second reclassification method (Case2).

***[25]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	71.06%	0.5277	18.08%	10.85%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*	*PERPETUAL SNOW / GLACIERS*
UA*	79.57%	38.38%	72.60%	94.35%
PA*	88.70	28.02%	45.32%	71.50%
K*	0.6112	0.2321	0.4991	0.8119
AD*	12.55%	12.74%	5.24%	0.08%
QD*	6.37%	3.83%	5.75%	0.24%

Table 29: Second Classification Method (Case2); Agreement measures with 30 m input data resolution between GLC2000 and Trento2000.

Analyzing the results of the two different classification method, the general agreement measures shows that the overall accuracy decreased by 20%, this explain the increase in both values of Allocation and Quantity disagreement. Among the sub classes, Permanent Snow are classified with the best accuracies (94.35% for the User's accuracy and 71.50% for the Producer's accuracy). This followed by Forest, Shrub/Grass, Beaches, Rocks, and Sparsely vegetated area are poorly classified with less accuracies.

A buffer 70 m eliminated around GLC polygon border (Figure 35) to eliminate the part of the disagreement according to the to the co-location tolerance. Table 30, list the General Agreement measures.

[25] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

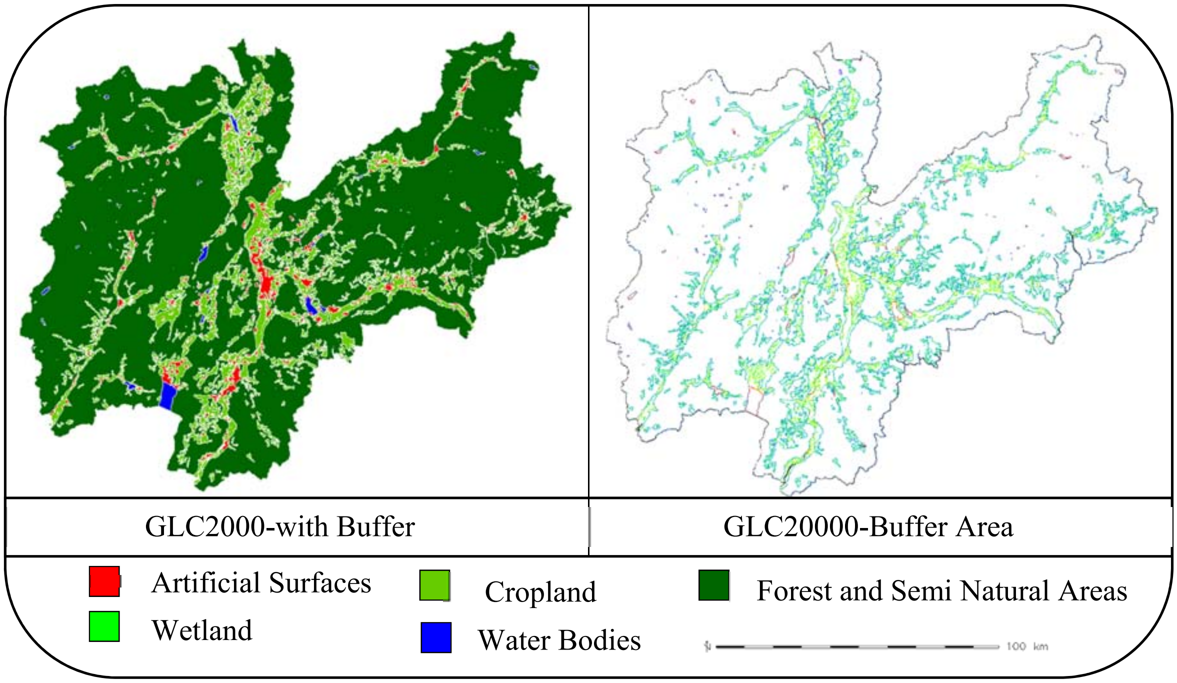


Figure 39: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Trento Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	95.20%	0.7562	2.53%	2.20%
30 m	94.90%	0.7516	2.64%	2.45%

Table 30: General Agreement Measures after Eliminating the Buffer (Trento Case).

The percentage of the cells that have been eliminated was about 12.21% with 62.87% overall accuracy corresponds to 30m input data resolution, while 13.79% with 64.02 % overall accuracy for 5m input data resolution. Moreover, the comparison shows the increasing of the overall accuracy and standard Kappa, which explains the decreasing in Allocation and Quantity disagreement. Table 31 reports commission and omission disagreement with and without buffer corresponding to 30 m resolution.

	Commission Error		**Omission Error**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	37.46%	24.20%	43.08%	42.70%
2. Cropland	44.01%	34.39%	17.10%	12.22%
3. Forest and semi Natural areas	2.12%	1.54%	6.04%	2.96%
4. Wetland	67.76%	48.60%	99.23%	99.23%
5. Water Surfaces	12.35%	0.43%	49.84%	44.72%

Table 31: GLC2000-Trento2000, Commission and Omission disagreement by pixel %.

Furthermore with second reclassification method (Case2), the cells that have been removed was about 19.00 % with 53.81 % overall accuracy (Figure 41). Table 32 list the general agreement measures with buffer.

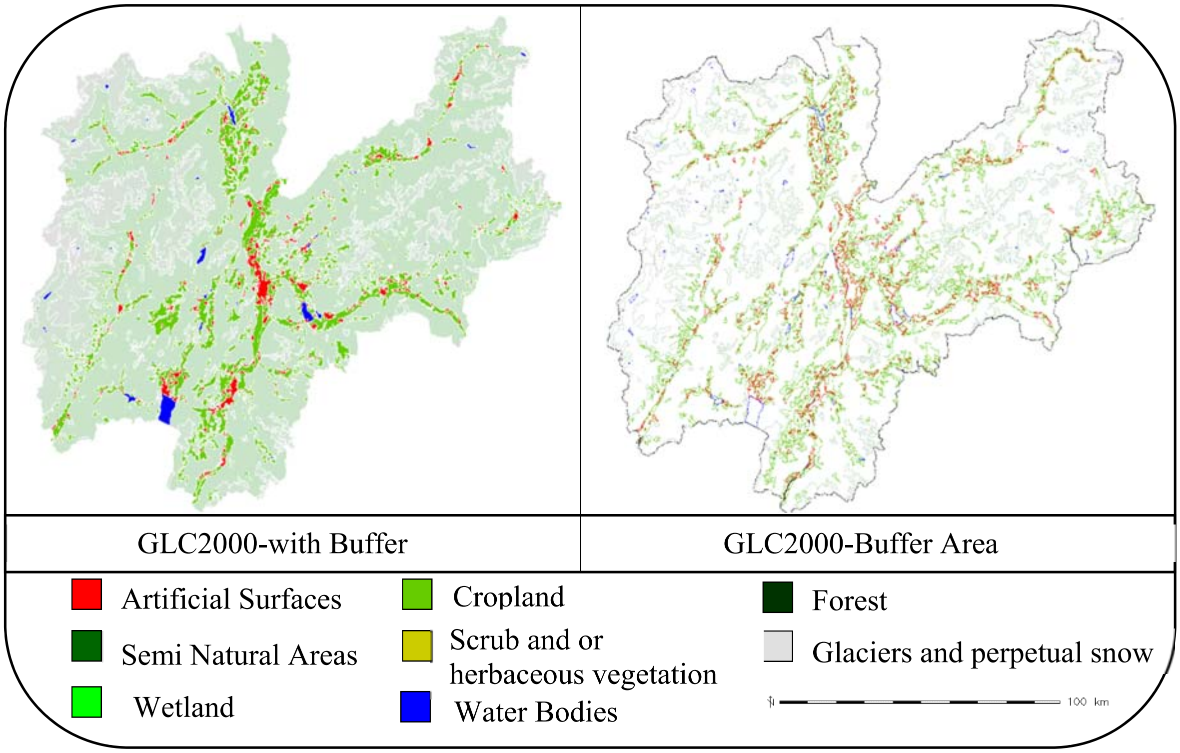


Figure 40: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Trento Case).

***[26]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	75.11%	0.5595	13.66%	11.23%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*	*PERPETUAL SNOW / GLACIERS*
UA*	81.29%	37.03%	77.63%	99.19%
PA*	93.09%	27.18%	45.80%	75.11%
K*	0.6426	0.2262	0.5218	0.8538
AD*	8.16%	12.32%	4.04%	0.01%
QD*	8.57%	3.55%	6.27%	0.21%

Table 32: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer (Trento Case).

3.4.3.2 Prov. Autonomous Bolzano

The confusion matrices and the agreement measures are represented in Table 33, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

[26] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	sum	UA	CE
1	87325	32729	17104	928	3232	141318	61.79%	38.21%
2	76693	839876	344222	2522	9537	1272850	65.98%	34.02%
3	18460	90337	6656594	8857	6233	6780481	98.17%	1.83%
4	44	78	776	38	101	1037	3.66%	96.34%
5	353	467	3011	168	17017	21016	80.97%	19.03%
sum	182875	963487	7021707	12513	36120	8216702		
PA	47.75%	87.17%	94.80%	0.30%	47.11%			
OE	52.25%	12.83%	5.20%	99.70%	52.89%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	92.50%	0.7287	3.73%	3.77%

CASE B (5 m resoulation):

GROUND TRUTH

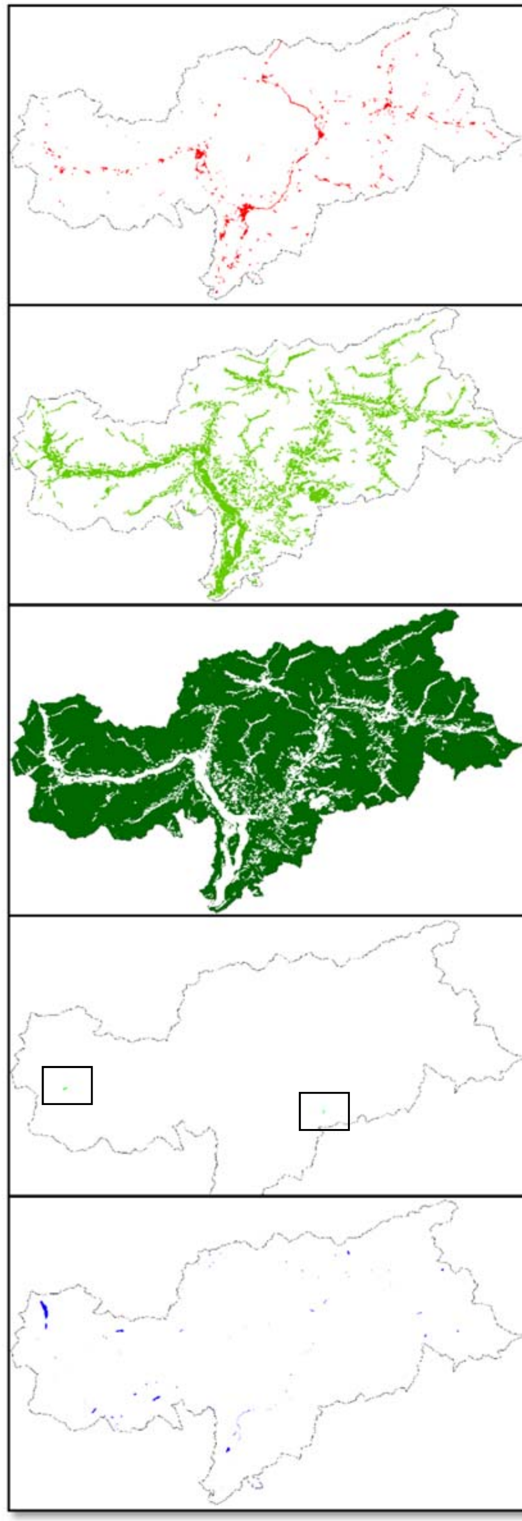
CLASSIFIED	1	2	3	4	5	sum	UA	CE
1	3134511	1184757	619893	33757	114801	5087719	61.61%	38.39%
2	2766207	30180189	12441339	90775	343632	45822142	65.86%	34.14%
3	671188	3310652	239569492	317543	228863	244097738	98.14%	1.86%
4	1631	2846	27852	1397	3606	37332	3.74%	96.26%
5	12795	17204	108300	6118	612282	756699	80.91%	19.09%
sum	6586332	34695648	252766876	449590	1303184	295801630		
PA	47.59%	86.99%	94.78%	0.31%	46.98%			
OE	52.41%	13.01%	5.22%	99.69%	53.02%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	92.46%	0.7271	3.78%	3.76%

Table 33: First Reclassification Method (Case 1) – Error matrices and Agreement measures for Different Input data Resolution between GLC2000 and Bolzano1999.

The results shows that the agreement measures are most similar with different input data resolution, the kappa values are high identify with high overall accuracy which explains the low values of Allocation and Quantity disagreement with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:



- **Artificial surfaced category**

	5 m	*30 m*
UA	61.61%	61.79%
PA	47.59%	47.75%
K	0.5278	0.5296
AD	1.32%	1.31%
QD	0.51%	0.51%

- **Cropland**

	5 m	*30 m*
UA	68.86%	65.98%
PA	86.99%	87.17%
K	0.7111	0.7128
AD	3.05%	3.01%
QD	3.67%	3.77%

- **Forest and Semi Natural area Category**

	5 m	*30 m*
UA	98.14%	98.17%
PA	94.78%	94.80%
K	0.7776	0.7791
AD	3.06%	3.02%
QD	2.93%	2.94%

- **Wetland**

	5 m	*30 m*
UA	3.74%	3.66%
PA	0.31%	0.30%
K	0.0055	0.0054
AD	0.02%	0.02%
QD	0.14%	0.14%

- **Open Water Category**

	5 m	*30 m*
UA	80.91%	80.97%
PA	46.98%	47.11%
K	0.5932	0.5944
AD	0.10%	0.10%
QD	0.18%	0.18%

The results shows that both Forest and semi Natural Areas and Open water category are classified with the best accuracies compared with Artificial cover, Cropland and wetland which have less accuracies.

Table 34 list the agreement measures between the compared maps GLC2000 and Bolzano1999 Corresponds to the second reclassification method (Case2).

***[27]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	74.07%	0.6254	18.17%	7.75%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*	*PERPETUAL SNOW / GLACIERS*
UA*	83.03%	63.06%	66.76%	59.52%
PA*	89.17	41.55%	66.69%	79.70%
K*	0.7293	0.4053	0.5989	0.6755
AD*	10.09%	9.85%	11.33%	0.65%
QD*	3.44%	6.90%	0.02%	0.54%

Table 34: Second Classification Method (Case2); Agreement measures with 30 m input data resolution between GLC2000 and Bolzano1999.

Analyzing the results of the two different classification method, the general agreement measures shows that the overall accuracy decreased by 18%, this explain the increase in both values of Allocation and Quantity disagreement. Forests are classified with the best accuracies (83.03% for the User's accuracy and 89.17% for the Producer's accuracy). This followed by Shrub/Grass, Beaches, Rocks, Sparsely vegetated area and Permanent Snow are poorly classified with less accuracies.

A buffer 70 m eliminated around GLC polygon border (Figure 42) to eliminate the part of the disagreement according to the to the co-location tolerance. Table 35, list the General Agreement measures.

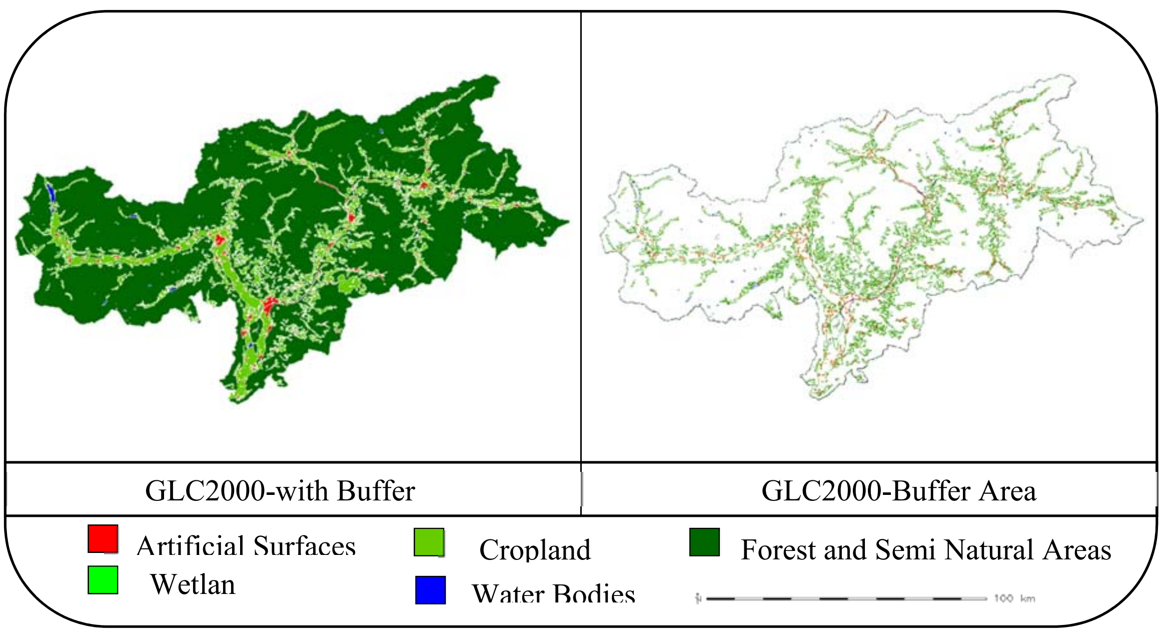


Figure 41: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Bolzano Case).

[27] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	96.31%	0.8159	1.88%	1.815
30 m	96.03%	0.8122	1.95%	2.01%

Table 35: General Agreement Measures after Eliminating the Buffer (Bolzano Case).

The percentage of the pixels that have been eliminated were about 12.25% with 67.24% overall accuracy corresponds to 30m input data resolution, while 13.84% with 68.50 % overall accuracy for 5m input data resolution. Moreover, the comparison shows the increasing of the overall accuracy and standard Kappa, which explains the decreasing in Allocation and Quantity disagreement. Table 36 reports commission and omission disagreement with and without buffer corresponding to 30 m resolution.

	Commission Error		**Omission Error**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	38.21 %	23.45%	52.25%	54.41 %
2. Cropland	34.02 %	24.72 %	12.83 %	8.39 %
3. Forest and semi Natural areas	1.83 %	1.09 %	5.22%	2.36 %
4. Wetland	96.34 %	98.05 %	99.70%	99.92 %
5. Water Surfaces	19.03%	1.14 %	52.89 %	46.45%

Table 36: GLC2000-Bolzano1999, Commission and Omission disagreement by pixel %.

Furthermore with second reclassification method (Case2), the cells that have been removed were about 23.98 % with 58.12 % overall accuracy (Figure38). Table 37 list the general agreement measures with buffer.

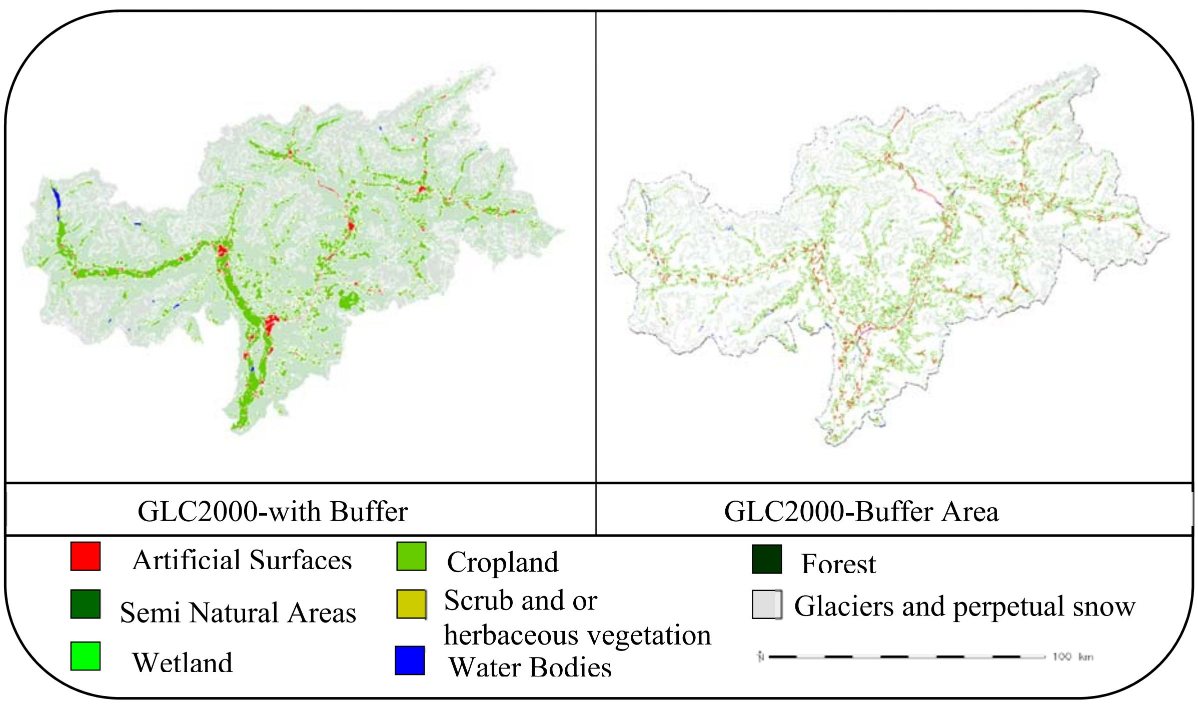


Figure 42: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Bolzano Case).

***[28]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	79.10%	0.6828	13.23%	7.67%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*	*PERPETUAL SNOW / GLACIERS*
UA*	85.79%	64.92%	70.80%	75.80%
PA*	94.66%	42.03%	70.76%	84.34%
K*	0.7902	0.4242	0.6486	0.7955
AD*	5.33%	8.64%	9.83%	0.43%
QD*	5.16%	6.70%	0.01%	0.15%

Table 37: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer (Bolzano Case).

3.4.4 Trentino-Alto Adige Case study Conclusion

In summary, the general agreement measures for both autonomous province Trento and Bolzano shows that eliminating the buffer around GLC polygon border gives better results with higher overall accuracies and higher standard kappa which explains the decrease in the Allocation and Quantity disagreement for the different reclassification methods. Moreover, analyzing the results for both Province, shows Forest are classified with the best accuracies compared with the other classes.

[28] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

3.5 FOURTH CASE STUDY: FRIULI–VENEZIA GIULIA

Friuli–Venezia Giulia is one of the 20 regions of Italy, and one of five autonomous regions with special statute (Figure 44)[29]. The capital is Trieste. It is Italy's most North-Eastern region. It covers an area of 7,858 km^2 and is the fifth smallest region of the country. It borders Austria to the north and Slovenia to the east. To the south it faces the Adriatic Sea and to the west its internal border is with the Veneto region. Figure 40 shows the overall workflow of the region.

Figure 43: Friuli-Venezia-Giulia Region.

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[29] http://en.wikipedia.org/wiki/Friuli-Venezia_Giulia

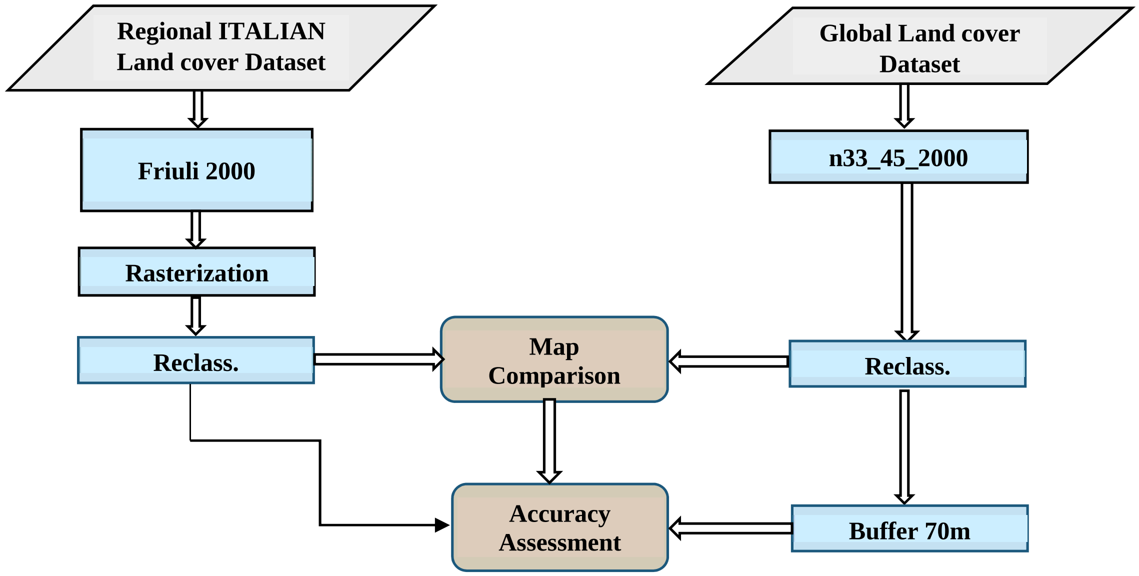


Figure 44: Overall workflow of Friuli-Venezia-Giulia region.

3.5.1 Friuli–Venezia Giulia Land cover layer

Friuli land cover map[30] was obtanied from Photo observation from satellite images, Aerial photos and comparison with other available data (Zoning plans, old soil covers, ancillary data, etc.)(Table 38), through Soil use updated to 2000 produced in the context of the "MOLAND FVG Project - Consumption and use of the territory of Friuli-Venezia Giulia" (2001-2002).

	FIRULI
YEAR	2000
SCALE	1:25’000
REF SYS	ETRS84/UTM33N
LEGEND	CORINE
SOURCE	Aerial photos
EXTENT	whole region

Table 38: Friuli land cover layer

3.5.2 Data processing

The comparison has been done between **GLC2000** and **Firuli2000**, Friuli vector layer was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Friuli raster maps at different cell sizes, respectively 30 m and 5 m, were calculated. The second important phase of data processing was relative to the different thematic classification of the two land cover maps.

[30] Metedata: http://irdat.regione.fvg.it/consultatore-dati-ambientali-territoriali/chooseOperation.do

To allow the comparison procedure, a reclassification of Friuli raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. Due to the differences in coastline between the two maps and to reduce the error around the Coastline, a new class (255) was added in order to calculate the common difference area between the two maps. The calculation has been done taking advantage of GRASS GIS module *r.mapcalc.* The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3. Figure 46 & 47 gives a visual overview for both reclassified Land Cover maps (GLC2000, Friuli2000).

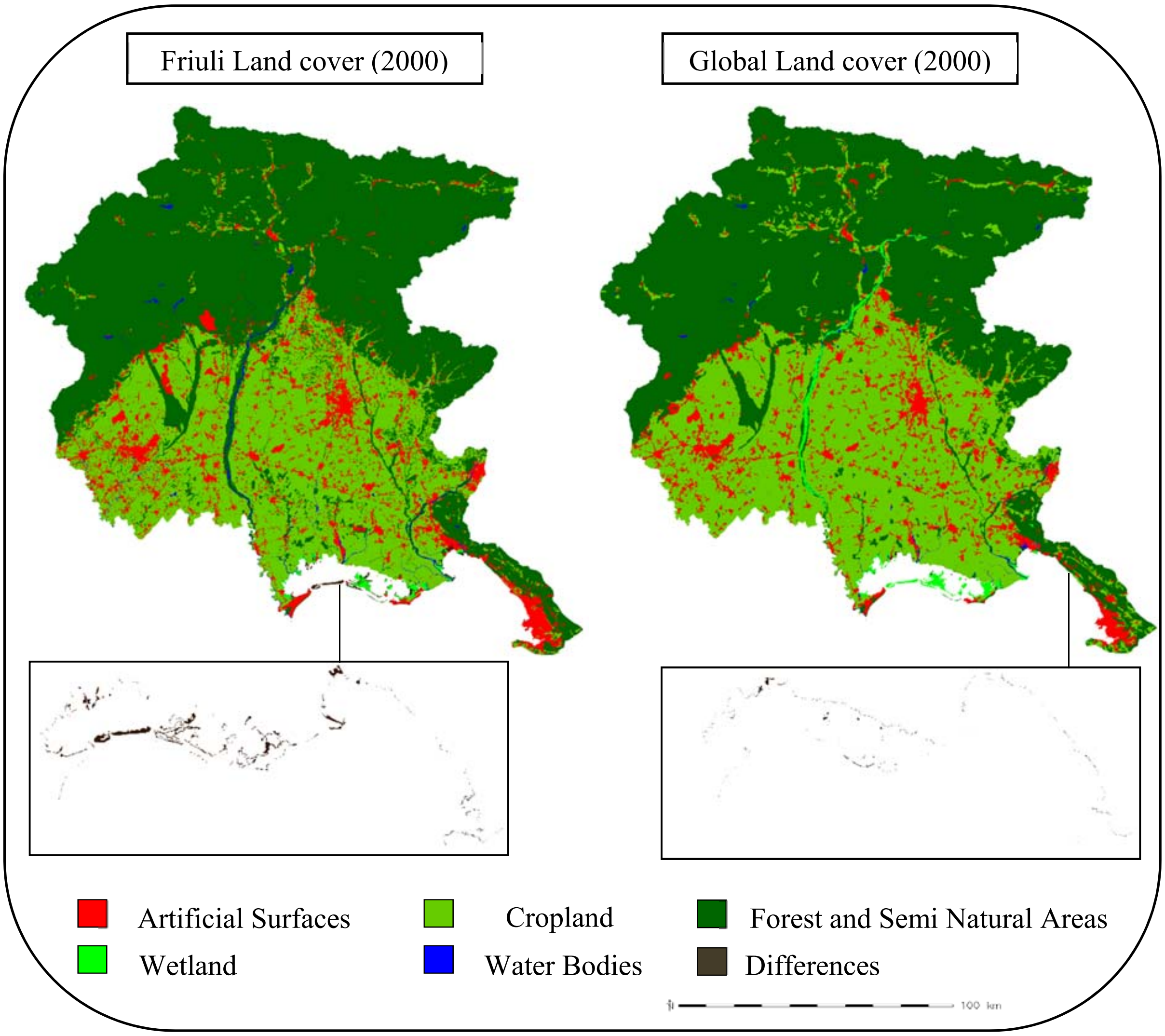


Figure 45: Visual Overview of Both Reclassified Friuli 2000 and GLC2000 (1st Classification)

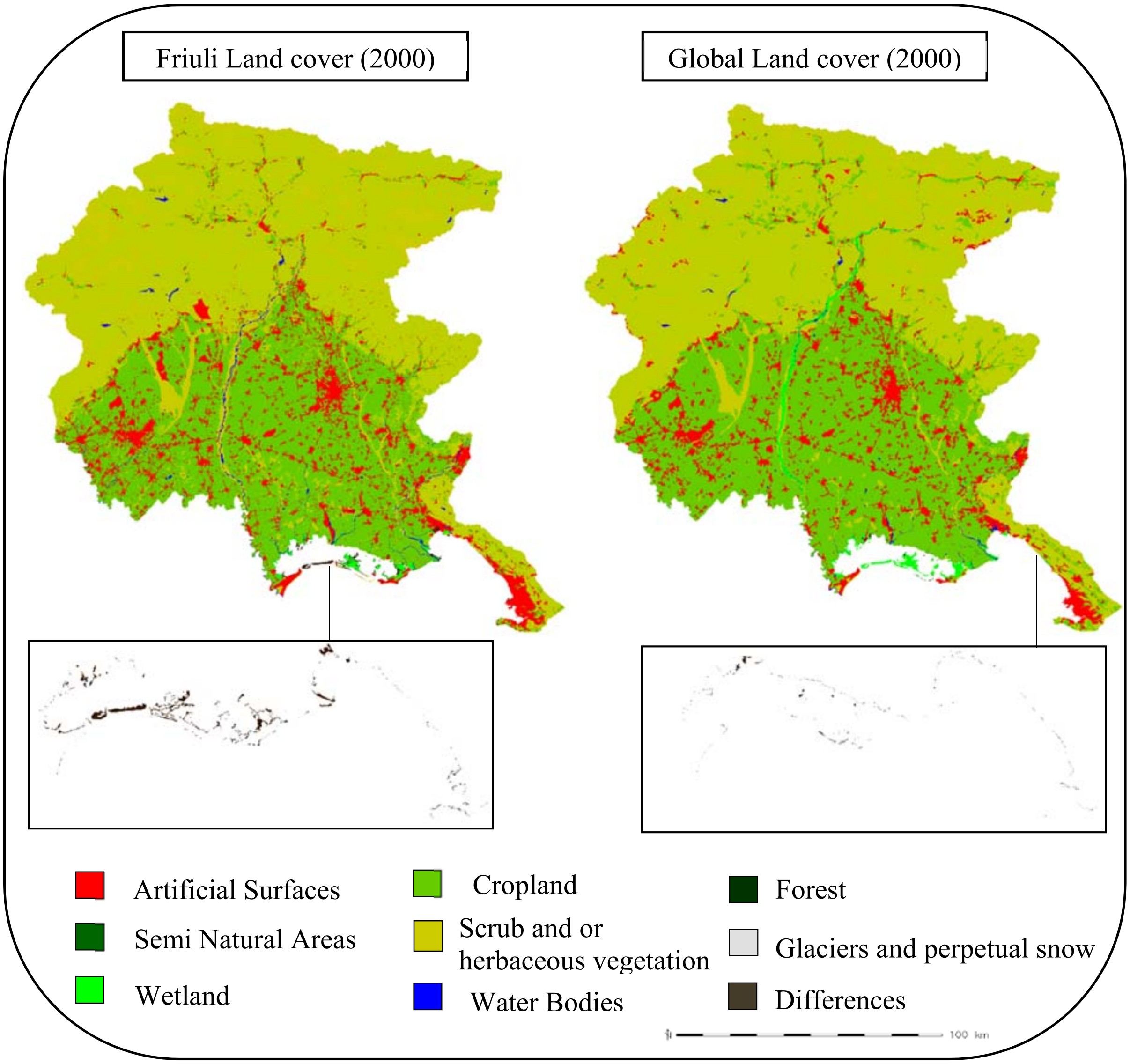


Figure 46: Visual Overview of Both Reclassified Friuli 2000 and GLC2000 (2nd Classification).

3.5.3 Accuracy Assessment

In a pixel based assessment, the accuracy assessment was derived from a comparison pixel by pixel between Reclassified Friuli Land cover map (REFERENCE MAP) and GLC (CLASSIFIED MAP).

The confusion matrices and the agreement measures are represented in Table 39, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	500431	132757	30314	907	968	1505	666882	75.04%	24.96%
2	207738	2826736	340537	2690	12354	518	3390573	83.37%	16.63%
3	61650	49387	4289543	1741	7897	899	4411117	97.24%	2.76%
4	1331	1673	37008	23039	12271	14117	89439	25.76%	74.24%
5	2560	2070	5232	762	16353	1313	28290	57.80%	42.20%
255	887	1100	572	569	191	0	3319	0.00%	100.00%
sum	774597	3013723	4703206	29708	50034	18352	8589620		
PA	64.61%	93.80%	91.20%	77.55%	32.68%	0.00%			
OE	35.39%	6.20%	8.80%	22.45%	67.32%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	89.13%	0.8104	5.79%	5.08%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	17978791	4808202	1097497	32489	35756	54957	24007692	74.89%	25.11%
2	7512403	101712604	12273081	96784	446870	19319	122061061	83.33%	16.67%
3	2221975	1789807	154408315	62531	283962	32965	158799555	97.23%	2.77%
4	47821	60748	1332232	827687	441344	509972	3219804	25.71%	74.29%
5	92260	76552	189169	27510	586122	47473	1019086	57.51%	42.49%
255	33564	40148	20915	21866	6934	0	123427	0.00%	100.00%
sum	27886814	108488061	169321209	1068867	1800988	664686	217880139		
PA	64.47%	93.75%	91.19%	77.44%	32.54%	0.00%			
OE	35.53%	6.25%	8.81%	22.56%	67.46%	100.00%			

GENERAL AGREEMENT MEASURES

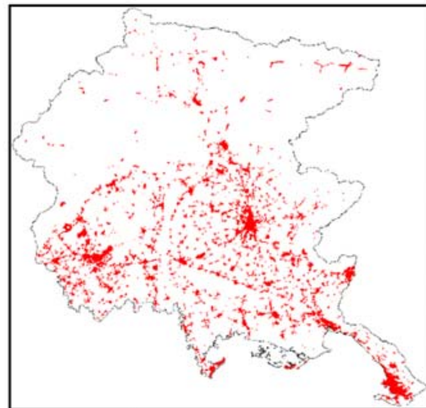
	OA	*K*	*AD*	*QD*
5 m	89.10%	0.8098	5.82%	5.08%

Table 39: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2000 and Friuli 2000.

The agreement measures are most similar with both input data resolution, the kappa values are high identify with high overall accuracy. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

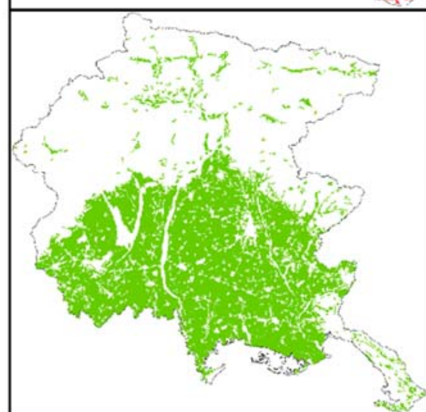
- **Artificial surfaced category**

	5 m	*30 m*
UA	74.89%	75.04%
PA	64.47%	64.61%
K	0.6649	0.8135
AD	3.90%	3.88%
QD	1.25%	1.25%



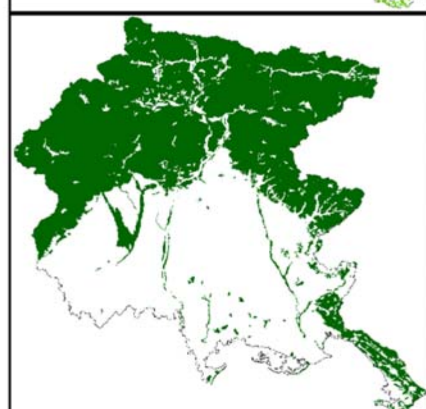
- **Cropland**

	5 m	*30 m*
UA	83.33%	83.37%
PA	93.75%	93.80%
K	0.8128	0.8135
AD	4.38%	4.35%
QD	4.39%	4.39%



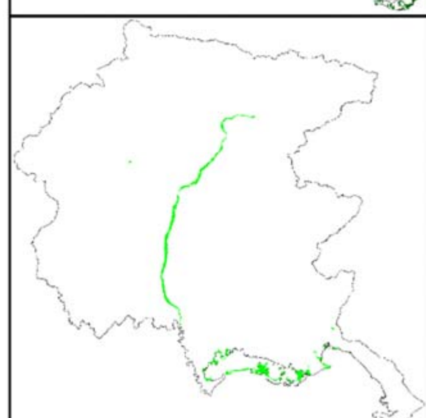
- **Forest and Semi Natural area Category**

	5 m	*30 m*
UA	97.23%	97.24%
PA	91.19%	91.20%
K	0.8748	0.8751
AD	2.84%	2.83%
QD	3.40%	3.40%



- **Wetland**

	5 m	*30 m*
UA	25.71%	25.76%
PA	77.44%	77.55%
K	0.3828	0.3835
AD	0.16%	0.16%
QD	0.70%	0.70%



➢ Open Water Category

	5 m	*30 m*
UA	57.51%	57.80%
PA	32.54%	32.68%
K	0.4132	0.4151
AD	0.28%	0.28%
QD	0.25%	0.25%

The results shows that the best accuracies occur in Forest and Semi Natural Areas class (97.23% User's accuracy and 91.19% Producer's accuracy) compared with the other classes.

Table 40 list the general agreement measures corresponding to the comparison that have been done between Friuli2000 and GLC2000, with second reclassification method (Case2).

***[31]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	79.54%	0.7060	13.84%	6.49%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	84.48%	56.12%	71.07%
PA*	87.22%	42.46%	45.21%
K*	0.7700	0.4318	0.5192
AD*	9.66%	7.00%	2.36%
QD*	1.23%	2.56%	2.33%

Table 40: Second Classification Method (Case2); Agreement measures between reclassified GLC2000 and Friuli2000 with 30 m input data resolution.

Comparing the results of the two different classification method, the general agreement measures shows that the overall accuracy decreased by 10%, this explain the increase in both values of Allocation and Quantity disagreement. Among the sub classes, Forest are classified with the high accuracies (84.48% for the User's accuracy and 87.22% for the Producer's accuracy). This followed by Shrub/Grass, Beaches, Rocks, and Sparsely vegetated area are poorly classified with less accuracies. It has been noticed that there was pixels corresponds to Permanent snow class in GLC2000 in the mean while there wasn't pixels corresponds to it in Friuli land cover layer which gives us Null values in the agreement measures.

A buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy to eliminate the part of the disagreement (Figure 48). Table 41 presents the recalculation of the agreement statistics.

[31] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

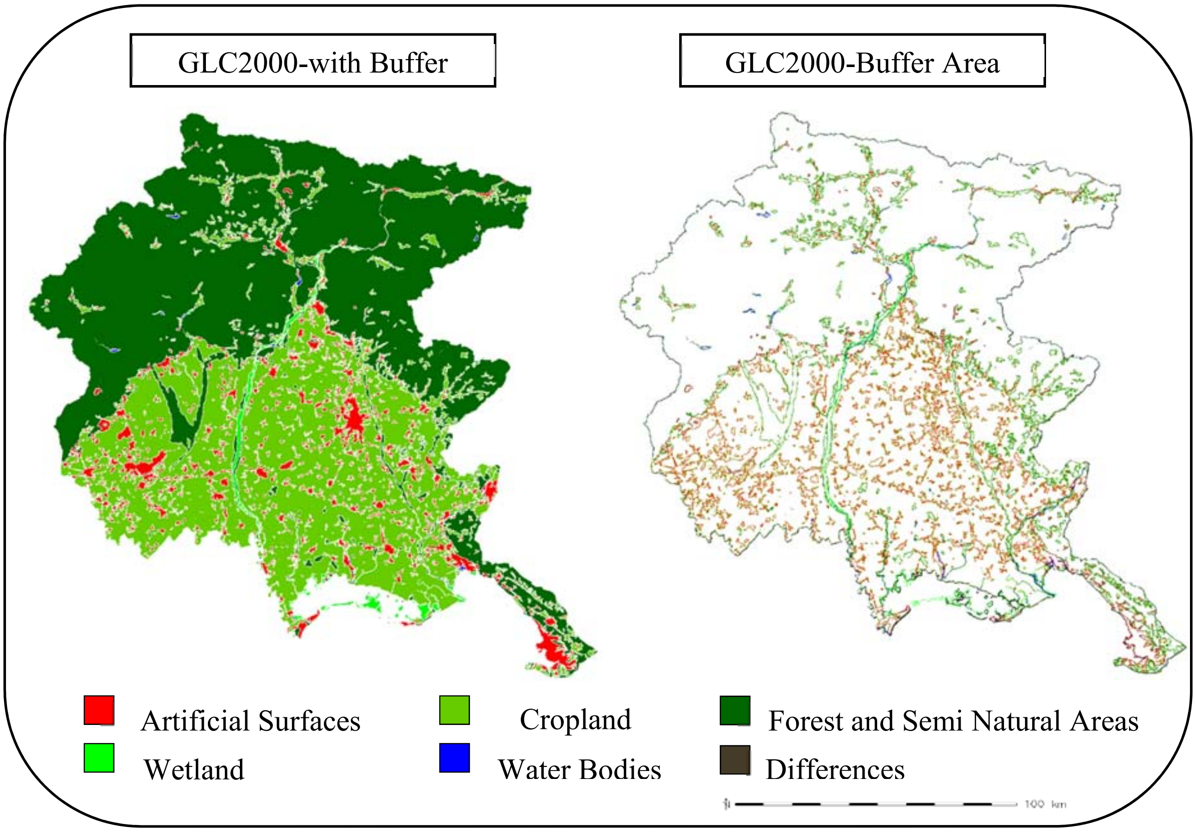


Figure 47: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Friuli2000 Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	93.72%	0.8823	2.18%	4.09%
30 m	93.38%	0.8770	2.39%	4.23%

Table 41: General Agreement measures after elimination of Buffer between Reclassified GLC2000 and Friuli2000.

A 13.48% of the pixels have been eliminated with 61.84% overall accuracy corresponds to 30 m input data resolution while 15.11% with 63.11% overall accuracy corresponds to 5m input data resolution. Table 42 list the Commission and Omission disagreement by Pixel% corresponds to 30 m input data resolution which shows the decreasing in both errors with eliminating the buffer.

	Commission Error		**Omission Error**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	24.96 %	13.01 %	35.39 %	34.54 %
2. Cropland	16.63 %	11.76 %	6.20 %	2.23 %
3. Forest and semi Natural areas	2.76 %	1.65 %	8.80 %	5.72 %
4. Wetland	74.24 %	67.46 %	22.45 %	15.49 %
5. Water Surfaces	42.20 %	26.69 %	67.32%	79.88 %

Table 42: Friuli2000, Commission and Omission disagreement by pixel%.

Furthermore with second reclassification method (Case2), the cells that have been removed was about 21.06 % with 56.28 % overall accuracy (Figure 49). Table 43 list the general agreement measures with buffer.

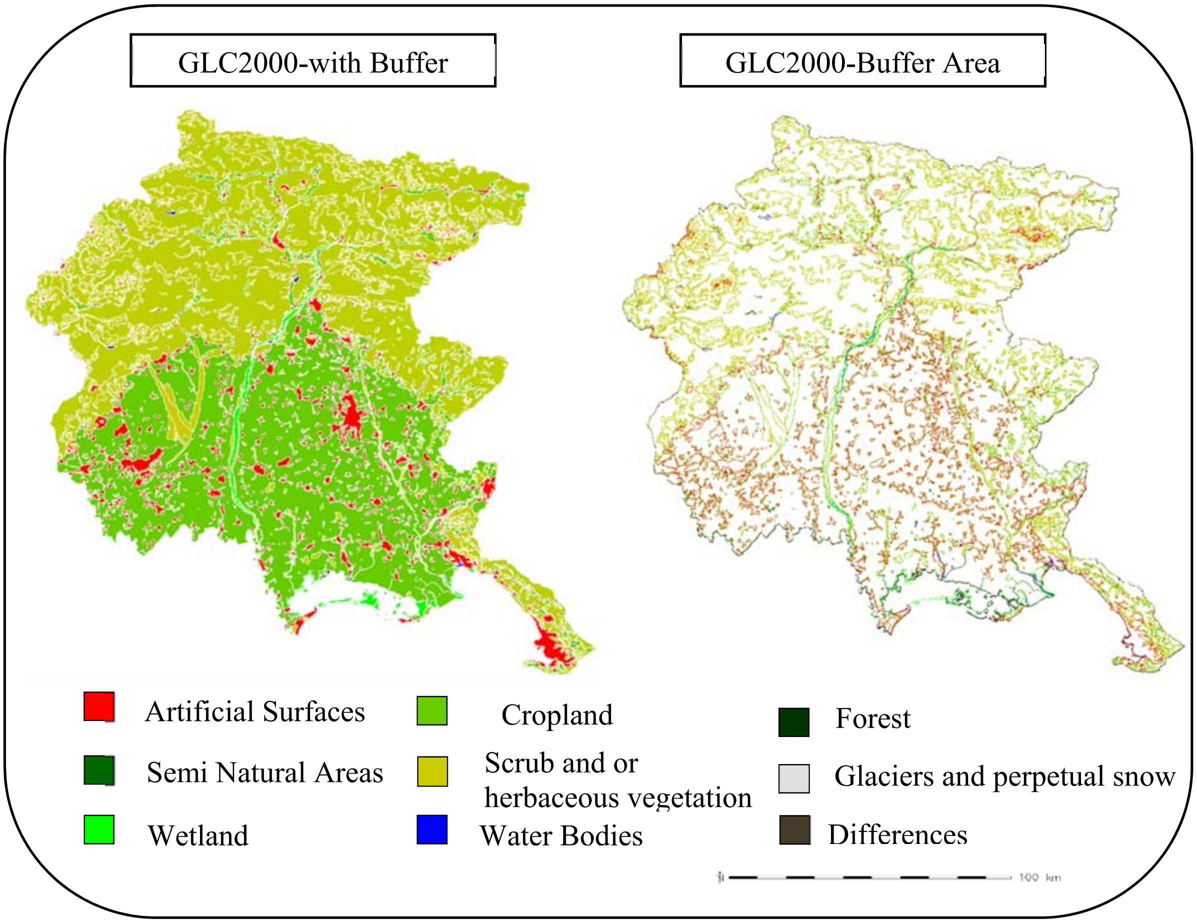


Figure 48: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Friuli2000 Case).

***[32]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	85.80%	0.7832	7.51%	6.68%

	FORESTS	***SHRUB/GRASS***	***BEACHES,ROCKS,SPARSELY VEGETATED AREAS…***
UA*	87.94%	63.24%	80.75%
PA*	92.22%	43.98%	44.93%
K*	0.8297	0.4803	0.5623
AD*	6.30%	4.62%	1.03%
QD*	1.97%	2.75%	2.13%

Table 43: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer (Friuli2000 Case).

[32] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

3.5.4 Friuli–Venezia Giulia Case Study Conclusion

The agreement measures shows that the best accuracies occur at Forest Class with different input data resolution and different reclassification methods compared with the other classes. The standard kappa values are high identify with high overall accuracy which explains the less values of Allocation and Quantity disagreement. In summary, eliminating the buffer around GLC polygon border gives better agreement measures.

3.6 Fifth Case Study: Veneto Region

Veneto is one of the twenty regions of Italy (Figure 50)[33]. Its population is about five million, ranking fifth in Italy. The region's capital and largest city is Venice. Veneto is the 8th largest region in Italy, with a total area of 18,398.9 km^2. It is located in the north-eastern part of Italy and is bordered to the east by Friuli Venezia Giulia, to the south by Emilia-Romagna, to the west by Lombardy and to the north by Trentino-Alto Adige. At its northernmost corner it borders also on Austria. Figure 51, shows the Overall workflow of the region

Figure 49: Veneto Region.

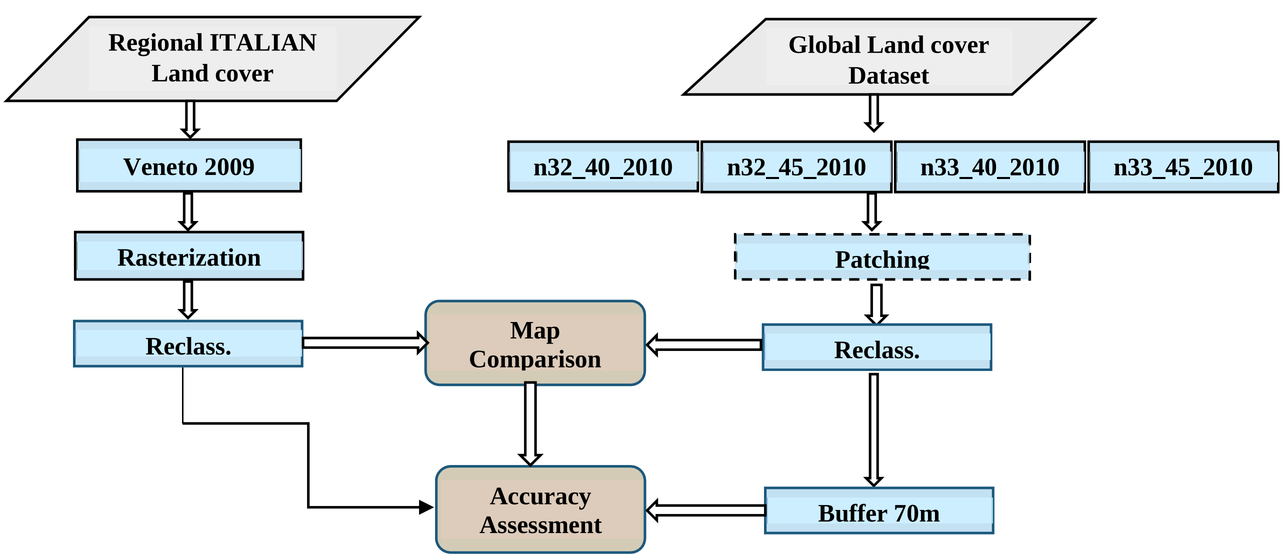


Figure 50: Overall Workflow of Veneto Region

[33] http://en.wikipedia.org/wiki/Friuli-Venezia_Giulia

3.6.1 Veneto Land Cover Database

The Database[34] of Cover Soil takes its first plant by the implementation of DB GSE Land - Urban Atlas, using SPOT 5 satellite images, multispectral bands (10 m) and panchromatic (2.5 m). And spatial data of various kinds (DB TeleAtlas, Regional Technical Numerica, DEM, Paper, Forest road graph). In the first embodiment, the classification has been carried out with the support of the eCognition software using an object-oriented approach. The entire process of verification and review and was performed by photo-interpretation in video color digital orthophotos produced by Compagnia Generale Rispreseaeree SpA for the period 2006/2007 (edition "TerraItalyTM" Digital RGB).

Once the database G.S.E. Land - Urban Atlas, it proceeded with the deepening of the classification of suburban areas. The theming of the Territories Agricultural and occurred through spatial cadastral statements (i.e. the Regional Information System for Primary Sector (SISP) and the Information System of the paying agency (AVEPA)); theming Territories Forest and semi-natural areas is based on the Charter and the Regional Forest whose thematic content were included in the classes of the legend of the Soil Map of the coverage while maintaining the groupings by Category (level IV) and by type (level V). The theming of the Environment and Environment wet water and was carried through the interpretation of digital orthophotos.

	VENETO
YEAR	2007-2009
SCALE	1:10’000
REF SYS	GAUSS-BOAGA / OVEST
LEGEND	CORINE
SOURCE	Orthophots
EXTENT	whole region

Table 44: Veneto Land Cover Layer.

3.6.2 Data processing

The Comparison has been done between **GLC2010** and Land cover map of **Veneto region 2009**. The vector layer was available in GUSS-BOAGA reference system while GLC was available in WGS84/UTM32-33. Therefore, re-projection for both raster and vector maps was needed. The re- projection of Veneto vector was done taking advantage of GRASS GIS *v.proj* module. Moreover, the re-projection for GLC raster map was done using GRASS GIS *r.proj*. Furthermore, GLC was available in four different tiles, therefore a patching procedure was needed to obtain the area corresponding to Veneto region.

[34]Metadata: http://idt.regione.veneto.it/app/metacatalog/getMetadata/?id=551&isIe=false

Then, Veneto vector map was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Veneto raster maps at different cell sizes, respectively 30 m and 5 m, were calculated.

Secondly, to allow the comparison procedure, a reclassification of Veneto raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. Due to the differences in coastline between the two maps and to reduce the error around the Coastline, a new class (255) was added in order to calculate the common difference area between the two maps. It was notice that there is no pixels to add to Veneto vector layer. The calculation has been done taking advantage of GRASS GIS module *r.mapcalc.* The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3. Figure 52 & 53 gives a visual overview of both reclassified Land cover maps (Veneto2009, GLC2010).

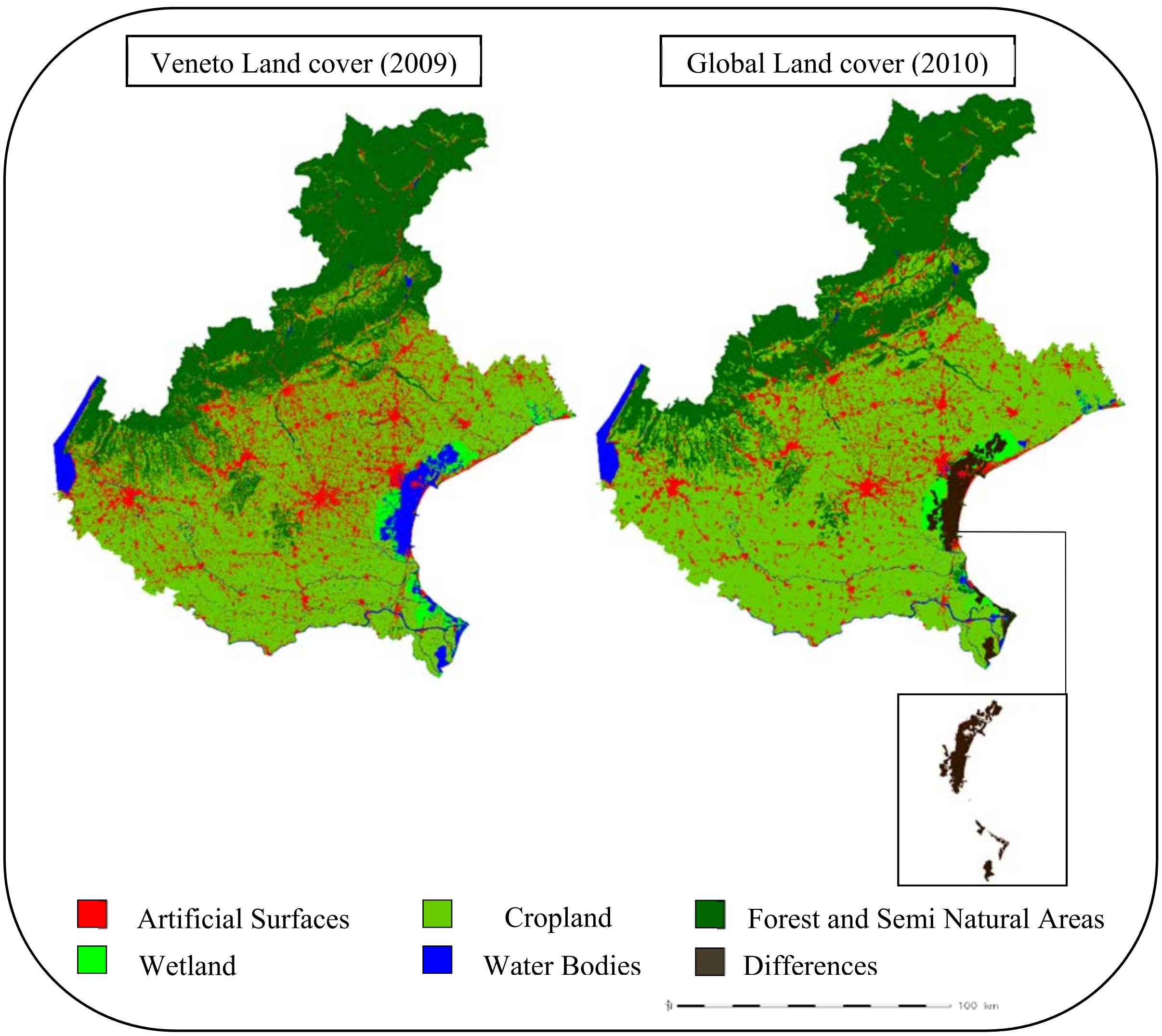


Figure 51: Visual Overview of Both Reclassified Veneto2009 and GLC2000 (1st Classification).

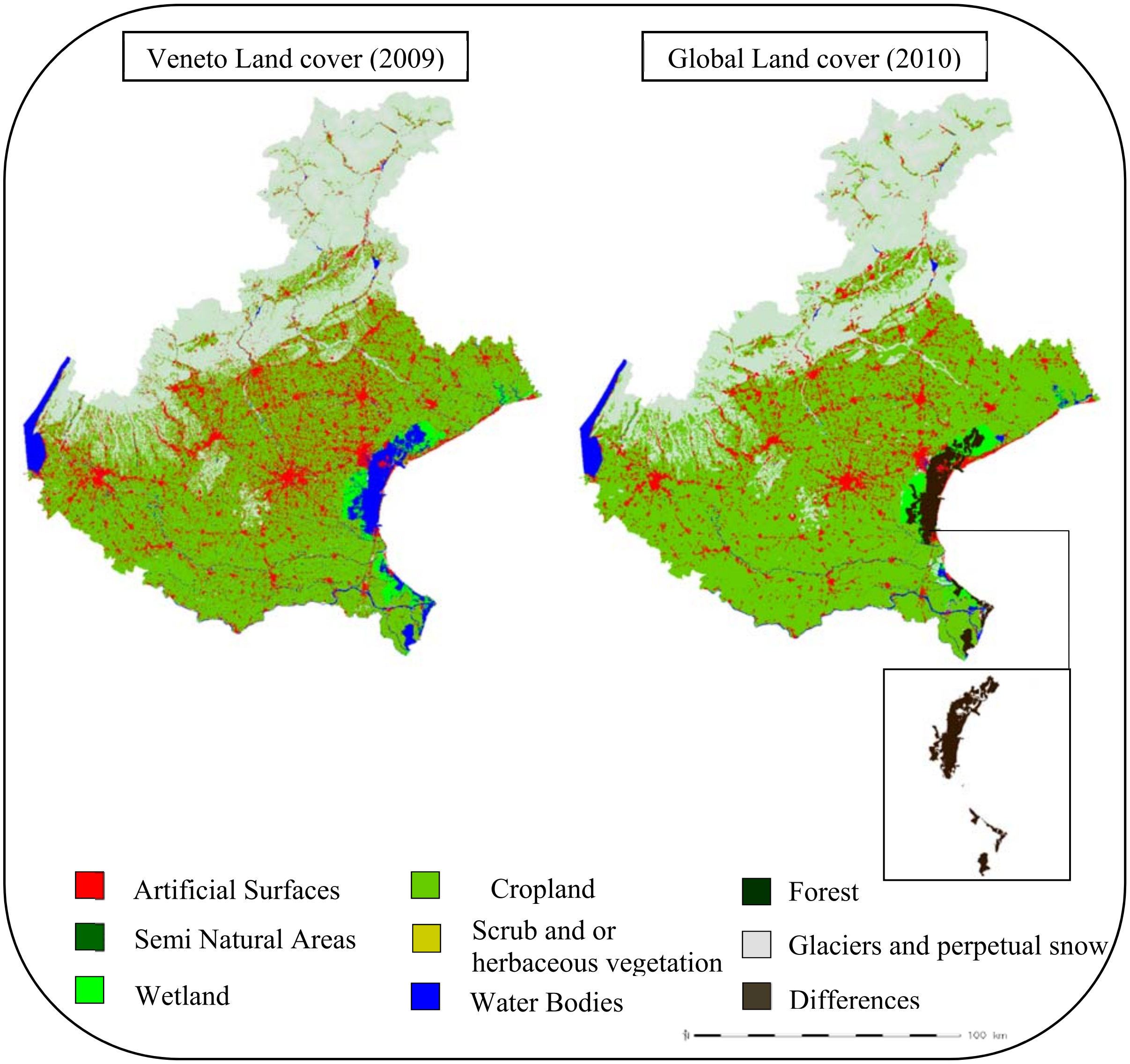


Figure 52: Visual Overview of Both Reclassified Veneto2009 and GLC2000 (2nd Classification).

3.6.3 Accuracy Assessment

In a pixel based assessment, the accuracy assessment was derived from a comparison pixel by pixel between Reclassified Veneto Land cover map (REFERENCE MAP) and GLC (CLASSIFIED MAP).

The confusion matrices and the agreement measures are represented in Table 45, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	1428678	403959	63219	379	14469	0	1910704	74.77%	25.23%
2	1211967	9512933	642249	43792	117887	0	11528828	82.51%	17.49%
3	85085	260530	5541427	30854	25149	0	5943045	93.24%	6.76%
4	4131	10244	2847	210135	39290	0	266647	78.81%	21.19%
5	5758	14355	12798	29492	313542	0	375945	83.40%	16.60%
255	1422	442	988	29780	394975	0	427607	0.00%	100.00%
sum	2737041	10202463	6263528	344432	905312	0	20452776		
PA	52.20%	93.24%	88.47%	61.01%	34.63%	#DIV/0!			
OE	47.80%	6.76%	11.53%	38.99%	65.37%	#DIV/0!			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	83.15%	0.7266	8.27%	8.58%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	51315352	14637620	2287260	13949	530574	0	68784755	74.60%	25.40%
2	43704920	342305334	23182893	1576495	4269738	0	415039380	82.48%	17.52%
3	3077465	9426843	199428603	1110545	907594	0	213951050	93.21%	6.79%
4	149559	368803	100969	7561087	1418747	0	9599165	78.77%	21.23%
5	215229	538964	468161	1062372	11249825	0	13534551	83.12%	16.88%
255	55479	17355	36881	1077510	14207220	0	15394445	0.00%	100.00%
sum	98518004	367294919	225504767	12401958	32583698	0	217880139		
PA	52.09%	93.20%	88.44%	60.97%	34.53%	#DIV/0!			
OE	47.91%	6.80%	11.56%	39.03%	65.47%	#DIV/0!			

GENERAL AGREEMENT MEASURES

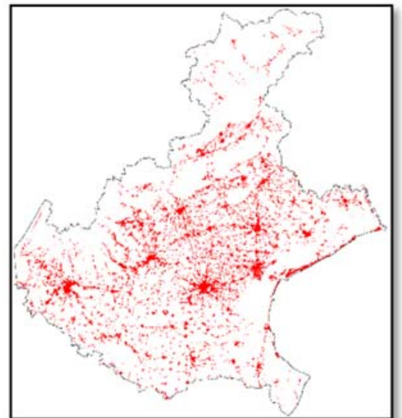
	OA	*K*	*AD*	*QD*
5 m	83.10%	0.7258	8.38%	8.58%

Table 45: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2010 and Veneto2009.

The results shows that the agreement measures are most similar with different input data resolution, the kappa values are high identify with high overall accuracy which explains the low values of Allocation and Quantity disagreement with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

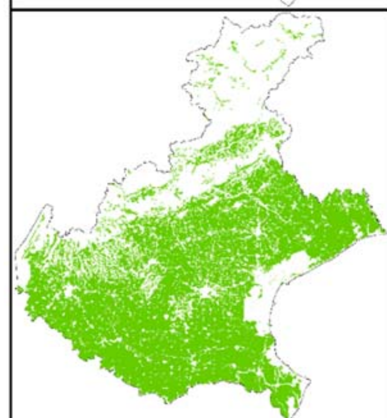
➢ Artificial surfaced category

	5 m	*30 m*
UA	74.60%	74.77%
PA	52.09%	52.20%
K	0.5957	0.5672
AD	4.75%	4.71%
QD	4.04%	4.04%



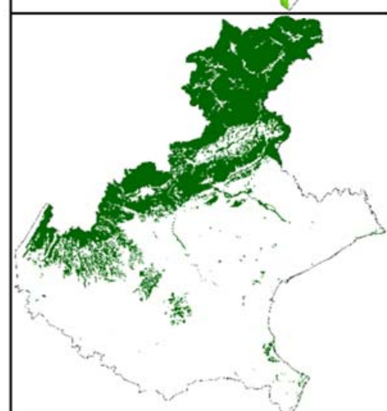
➢ Cropland

	5 m	*30 m*
UA	82.48%	82.51%
PA	93.20%	93.24%
K	0.7346	0.7355
AD	6.79%	6.74%
QD	6.48%	6.49%



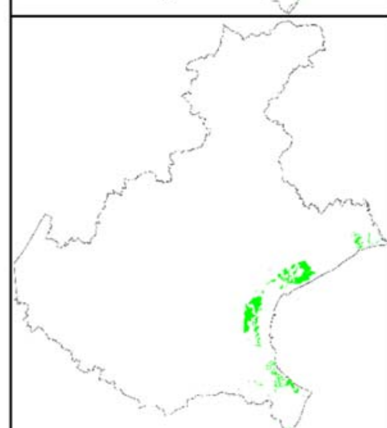
➢ Forest and Semi Natural area Category

	5 m	*30 m*
UA	93.21%	93.24%
PA	88.44%	88.47%
K	0.8684	0.8688
AD	3.94%	33.93%
QD	1.57%	1.75%



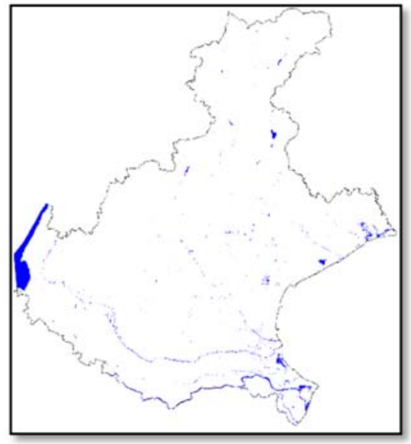
➢ Wetland

	5 m	*30 m*
UA	78.77%	78.81%
PA	60.97%	61.06%
K	0.6827	0.6831
AD	0.55%	0.55%
QD	0.38%	0.38%



- **Open Water Category**

	5 m	*30 m*
UA	83.12%	83.40%
PA	34.53%	34.63%
K	0.4742	0.4758
AD	0.62%	0.61%
QD	2.59%	2.59%



The results shows that Both Cropland and Forest and Semi Natural Areas are classified with the best accuracies compared with the other classes. On other hand, Table 46 list the agreement measures between the compared maps GLC2010 and Veneto2009 corresponds to the Second reclassification method.

***[35]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	78.27%	0.6677	12.47%	6.90%

	FOREST	**SHRUB/GRASS**	**BEACHES,ROCKS,SPARSELY VEGETATED AREAS…**	**PERPETUAL SNOW / GLACIERS**
UA*	83.21%	56.61%	64.26%	1.07%
PA*	80.47%	44.73%	61.35%	89.66%
K*	0.7666	0.4755	0.6169	0.0210
AD*	7.30%	3.59%	1.98%	0.00%
QD*	0.74%	1.10%	0.13%	0.41%

Table 46: Second Classification Method (Case2); Agreement measures between compared maps GLC2010 and Veneto2009 with 30 m input data resolution.

Analyzing the results of the two different classification method, the general agreement measures shows that the overall accuracy decreased by 5%, which explains the increase in the allocation and Quantity disagreement values. It has been noticed that the Allocation disagreement value increased while the Quantity disagreement value decreased. Among the sub classes, Forest are classified with the best accuracies (83.21% for the User's accuracy and 80.47% for the Producer's accuracy). This followed by Shrub/Grass, Beaches, Rocks, Sparsely vegetated area and Permanent snow are poorly classified with less accuracies.

A buffer 70 m wide eliminated around GLC polygon border (Figure 54) to eliminate the part of the disagreement according to the to the co-location tolerance. Table 47 list the Agreement measures after eliminating the Buffer.

[35] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

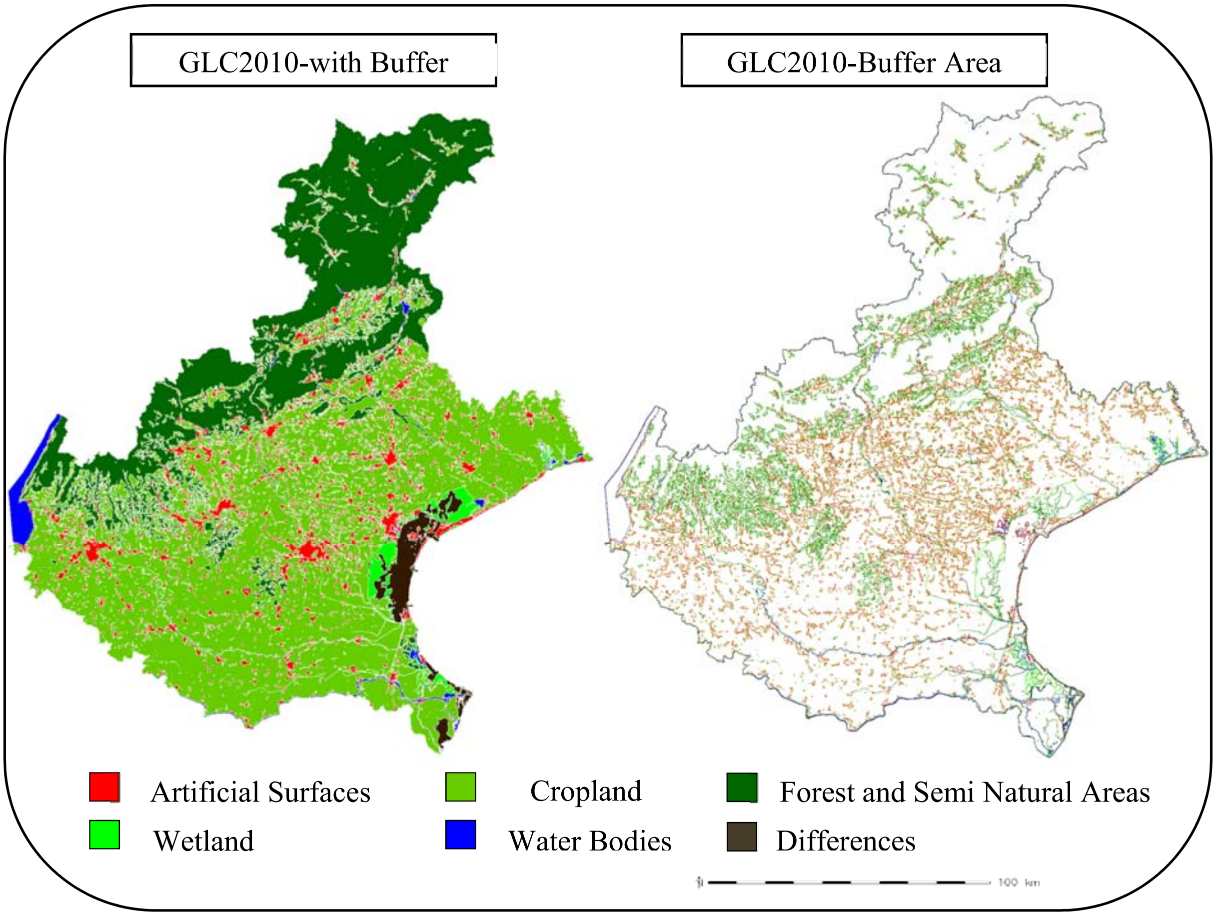


Figure 53: First Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Veneto Case.)

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	87.64%	0.7899	3.91%	8.46%
30 m	87.33%	0.7857	4.19%	8.46%

Table 47: General Agreement Measures between GLC2010 and Veneto2009 after the Elimination of a Buffer.

Around 16.42% pixels has been eliminated with 61.89% overall accuracy corresponds to 30 m input data resolution. Further, 18.42% pixels has been eliminated with 63.00% overall accuracy corresponds to 5 m data resolution which gives us better results.

Table 48, list the Commission and Omission disagreement by pixel (%) corresponds to 30m input data resolution.

	Commission Error		**Omission Error**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	25.23%	16.27%	47.80%	51.86%
2. Cropland	17.49%	13.52%	6.76%	3.17%
3. Forest and semi Natural areas	6.76%	4.09%	11.53%	7.34%
4. Wetland	21.19%	16.59%	38.99%	34.01%
5. Water Surfaces	16.60%	7.81%	65.37%	67.56%

Table 48: GLC2010-Veneto2009, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the pixels that have been eliminated were about 19.84 % with 58.71 % overall accuracy (Figure 55). Table 49, list the general agreement measures after eliminating the buffer corresponds to 30m input data resolution.

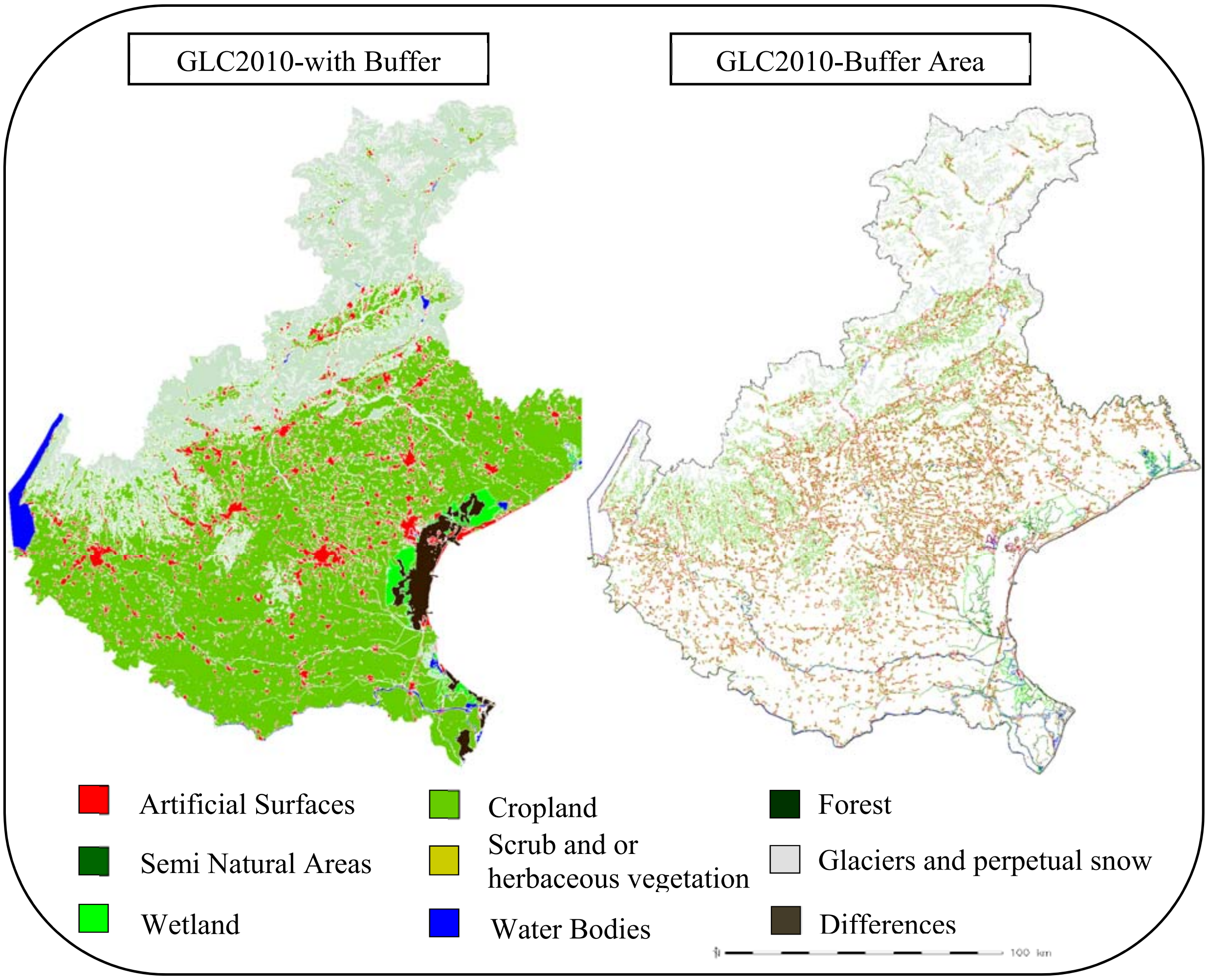


Figure 54: Second Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Veneto2009 case).

***[36]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	83.11	0.7244	7.70%	6.83%

	FOREST	**SHRUB/GRASS**	**BEACHES,ROCKS,SPARSELY VEGETATED AREAS…**	**PERPETUAL SNOW / GLACIERS**
UA*	86.93%	64.06%	71.74%	1.73%
PA*	86.50%	47.31%	65.84%	98.40%
K*	0.8293	0.5253	0.6798	0.0339
AD*	8.78%	2.49%	1.20%	0.00%
QD*	0.11%	1.23%	0.19%	0.26%

Table 49: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer (Veneto2009 Case).

3.6.4 Veneto Case Study Conclusion

As a result, eliminating a buffer around GLC polygon border gives better agreement measures. In both assessment, Forest is classified with the best accuracies compared with the other classes using different reclassification method and different input data resolution. The overall accuracy is high associated with high value for Standard kappa, which explains low values of the total disagreement.

[36] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.7 SIXTH CASE STUDY: EMILIA ROMAGNA REGION

Emilia-Romagna is an administrative Region of Northern Italy (Figure 56)[37]. Its capital is Bologna. The region consists of nine provinces and covers an area of 22,446 km^2 (8,666 sq. mi.), ranking sixth in Italy. It is one of the wealthiest and most developed regions in Europe, with the third highest GDP per capita in Italy. Nearly half of the region (48%) consists of plains while 27% is hilly and 25% mountainous. The mountains stretch for more than 300 km (186.41 mi) from the north to the south-east, with only three peaks above 2,000 m - Monte Cimone (2,165 m), Monte Cusna (2,121 m) and Alpe di Succiso (2,017 m). Figure 57, shows the overall workflow of the region.

Figure 55: Emilia Romagna Region.

[37] http://en.wikipedia.org/wiki/Emilia-Romagna

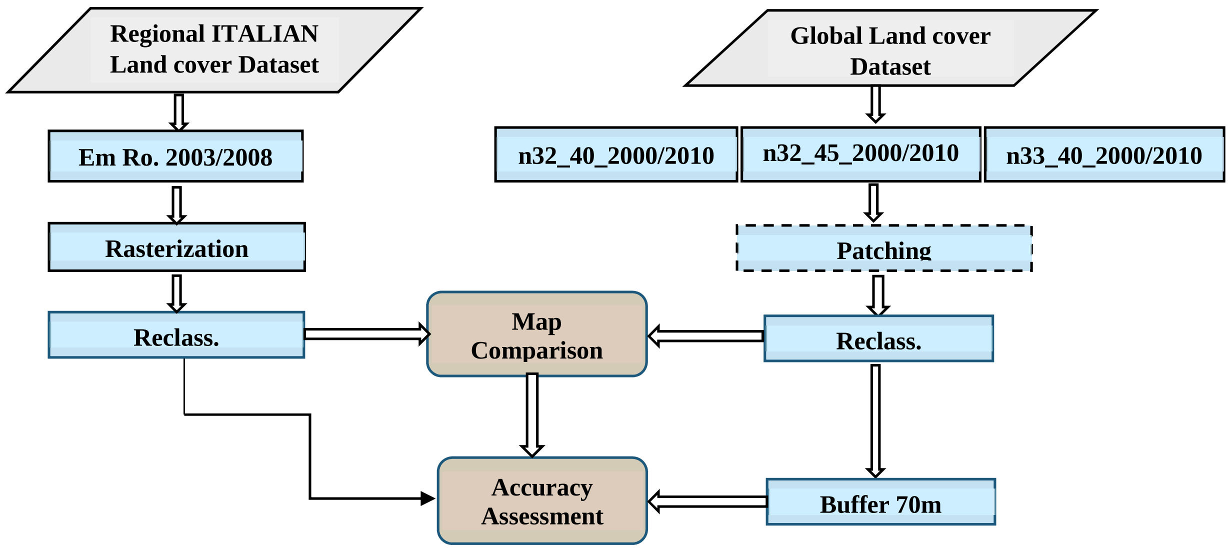


Figure 56: Overall workflow of Emilia Romagna Region.

3.7.1 Emilia Romagna land cover layer

Currently there is three release for Emilia Romagna land cover Database as listed in Table 50.

	EMILIA ROM.	EMILIA ROM.	EMILIA ROM.
YEAR	2003	2008	2011
SCALE	1:25’000	1:25’000	1:25’000
REF SYS	WGS84/UTM32N	WGS84/UTM32N	WGS84/UTM32N
LEGEND	CORINE	CORINE	CORINE
SOURCE	QuickBird 2002 – 2005 (mainly 2003)	Orthophotos AGEA 2007-2008 (mainly 2008, only 7 municipalities in 2007)	Orthophotos AGEA color (RGB).
EXTENT	whole region	whole region	whole region

Table 50: Emilia Romagna Land cover Database.

- **Emilia Romagna 2003** [38] was obtained from High-resolution QuickBird satellite orthoimagery (acquisition period 2002-2005). Base data type of georeferenced vector containing homogeneous groupings of data referring to the various types of land use in 2003, scale 1: 25,000. The need to update your information for a thematism subject to rapid changes over time, led to the design of a database perfectly aligned with the specifications of Corine Land Cover. This edition is the legend has been adopted 83 categories over four levels, the first three derived from Corine Land Cover and fourth calibrated on regional peculiarities. This edition also includes new 7 municipalities of Valmarecchia.

- **Emilia Romagna 2008** [39] Base data type of georeferenced vector containing homogeneous groupings of data referring to different types of land use in 2008, the reference scale 1: 25,000. The need to update your information for a thematic map is subject to rapid changes over time led to the preparation of the 2008 edition which has been achieved by the use of orthophotos AGEA color (RGB). This new edition also includes 7 new municipalities of Valmarecchia. This edition was produced by updating the polygonal cover of 2003 has remained the same classification system (with the first three levels derived from Corine Land Cover) and the same dimensions (minimum area, minimum size, etc..). All this allows to perform with precision the various types of comparison between the two editions.

- **Emilia Romagna 2011** [40] Base data type of georeferenced vector containing homogeneous groupings of data referring to different types of land use in 2011, the reference scale 1: 25,000. The need to update your information for a thematic map is subject to rapid changes over time led to the preparation of the 2011 edition which has been achieved by the use of orthophotos AGEA color (RGB). This new edition, which for now is limited to the territory of the Province of Bologna, was produced by updating the polygonal coverage in 2008: it has kept the same classification system (with the first three levels derived from Corine Land Cover) and same dimensional characteristics (minimum area, minimum size, etc...). All this allows to perform with precision the various types of comparison between the two editions

3.7.2 Data Processing

The First Comparison has been done between **GLC2000** and Land cover map of **Emilia Romagna region year 2003**. The second comparison has been done between **GLC2010** and since there was two available layers 2008 and 2011, Land cover map of **Emilia Romagna region year 2008** has been chosen for the comparison by cause of that it was available for the whole region.

[38] Metadata: http://servizigis.regione.emiliaromagna.it/ctwmetadatiRER/metadatoISO.ejb?stato_IdMetadato=iOrg01iEnP1idMetadato76869
[39] Metadata: http://servizigis.regione.emiliaromagna.it/ctwmetadatiRER/metadatoISO.ejb?stato_IdMetadato=iOrg01iEnP1idMetadato76868
[40] Metadata: http://servizigis.regione.emiliaromagna.it/ctwmetadatiRER/metadatoISO.ejb?stato_IdMetadato=iOrg01iEnP1idMetadato77437

The Data processing procedure for both comparisons is as following; Firstly, the Emilia Romagna vector layer was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Emilia Romagna raster maps at different cell sizes, respectively 30 m and 5 m, were calculated.

Moreover, re-projection for GLC raster map was need as GLC raster map was available in three different tiles corresponding to Emilia Romagna region, and one tile has different reference system WGS84/UTM33. The re-projection has been done by means of GRASS GIS *r.proj* module. Then a patching procedure has been done to obtain the area corresponding to Emilia Romagna region.

The second important phase of data processing was relative to the different thematic classification of the two land cover maps. To allow the comparison procedure, a reclassification of Emilia Romagna raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. Due to the differences in coastline between the two maps and to reduce the error around the Coastline, a new class (255) was added in order to calculate the common difference area between the two maps. The calculation has been done taking advantage of GRASS GIS module *r.mapcalc*. Moreover, the patching procedure was needed to add the difference pixels with respect to one to another to both mas. The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3.

3.7.2.1 GLC2000-Emilia Rom.2003

Figure 58 &59 gives a visual overview for both reclassified Land Cover maps (GLC2000, Emilia Ro. 2003).

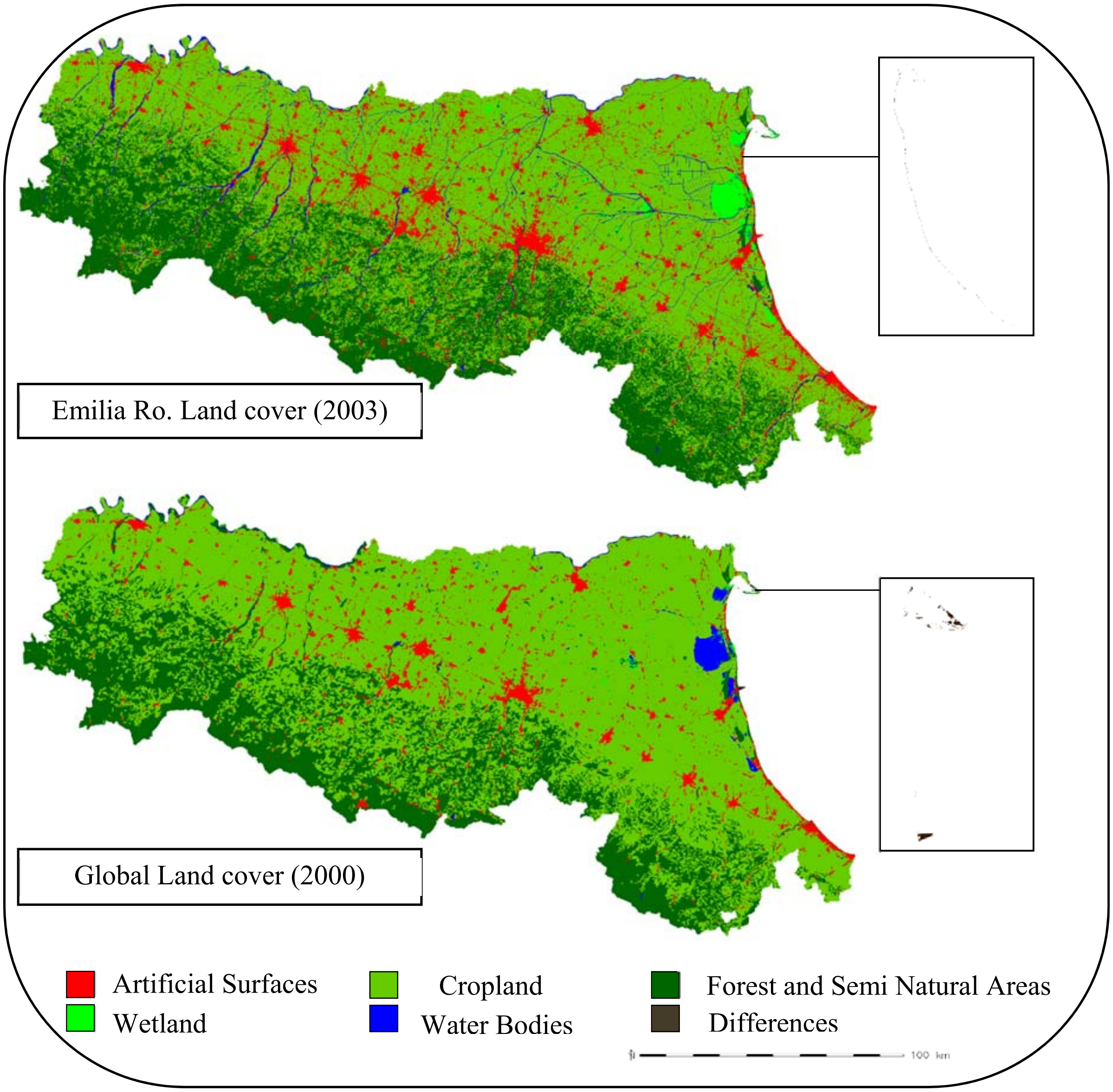


Figure 57: Visual Overview of Both Reclassified Emilia Rom. 2003 and GLC2000 (1st Classification)

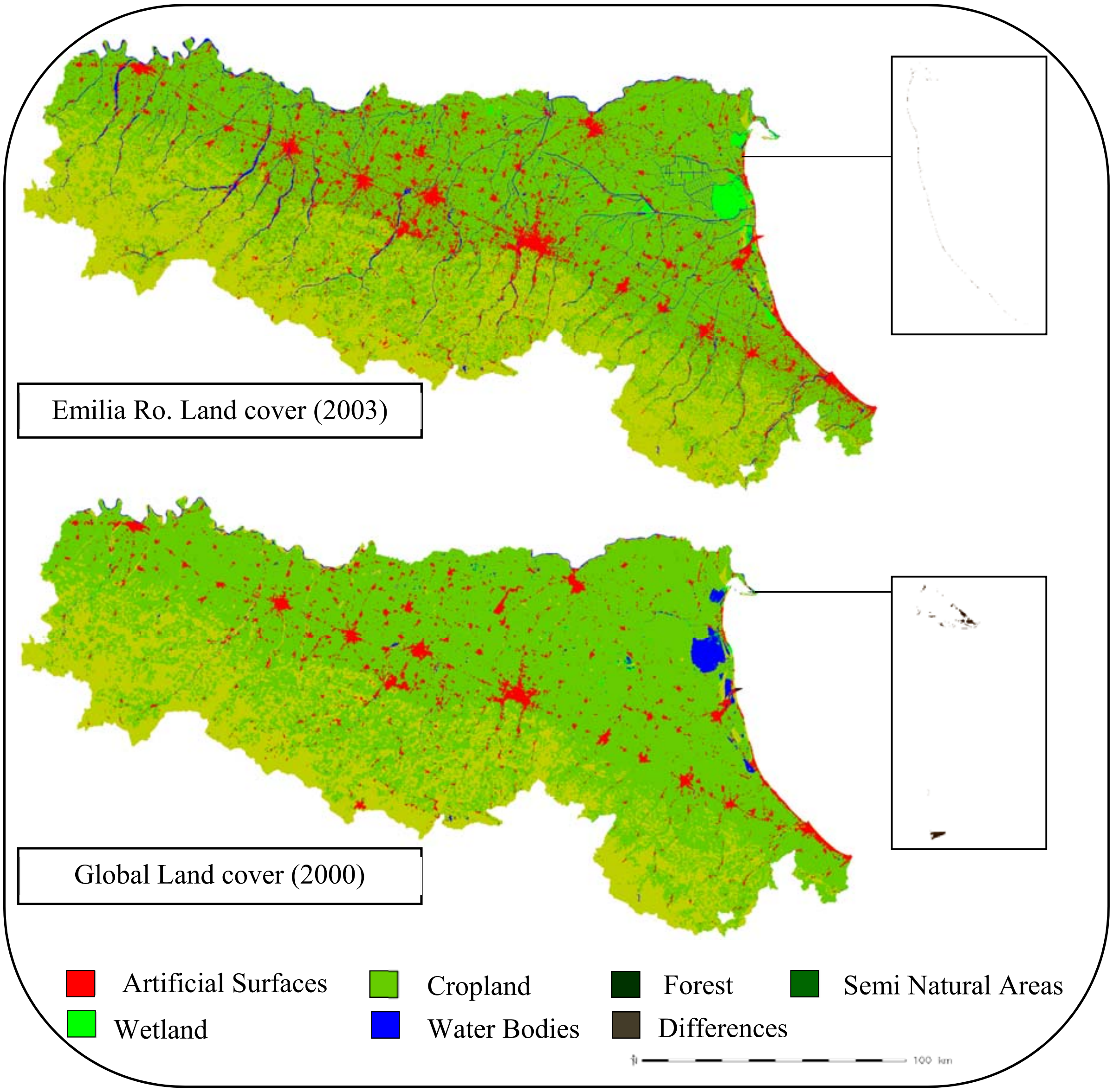


Figure 58: Visual Overview of Both Reclassified Emilia Rom. 2003 and GLC2000 (2^{nd} Classification)

3.7.2.2 GLC2010-Emilia Rom.2008

Figure 60 & 61 gives a visual overview for both reclassified Land Cover maps (GLC2000, Emilia Ro. 2003).

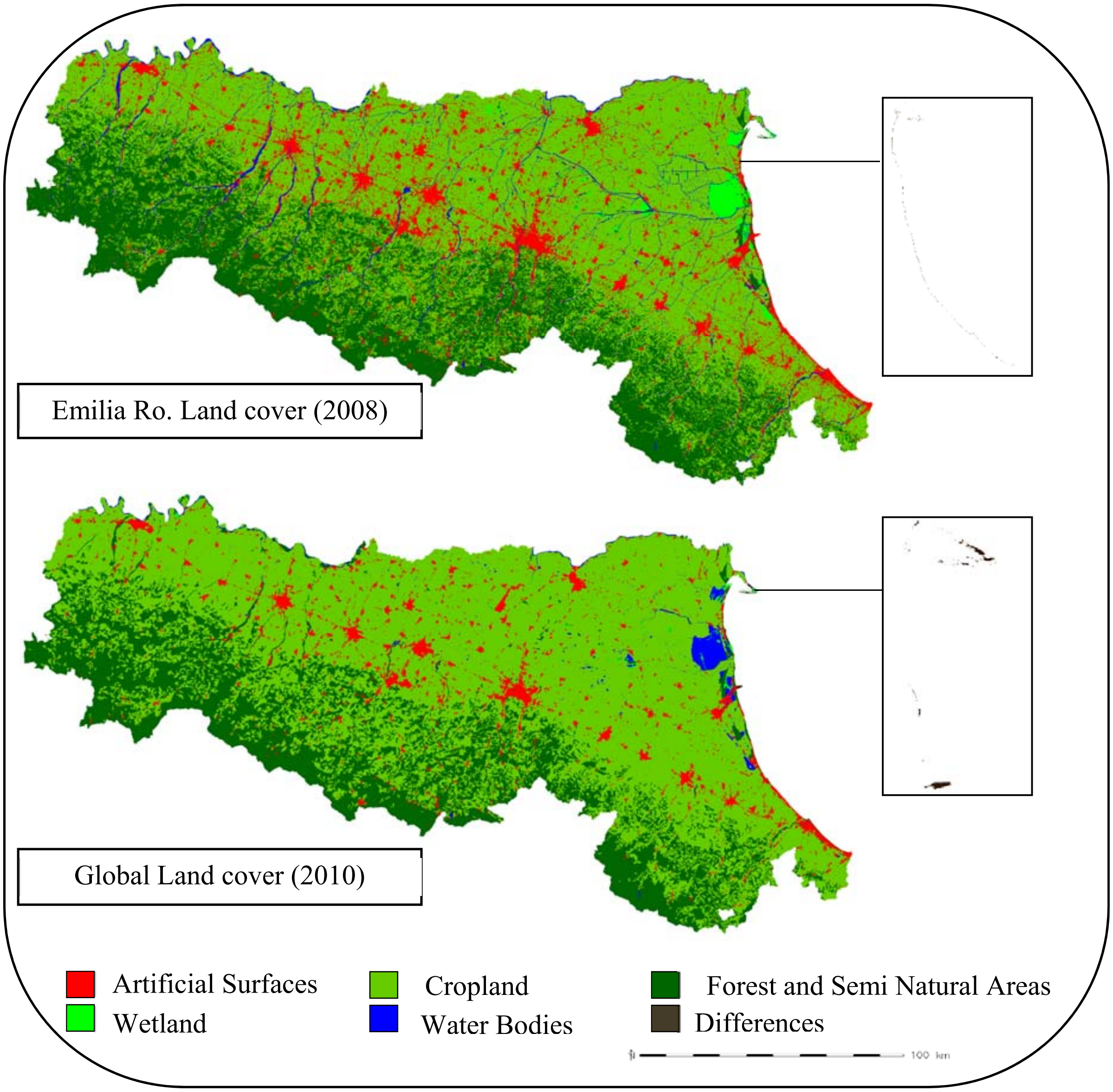


Figure 59: Visual Overview of Both Reclassified Emilia Rom. 2008 and GLC2010 (1st Classification)

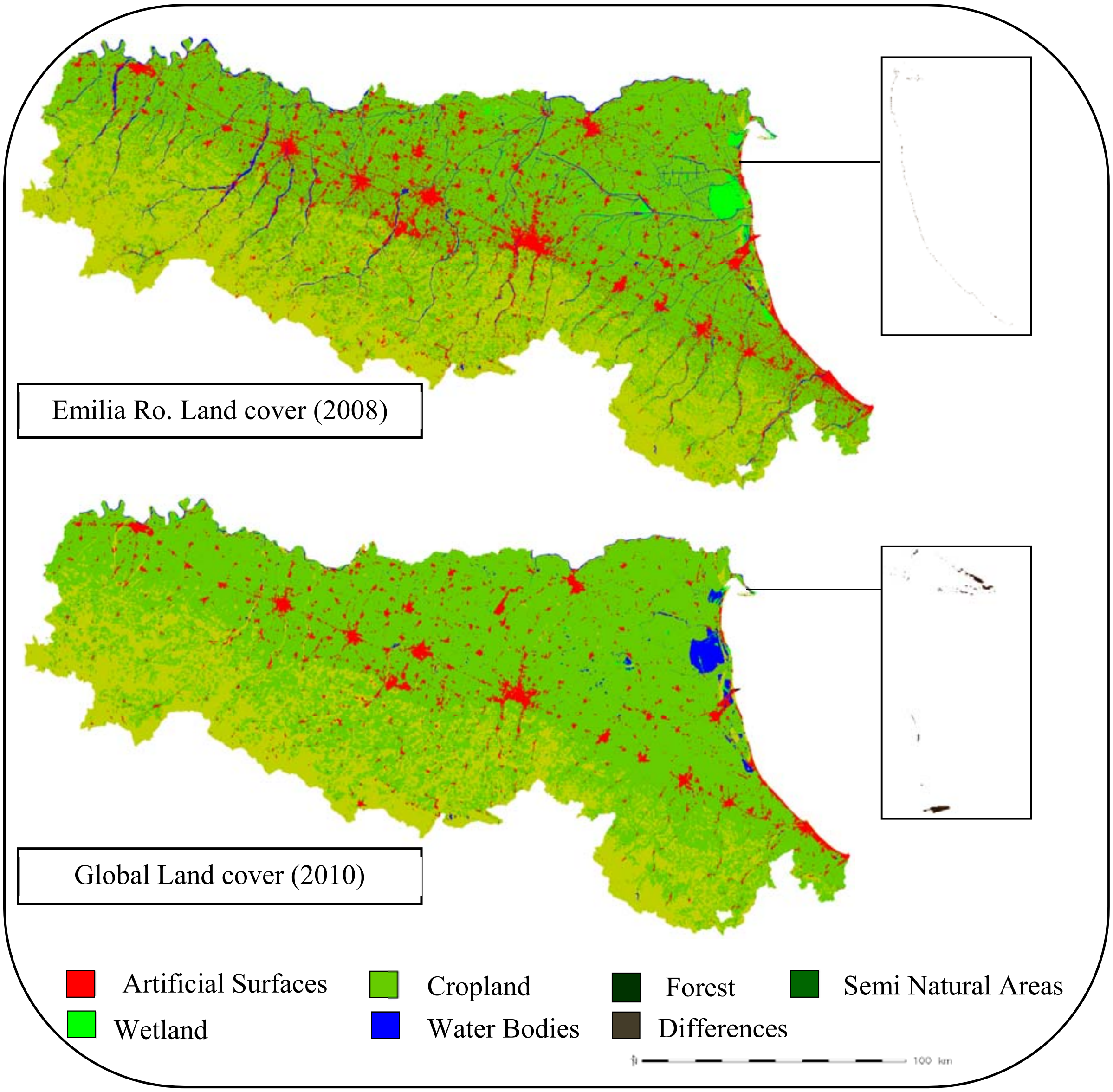


Figure 60: Visual Overview of Both Reclassified Emilia Rom. 2003 and GLC2010 (2nd Classification)

3.7.3 Accuracy Assessment

In a pixel based assessment, the accuracy assessment was derived from a comparison pixel by pixel between Reclassified Emilia Romagna Land cover map (REFERENCE MAP) and GLC (CLASSIFIED MAP).

3.7.3.1 GLC2000-Emilia Rom.2003

The confusion matrices and the agreement measures are represented in Table 51, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	1061265	136215	32435	1559	19892	805	663866	84.75%	15.25%
2	987569	14044332	1564106	37637	336192	192	723165	82.76%	17.24%
3	73174	571983	5557616	9602	148384	3014	4652815	87.33%	12.67%
4	2826	2774	3335	35124	14322	490	3958	59.66%	40.34%
5	8906	6055	3665	191001	86399	22	7077	29.18%	70.82%
255	2319	0	614	1932	245	0	1250	0.00%	100.00%
sum	2136059	14761359	7161771	276855	605434	4523	24946001		
PA	49.68%	95.14%	77.60%	12.69%	14.27%	0.00%			
OE	50.32%	4.86%	22.40%	87.31%	85.73%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	83.32%	0.6790	7.82%	8.86%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	38148830	4950237	1173470	56342	719502	29695	45078076	84.63%	15.37%
2	35602829	505379007	56452266	1358381	12121916	7228	610921627	82.72%	17.28%
3	2640805	20728278	199935305	345955	5334792	109097	229094232	87.27%	12.73%
4	101335	102721	120403	1262374	514695	17801	2119329	59.56%	40.44%
5	322130	228005	134635	6874097	3099253	807	10658927	29.08%	70.92%
255	84164	0	22313	69677	9033	0	185187	0.00%	100.00%
sum	76900093	531388248	257838392	9966826	21799191	164628	898057378		
PA	49.61%	95.11%	77.54%	12.67%	14.22%	0.00%			
OE	50.39%	4.89%	22.46%	87.33%	85.78%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	83.27%	0.6781	7.87%	8.86%

Table 51: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2000 and Emilia Rom. 2003

The agreement measures are most similar with different input data resolution, the kappa values are good identify with high overall accuracy. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

➢ **Artificial surfaced category**

	5 m	*30 m*
UA	84.63%	84.75%
PA	49.61%	49.69%
K	0.6002	0.6012
AD	1.54%	1.53%
QD	3.54%	3.54%

➢ **Cropland**

	5 m	*30 m*
UA	82.72%	82.76%
PA	95.11%	95.14%
K	0.6863	0.6873
AD	5.97%	5.75%
QD	8.86%	8.85%

➢ **Forest and Semi Natural area Category**

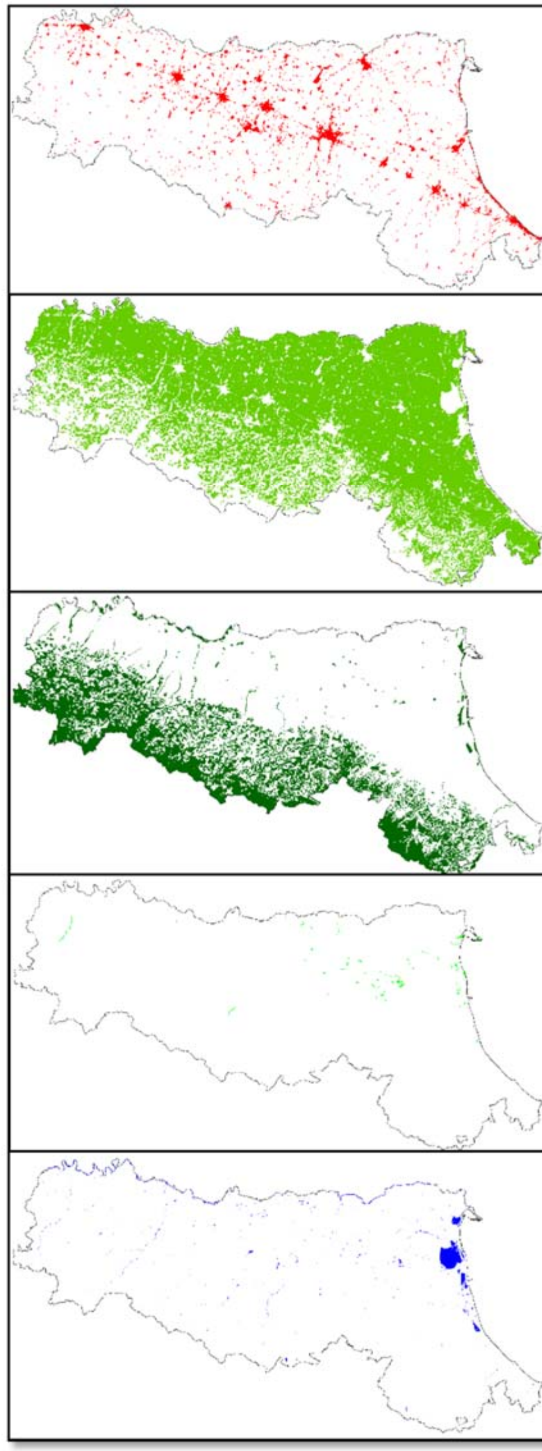
	5 m	*30 m*
UA	87.72%	87.33%
PA	77.54%	77.60%
K	0.7550	0.7558
AD	6.49%	6.49%
QD	3.20%	3.20%

➢ **Wetland**

	5 m	*30 m*
UA	59.56%	59.66%
PA	12.67%	12.69%
K	0.2058	0.2062
AD	0.19%	0.19%
QD	0.87%	0.87%

➢ **Open Water Category**

	5 m	*30 m*
UA	29.08%	29.18%
PA	14.22%	14.27%
K	0.1779	0.1786
AD	1.68%	1.68%
QD	1.24%	1.24%



As a result, Artificial cover, Cropland and Forest and Semi Natural areas are classified with high accuracies and good standard Kappa values, following by Wetland and Open water which are classified with less accuracies and low standard kappa values.

Corresponding to the second reclassification method (Case2), Table 52 represent the Agreement measures between the compared maps GLC2000 and Emilia Rom. 2003.

***[41]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	80.63%	0.6416	10.51%	8.86%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	85.72%	33.48%	19.96%
PA*	76.95%	29.60%	13.80%
K*	0.7560	0.2883	0.1562
AD*	6.11%	4.55%	1.12%
QD*	2.44%	0.45%	0.31%

Table 52: Second Classification Method (Case2); Agreement measures between compared maps GLC2000 and Emilia Rom. 2003 with 30 m input data resolution.

A buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy (Figure 62) to eliminate the part of disagreement according to co-location tolerance. The agreement measures are recalculated (Table 53).

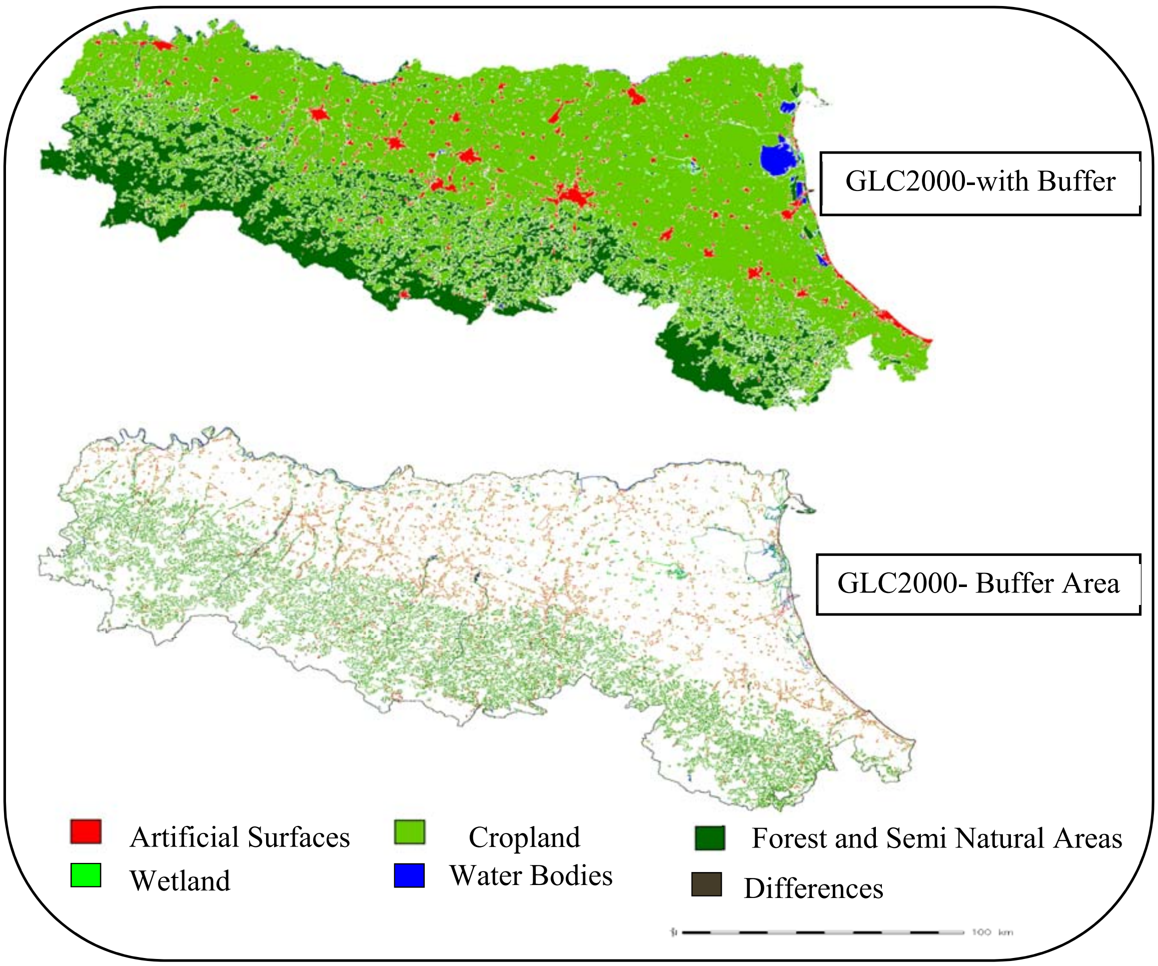


Figure 61: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Emilia Rom. 2003 Case).

[41] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	87.63%	0.7333	4.95%	7.69%
30 m	87.08%	0.7302	5.14%	7.78%

Table 53: General Agreement Measures between GLC2000 and Emilia Rom. 2003 after the Elimination of a Buffer.

Eliminating the part of the disagreement that can attribute to the co-location inaccuracy gives us better results, higher overall accuracy and Standard Kappa values and decreasing in Allocation and Quantity disagreement values. The percentage of the pixels that have been eliminated were about 14.87 % with 61.82% overall accuracy. Table 54 represent the Commotion and Omission Disagreement by pixel% correspond to 30m input data resolution.

	Commission Error		**Omission Error**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	15.25%	9.03%	50.32%	52.72%
2. Cropland	17.24%	13.44%	4.86%	2.89%
3. Forest and semi Natural areas	12.67%	9.01%	22.40 %	18.06%
4. Wetland	40.34%	32.83%	87.31 %	93.23%
5. Water Surfaces	70.82%	86.38%	85.73%	92.66%

Table 54: GLC2000-Emilia Rom. 2003, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the cells that have been removed was about 16.52 % with 57.73 % overall accuracy (Figure 63). Table 55 list the general agreement measures with buffer.

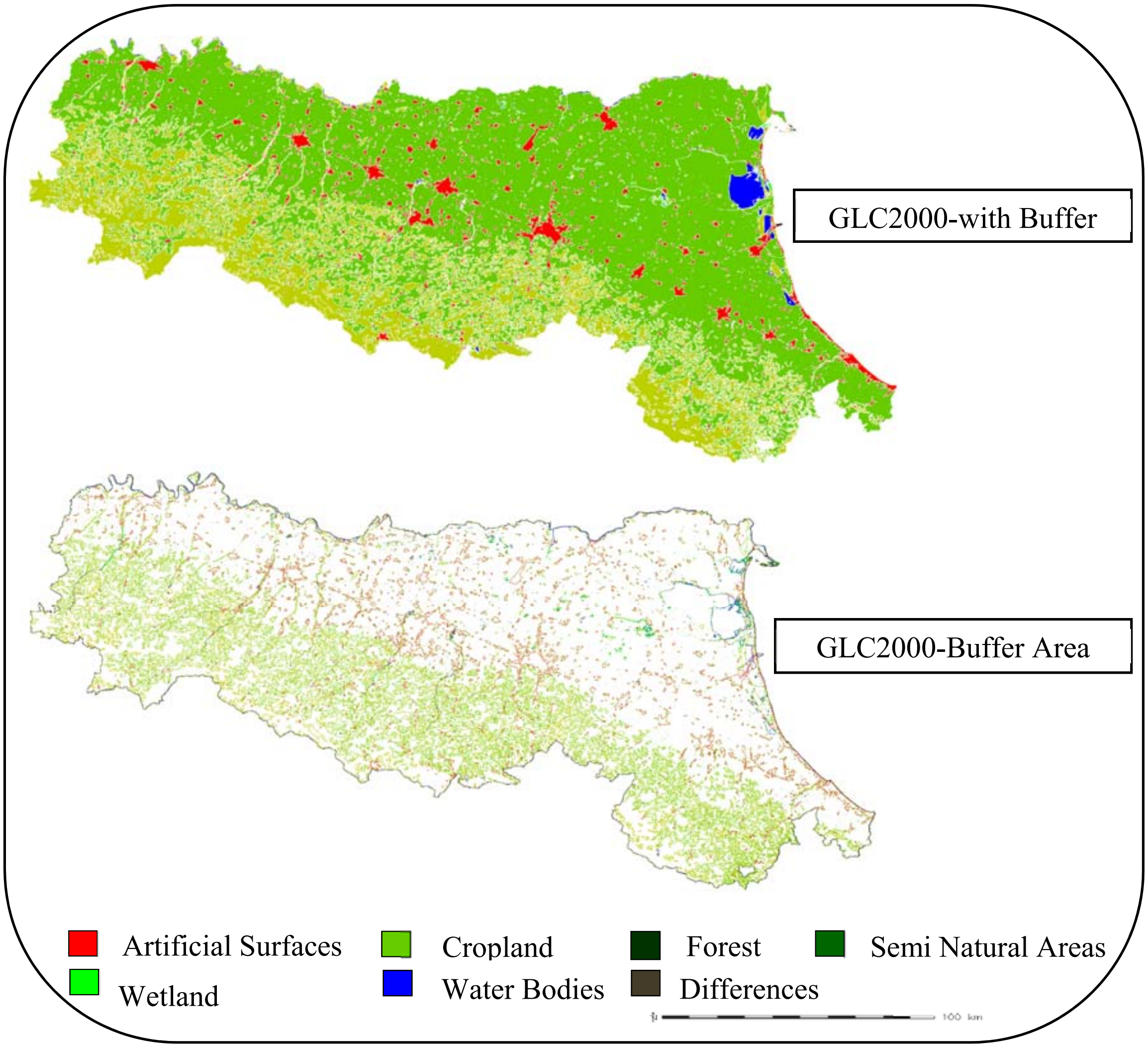


Figure 62: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Emilia Rom. 2003 Case).

*[42]GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	85.29%	0.6952	6.59%	8.11%

	FORESTS	***SHRUB/GRASS***	***BEACHES,ROCKS,SPARSELY VEGETATED AREAS…***
UA*	89.62%	38.70%	32.66%
PA*	82.51%	28.91%	13.36%
K*	0.8234	0.3121	0.1859
AD*	4.04%	2.93%	0.44%
QD*	1.68%	0.81%	0.47%

Table 55: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer between reclassified maps GLC2000-Emilia Rom.2003.

[42] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.7.3.2 GLC2010-Emilia Rom.2008

The confusion matrices and the agreement measures are represented in Table 56, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	1103151	126106	28645	1205	19379	728	1279214	86.24%	13.76%
2	1107166	13869152	1566010	42202	341647	283	16926460	81.94%	18.06%
3	82396	563203	5565974	11994	159063	3581	6386211	87.16%	12.84%
4	1412	1881	3861	29371	9919	339	46783	62.78%	37.22%
5	12307	6377	3740	198301	83014	3	303742	27.33%	72.67%
255	1871	0	393	1457	301	0	4022	0.00%	100.00%
sum	2308303	14566719	7168623	284530	613323	4934	24946423		
PA	47.79%	95.21%	77.64%	10.32%	13.54%	0.00%			
OE	52.21%	4.79%	22.36%	89.68%	86.46%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	82.78%	0.6721	7.76%	9.46%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	39659357	4582926	1037267	43588	701265	27017	46051420	86.12%	13.88%
2	39909386	499102326	56495309	1521508	12312191	10488	609351208	81.91%	18.09%
3	2974585	20393996	200256833	432115	5718403	129464	229905396	87.10%	12.90%
4	51105	68016	139336	1057254	356235	12344	1684290	62.77%	37.23%
5	444300	240839	137338	7135489	2976810	100	10934876	27.22%	72.78%
255	68185	0	14542	52570	10869	0	146166	0.00%	100.00%
sum	83106918	524388103	258080625	10242524	22075773	179413	898073356		
PA	47.72%	95.18%	77.59%	10.32%	13.48%	0.00%			
OE	52.28%	4.82%	22.41%	89.68%	86.52%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	82.74%	0.6713	7.80%	9.46%

Table 56: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2010 and Emilia Rom. 2008.

The agreement measures are most similar with different input data resolution, the kappa values are good identify with high overall accuracy. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

- **Artificial surfaced category**

	5 m	*30 m*
UA	86.12%	86.24%
PA	47.72%	47.79%
K	0.5869	0.5878
AD	1.42%	1.41%
QD	4.13%	4.13%

- **Cropland**

	5 m	*30 m*
UA	81.91%	81.94%
PA	95.18%	95.21%
K	0.6789	0.6798
AD	5.63%	5.59%
QD	9.46%	9.46%

- **Forest and Semi Natural area Category**

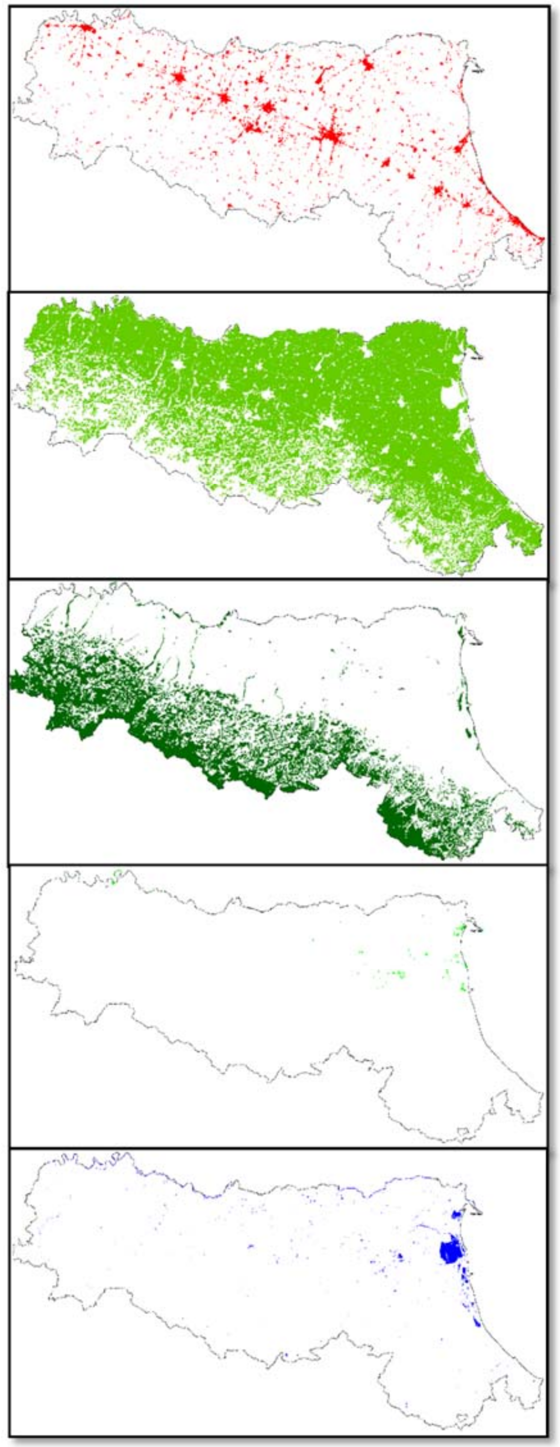
	5 m	*30 m*
UA	87.10%	87.16%
PA	77.59%	77.64%
K	0.7542	0.7549
AD	6.60%	6.58%
QD	3.14%	3.14%

- **Wetland**

	5 m	*30 m*
UA	62.77%	62.78%
PA	10.32%	10.32%
K	0.1746	0.1746
AD	0.14%	0.14%
QD	0.95%	0.95%

- **Open Water Category**

	5 m	*30 m*
UA	27.22%	27.33%
PA	13.48%	13.54%
K	0.1668	0.1675
AD	1.68%	1.77%
QD	1.24%	1.24%



As a result, Artificial cover, Cropland and Forest and Semi Natural areas are classified with high accuracies and good standard Kappa values, following by Wetland and Open water which are classified with less accuracies and low standard kappa values.

Corresponding to the second reclassification method (Case2), Table 57 represent the Agreement measures between the compared maps GLC2010 and Emilia Rom. 2008.

***[43]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	80.16%	0.6366	10.38%	9.46%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	85.63%	33.39%	20.11%
PA*	77.08%	29.49%	14.18%
K*	0.7560	0.2878	0.1592
AD*	6.18%	4.46%	1.16%
QD*	2.39%	0.44%	0.30%

Table 57: Second Classification Method (Case2); Agreement measures between compared maps GLC2010 and Emilia Rom. 2008 with 30 m input data resolution.

A buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy (Figure 64) to eliminate the part of disagreement according to co-location tolerance. The agreement measures are recalculated (Table 58).

[43] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

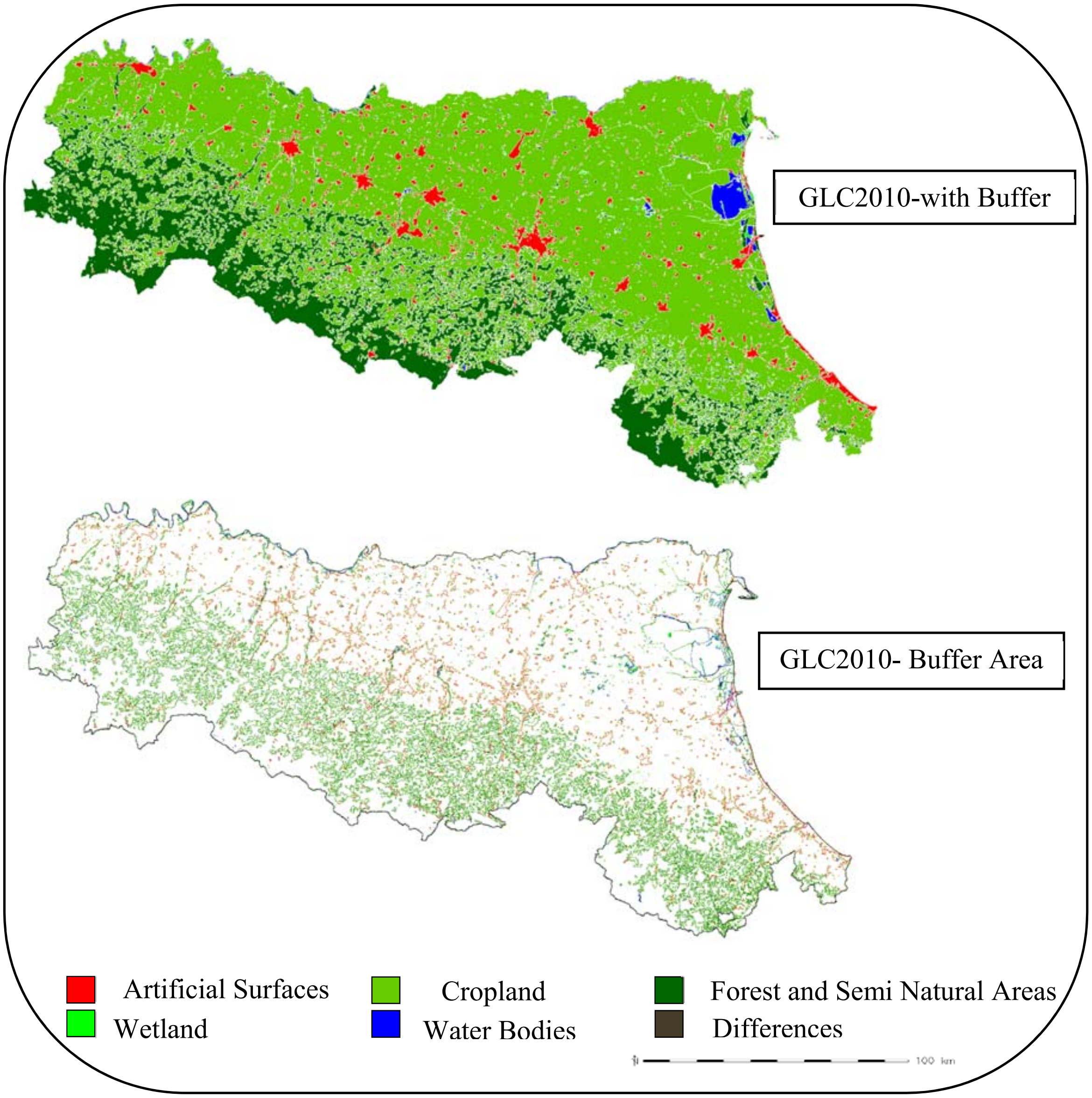


Figure 63: First Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Emilia Rom. 2008 Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	87.02%	0.7299	4.71%	8.27%
30 m	86.69%	0.7261	4.92%	8.38%

Table 58: General Agreement Measures between GLC2010 and Emilia Rom. 2008 after the Elimination of a Buffer.

Eliminating the part of the disagreement that can attribute to the co-location inaccuracy gives us better results, higher overall accuracy and Standard Kappa values and decreasing in Allocation and Quantity disagreement values. The percentage of the pixels that have been eliminated were about 14.89 % with 60.43% overall accuracy. Table 59 represent the Commotion and Omission Disagreement by pixel% correspond to 30 m input data resolution.

	Commission Error		Omission Error	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	13.76%	7.76 %	52.21%	52.42 %
2. Cropland	18.06%	14.12 %	4.79 %	2.66 %
3. Forest and semi Natural areas	12.84%	8.80 %	22.36 %	17.95 %
4. Wetland	37.22%	31.49 %	89.68 %	93.12%
5. Water Surfaces	72.67%	87.76 %	86.46 %	93.61 %

Table 59: GLC2000-Emilia Rom. 2003, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the cells that have been removed was about 16.56 % with 56.08 % overall accuracy (Figure 65). Table 60 list the general agreement measures with buffer.

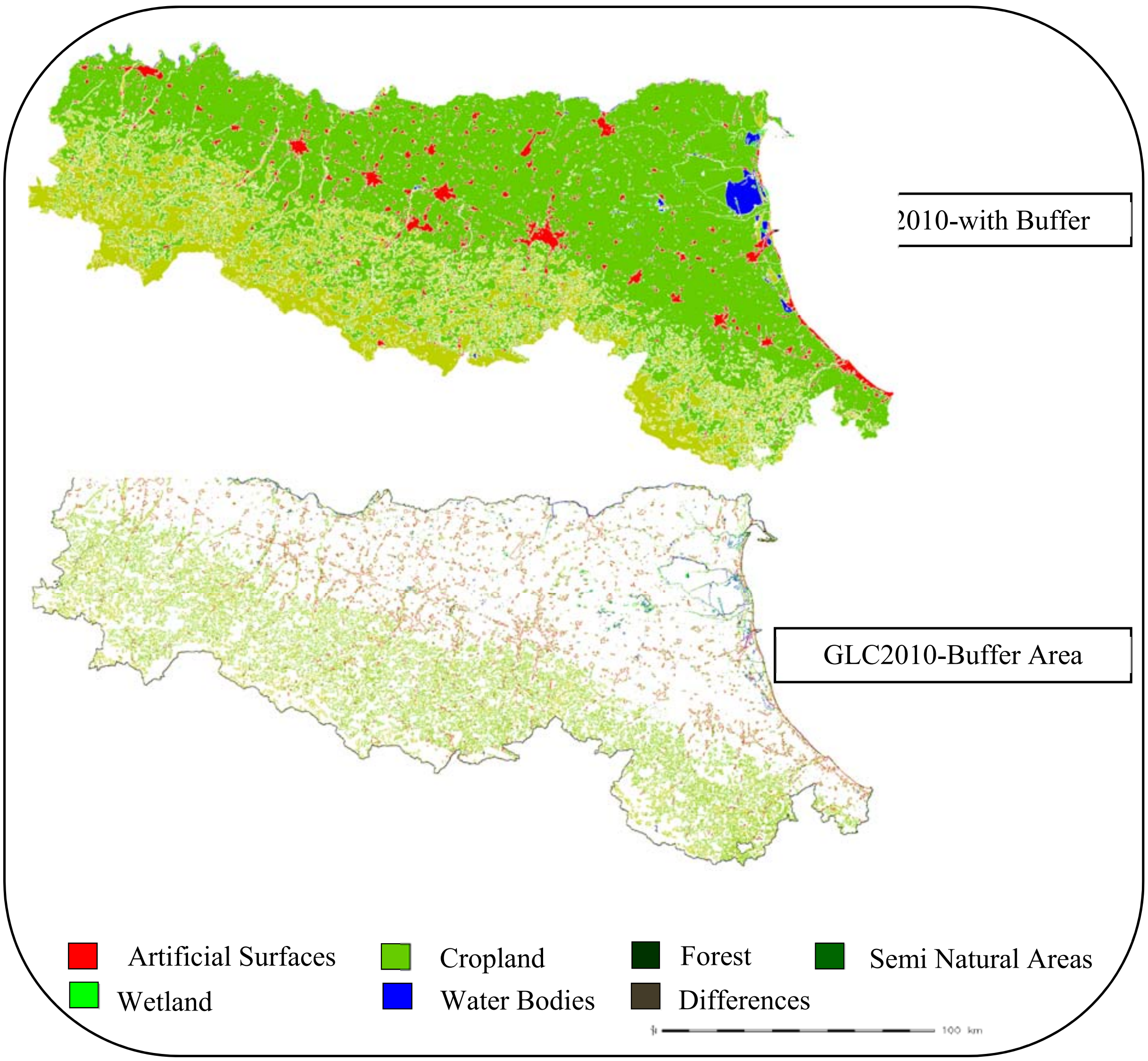


Figure 64: Second Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Emilia Rom. 2008 Case).

***[44]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	84.94%	0.6923	6.32%	8.74%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	90.16%	38.34%	29.48%
PA*	82.60%	28.51%	13.58%
K*	0.8266	0.3086	0.18189
AD*	3.87%	2.86%	0.52%
QD*	1.80%	0.80%	0.43%

Table 60: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer between reclassified maps GLC2010-Emilia Rom.2008.

3.7.4 Emilia Romagna Case Study Conclusion

In a summery, the analysis shows that Agreement measures are mostly similar with different input data resolution in both comparison assessment. The Overall accuracy is high identify with good Standard Kappa value. The Allocation and Quantity disagreement values are stable in both assessment. Forest and Cropland are classified with the best accuracies compared with the other classes which are poorly classified.

[44] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.8 SEVENTH CASE STUDY: SARDINIA REGION

Sardinia is the second largest island in the Mediterranean Sea, with an area of 23,821 Km^2 and an autonomous region of Italy (Figure 66)[45]. The nearest land masses are (clockwise from north) the island of Corsica, the Italian Peninsula, Sicily, Tunisia, The Balearic Islands, and Provence. The Tyrrhenian Sea portion of the Mediterranean Sea is directly to the east of Sardinia between the Sardinian east coast and the west coast of the Italian mainland peninsula. The Strait of Bonifacio is directly north of Sardinia and separates Sardinia from the French island of Corsica. The region has its capital in its largest city, Cagliari, and is divided into eight provinces. Figure 67, the overall workflow of the region.

Figure 65: Sardinia Region.

[45] http://en.wikipedia.org/wiki/Sardinia

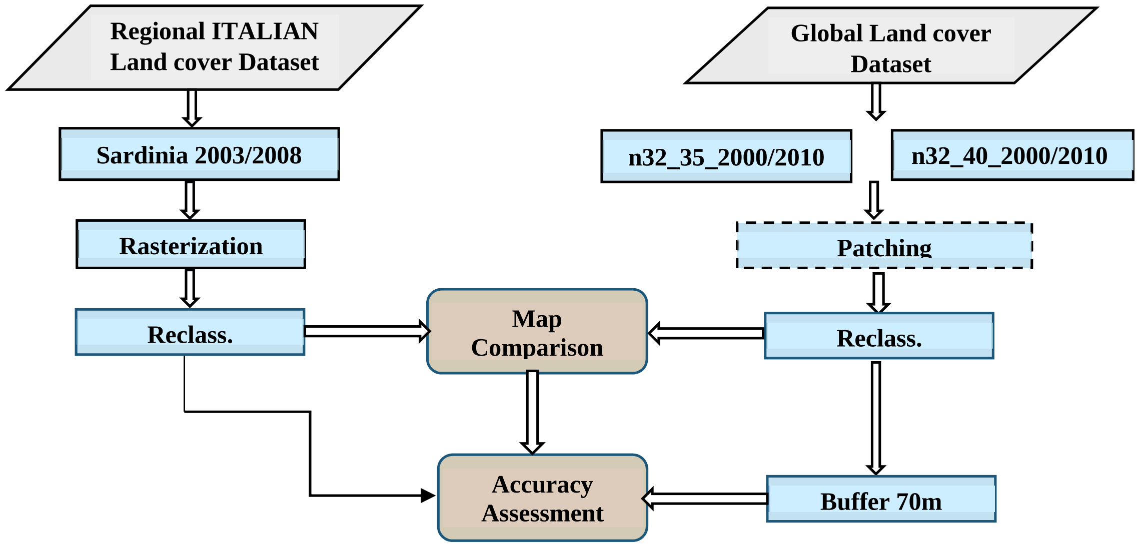


Figure 66: Overall Workflow of Sardinia region.

3.8.1 Sardinia Land Cover layer

Currently there is two land cover layer of Sardinia region list in Table 61.

	SARDINIA	SARDINIA
YEAR	1997 - 2000	2005 - 2007
SCALE	1:25'000	1:25'000
REF SYS	ROMA40	ROMA40
LEGEND	CORINE	CORINE
SOURCE	Orthophotos AIMA 1997, LandSat 97/98, IT2000	Update based on orthophotos AGEA 2003, Orthopoto 2004, Ikonos 2005-06, Landsat 2003, Aster 2004
EXTENT	whole region	whole region

Table 61: Land Cover layer of Sardinia region.

- **Sardinia 2003**[46] was obtained from photo interpretation of orthophotos AIMA 97, 97/98 LandSat images, orthophotos IT2000, Regional Technical Paper, inspections, and attribution of the classification of objects according to the legend, and the coding of the project CORINE Landover amended and adapted to the regional situation. The minimum unit has mapped area of 1 hectare within the urban area and 1.5 hectares in extra urban areas.

[46] Metadata: http://www.sardegnaterritorio.it/webgis/catalogodati/metadatiDC?idMetadato=4101&idEnte=1

- **Sardinia 2008**[47] Extraction of polygonal elements of the map of the Use of Soil 2008 the figure is based on the data of land use map of the 2003 updated data has been acquired or vector retrieved from databases or for photo-interpretation, by digitizing a video, based on orthophotos 2004 AGEA 2003 and Ikonos. Each entity has been elaborated in ESRI shapefile format, and then exported to ArcInfo E00 format. In addition, for the assignment of the classification of objects according to the legend defined by the Charter on the Use of Land in 2003, were used various auxiliary materials and carried out inspections of 4000 points distributed on the territory. The legend of the thematic layers in question has been defined by the Charter of the use of soil in 2003, this is derived from the Corine Land Cover legend detailed in the fourth and fifth level with respect to the territory of Sardinia.

3.8.2 Data Processing

The First Comparison has been done between GLC2000 and Land cover map of Sardinia region year 2003. The second comparison has been done between GLC2010 and Land cover map of Sardinia region year 2008 has been chosen for the comparison by cause of that it was available for the whole region.

The Data processing procedure for both comparisons is as following; Firstly, the Sardinia vector layer was available with ROMA40 reference system while GLC was available with WGS84/UTM32-33 reference system, therefore a re-projection for the vector file was needed. The re-projection has been done by means of GRASS GIS v.proj Module then the vector file was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Sardinia raster maps at different cell sizes, respectively 30 m and 5 m, were calculated. Moreover, GLC raster map was available in two different tiles corresponding to Sardinia region, a patching procedure has been done to obtain the area corresponding to Sardinia region.

The second important phase of data processing was relative to the different thematic classification of the two land cover maps. To allow the comparison procedure, a reclassification of Sardinia raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. Due to the differences in coastline between the two maps and to reduce the error around the Coastline, a new class (255) was added in order to calculate the common difference area between the two maps. The calculation has been done taking advantage of GRASS GIS module *r.mapcalc.* Moreover, the patching procedure was needed to add the difference pixels with respect to one to another to both mas. The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3.

[47] Metadata: http://www.sardegnaterritorio.it/webgis/catalogodati/metadatiDC?idMetadato=12327&idEnte=1

3.8.2.1 GLC2000-Sardinia2003

Figure 68 & 69 gives a visual overview for both reclassified Land Cover maps (GLC2000, Sardinia 2003).

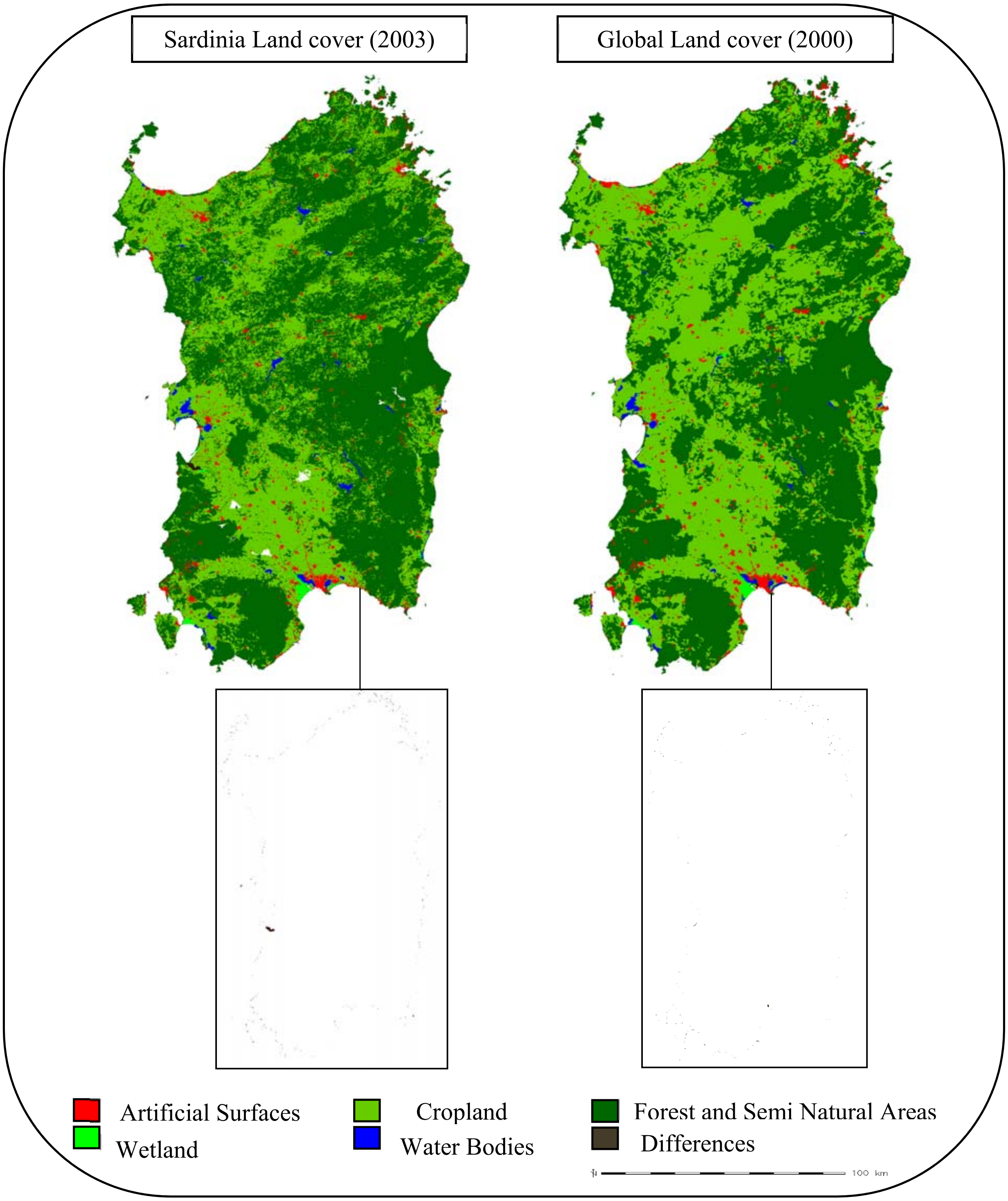


Figure 67: Visual Overview of Both Reclassified Sardinia 2003 and GLC2000 (1st Classification).

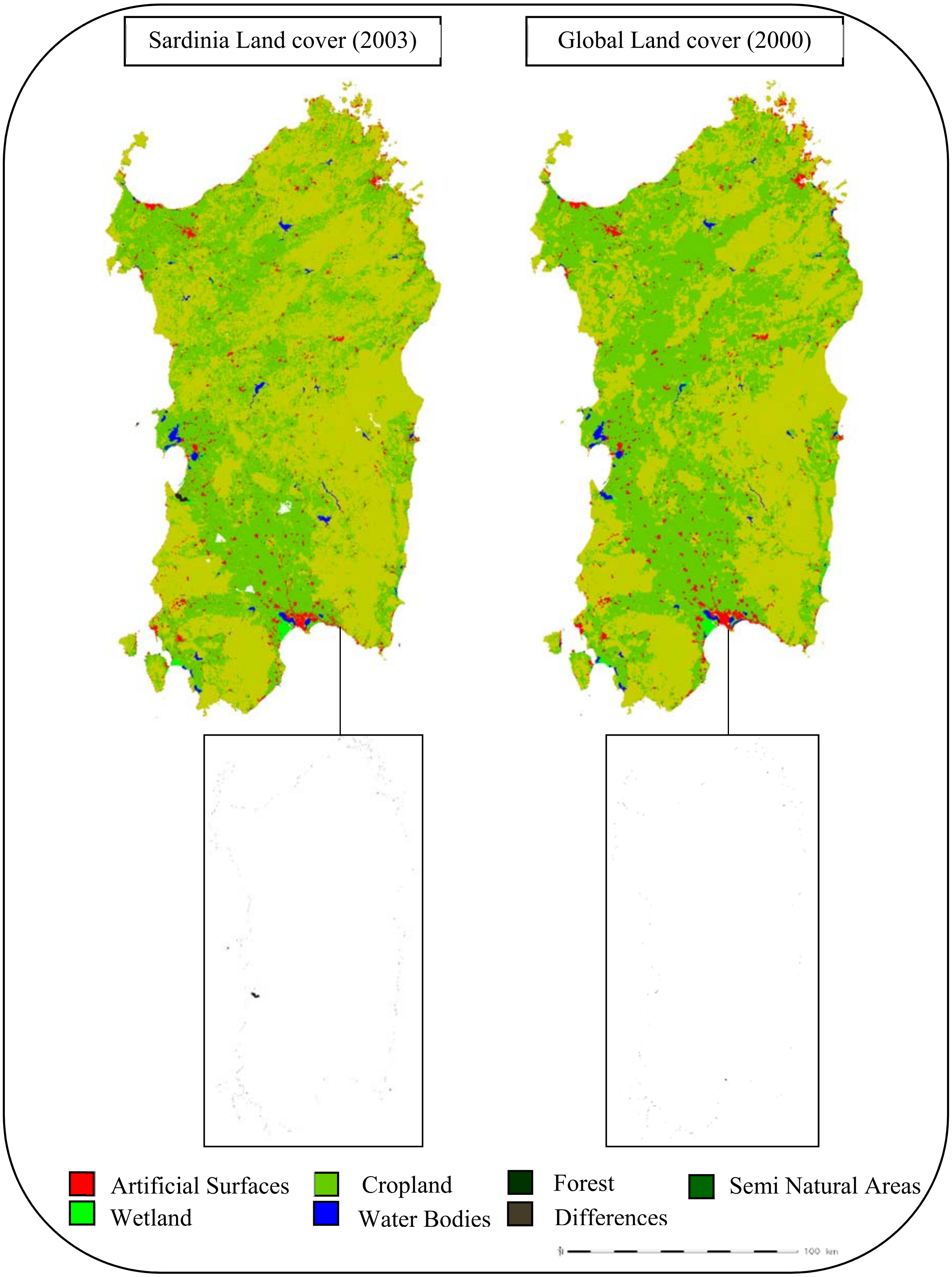


Figure 68: Visual Overview of Both Reclassified Sardinia 2003 and GLC2000 (2nd Classification).

3.8.2.2 GLC2010-Sardinia2008

Figure 70 & 71 gives a visual overview for both reclassified Land Cover maps (GLC2000, Sardinia 2008).

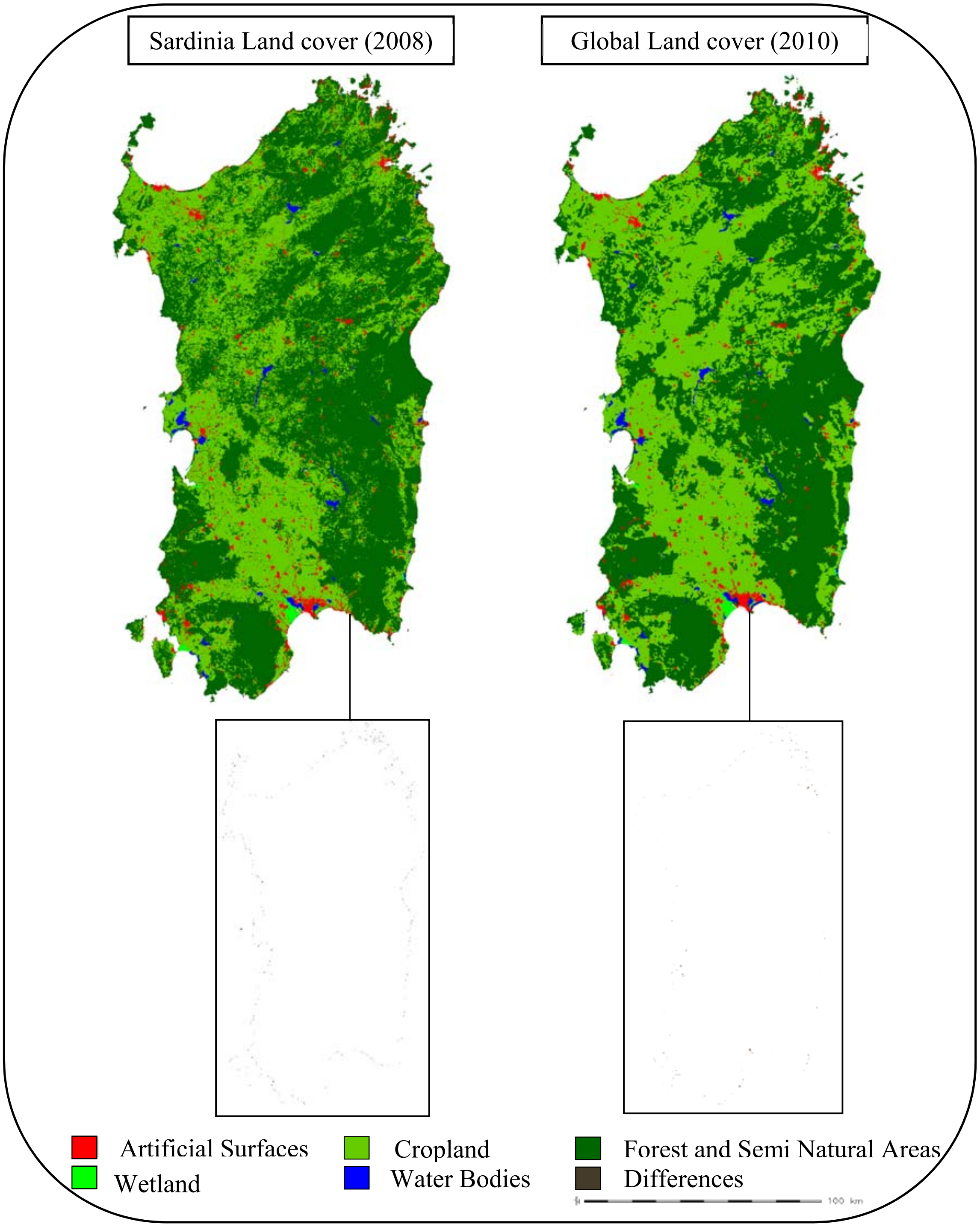


Figure 69: Visual Overview of Both Reclassified Sardinia 2008 and GLC2010 (1st Classification).

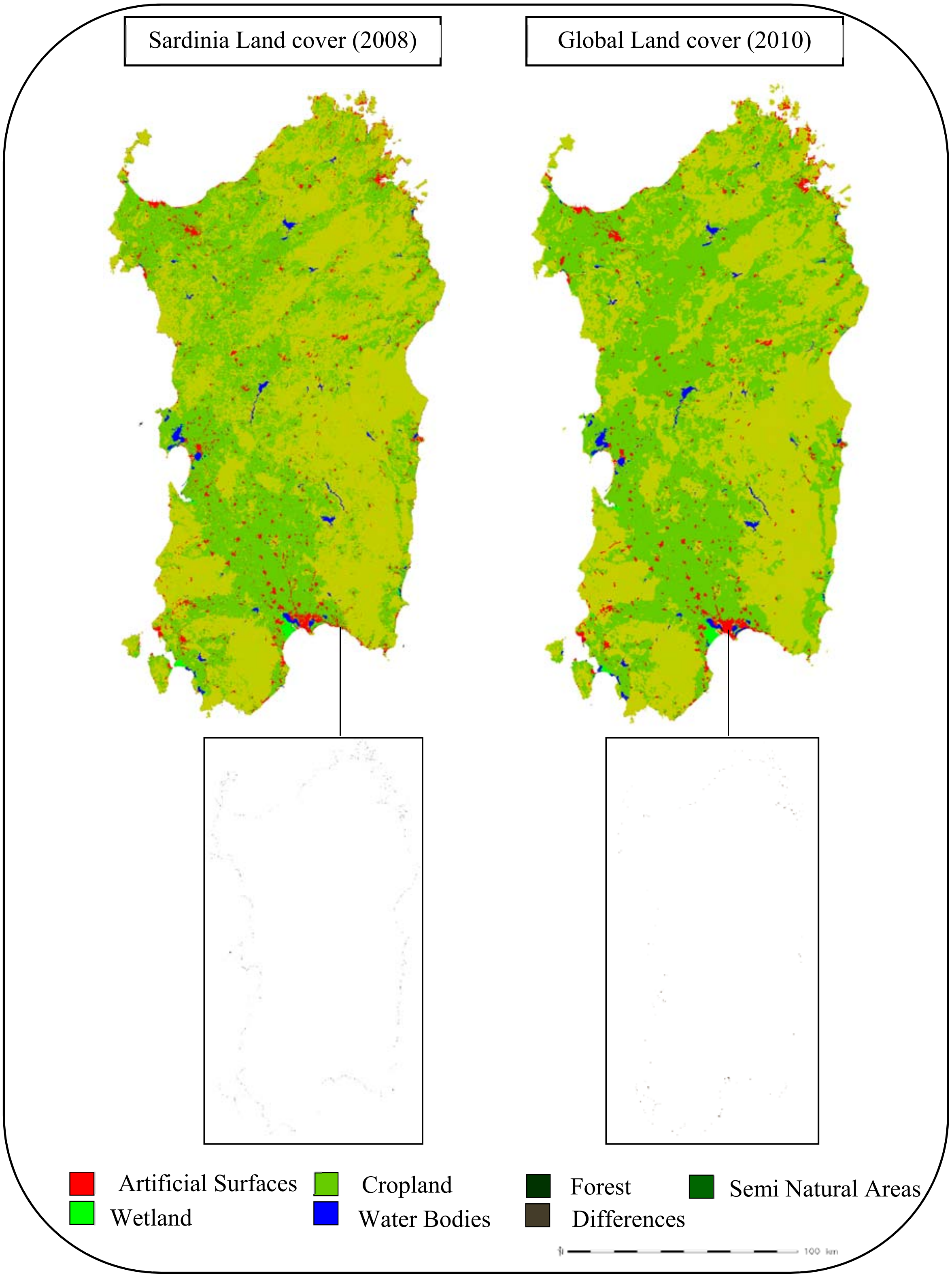


Figure 70: Visual Overview of Both Reclassified Sardinia 2008 and GLC2010 (2^{nd} Classification).

3.8.3 Accuracy Assessment

In a pixel based assessment, the accuracy assessment was derived from a comparison pixel by pixel between Reclassified Sardinia Land cover map (REFERENCE MAP) and GLC (CLASSIFIED MAP).

3.8.3.1 GLC2000-Sardinia 2003

The confusion matrices and the agreement measures are represented in Table 62, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	487974	137616	96744	1568	1739	5447	731088	66.75%	33.25%
2	186317	8846836	3259855	15539	20256	4895	12333698	71.73%	28.27%
3	56194	1000057	12288701	12158	27237	27773	13412120	91.62%	8.38%
4	1101	6646	7128	60066	10274	980	86195	69.69%	30.31%
5	2070	2952	5200	18178	139499	10923	178822	78.01%	21.99%
255	1921	165	8280	1391	2604	0	14361	0.00%	100.00%
sum	735577	9994272	15665908	108900	201609	50018	26756284		
PA	66.34%	88.52%	78.44%	55.16%	69.19%	0.00%			
OE	33.66%	11.48%	21.56%	44.84%	30.81%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	81.56%	0.6544	9.69%	8.74%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	17535408	4970011	3491420	56694	62884	202887	26319304	66.63%	33.37%
2	6725774	318389464	117424748	559617	734315	180480	444014398	71.71%	28.29%
3	2030279	36073798	442291690	437926	983635	1018859	482836187	91.60%	8.40%
4	39936	239701	256300	2160628	370486	35969	3103020	69.63%	30.37%
5	74971	110216	192354	655475	5011740	392718	6437474	77.85%	22.15%
255	72324	7310	326209	50587	93435	0	549865	0.00%	100.00%
sum	26478692	359790500	563982721	3920927	7256495	1830913	963260248		
PA	66.22%	88.49%	78.42%	55.11%	69.07%	0.00%			
OE	33.78%	11.51%	21.58%	44.89%	30.93%	100.00%			

GENERAL AGREEMENT MEASURES

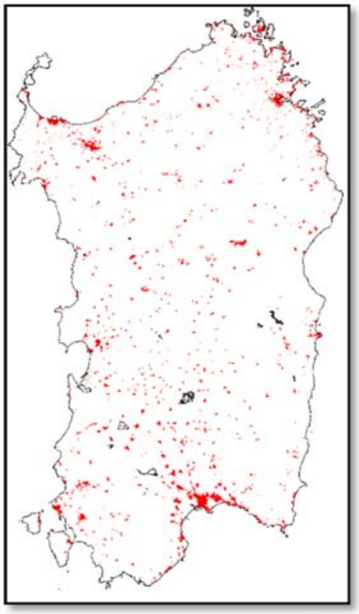
	OA	*K*	*AD*	*QD*
5 m	81.53%	0.6539	9.72%	8.74%

Table 62: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2000 and Sardinia2003.

The agreement measures are most similar with different input data resolution, the kappa values are good identify with high overall accuracy. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

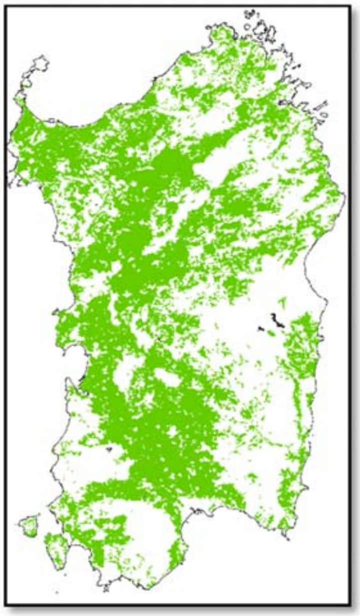
- **Artificial surfaced category**

	5 m	*30 m*
UA	66.63%	66.75%
PA	66.22%	66.34%
K	0.6548	0.6560
AD	1.82%	1.82%
QD	0.02%	0.02%



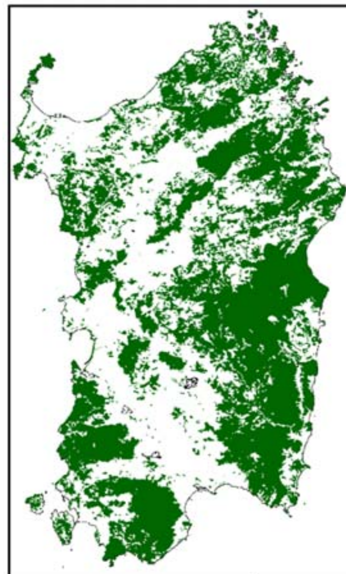
- **Cropland**

	5 m	*30 m*
UA	71.71%	71.73%
PA	88.49%	88.52%
K	0.6462	0.6466
AD	8.60%	8.58%
QD	8.74%	8.74%



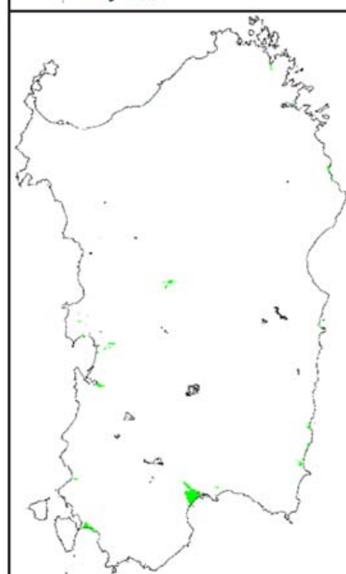
➢ Forest and Semi Natural area Category

	5 m	*30 m*
UA	91.60%	91.62%
PA	78.42%	78.44%
K	0.6630	0.6634
AD	8.42%	8.40%
QD	8.42%	8.42%



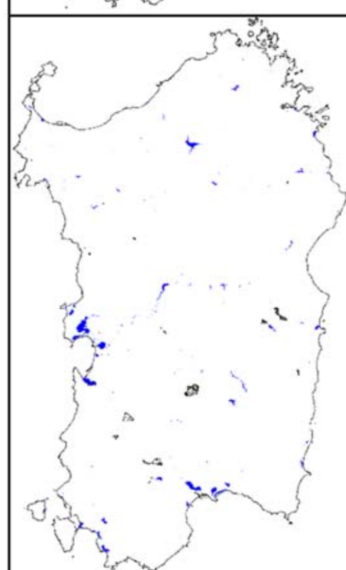
➢ Wetland

	5 m	*30 m*
UA	69.63%	69.69%
PA	55.11%	55.16%
K	0.6138	0.6144
AD	0.20%	0.20%
QD	0.08%	0.08%



➢ Open Water Category

	5 m	*30 m*
UA	77.85%	78.01%
PA	69.07%	69.19%
K	0.7301	0.7315
AD	0.30%	0.29%
QD	0.13%	0.09%



As a result, it has been realized that all the classes are classified with good standard kappa values with good accuracies and stable values for Allocation and Quantity Disagreement with different input data resolution.

Corresponding to the second reclassification method (Case2), Table 63 represent the Agreement measures between the compared maps GLC2000 and Sardinia 2003.

***[48]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	67.40%	0.6416	23.58%	8.74%

	FOREST	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	56.77%	67.12%	50.29%
PA*	45.06%	62.23%	22.52%
K*	0.3955	0.4624	0.2976
AD*	12.72%	21.61%	1.38%
QD*	4.12%	2.54%	1.71%

Table 63: Second Classification Method (Case2); Agreement measures between compared maps GLC2000 and Sardinia 2003 with 30 m input data resolution.

Analyzing the results corresponds to the comparison between both reclassified methods shows that the Overall accuracy has been decreased by 14% in the second reclassification method with less standard kappa values and the Allocation disagreement value had been increased while stable value for the Quantity disagreement.

A buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy (Figure 72) to eliminate the part of disagreement according to co-location tolerance. The agreement measures are recalculated. (Table 64).

[48] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

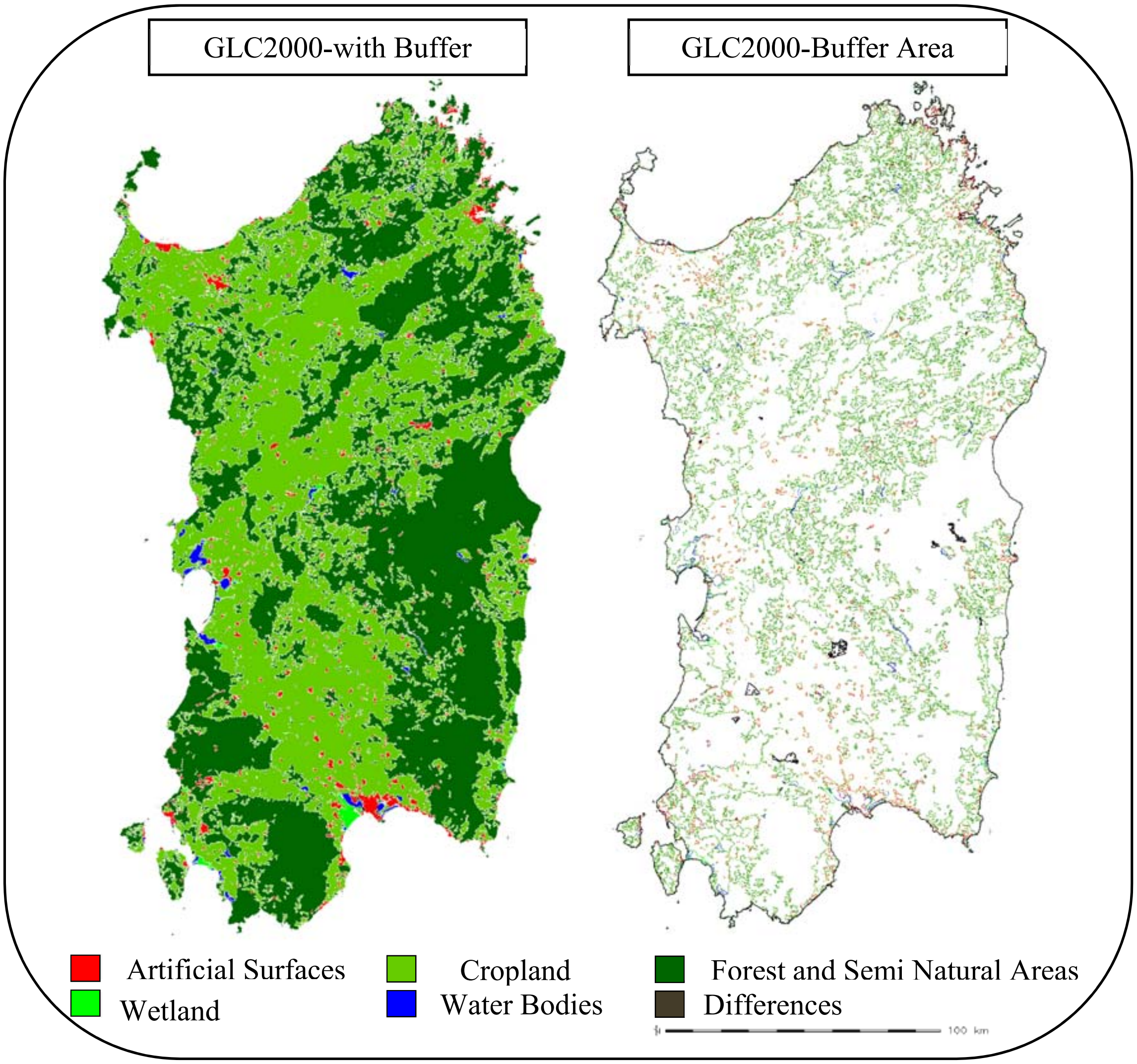


Figure 71: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Sardinia 2003 Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	84.89%	0.7105	6.87%	8.24%
30 m	84.59%	0.7055	7.12%	8.29%

Table 64: General Agreement Measures between GLC2000 and Sardinia 2003 after the Elimination of a Buffer.

Eliminating the part of the disagreement that can attribute to the co-location inaccuracy gives us better results, higher overall accuracy and Standard Kappa values and decreasing in Allocation and Quantity disagreement values. The percentage of the pixels that have been eliminated were about 11.60 % with 58.49% overall accuracy. Table 65 represent the Commotion and Omission Disagreement by pixel% correspond to 30m input data resolution.

	Commission		Omission	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	33.25%	22.88 %	33.66%	31.90 %
2. Cropland	28.27%	25.02 %	11.48 %	8.63 %
3. Forest and semi Natural areas	8.38%	6.36 %	21.56 %	18.92 %
4. Wetland	30.31%	19.32 %	44.84 %	34.87%
5. Water Surfaces	21.99%	17.01 %	30.81 %	22.38 %

Table 65: GLC2000-Sardinia 2003, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the cells that have been removed was about 16.28% with 49.29 % overall accuracy (Figure 68). Table 66 list the general agreement measures with buffer.

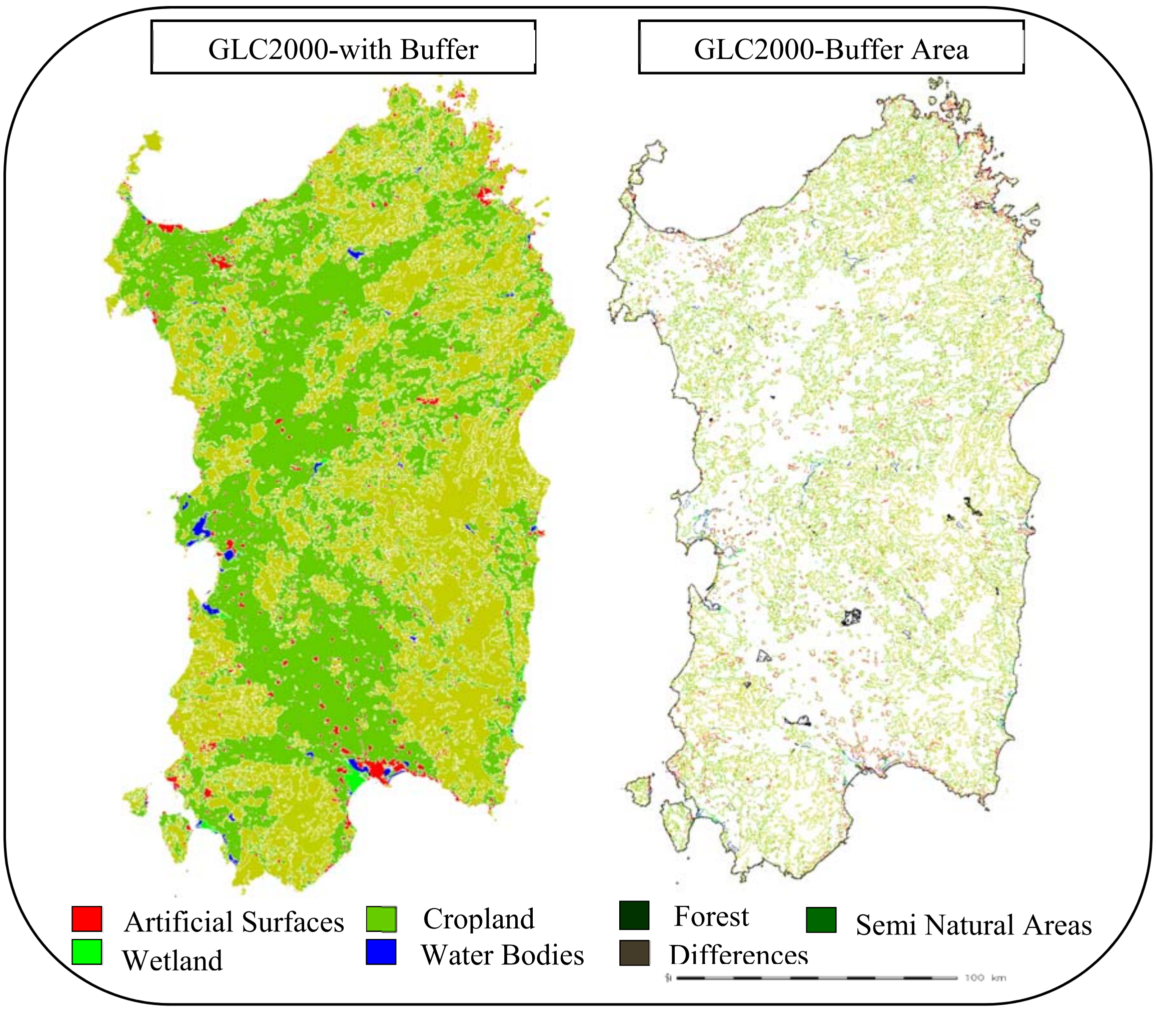


Figure 72: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Sardinia 2003 Case).

***[49]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	70.93%	0.5623	20.11%	8.69%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	59.70%	69.88%	56.61%
PA*	46.07%	65.13%	20.93%
K*	0.4215	0.5115	0.2948
AD*	12.17%	19.38%	0.91%
QD*	4.47%	2.35%	1.79%

Table 66: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer between reclassified maps GLC2000-Sardinia.2003.

3.8.3.2 GLC2010-Sardinia 2008

The confusion matrices and the agreement measures are represented in Table 67, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	482594	133679	79026	1339	922	5095	702655	68.68%	31.32%
2	280543	8860084	3042018	11733	17824	8084	12220286	72.50%	27.50%
3	95853	1240510	12161549	12683	9535	33505	13553635	89.73%	10.27%
4	1108	8388	7925	55910	3340	1053	77724	71.93%	28.07%
5	2700	11186	23087	19070	178742	304	235089	76.03%	23.97%
255	2475	836	9458	1679	2189	0	16637	0.00%	100.00%
sum	865273	10254683	15323063	102414	212552	48041	26806026		
PA	55.77%	86.40%	79.37%	54.59%	84.09%	0.00%			
OE	44.23%	13.60%	20.63%	45.41%	15.91%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30m	81.10%	0.6471	11.49%	7.42%

[49] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	17345139	4827798	2852422	48262	33748	188209	25295578	68.57%	31.43%
2	10115018	318873215	109579947	422991	647124	291716	439930011	72.48%	27.52%
3	3460396	44730212	437713440	455116	348053	1223485	487930702	89.71%	10.29%
4	40041	302754	284452	2012885	120214	37886	2798232	71.93%	28.07%
5	97456	406179	835293	686894	6426208	11204	8463234	75.93%	24.07%
255	91793	30343	359210	61243	78836	0	621425	0.00%	100.00%
sum	31149843	369170501	551624764	3687391	7654183	1752500	965039182		
PA	55.68%	86.38%	79.35%	54.59%	83.96%	0.00%			
OE	44.32%	13.62%	20.65%	45.41%	16.04%	100.00%			

GENERAL AGREEMENT MEASURES

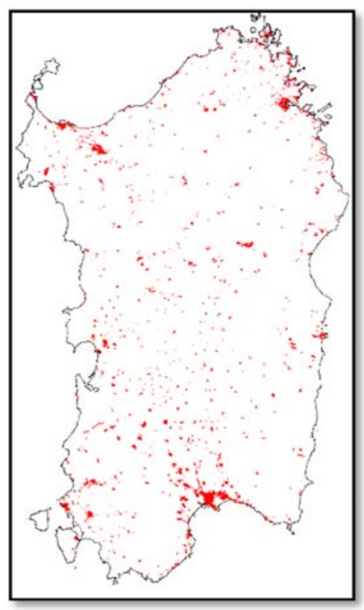
	OA	*K*	*AD*	*QD*
5m	81.07%	0.6466	11.51%	7.42%

Table 67: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2010 and Sardinia2008.

The agreement measures are most similar with different input data resolution, the kappa values are good identify with high overall accuracy. The values of Allocation and Quantity disagreement are stable with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

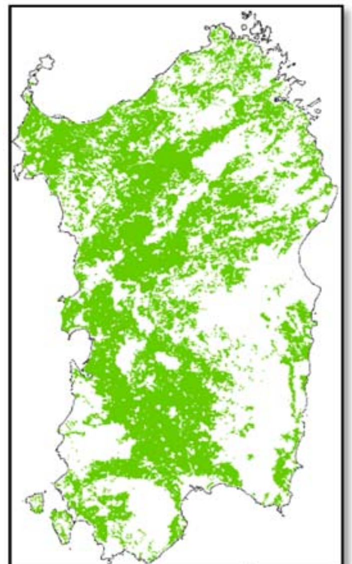
- **Artificial surfaced category**

	5 m	*30 m*
UA	68.57%	68.68%
PA	55.68%	55.77%
K	0.6031	0.6041
AD	1.65%	1.64%
QD	0.61%	0.61%



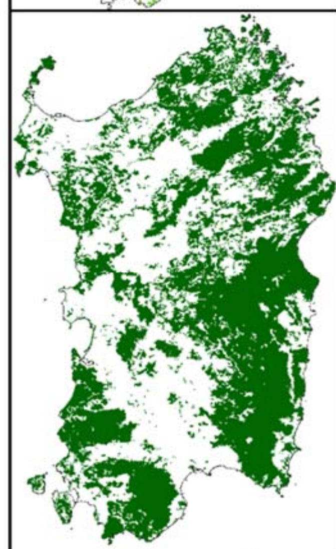
➢ Cropland

	5 m	*30 m*
UA	72.48%	72.50%
PA	86.38%	86.40%
K	0.6374	0.6377
AD	10.42%	10.41%
QD	7.33%	7.33%



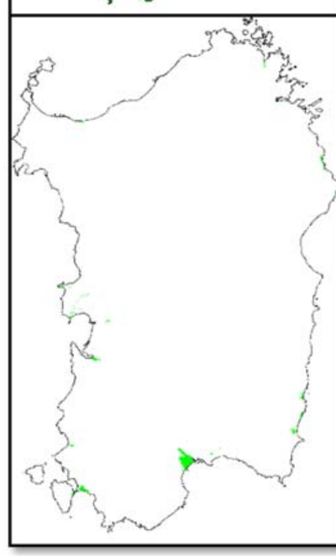
➢ Forest and Semi Natural area Category

	5 m	*30 m*
UA	89.71%	89.73%
PA	79.35%	79.37%
K	0.6593	0.6597
AD	10.41%	10.39%
QD	6.60%	6.60%



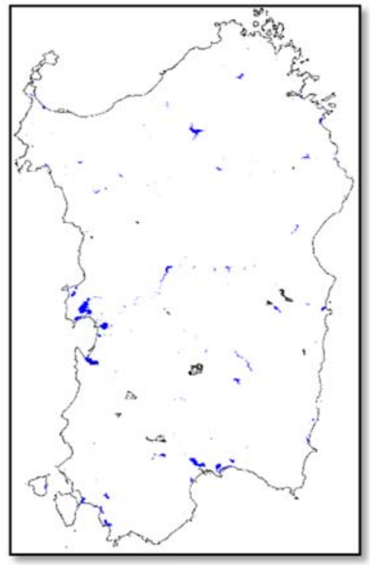
➢ Wetland

	5 m	*30 m*
UA	71.93%	71.93%
PA	54.59%	54.59%
K	0.6195	0.6195
AD	0.16%	0.16%
QD	0.09%	0.09%



- **Open Water Category**

	5 m	*30 m*
UA	75.93%	76.03%
PA	83.96%	84.09%
K	0.7957	0.7969
AD	0.25%	0.25%
QD	0.08%	0.08%



As a result, it has been realized that all the classes are classified with good standard kappa values with good accuracies and stable values for Allocation and Quantity Disagreement with different input data resolution.

Corresponding to the second reclassification method (Case2), Table 68 represent the Agreement measures between the compared maps GLC2010 and Sardinia 2008.

***[50]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	62.27%	0.4581	21.95%	16.13%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	43.91%	66.55%	36.71%
PA*	62.25%	38.61%	20.06%
K*	0.3578	0.3198	0.2462
AD*	15.75%	13.13%	1.71%
QD*	8.72%	14.19%	1.12%

Table 68: Second Classification Method (Case2); Agreement measures between compared maps GLC2010 and Sardinia 2008 with 30 m input data resolution.

Analyzing the results corresponds to the comparison between both reclassified methods shows that the Overall accuracy has been decreased by 18% in the second reclassification method with less standard kappa values which explains the increased values for Allocation and Quantity disagreement.

A buffer 70 m wide has been eliminated around the GLC polygons border for each class corresponding to 70 m GLC location accuracy (Figure 74) to eliminate the part of disagreement according to co-location tolerance. The agreement measures are recalculated. (Table 69).

[50] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

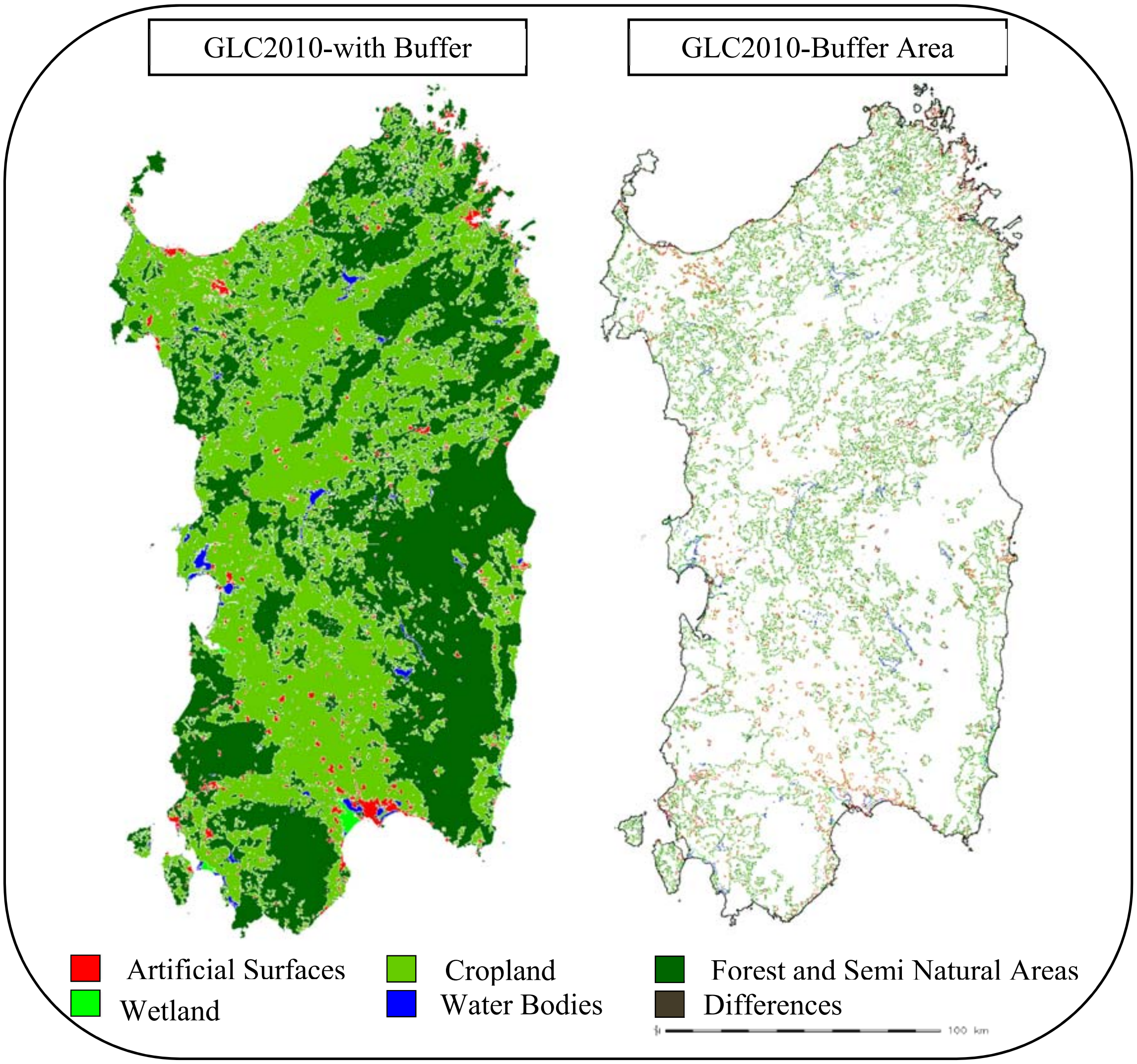


Figure 73: First Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Sardinia 2008 Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	84.89%	0.7105	6.87%	8.24%
30 m	84.23%	0.6994	8.90%	6.86%

Table 69: General Agreement Measures between GLC2010 and Sardinia 2008 after the Elimination of a Buffer.

Eliminating the part of the disagreement that can attribute to the co-location inaccuracy gives us better results, higher overall accuracy and Standard Kappa values and decreasing in Allocation and Quantity disagreement values. The percentage of the pixels that have been eliminated were about 11.63 % with 57.26% overall accuracy. Table 70 represent the Commotion and Omission Disagreement by pixel% correspond to 30m input data resolution.

	Commission		Omission	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
6. Artificial cover	31.32%	20.02%	44.23%	44.39%
7. Cropland	27.50%	24.13%	13.60%	10.79%
8. Forest and semi Natural areas	10.27%	8.24%	20.63%	17.82%
9. Wetland	28.07%	15.95%	45.41%	34.05%
10. Water Surfaces	23.97%	12.29%	15.91%	8.33%

Table 70: GLC2000-Sardinia 2003, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the cells that have been removed were about 15.66 % with 44.89 % overall accuracy (Figure 70). Table 71 list the general agreement measures with buffer.

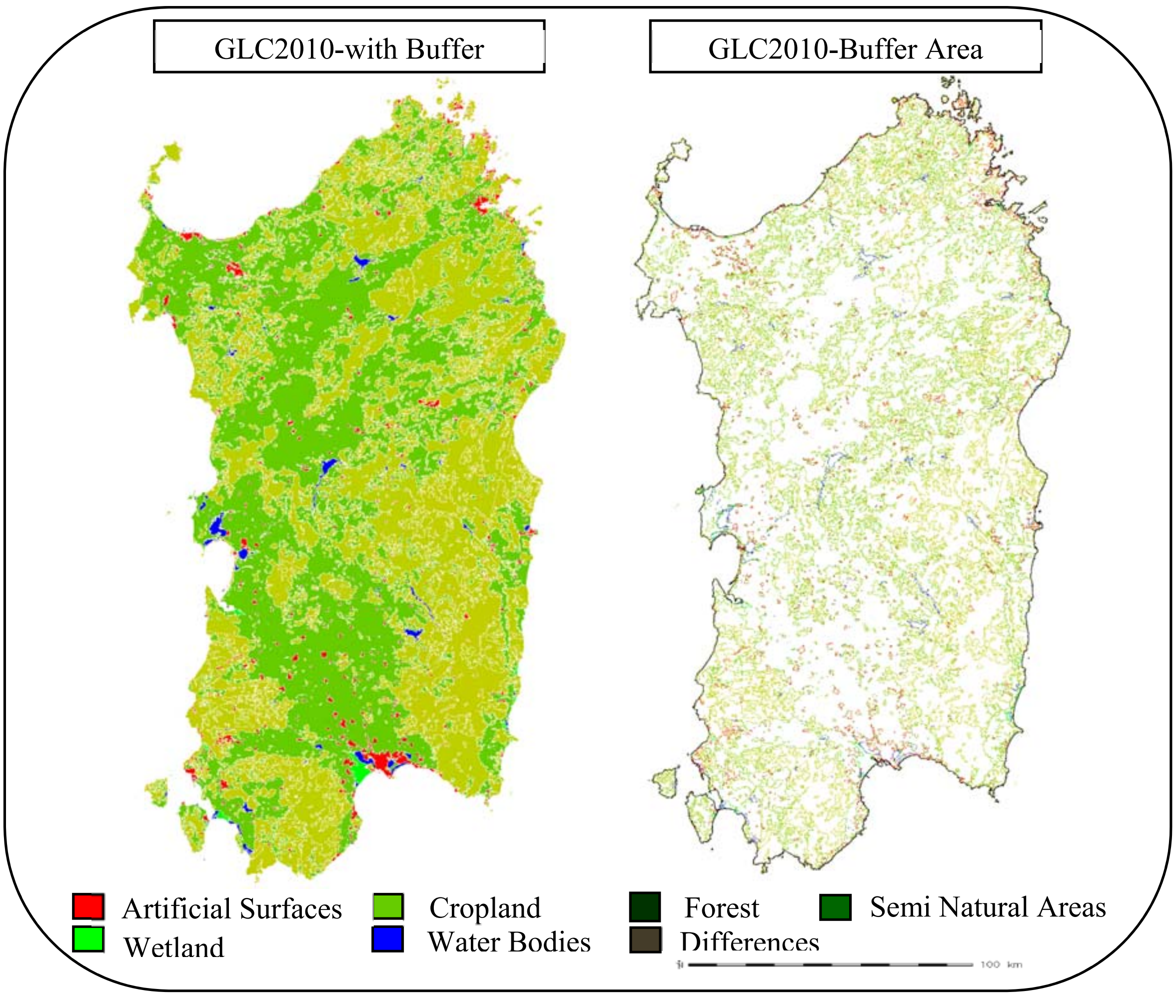


Figure 74: Second Reclassification Method: Buffer of 70 m eliminated around GLC2010 polygons border (Sardinia 2008 Case).

***[51]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	65.50%	0.4949	18.29%	16.21%

	FORESTS	*SHRUB/GRASS*	*BEACHES,ROCKS,SPARSELY VEGETATED AREAS…*
UA*	45.54%	69.41%	39.51%
PA*	64.28%	39.60%	18.20%
K*	0.3819	0.3484	0.2384
AD*	14.93%	11.49%	1.25%
QD*	8.60%	14.14%	1.21%

Table 71: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer between reclassified maps GLC2010-Sardinia.2008.

3.8.4 Sardinia Case Study Conclusion

In a summery, for both assessments, the analysis shows that Agreement measures are mostly similar with different input data resolution corresponds to the first reclassification method identify with high Overall Accuracy and good Standard Kappa value for the different classes. On other hand, the agreement measures corresponds to the second reclassification method shows the decreasing of the Overall Accuracy identified with poor value for Standard Kappa which explains the increasing in both Allocation and Quantity disagreement. This is could be due to the fact that the source of Sardinia land cover maps were not homogeneously relevant with GLC2000 and GLC2010.

[51] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.9 EIGHTH CASE STUDY: ABRUZZO REGION

Abruzzo is the northernmost region of Southern Italy (Figure 76)[52], with an area of about 10,763 km^2 and its western border lies less than 50 miles (80 km) east of Rome. The region, divided into the provinces of L'Aquila, Teramo, Pescara and the Chieti, borders the region of Marche to the north, Lazio to the west and south-west, Molise to the south-east, and the Adriatic Sea to the east. Abruzzo is split into a mountainous area in the west with the Gran Sasso D'italia, and into a coastal area on the eastern side with the beaches of the Adriatic Sea. Figure 77, shows the overall workflow for Abruzzo region.

Figure 75: Abruzzo Region

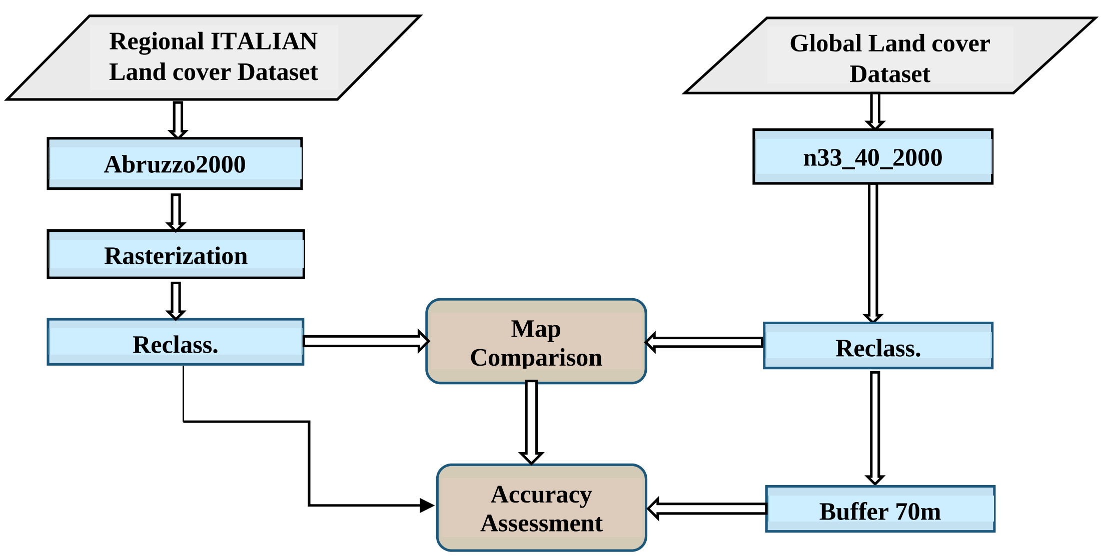


Figure 76: overall workflow for Abruzzo Region.

[52] http://en.wikipedia.org/wiki/Abruzzo

3.9.1 Abruzzo land Cover layer

Abruzzo land cover layer[53] (Table 72) was obtained from digital orthoimagery produced by AIMA in 1997 (scale 1: 10,000) and Landsat TM5 images (30x30 pixels meters), acquired in three steps corresponding to late spring, summer and winter to cover significant phenological phases of the natural vegetation and the main agricultural crops . In order to calibrate the work of photo interpretation 1000 points of known coordinates were chosen. The legend derives directly from the Corine Land Cover and is structured into four levels of analysis; the first level of classification is as follows: 1) Artificial Surfaces (Environment urbanized); 2) Agricultural areas used (Environment cultivated); 3) Wooded areas and semi-natural environment; 4) Environment wet; 5) Environment of the water. The reference system is the WGS84/UTM33.

	ABRUZZO
YEAR	1997(Ed.2000)
SCALE	1:25’000
REF SYS	WGS84/UTM33N
LEGEND	CORINE
SOURCE	Orthoimagery
EXTENT	whole region

Table 72: Abruzzo land cover layer.

3.9.2 Data processing

The Comparison has been done between **GLC2000** and Land cover map of **Abruzzo region2000**. Abruzzo vector map was rasterized through the GRASS GIS module *v.to.rast*. To test the influence of the data resolution on the comparison results, two Abruzzo raster maps at different cell sizes, respectively 30 m and 5 m, were calculated.

Secondly, to allow the comparison procedure, a reclassification of Abruzzo raster maps and GLC raster map according to the CORINE categories was carried out by means of the *r.reclass* module. Due to the differences in coastline between the two maps and to reduce the error around the Coastline, a new class (255) was added in order to calculate the common difference area between the two maps. The calculation has been done taking advantage of GRASS GIS module *r.mapcalc*. Then a patching procedure was needed to add the differences pixel to both maps. The first reclassification (Case1) considered the first five classes of CORINE legend, while the second reclassification (Case2) was performed taking into account the four Sub-classes of category 3.

[53] Metadata: http://www.regione.abruzzo.it/xcartografia/docs/CUsoSuolo25_2000/UsoSuolo2000.pdf

Figure 78 & 79 gives a visual overview of both reclassified Land cover maps (Abruzzo2000-GLC2000).

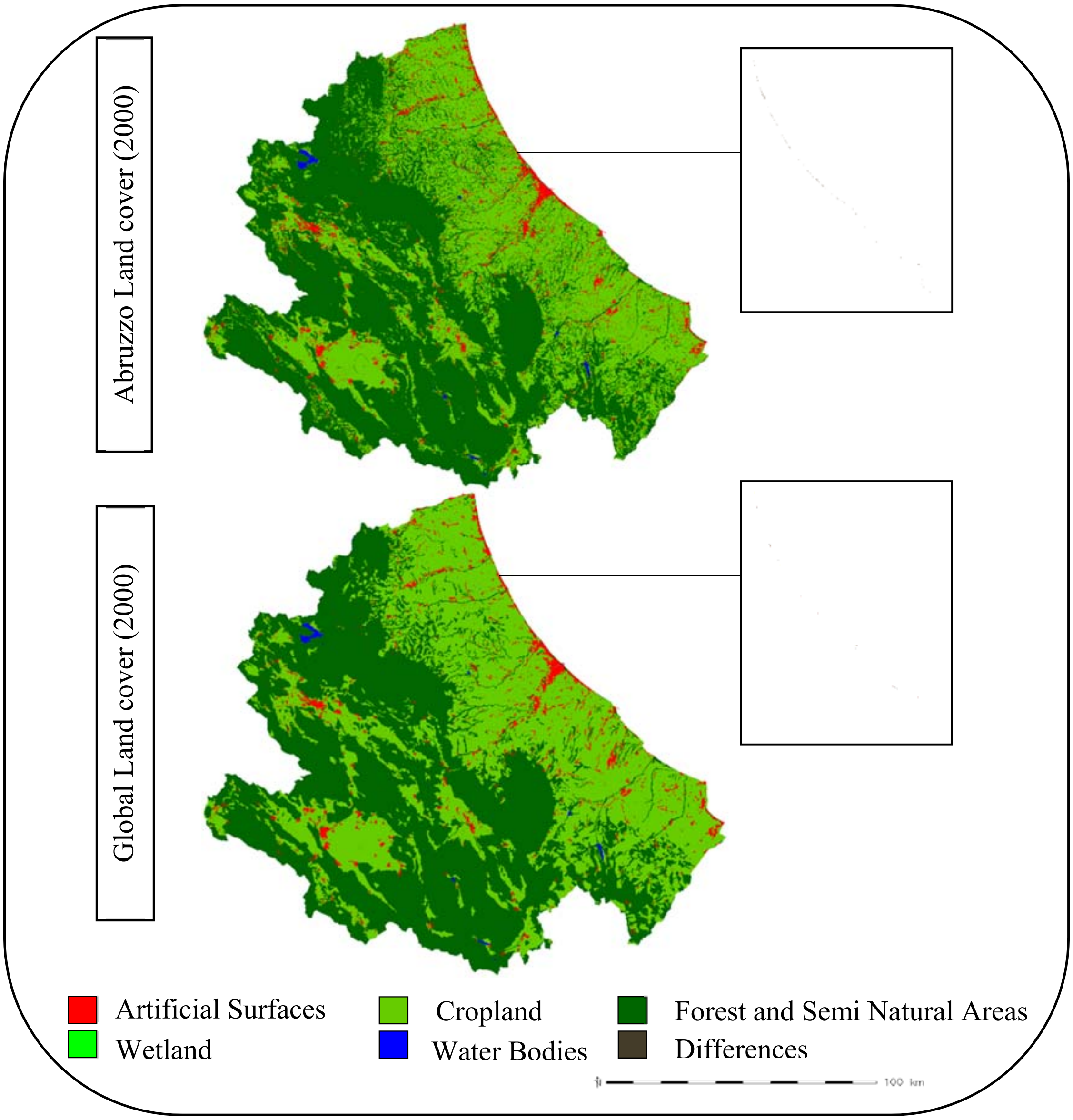


Figure 77: Visual Overview of Both Reclassified Abruzzo2000 and GLC2000 (1st Classification).

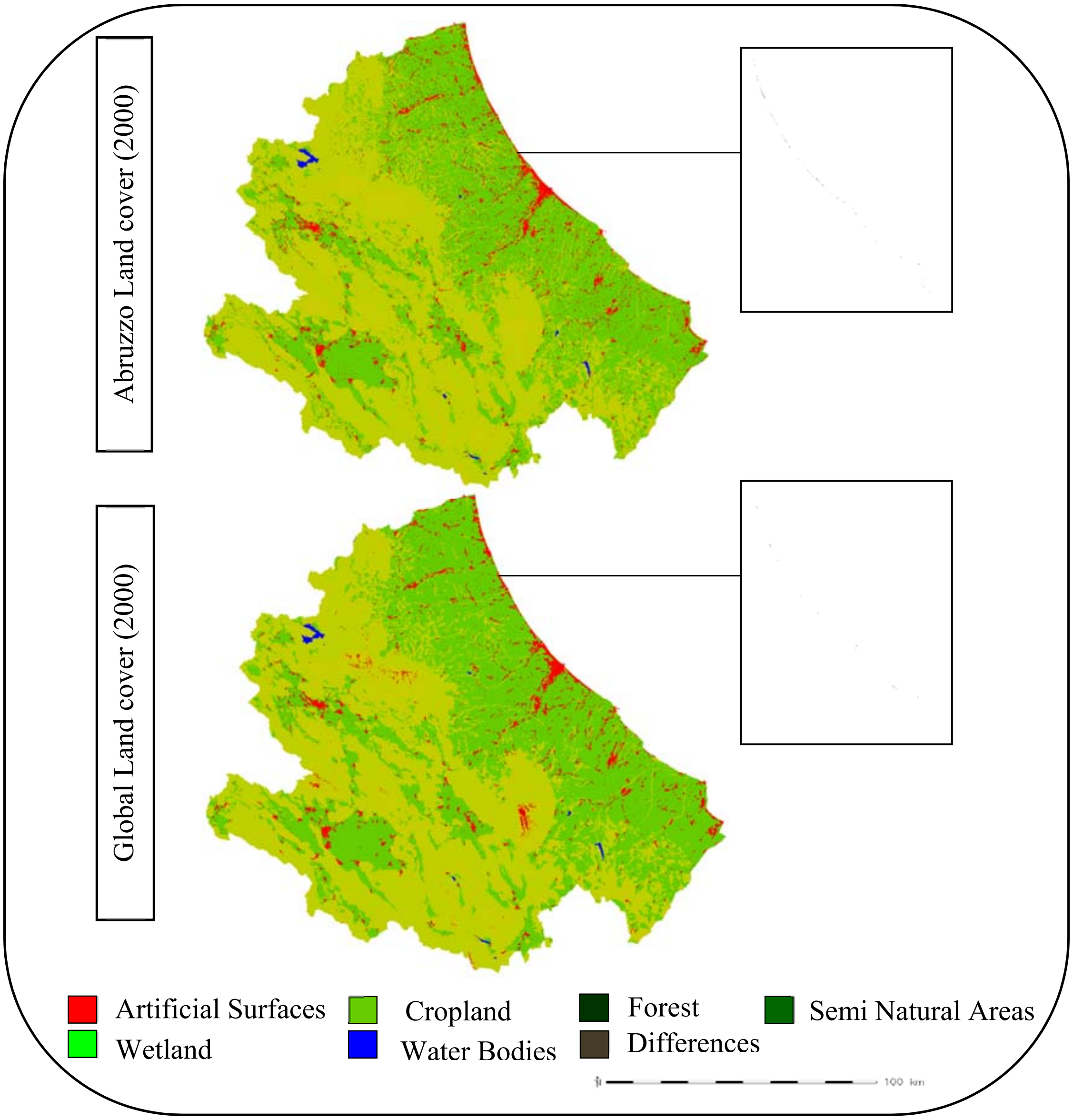


Figure 78: Visual Overview of Both Reclassified Abruzzo2000 and GLC2000 (2^{nd} Classification).

3.9.3 Accuracy Assessment

In a pixel based assessment, the accuracy assessment was derived from a comparison pixel by pixel between Reclassified Abruzzo Land cover map (REFERENCE MAP) and GLC (CLASSIFIED MAP).

The confusion matrices and the agreement measures are represented in Table 73, corresponding to the fist reclassification method which shows the statistics that have recommended in this study such as User's and Producer's accuracy, Overall accuracy, Commission and Omission error, Cohen's Kappa, Allocation and Quantity Disagreement.

CASE A (30 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	273702	106172	16162	0	123	472	396631	69.01%	30.99%
2	179830	4357741	763675	123	3725	308	5305402	82.14%	17.86%
3	18931	481724	5753295	66	3898	1843	6259757	91.91%	8.09%
4	0	47	190	0	11	0	248	0.00%	100.00%
5	473	1332	1385	8	22934	0	26132	87.76%	12.24%
255	282	40	473	0	54	0	849	0.00%	100.00%
sum	473218	4947056	6535180	197	30745	2623	11989019		
PA	57.84%	88.09%	88.04%	0.00%	74.59%	0.00%			
OE	42.16%	11.91%	11.96%	100.00%	25.41%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
30 m	86.81%	0.7518	10.20%	2.99%

CASE B (5 m resoulation):

GROUND TRUTH

CLASSIFIED	1	2	3	4	5	255	sum	UA	CE
1	9820811	3842880	593279	0	4366	17451	14278787	68.78%	31.22%
2	6499550	156778273	27563269	4432	136001	12238	190993763	82.09%	17.91%
3	690849	17406903	207040135	2431	143211	66529	225350058	91.87%	8.13%
4	0	1697	6822	0	409	0	8928	0.00%	100.00%
5	17086	49285	51791	288	822235	28	940713	87.41%	12.59%
255	10527	1753	18916	0	1923	0	33119	0.00%	100.00%
sum	17038823	178080791	235274212	7151	1108145	96246	431605368		
PA	57.64%	88.04%	88.00%	0.00%	74.20%	0.00%			
OE	42.36%	11.96%	12.00%	100.00%	25.80%	100.00%			

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	86.76%	0.7509	10.25%	2.99%

Table 73: First Reclassification Method (Case 1) - Error matrices and Agreement measures for Different Input data Resolution between GLC2000 and Abruzzo2000.

The results shows that the agreement measures are most similar with different input data resolution, the kappa values are high identify with high overall accuracy which explains the low values of Allocation and Quantity disagreement with different input data resolution. Other metrics of overall and per-class accuracy can be derived from a confusion matrix as following:

- **Artificial surfaced category**

	5 m	*30 m*
UA	68.78%	69.01%
PA	57.64%	57.84%
K	0.6133	0.6155
AD	2.07%	2.05%
QD	0.64%	0.64%

- **Cropland**

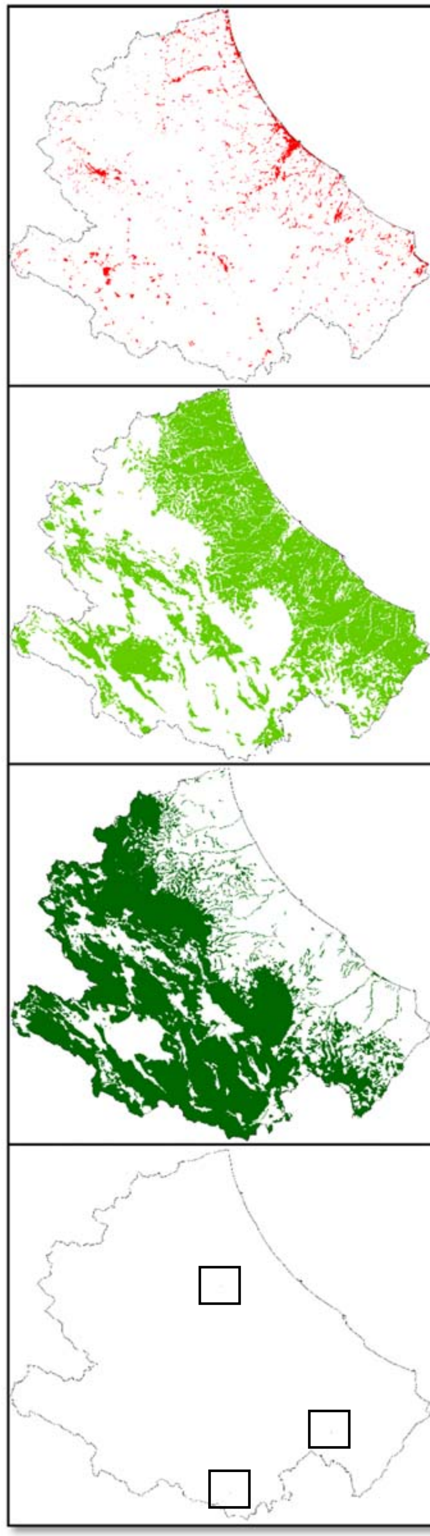
	5 m	*30 m*
UA	82.09%	82.14%
PA	88.04%	88.09%
K	0.7375	0.7383
AD	9.87%	9.83%
QD	2.99%	2.99%

- **Forest and Semi Natural area Category**

	5 m	*30 m*
UA	91.87%	91.91%
PA	88.00%	88.04%
K	0.7835	0.7842
AD	8.48%	8.45%
QD	2.30%	2.30%

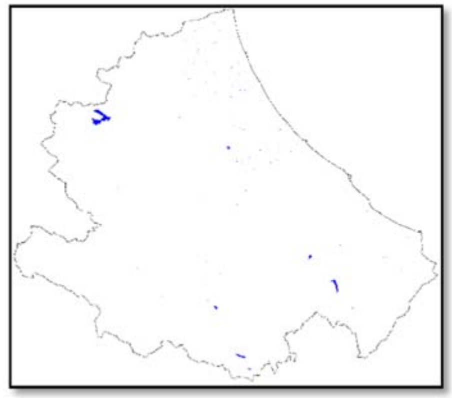
- **Wetland**

	5 m	*30 m*
UA	0.00%	0.00%
PA	0.00%	0.00%
K	-0.00002	-0.00002
AD	0.00%	0.00%
QD	0.00%	0.00%



➢ Open Water Category

	5 m	*30 m*
UA	87.41%	87.76%
PA	74.20%	74.59%
K	0.8022	0.8060
AD	0.05%	0.05%
QD	0.04%	0.04%



The results shows that Both Forest and Semi Natural Areas and Open water category are classified with the best accuracies identify with good Kappa value compared with the other classes. On other hand, Table 74 list the agreement measures between the compared maps GLC2000 and Abruzzo2000 corresponds to the Second reclassification method.

***[54]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30 m	78.00%	0.6796	16.05%	5.91%

	FOREST	**SHRUB/GRASS**	**BEACHES,ROCKS,SPARSELY VEGETATED AREAS…**
UA*	76.47%	75.34%	61.53%
PA*	84.19%	61.89%	45.42%
K*	0.7243	0.5875	0.5114
AD*	8.44%	10.03%	1.71%
QD*	2.70%	4.42%	0.82%

Table 74: Second Classification Method (Case2); Agreement measures between compared maps GLC2000 and Abruzoo2000 with 30 m input data resolution.

Analyzing the results of the two different classification method, the general agreement measures shows that the overall accuracy decreased by 8%, which explains the increase in the allocation and Quantity disagreement values. Among the sub classes, Forest are classified with the best accuracies (76.47% for the User's accuracy and 84.19% for the Producer's accuracy) compared with the other subclasses

A buffer 70 m wide eliminated around GLC polygon border (Figure 80) to eliminate the part of the disagreement according to the to the co-location tolerance. Table 75 list the Agreement measures after eliminating the Buffer.

[54] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution

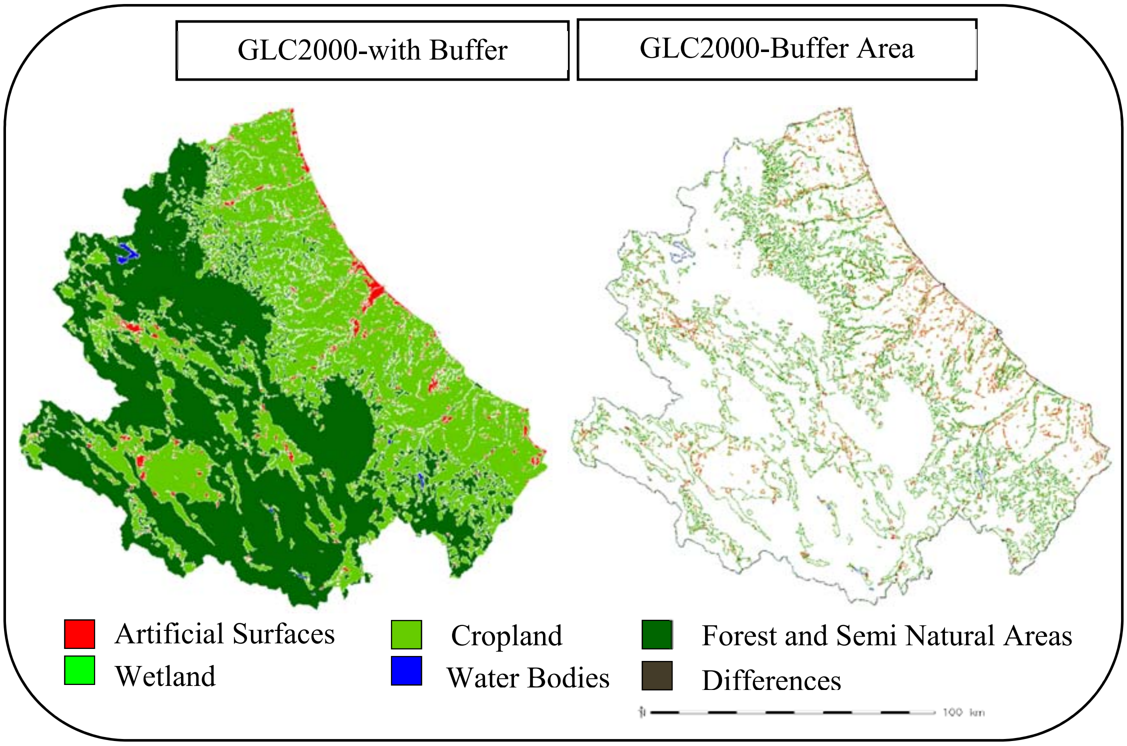


Figure 79: First Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Abruzzo Case).

GENERAL AGREEMENT MEASURES

	OA	*K*	*AD*	*QD*
5 m	90.26%	0.8101	6.56%	3.18%
30 m	89.98%	0.8057	6.83%	3.18%

Table 75: General Agreement Measures between GLC2000 and Abruzzo2000 after the Elimination of a Buffer.

Around 12.48% pixels has been eliminated with 64.56% overall accuracy corresponds to 30 m input data resolution. Further, 14.22% pixels has been eliminated with 65.76% overall accuracy corresponds to 5 m data resolution which gives us better results.

Table 76, list the Commission and Omission disagreement by pixel (%) corresponds to 30m input data resolution.

	Commission		**Omission**	
	No Buffer	**Buffer**	**No Buffer**	**Buffer**
1. Artificial cover	30.99%	17.93%	42.16%	44.70%
2. Cropland	17.86%	14.96%	11.91%	8.29%
3. Forest and semi Natural areas	8.09%	5.79%	11.95%	9.55%
4. Wetland	100.00%	100.00%	100.00%	100.00%
5. Water Surfaces	12.24%	0.42%	25.41%	16.08%

Table 76: GLC2000-Abruzzo2000, Commotion and Omission Disagreement by pixel%.

Furthermore with second reclassification method (Case2), the pixels that have been eliminated were about 19.36 % with 57.59 % overall accuracy (Figure 81).

Table 77, list the general agreement measures after eliminating the buffer corresponds to 30m input data resolution.

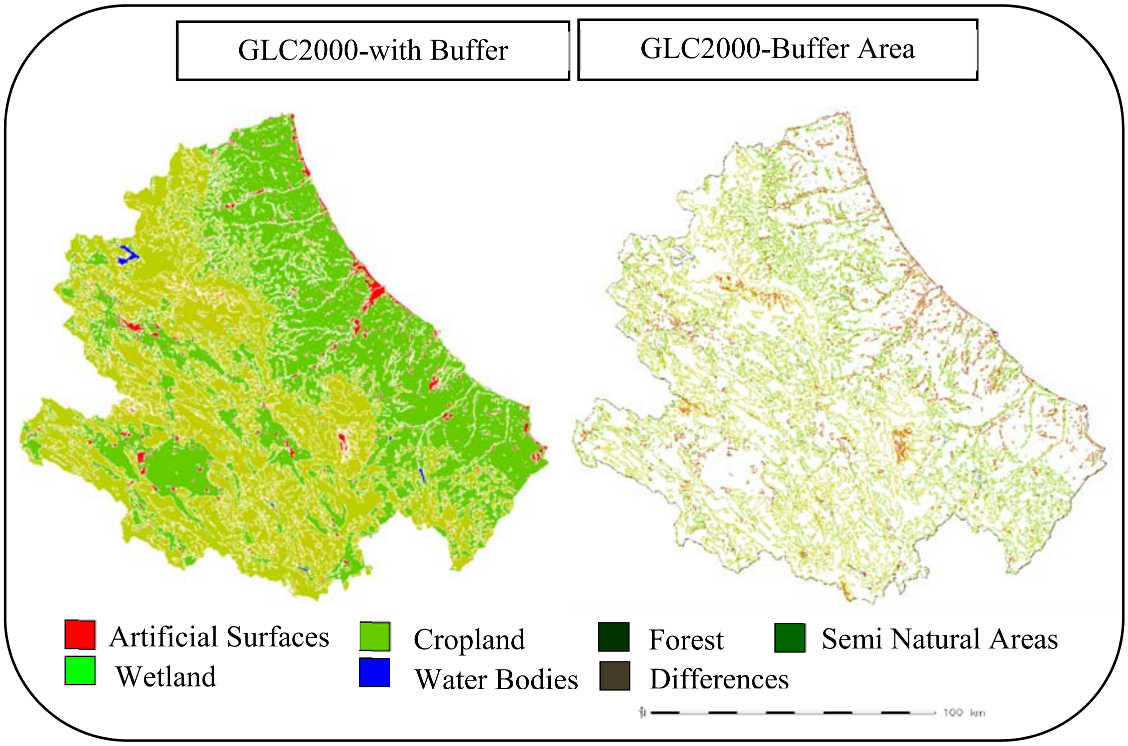


Figure 80: Second Reclassification Method: Buffer of 70 m eliminated around GLC2000 polygons border (Abruzzo Case).

***[55]GENERAL AGREEMENT MEASURES**

	OA	*K*	*AD*	*QD*
30m	82.91%	0.7437	11.68%	5.41%

	FOREST	**SHRUB/GRASS**	**BEACHES,ROCKS,SPARSELY VEGETATED AREAS…**
UA*	83.14%	79.20%	65.54%
PA*	87.60%	66.81%	44.96%
K*	0.7955	0.6498	0.5241
AD*	6.81%	8.21%	1.15%
QD*	1.47%	3.66%	0.76%

Table 77: Second Classification Method (Case2); Agreement measures with 30 m input data resolution after eliminating the buffer (Abruzzo Case).

[55] Note: the result referred to 30 m resolution m dataset; there is no significance difference between different input data resolution.

3.9.4 Abruzzo Case Study Conclusion

As a result, eliminating a buffer around GLC polygon border gives better agreement measures. In both assessment, Forest and Open water category are classified with the best accuracies compared with the other classes using different reclassification method and different input data resolution. The overall accuracy is high associated with high value for Standard kappa, which explains low values of the total disagreement.

CHAPTER 4

4 SUMMERY

The production of thematic maps, such as those depicting land cover, using an image classification is one of the most common applications of remote sensing. Considerable research has been directed at the various components of the mapping process, including the assessment of accuracy. Although thematic maps are an imperfect model of the environment, they are widely used and often derived from remotely sensed data through some form of classification analysis. Performing global classifications of remotely sensed data provides for an internally consistent product which allows for the comparison of land cover between regions and continents. Global land-cover data are key sources of information for understanding the complex interactions between human activities and global change (Running 2008). They are also some of the most critical variables for climate change studies (Bounoua et al. 2002; Ge et al. 2007; Hibbard et al. 2010; Imaoka et al. 2010).They play a critical role in improving performances of ecosystem, hydrologic, and atmospheric models (Bounuoa et al. 2002; Foley et al. 2005; Jung et al. 2006). The value of the map is clearly a function of the accuracy of the classification. Unfortunately, the assessment of classification accuracy is not a simple task. Accuracy assessment in remote sensing has a long and, at times, contentious history. Accuracy assessment has, however, matured considerably and is now generally accepted to be a fundamental part of any thematic mapping exercise.

Although there is no accepted standard method of accuracy assessment or reporting, the topic has matured to the extent that the general format of these important components of the mapping exercise can be identified. Typically, for example, the community is urged to base accuracy assessment on the confusion matrix and provide at least one quantitative metric of classification accuracy together with appropriate confidence limits. Additionally, some general level of accuracy is typically specified as a target against which the classification may be evaluated. The confusion matrix lies at the core of much work on accuracy assessment and is frequently used without question to its suitability. The confusion matrix is used to provide a site-specific assessment of the correspondence between the image classification and ground conditions. The confusion matrix may, for example, be used to summarize the nature of the class allocations made by a classification and is the basis of many quantitative metrics of classification accuracy.

However, there are many problems with accuracy assessment. A key concern is that the basic assumptions underlying the assessment of classification accuracy may not be satisfied. Rarely, for instance, will the data used be truly site-specific due to problems of mixed pixels and mis-registration of the ground and remotely sensed data sets. The classes defined are also typically a generalization that may often be problematic. Moreover, rarely are the ground data an accurate representation of the ground conditions or the necessary information on the sampling design used in their acquisition provided.

Obtaining a reliable confusion matrix is, therefore, a weak link in the accuracy assessment chain (Smits et al., 1999), yet it remains central to most accuracy assessment and reporting. Until basic problems such as those associated with mixed pixels and data set registration are solved, the interpretation of the confusion matrix and accuracy metrics derived from it will remain problematic.

Although there have been many recent advances, the current status of accuracy assessment indicates that numerous problems remain to be solved. Thus, although the subject has matured considerably, there is scope for significant further development. A key concern is that the widely used approaches for accuracy assessment and reporting are often flawed. Despite the apparent objectivity of quantitative metrics of accuracy, it is important that accuracy statements be interpreted with care. Many factors may result in a misleading interpretation being derived from an apparently objective accuracy statement. This situation could have serious implications for some users and may lessen their confidence in remote sensing as a source of land cover data.

An accuracy assessment may be undertaken for different reasons. It could, for instance, be undertaken to provide an overall measure of the quality of a map, to form the basis of an evaluation of different classification algorithms or to attempt to help gain an understanding of errors. In each instance, different users may have different concerns about accuracy. They may, for example, be interested in the overall or global accuracy, the accuracy with which a specific class has been mapped, or the accuracy of area estimates. Furthermore, while some errors are of no concern to some users, they may be detrimental to others (DeFries & Los, 1999), yet rarely are misclassifications treated unequally (Naesset, 1996)[lxxxviii]. Similarly, no one classification will be optimal from the viewpoint of each different user (Brown et al., 1999; Lark, 1995). As classification accuracy has various components and users differ in their specific needs, it is important to measure the desired properties (Lark, 1995)[lxxxix].

Typically, the specified requirements take the form of a minimum level of overall accuracy, expressed numerically by some index such as the percentage of cases correctly allocated, and a desire for each class to be classified to comparable accuracy. Thus, for example, Thomlinson et al. (1999)[xc] set a target of an overall accuracy of 85% with no class less than 70% accurate. This 85% value is often used as if it is some standard universally valid threshold by which to evaluate any image classification. In reality the 85% threshold has a clear history and may have been appropriate for its specific purpose but should not be adopted as a general target. Researchers should set the target for their own investigation, this may be substantially higher or lower than 85%.

In This study, we could realized that the Overall accuracy varies between different regions and different reclassification methods with different input data resolution. Considering the First reclassification method the Overall Accuracy vary between 80% and 90%, on the other hand considering the Second reclassification method the Overall Accuracy vary between 67% and 80%.

Moreover, eliminating the part of the disagreement due to the co-location tolerance by eliminating a buffer around the GLC polygon border shows the increasing in the Overall accuracy for both reclassification method with different input data resolution as shown in Figure 81 and Figure 82. The high classification accuracies indicates the less part of disagreement between the comparison land cover maps. While the low classification accuracies indicates the higher part of the disagreement which could be due to the fact that images used for the classification of the land cover maps were taken in different dates.

Another part of the disagreement could be due to that the regional dataset's were independent with different thematic classification and resolution. Thus far, and in most of the literature, it has been assumed that the ground or reference data used in the assessment of classification accuracy are themselves an accurate representation of reality. In fact, the ground data are just another classification which may contain errors.

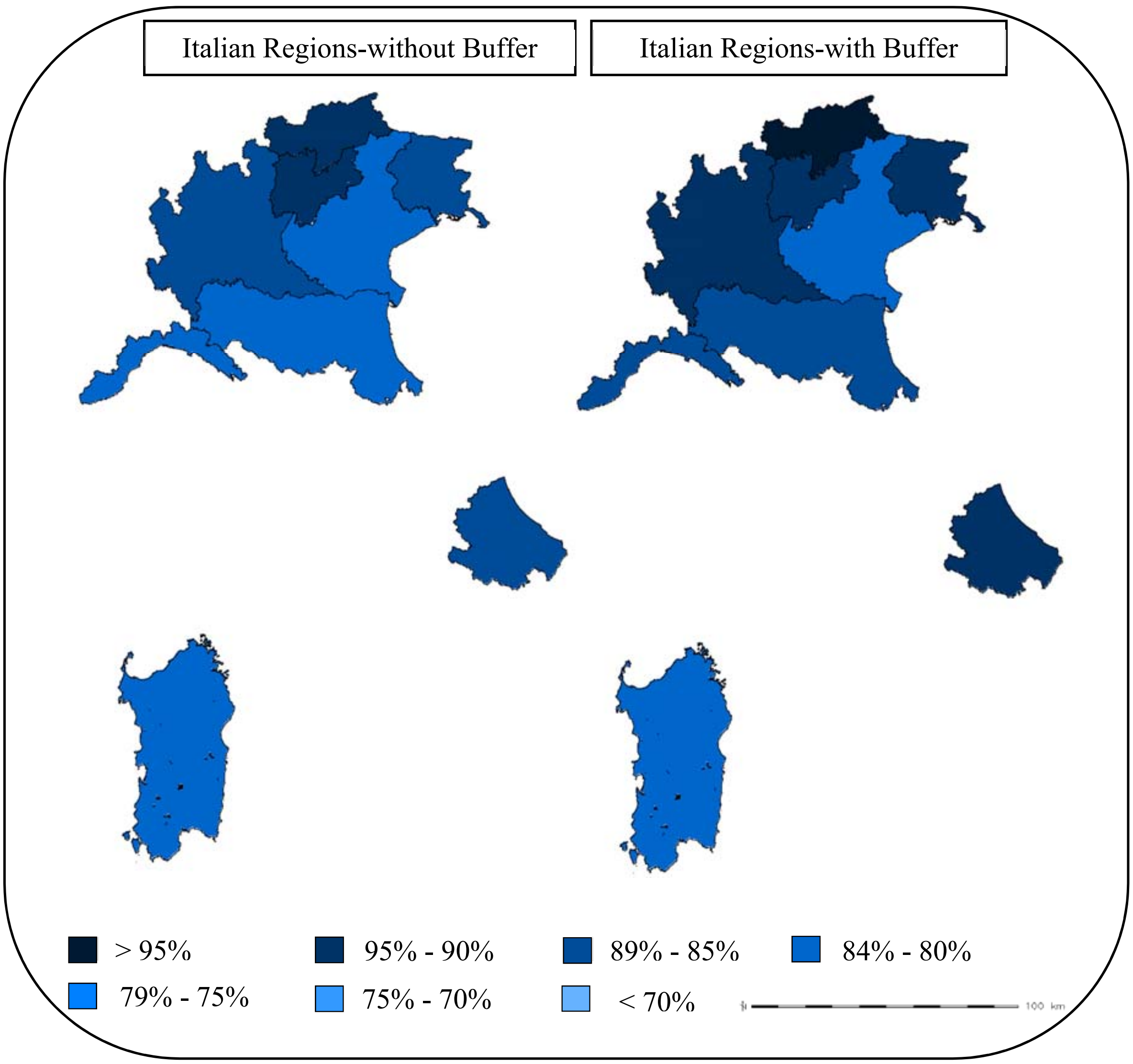


Figure 81: First Reclassification Method, The different Italian Regions classified according to the percentage of Overall accuracy.

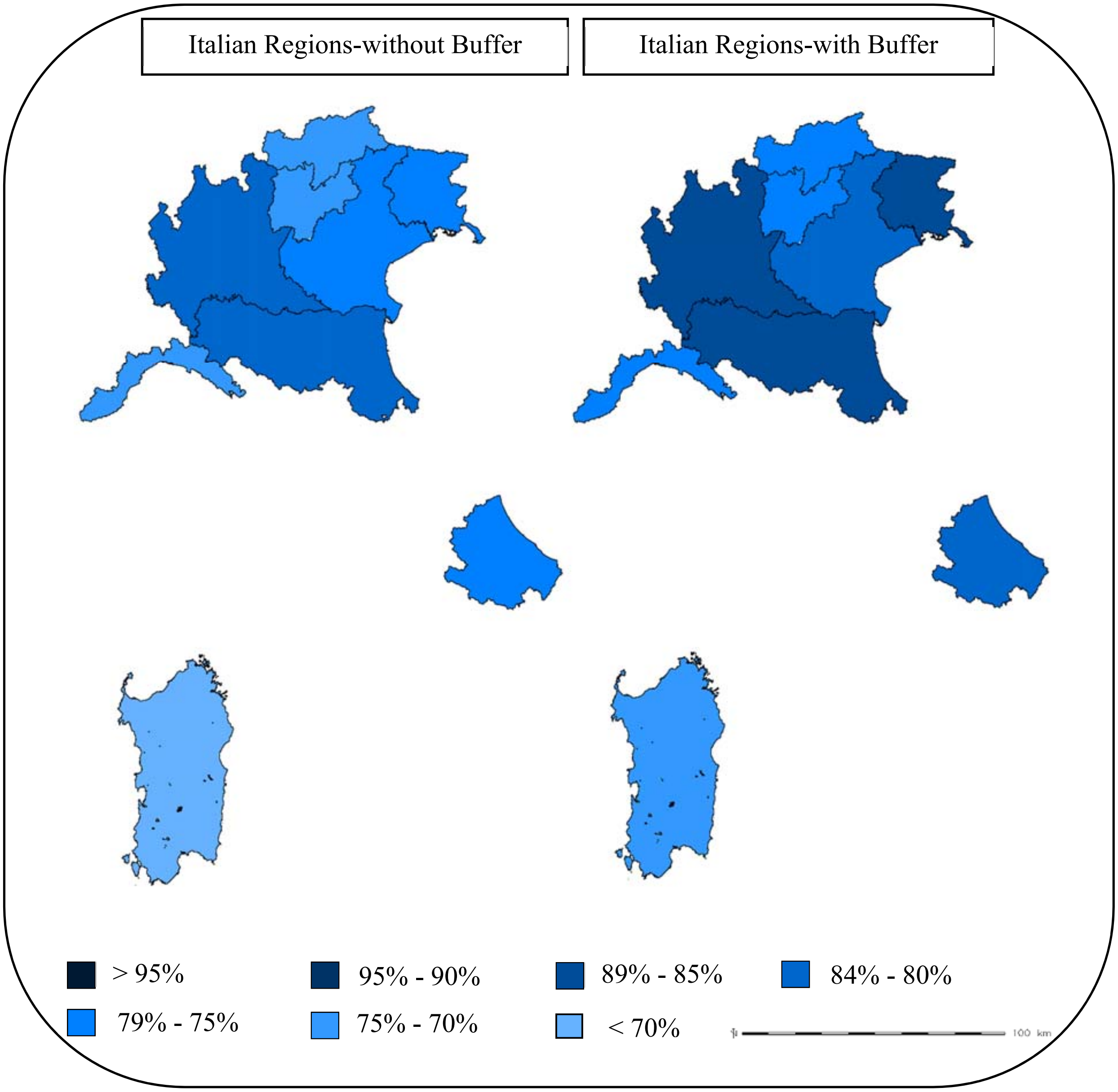


Figure 82: Second Reclassification Method, The different Italian Regions classified according to the percentage of Overall accuracy.

CHAPTER 5

5 AREAS OF FUTURE WORK

While there is a well-established core set of methods for accuracy assessment of thematic maps, there remains considerable need for future research and development. Areas of particular importance in this domain include:

- ***Standardization of land cover maps with respect to legends and mapping units.*** To date, most land cover maps have been made independent of existing maps and other mapping efforts. As a result it has proven difficult to compare and combine alternative land cover maps. Efforts to standardize land cover legends and the nature of the mapping units would greatly enhance the synergy between mapping efforts and prove beneficial to the science community.
- ***Analyzing, Classification and Validation services are needed with the help of open source geo-platform allowing sharing and comparing land covers.*** Different organizations have developed land cover maps. The classification methods used by the organizations are heterogeneous (Jun Chen 14 Jan 2014)[xci] number and type of classes to which the land has been classified is not the same, in addition, some land coverage areas has been miss-classified due to some problems related to image acquisition during various seasons which arise difficulty in geometric and radiometric correction, and other problems related to miss-handling of the spectral confusion and diversity across the globe. Therefore, implementing an open GLC information geo-platform will allow to explore citizen science for improving the land cover classification through geo-visualization and geo-crowdsourcing on internet and mobile platforms. Also providing GLC web-based services allowing to share and compare land cover data sets, evaluate the coherency and highlight the differences between developed land cover maps. The goal is to produce more accurate and consistent land cover data for more accurate environmental change studies, geographical understating and earth system modeling.
- ***The effect of spatial aggregation on accuracy estimates.*** Many users of land cover maps require spatially aggregated products and it is difficult to know the accuracy of these products even if accuracy assessment has been done on the maps that were aggregated. Methods for estimating the accuracy of spatially aggregated products from accuracy assessments at finer resolutions are needed.
- ***Sampling design can be tailored to meet multiple objectives for multiple users.*** Accuracy assessment typically have multiple users and objectives leading to interest in a variety of accuracy parameters and sub-regions of the mapped area. In those cases in which the accuracy objectives are limited, the need to satisfy the multiple objectives for multiple users it may be helpful if the information on issues such as the sampling design used to acquire the testing set, the confidence in the ground data labels, the classification protocols and lineage of the data sets used are provided.

- ***Reuse of existing validation samples***. Accuracy assessment is expensive primarily because of the costs associated with the validation samples. Thus, there is a strong motivation to use existing data collected for other purposes, and these data are typically difficult to incorporate in a design-based inference framework. Although theory exists to show how new and existing accuracy observations can be merged, more work is necessary to demonstrate the concept. The reuse of existing validation samples might significantly reduce the cost of future accuracy assessment efforts.

- ***Validation of change maps***. The validation of change maps poses new challenges and development of new methods is required. In the domain of validation of change detection there is considerable need for development of methods for separating land cover conversion from inter-annual variability in ecosystem response to climate variability. Integrating accuracy assessment of change with accuracy assessment of single-date land cover maps is a critical need for global monitoring of status and trends in land cover.
- ***Mis-registration, and Mixed pixels effects***. Particularly for coarse resolution imagery, the problems of mis-registration and mixed pixels, more research is needed to better characterize and understand these effects as they relate to accuracy assessment at coarse resolutions.
- ***Integrating the effect of error in the reference data.*** Conventional methods assume that the reference data ("ground truth") for the sample sites is accurate. It would be desirable to be able to estimate the effect of a known rate of error in the sample sites on the overall accuracy of a map. Although a number of approaches to this problem have been explored in the literature, practical techniques to accommodate reference data error remain to be devised.
- ***Error magnitude effects.*** Conventional methods treat all errors as equal in magnitude, which is clearly not true. Better methods for quantifying the importance of the various types of errors that occur in land cover maps would provide valuable additional information to the science community.
- ***Better understanding of users' needs for accuracy data.*** An improved understanding of the ways in which the science community uses land cover accuracy data would enhance the ability of future accuracy assessment efforts to provide the most useful information possible.
- ***Define priorities for improvements in land cover mapping.*** For requiring accurate and detailed land cover data, it would be beneficial to determine where future investment would be most beneficial for improving future land cover maps.

6 REFERENCES

[i] Sellers, P. J., Dickinson, R. E., Randall, D. A., Betts, A. K., Hall, F. G.,Berry, J. A., Collatz, G. J., Denning, A. S., Mooney, H. A., Nobre, C. A., Sato, N., Field, C. B., & Henderson-Sellers, A.(1997). Modeling the exchanges of energy, water, and carbon between continents and the atmosphere. Science, 275(5299), 502– 509.

[ii] Herold, M., Mayaux, P., Woodcock, C. E., Baccini, A., & Schmullius, C. (2008). Some challenges in global land cover mapping: An assessment of agreement and accuracy in existing 1 km datasets. Remote Sensing of Environment, 112, 2538−2556.

[iii] Olson, J. S., & Watts, J. (1982). Major world ecosystem complexes. In D. B. Jones (Ed.), Earth's vegetation and atmospheric carbon dioxide. Carbon dioxide review (pp. 388– 399). Oxford: Oxford Univ. Press.

[iv] Matthews, E. (1983). Global vegetation and land-use: new-high resolution data bases for climate studies. Journal of Climate and Applied Meteorology, 22, 474– 487.

[v] Wilson, M., & Henderson-Sellers, A. (1985). A global archive of land cover and soils data for use in general circulation climate models. Journal of Climatology, 5, 119–143.

[vi] Townshend, J. R. G., Justice, C., Li, W., Gurney, C., & McManus, J. (1991). Global land cover classification by remote sensing: present.

[vii] CNES (2000). "SPOT-Vegetation Instrument." Centre National pour l'Etudes d'Espace, http://spot4.cnes.fr/spot4_gb/, 06/06/2000.

[viii] Justice, C. O., E. Vermote, J. R. G. Townshend, R. Defries, D. P. Roy, D. K. Hall, V. V. Salomonson, J. L. Privette, G. Riggs, A. Strahler, W. Lucht, R. B. Myneni, Y. Knyazikhin, S. W. Running, R. R. Nemani, Z. Wan, A. R. Huete, W. van Leeuwen, R. E. Wolfe, L. Giglio, J.-P. Muller, P. Lewis and M. J. Barnsley (1998). "The Moderate Resolution Spectroradiometer (MODIS): Land remote sensing for global change research." *IEEE Transactions on Geoscience and Remote Sensing* **36**: 1228-1249.

[ix] ESA (2004). "MERIS Introduction." European Space Agency, http://envisat.esa.int/instruments/meris/, 07/22/04.

[x] Loveland, T. R., B. C. Reed, J. F. Brown, D. O. Ohlen, Z. Zhu, L. Yang and J. W. Merchant (2000). "Development of a global land cover characteristics database and IGBP DISCover from 1 km AVHRR data." *International Journal of Remote Sensing* **21**(6-7): 1303-1330.

[xi] DeFries, R. S., M. C. Hansen and J. R. G. Townshend (2000). "Global continuous fields of vegetation characteristics: A linear mixture model applied to multi-year 8 km AVHRR data." *International Journal of Remote Sensing* **21**(6-7): 1389-1414.

[xii] Bartholomé, E., and A. S. Belward. 2005. "GLC2000: A New Approach to Global Land Cover Mapping from Earth Observation Data." *International Journal of Remote Sensing* 26: 1959–77.

[xiii] Friedl, M. A., D. K. Mciver, J. C. F. Hodges, X. Y. Zhang, D. Muchoney, A. H. Strahler, C. E. Woodcock, S. Gopal, A. Schneider, A. Cooper, A. Baccini, F. Gao, and C. Schaaf. 2002. "Global Land Cover Mapping from MODIS: Algorithms and Early Results." *Remote Sensing of Environment* 83: 287-302.
Friedl, M. A., D. Sulla-Menashe, B. Tan, A. Schneider, N. Ramankutty, A. Sibley, and X. M. Huang. 2010. "MODIS Collection 5 Global Land Cover: Algorithm Refinements and Characterization of New Datasets." *Remote Sensing of Environment* 114: 168–82.

[xiv] Arino, O., P. Bicheron, F. Achard, J. Latham, R. Witt, and J. L. Weber. 2008. "GLOBCOVER the Most Detailed Portrait of Earth." *ESA Bulletin-European Space Agency* 136: 24–31.
Bontemps, S., P. Defourney, E. Van Bogaert, and O. Arino. 2010. *GLOBCOVER2009 Products Description and Validation Report*. Accessed January 20, 2012.
https://globcover.s3.amazonaws.com/LandCover2009/GLOBCOVER2009_Validation_Report_1.0.pdf.

[xv] Tateishi, R., B. Uriyangqai, H. Al-Bilbisi, M. A. Ghar, J. Tsend-Ayush, T. Kobayashi, A. Kasimu, H. N. Thanh, A. Shalaby, B. Alsaaideh, T. Enkhzaya, G. Tana, and H. P. Sato. 2011. "Production of Global Land Cover, GLCNMO." *International Journal of Digital Earth* 4: 22–49.

xvi Di Gregorio, A. 2005. FAO Land Cover Classification System. FAO Environment and Natural Resources Service Series, No. 8. Rome: FAO.

[xvii] Townshend, J., C. Justice, W. Li, C. Gurney and J. McManus (1991). "Global land cover classification by remote sensing—Present capabilities and future possibilities." *Remote Sensing of Environment* **35**(2-3): 243-255.

[xviii] Scepan, J. 1999. "Thematic Validation of High-Resolution Global Land-Cover Data Sets." *Photogrammetric Engineering and Remote Sensing* 65: 1051–60.

[xix] Mayaux, P., H. Eva, J. Gallego, A. Strahler, M. Herold, S. Agrawal, S. Naumov, E. Eduardo, C. M. Di Bella, C. Ordoyne, Y. Kopin, and P. S. Roy. 2006. "Validation of the Global Land Cover 2000 Map." *IEEE Transactions on Geoscience and Remote Sensing* 44: 1728–39.

[xx] Niu, Z. G., P. Gong, X. Cheng, J. H. Guo, L. Wang, H. B. Huang, S. Q. Shen, Y. Z. Wu, X. F. Wang, X. W. Wang, Q. Ying, L. Liang, L. N. Zhang, L. Wang, Q. Yao, Z. Z. Yang, Z. Q. Guo, and Y. J. Dai. 2009. "Geographical Characteristics of China's Wetland Derived from Remote Sensing." *Science in China Series D (Earth Sciences)* 52: 723–38.
Fritz, S., L. See, and F. Rembold. 2010. "Comparison of Global and Regional Land Cover Maps with Statistical Information for the Agricultural Domain in Africa." *International Journal of Remote Sensing* 31: 2237–56.

[xxi] Sedano, F., P. Gong, andM. Ferrao. 2005. "Land Cover Assessment with MODIS Imagery in Southern African Miombo Ecosystems." *Remote Sensing of Environment* 98: 429–41.
[xxii] Frey, K. E., and L. C. Smith. 2007. "How Well Do We Know Northern Land Cover? Comparison of Four Global Vegetation and Wetland Products with a New Ground-Truth Database for West Siberia." *Global Biogeochemical Cycles* 21: GB1016.

[xxiii] Mccallum, I., M. Obersteiner, S. Nilsson, and A. Shvidenko. 2006. "A Spatial Comparison of Four Satellite Derived 1 km Global Land Cover Datasets." *International Journal of Applied Earth Observation and Geoinformation* 8: 246–55.

[xxiv] Jung, M., K. Henkel, M. Herold, and G. Churkina. 2006. "Exploiting Synergies of Global Land Cover Products for Carbon Cycle Modeling." *Remote Sensing of Environment* 101: 534– 53.

[xxv] Sterling, S. M., and A. Ducharne. 2008. "Comprehensive Data Set of Global Land Cover Change for Land Surface Model Applications." *Global Biogeochemical Cycles* 22: GB3017.

[xxvi] Tchuenté, A. T. K., J. L. Roujean, and S. M. De Jong. 2011. "Comparison and Relative Quality Assessment of the GLC2000, GLOBCOVER, MODIS and ECOCLIMAP Land Cover Data Sets at the African Continental Scale." *International Journal of Applied Earth Observation and Geoinformation* 13: 207–19.

[xxvii] Imhoff, M. L. 1997. "A Technique for Using Composite DMSP/OLS 'City Lights' Satellite Data to Map Urban Area." *Remote Sensing of Environment* 61: 361–70.
Gong, P., Z. G. Niu, X. Cheng, K. Y. Zhao, D. M. Zhou, J. H. Guo, L. Liang, X. F. Wang, D. D. Li, H. B. Huang, Y. Wang, K. Wang, W. N. Li, X. W. Wang, Q. Ying, Z. Z. Yang, Y. F. Ye, Z. Li, D. F. Zhuang, Y. B. Chi, H. Z. Zhou, and J. Yan. 2010. "China's Wetland Change (1990–2000) Determined by Remote Sensing." *Science in China Series D (Earth Sciences)* 53: 1036–42.

[xxviii] Ramankutty, N., and J. A. Foley. 1998. "Characterizing Patterns of Global Land Use: An Analysis of Global Cropland Areas." *Global Biogeochemical Cycles* 12: 667–85.
Ramankutty, N., and J. A. Foley. 1999. "Estimating Historical Changes in Global Land Cover: Croplands from 1700 to 1992." *Global Biogeochemical Cycles* 13: 997–1027.

[xxix] Sheng, Y. W., C. A. Shah, and L. C. Smith. 2008. "Automated Image Registration for Hydrologic Change Detection in the Lake Rich Arctic." *IEEE Geoscience and Remote Sensing Letters* 5:414–18.

[xxx] Pu, R., Z. Li, P. Gong, I. Csiszar, R. Fraser, W. -M. Hao, S. Kondragunta, and F. Weng. 2007. "Development and Analysis of a 12-Year Daily 1-km Forest Fire Data across the North America from NOAA/AVHRR Data." *Remote Sensing of Environment* 108: 198–208.
Chuvieco, E., L. Giglio, and C. Justice. 2008. "Global Characterization of Fire Activity: Toward Defining Fire Regimes from Earth Observation Data." *Global Change Biology* 14: 1488–502.

[xxxi] DeFries, R., J. R. G. Townshend, and M. Hansen. 1999. "Continuous Fields of Vegetation Characteristics at the Global Scale at 1-km Resolution." *Journal of Geophysical Research* 104, D14: 16911–23. doi:10.1029/1999JD900057.
Clinton, N., P. Gong, Z. Y. Jin, Z. Zhu, and B. Xu. 2009. "Meta-Prediction of *Bromus tectorum* Invasion in Central Utah, U.S.A." *Photogrammetric Engineering and Remote Sensing* 75:689–701.

[xxxii] Witten, I. H., and E. Frank. 2005. *Data Mining, Practical Machine Learning Tools and Techniques*, 525p. San Francisco, CA: Morgan Kaufmann Publishers.

[xxxiii] Carreiras, J. M. B., J. M. C. Preira, and Y. E. Shimabukuro. 2006. "Land-Cover Mapping in the Brazilian Amazon Using SPOT-4 Vegetation Data and Machine Learning Classification Methods." *Photogrammetric Engineering and Remote Sensing* 72: 897–910.

[xxxiv] Aksoy, S., K. Koperski, C. Tusk, and G.Marchis. 2009. “Land Cover Classification with Multi-Sensor Fusion of Partly Missing Data.” *Photogrammetric Engineering and Remote Sensing* 75: 577–93.

[xxxv] Yu, L., and P. Gong. 2012. “Google Earth as a Virtual Globe Tool for Earth Science Applications.” *International Journal of Remote Sensing* 33: 3966–86.

[xxxvi] Adler-Golden, S. M., M.W. Matthew, L. S. Bernstein, R. Y. Levine, A. Berk, S. C. Richtsmeier P. K. Acharya, G. P. Anderson, G. Felde, J. Gardner, M. Hoke, L. S. Jeong, B. Pukall, A. Ratkowski, and H.-H. Burke. 1999. “Atmospheric Correction for Short-Wave Spectral Imagery Based on MODTRAN4.” *SPIE Proceedings, Imaging Spectrometry* 3753: 61–9.

[xxxvii] Bradski, G. 2000. “The OpenCV Library.” *Dr. Dobb’s Journal of Software Tools* 25, no. 11: 120,122-5.
Hall, M., E. Frank, G. Holmes, B. Pfahringer, P. Reutemann, and I. H. Witten. 2009. “The WEKA Data Mining Software: An Update.” *SIGKDD Explorations* 11: 10–18.
Chang, C. C., and C. J. Lin. 2011. “LIBSVM: A Library for Support Vector Machines.” *ACM Transactions on Intelligent Systems and Technology* 2: 27:1–27.

xxxviii Huang, C. Q., L. S. Davis, and J. R. G. Townshend. 2002. “An Assessment of Support Vector Machine for Land Cover Classification.” International Journal of Remote Sensing 23: 723–49.

[xxxix] Caruana, R., and A. Niculescu-Mizil. 2006. “An Empirical Comparison of Supervised Learning Algorithms.” In *Proceedings of the 23rd International Conference on Machine Learning*. Pittsburgh, PA.

[xl] Olson, D. M., E. Dinerstein, E. D.Wikramanayake, N. D. Burgess, G. V. N. Powell, E. C. Underwood, J. A. D‘amico, I. Itoua, H. E. Strand, J. C. Morrison, C. J. Loucks, T. F. Allnutt, T. H. Ricketts, Y. Kura, J. F. Lamoreux, W. W. Wettengel, P. Hedao, and K. R. Kassem. 2001. “Terrestrial Ecoregions of the World: A New Map of Life on Earth.” *BioScience* 51:933–8.

[xli] Dai, Y. J., X. Zeng, R. E. Dickinson, I. Baker, G. Bonan, M. Bosilovich, S. Denning, P. Dirmeyer, P. Houser, G. Niu, K. Oleson, A. Sclosser, and Z. L. Yang. 2003. “The Common Land Model.” *Bulletin of American Meteorological Society* 84: 1013–23.

[xlii] Sterling, S. M., and A. Ducharne. 2008. “Comprehensive Data Set of Global Land Cover Change for Land Surface Model Applications.” *Global Biogeochemical Cycles* 22: GB3017.

[xliii] Gong, P., J. R.Miller, and M. Spanner. 1994. “Forest Canopy Closure from Classification and Spectral Unmixing: A Multi-Sensor Evaluation of Application to an Open Canopy.” *IEEE Transactions on Geoscience and Remote Sensing* 32: 1067–80.
Roberts, D. A., M. Gardner, R. Church, S. Ustin, G. Scheer, and R. O. Green. 1998. “Mapping Chaparral in the Santa Monica Mountains Using Multiple Endmember Spectral Mixture Models.” *Remote Sensing of Environment* 65: 267–79.

[xliv] Gong, P., Y. Sheng, and G. S. Biging. 2002. “3D Model-Based Tree Measurement from High Resolution Aerial Imagery.” *Photogrammetric Engineering and Remote Sensing* 68: 1203–12.

[xlv] Neumann, M., L. Ferro-Famil, and A. Reigber. 2010. "Estimation of Forest Structure, Ground, and Canopy Layer Characteristics from Multibaseline polarimetric interferometric SAR Data." *IEEE Transaction on Geoscience and Remote Sensing* 40: 1086–104.

[xlvi] Lefsky, M. A. 2010. "A Global Forest Canopy Height Map from the Moderate Resolution Imaging Spectroradiometer and the Geoscience Laser Altimeter System." *Geophysical Research Letters* 37: L15401.
Simard, M., N. Pinto, J. B. Fisher, and A. Baccini. 2011. "Mapping Forest Canopy Height Globally with Spaceborne Lidar." *Journal of Geophysical Research – Biogeosciences* 116: G04021.

[xlvii] Dronova, I., L. Wang, and P. Gong. 2011. "Object-Based Analysis and Change Detection of Major Wetland Cover Types and Their Classification Uncertainty during the Low Water Period at Poyang Lake, China." *Remote Sensing of Environment* 115: 3220–36.

[xlviii] Cowardin, L. M. 1977. *Classification of Wetlands and Deep-Water Habitats of the United States*. Washington, DC: US Department of the Interior.

[xlix] Congalton, R. G. and K. Green (1999). *Assessing the Accuracy of Remotely Sensed Data: Principles and Practices*. Boca Raton, Lewis Publishers 160 pp.
Foody, G. M. (2002). "Status of land cover classification accuracy assessment." *Remote Sensing of Environment* **80**: 185-201.

[l] Brown, J. F., T. R. Loveland, D. O. Ohlen and Z. Zhu (1999). "The global land-cover characteristics database: The user's perspective." *Photogrammetric Engineering and Remote Sensing* **65**:1069-1074.

[li] Lark, R. M. (1995). "Components of accuracy of maps with special reference to discriminant analysis on remote sensor data." *International Journal of Remote Sensing* **16**: 1461-1480.
Boschetti, L., S. P. Flasse and P. A. Brivio (2004). "Analysis of the conflict between omission and commission in low spatial resolution dichotomic thematic products: The Pareto Boundary." *Remote Sensing of Environment* **91**: 280-292.

[lii] Swain, P. H. (1978). "Fundamentals of pattern recognition in remote sensing." In: *Remote Sensing: The Quantitative Approach*. P. H. Swain and S. M. Davis, Eds. New York, McGraw Hill, pp. 136-187.
Hammond, T. O. and D. L. Verbyla (1996). "Optimistic bias in classification accuracy assessment." *International Journal of Remote Sensing* **17**: 1261-1266.

[liii] Stehman, S. V. and R. L. Czaplewski (1998). "Design and analysis for thematic map accuracy assessment: Fundamental principles." *Remote Sensing of Environment* **64**: 331-344.
Stehman, S. V. (1995). "Thematic map accuracy assessment from the perspective of finite population sampling." *International Journal of Remote Sensing* **16**: 589-593.
Stehman, S. V. (1999*a*). "Basic probability sampling designs for thematic map accuracy assessment." *International Journal of Remote Sensing* **20**: 2423-2441.

[liv] Rosenfield, G. H., K. Fitzpatrick-Lins and H. S. Ling (1982). "Sampling for thematic map accuracy testing." *Photogrammetric Engineering and Remote Sensing* **48**: 131-137.
Thomas, I. L. and G. M. Allcock (1984). "Determining the confidence level for a classification." *Photogrammetric Engineering and Remote Sensing* **50**: 1491-1496.

[lv] Hagen, A. (2003). "Fuzzy set approach to assessing similarity of categorical maps." *International Journal of Geographical Information Science* **17**: 235-249.

[lvi] Estes, J., A. Belward, T. Loveland, J. Scepan, A. Strahler, J. Townshend and C. Justice (1999). "The way forward." *Photogrammetric Engineering and Remote Sensing* **65**: 1089-1093.
Loveland, T. R., Z. Zhu, D. O. Ohlen, J. F. Brown, B. C. Reed and L. Yang (1999). "An analysis of the IGBP global land-cover characterisation process." *Photogrammetric Engineering and Remote Sensing* **65**: 1021-1032.

[lvii] Gopal, S. and C. Woodcock (1994). "Theory and methods for accuracy assessment of thematic maps using fuzzy sets." *Photogrammetric Engineering and Remote Sensing* **60**: 81-188.
Foody, G. M. (1996). "Approaches for the production and evaluation of fuzzy land cover classification from remotely-sensed data." *International Journal of Remote Sensing* **17**:1317-1340.
Shalan, M. A., M. K. Arora and J. Elgy (2004). "CASCAM: Crisp and soft classification accuracy measurement software." In: *GeoDynamics: Modelling Spatial Change and Process*. P.M. Atkinson, G. M. Foody, S. E. Darby and F. Wu, Eds. Boca Raton, CRC Press, 440 pp.

[lviii] Smits, P. C., S. G. Dellepiane and R. A. Schowengerdt (1999). "Quality assessment of image classification algorithms for land-cover mapping: A review and proposal for a cost-based approach." *International Journal of Remote Sensing* **20**: 1461-1486.

[lix] Comber, A. J., P. F. Fisher and R. A. Wadsworth (2004). "Identifying land cover change using a semantic statistical approach." In: *GeoDynamics: Modelling Spatial Change and Process*. P. M. Atkinson, G. M. Foody, S. E. Darby and W. F., Eds. Boca Raton, FL, CRC Press, 440 pp.

[lx] Finn, J. T. (1993). "Use of average mutual information index in evaluating classification error and consistency." *International Journal of Geographical Information Systems* **7**: 349-366.

[lxi] Stehman, S. V. (2004*a*). "A critical evaluation of the normalized error matrix in map accuracy assessment." *Photogrammetric Engineering and Remote Sensing* **70**: 743-751.

[lxii] Congalton, R. G. (1991). "A review of assessing the accuracy of classifications of remotely sensed data." Remote Sensing of Environment 37: 35-46.

[lxiii] Carmel, Y. (2004). "Aggregation as a means of increasing thematic map accuracy." In: *GeoDynamics: Modelling Spatial Change and Process*. P. M. Atkinson, G. M. Foody, S. E. Darby and F. Wu, Eds. Boca Raton, FL, CRC Press, 440 pp.

[lxiv] Congalton, R G and Green, K., 2009 *assessing the Accuracy of Remotely Sensed Data: Principles and Practices*, 2nd edition, Boca Raton, Lewis Publishers.
[lxv] Story, M. and R. G. Congalton (1986). "Accuracy assessment: A user's perspective." *Photogrammetric Engineering and Remote Sensing* **52**: 397-399.

[lxvii] Trodd, N. M. (1995). *Uncertainty in land cover mapping for modelling land cover change*. Proceedings of RSS 95: Remote Sensing in Action, Nottingham, Remote Sensing Society, pp. 1138-1145.

[lxviii] Cohen, J. (1960). A coefficient of agreement of nominal scales. Educational and Psychological Measurement, 20, 37–46.

[lxix] Congalton, R. G., R. G. Oderwald and R. A. Mead (1983). "Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques." *Photogrammetric Engineering and Remote Sensing* **49**: 1671-1678.

[lxx] Congalton, R. G. (1991). A review of assessing the accuracy of classifications of remotely sensed data. Remote Sensing of Environment, 37, 35−46.

[lxxi] VISSER, H. and DE NIJS, T., 2006, The map comparison kit. *Environmental Modeling and Software*, **21**, pp. 346–358. ERDAS INC, 2008, Field Guide, Vol. 2 (Norcross, GA: Erdas).
EASTMAN, J.R., 2009, IDRISI Taiga Tutorial. Accessed in IDRISI 16.05 (Worcester, MA: Clark University).

[lxxii] Foody, G. M., 2008, Harshness in image classification accuracy assessment, *International Journal of Remote Sensing*, 29, 3137–3158.

[lxxiii] Robert Gilmore Pontius Jr & Marco Millones (2011): Death to Kappa: birth of quantity disagreement and allocation disagreement for accuracy assessment, *International Journal of Remote Sensing*, 32:15, 4407-4483. http://dx.doi.org/10.1080/01431161.2011.552923

[lxxiv] Ma, Z. and R. L. Redmond (1995). "Tau coefficients for accuracy assessment of classification of remote sensing data." *Photogrammetric Engineering and Remote Sensing* **61**: 435-439.
Foody, G. M., N. A. Campbell, N. M. Trodd and T. F. Wood (1992). "Derivation and applications of probabilistic measures of class membership from the maximum likelihood classification." *Photogrammetric Engineering and Remote Sensing* **58**: 1335-1341.

[lxxv] Lndis, J., Koch, G., 1977. The measurement of observer agreement for categorical data. Biometrics. 33, 159-174.

[lxxvi] Stehman, S.V., 2006. Design, analysis, and inference for studies comparing thematic accuracy of classified remotely sensed data: a special case of map comparison. *Journal of Geographical Systems*, 8, 209-226.

[lxxvii] Hargrove, W.W., Hoffman F.M., Hessburg P.F., 2006. Map curves: a quantitative method for comparing categorical maps. *Journal of Geographical Information Systems*, 8, 187-208

[lxxviii] Liu, C., Frazier P., and Kumar L., 2007. Comparative assessment of the measures of thematic classification accuracy. *Remote sensing of environment*, 107, 606-616.

[lxxix] Kuzera, K., and Pontius R.G. 2008. Importance of matrix construction for multiple-resolution categorical map comparison. *GIS and Remote Sensing*, 45(3): 249-274.

[lxxx] Mc Callum I., Obersteiner, Nilsson S., Shividenko A., 2006. A spatial comparison four satellite derived 1km global land cover datasets. International Journal of Applied Earth Observation and Geo-information, 8, 246-255.

[lxxxi] Hagen, A., 2002. Approaching human judgment in the automated comparison of categorical maps. Proceedings of the 4th International Conference on Recent Advances in Soft Computing, pp. 393-399, Nottingham(UK),December 2002.

[lxxxii] White, R., 2006. Pattern based map comparisons. *Journal of Geographical Systems*, 8, 145-164.

[lxxxiii] Pontius, R.G., and Cheuk M.L., 2006. A generalized cross-tabulation matrix to compare soft-classified maps at multiple resolutions. *International Journal of Geographical Information Science* 20(1), 1-30.
Pontius, R.G. and Connors J., 2009. Range of categorical associations for comparison of maps with mixed pixels. *Photogrammetric Engineering and Remote Sensing*, 75(8), 963-969.
Pontius R.G. and Suedmeyer, B., 2004. Components of agreement in categorical maps at multiple resolutions. In Remote Sensing and GIS Accuracy Assessment. R. S. Lunetta and J. G. Lyon (eds). CRC Press, Boca Raton FL. p.233-251.

[lxxxiv] Neteler, M., Bowman, M.H., Landa, M. and Metz, M. (2012): *GRASS GIS: a multi-purpose Open Source GIS*. Environmental Modelling & Software, 31: 124-130.

[lxxxv] Gallego, F.J. Carfagna, E., Peedell S., 1999, The use of CORINE Land Cover to improve area frame survey estimates. *Research in Official Statistics*, Vol 2, no 2, pp. 99-122

[lxxxvi] Bonomi, A., Scaramellini, G., Treu, M.C., Lanzani, A., Bolognesi, C., Pretolani ,R., Colucci, A., Agnoletti, M., Santoro, A., Pettenella, D., Sartori, F., Bracco F., Pileri P. (2012) Land cover changes in Lombardy over the last 50 years. Regione Lombardia, DG Agricoltura, Territorio e urbanistica, Sistemi verdi e paesaggio. ISBN 9788890584138

[lxxxvii] Bossard, M., Feranec, J., Otahel, J. (2000) CORINE Land cover Technical Guide- Addendum2000. Technical report No.40. Copenhagen(EEA). http://www.eea.europa.eu/publications/tech40add . Accessed 10 March 2014
Cohen, J. (1960). A coefficient of agreement of nominal scales. *Educational and Psychological Measurement*, 20: 37-46

[lxxxviii] Naesset, E. (1996). Use of weighted kappa coefficient in classification error assessment of thematic maps. International Journal of Geographical Information Systems, 10, 591– 604.
[lxxxix] Lark, R. M. (1995). Components of accuracy of maps with special reference to discriminant analysis on remote sensor data. International Journal of Remote Sensing, 16, 1461–1480.

[xc] Thomlinson, J. R., Bolstad, P. V., & Cohen, W. B. (1999). Coordinating methodologies for scaling land cover classifications from site-specific to global: steps toward validating global map products. Remote Sensing of Environment, 70, 16– 28.

[xci] Jun Chen. April-May 2014. “ISPRS supports Future Earth initiative with Global Land Cover Information”, GEO Informatics magazine for Surveying, mapping and GIS Professionals.