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Comparison of Global and Continental Land Cover Products for Selected Study Areas in South Central and Eastern European Region

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1   Information Technologies Institute, Centre for Research and Technology Hellas (CERTH), 57001 Thessaloniki, Greece
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Abstract: Land cover is one of the key terrestrial variables used for monitoring and as input for modelling in support of achieving the United Nations Strategical Development Goals. Global and Continental Land Cover Products (GCLCs) aim to provide the required harmonized information background across areas; thus, they are not being limited by national or other administrative nomenclature boundaries and their production approaches. Moreover, their increased spatial

resolution, and consequently their local relevance, is of high importance for users at a local scale. During the last decade, several GCLCs were developed, including the Global Historical Land-Cover Change Land-Use Conversions (GLC), the Globeland-30 (GLOB), Corine-2012 (CLC) and GMES/ Copernicus Initial Operation High Resolution Layers (GIOS). Accuracy assessment is of high importance for product credibility towards incorporation into decision chains and implementation procedures, especially at local scales. The present study builds on the collaboration of scientists participating in the Global Observations of Forest Cover—Global Observations of Land Cover Dynamics (GOFC-GOLD), South Central and Eastern European Regional Information Network (SCERIN). The main objective is to quantitatively evaluate the accuracy of commonly used GCLCs at selected representative study areas in the SCERIN geographic area, which is characterized by extreme diversity of landscapes and environmental conditions, heavily affected by anthropogenic impacts with similar major socio-economic drivers. The employed validation strategy for evaluating and comparing the different products is detailed, representative results for the selected areas from nine SCERIN countries are presented, the specific regional differences are identified and their underlying causes are discussed. In general, the four GCLCs products achieved relatively high overall accuracy rates: 74–98% for GLC (mean: 93.8%), 79–92% for GLOB (mean: 90.6%), 74–91% for CLC (mean: 89%) and 72–98% for GIOS (mean: 91.6%), for all selected areas. In most cases, the CLC product has the lower scores, while the GLC has the highest, closely followed by GIOS and GLOB. The study revealed overall high credibility and validity of the GCLCs products at local scale, a result, which shows expected benefit even for local/regional applications. Identified class dependent specificities in different landscape types can guide the local users for their reasonable usage in local studies. Valuable information is generated for advancing the goals of the international GOFC-GOLD program and aligns well with the agenda of the NASA Land-Cover/Land-Use Change Program to improve the quality and consistency of space-derived higher-level products.

1. Introduction

Standardized global and continental land cover (GCLC) products provide key terrestrial reference baseline data for numerous global, regional and national scale applications and inputs for large scale economic land use and ecosystem modelling. In the last decade, several global and continental land cover products of varied spatial resolution have been developed for example, Globeland-30, Corine-2012, GlobeCover-2009, Global Historical Land-Cover Change and Land-Use Conversions, UMD land-cover product [1]. Recent studies have shown that when global land cover products are compared, there are significant spatial disagreements across land cover types [2,3]. This is due to the actual thematic class definition, which can be quite different from product to product, the use of different satellite sensors, the classification methodologies and the lack of sufficient in situ data. Accurate datasets with estimates of the state and dynamics of terrestrial land cover are needed for environmental change studies, land resource management, climate modelling and sustainable development [4–8].

Validation is a crucial part of the land-cover mapping process, since without proper evaluation against higher-quality reference data, any land-cover map remains an untested hypothesis that cannot be used as basis for practical applications [9] and management decisions. Validation, as defined in the CEOS-LVP report (Committee in Earth Observation Satellites, www.ceos.org), is an established process including quality control, qualitative assessment, cross-comparisons, confidence maps and accuracy assessment. Several studies have validated global and continental land cover products to analyse their strengths and weakness. Different approaches exist for the high resolution GCLC products validation.

These include validation within the product development [10,11], or independent validation by third parties either reported in scientific literature [8,12,13] or requested by the agencies that are responsible for the product development [14]. The GCLC products are validated by different methods, for example, sample based validation using reference datasets [8,15–17] or inter-comparison with other well established products [10,18,19]. The authors [20] compared four satellite-derived 1 km land cover datasets (IGBP [21], UMD [22], GLC2000 [23] and MODIS [24]) based on the map of agreement of seven study areas around the globe. South America gained the highest (82%) agreement of the four global land cover datasets. The authors [3] found a critical disagreement in cropland and forest cover between a given pair of land cover maps (GlobCover, MODIS map and GLC-2000) using a concept of Minimum Measurable Disagreement [2,25]. The accuracy was 76%, 77% and 57.6% for the cropland and 81%, 80% and 60% for the forest, correspondently. The authors [8] reported the high weighted overall accuracy rates of 89%, 90% and 86% for CORINE Land Cover 2012, GIO High Resolution Layers and Globeland30 datasets, respectively, using analysis based on Google Earth imagery.

Though different aspects might be considered for the product validation (e.g., completeness, logical consistency, positional accuracy), thematic accuracy assessment represents the core part of the product validation. Error matrices and derived standard accuracy measures as overall accuracy, user´s and producer's accuracies are the commonly reported quantity allowing comparable and consistent accuracy assessment [26]. Therefore, thematic accuracy assessment was used in the present study for the validation of the GCLCs products in selected study areas of the SCERIN region. The specificity of the high resolution GCLC products is their wide coverage on one hand and their local relevance and local utility on the other hand [10]. From this respect, despite the validation of the GCLC products at broader scale, validation of the high resolution GCLC products in specific areas at local scale is important to deliver information on their local usability for the local applications.

This study represents a multinational coordinated effort in the region of South, Central and Eastern European Regional Information Network (SCERIN (http://csebr.cz/scerin/)), an established network of the Global Observation of Forest and Land Cover Dynamics (GOFC-GOLD) project of the Global Terrestrial Observation System (GTOS) (Figure 1), towards identifying possible discrepancies among the recently available land cover information in terms of accuracy and confidence. In particular, the study aims to contribute to the validation and comparison of four GCLCs products (GLCs, CORINE Land Cover 2012, GIO High Resolution Layers and Globeland30) against a common (more or less—see Section 2.4) validation dataset, that is, not directly among each other but indirectly through their accuracy assessment results with the status on the ground. The goal was to quantitatively and qualitatively assess the uncertainties of the considered products over selected representative study areas in the SCERIN region and in relation to land cover classes like arable land, impervious surfaces, forests and water bodies. The issue of validation for the GCLC products is highly topical for SCERIN scientists and professionals to support large-scale measurements of the ecosystem parameters and natural processes in the region. This effort aims to contribute to the goals of the international GOFC-GOLD program and furthers the agenda of the NASA LCLUC Program to improve the quality of space-derived higher-level products.
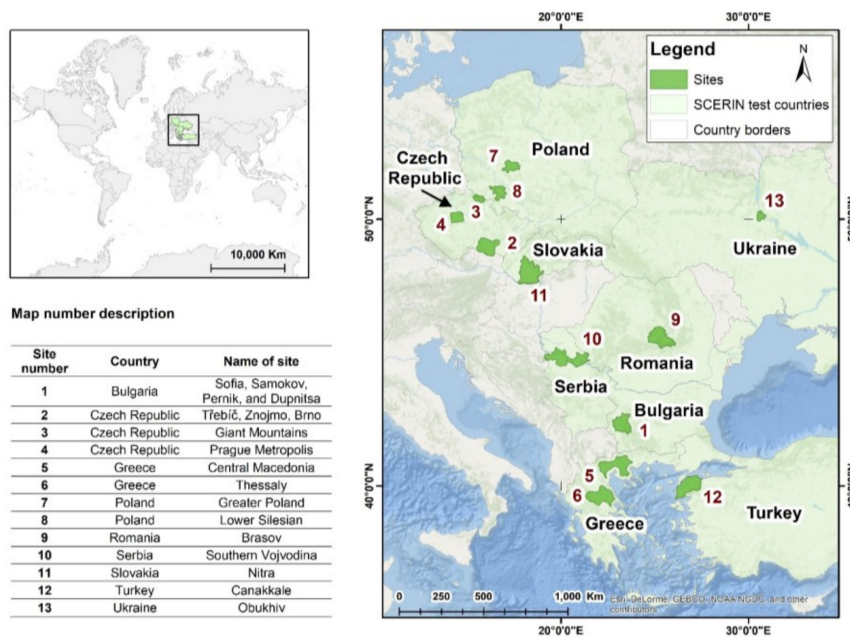
Figure 1. Study areas location with sites' numbers and names.

2. Materials and Methods

2.1. Study Areas

The SCERIN region is characterized by long-term heavy anthropogenic impacts with prevailing socio-economic drivers leading to intensive large-scale land cover and land use changes [27,28]. The 13 study areas cover 53,562 km^2 along a latitudinal as well as longitude transect in the region from Central (CZ, PL, UA) to South (GR, TR) Europe (Figure 1, Table 1). The study areas represent the diverse heterogeneity of the regions, expressed by different land cover and land use (LCLU) classes and elevation gradients (Figure 2). Most of the study areas include arable land, grassland, forest and urban areas. Several areas also include rare LCLU classes as pastures, barren land. Territorial differences in land cover and land use changes have been evident in the study areas since 1990. Countries in the central part of study area (e.g., CZ, SK, HU) have been affected by more intensive and wider spectrum of changes (often antagonistic: intensification and urbanization as well as land abandonment and afforestation). On the other hand, the southern countries (e.g., BG, GR) and the central parts of Poland and Romania experienced an overall lower intensity of changes. Significant changes occurred over agricultural land. Intensification of resources (mainly over-grazing) has been a prominent trend especially in Central Europe [27,29]. Urbanization has shown a trend of intensive increase, as well as population concentration in the big cities, towards which the main flow of investment have been aimed [30]. The main socio-economic drivers in Central and Eastern Europe are the transition from a rural to urban society and the shift in Central and Eastern Europe to post-socialism [31]. In addition, climate change continue to interfere with the anthropogenic factors in the region, with adverse consequences on ecosystem services and function [28]. The relevance of the selected study areas to the prevailing climatic conditions in the SCERIN region is of high importance and is evident in Figure 3.

Table 1. Geographic features of the areas used for validation.

N (Area, km^2)	Study Area Description
1 (3901)	**Bulgaria (BG) study area *Sofia*** consists of the following administrative units: *Pernik* municipality (477.2 km^2), *Dupnitsa* municipality (329.1 km^2), *Radomir* municipality (540.49 km^2), *Samokov* municipality (1209.9 km^2) and *Sofia City* municipality with the capital city of Sofia (1344 km^2). The land is predominantly mountainous. To the North are the southern slopes of the *Balkan* Mountains and to the south rises the *Rila* Mountains with the highest point in the Balkan Peninsula—*Musala* (2925 m a.s.l.). There are also several smaller mountains such as *Vitosha* (2290 m a.s.l.), *Plana* (1337 m a.s.l.), *Lyulin* (1256 m a.s.l.), *Lozenska* (1190 m a.s.l.) and spacious valleys such as Sofia's (1180 km^2, 550 m a.s.l.), Dupnitsa's (520–700 m a.sl.), Pernik (750 m a.sl.) and Samokov's (185 km^2, 950 m a.s.l) kettles. The study area has almost all land-cover types represented in Bulgaria, which imposed its choice. Google Earth dataset was used for the validation.
2 (3998)	**Czech Republic (CZ) study area *Třebíč-Znojmo-Brno*** is located in Moravian part of the country. The landscape is formed mainly by agricultural use with addition of forest, urban and water land covers. The area is characterized by elevational gradient from 150 m to 650 m a.s.l. and covers six agricultural climatic zones ranging from very warm to slightly cold. Google Earth dataset together with airborne hyperspectral data were used for the validation.
3 (803)	**Czech Republic (CZ) study area *Giant Mountains*** (Krkonoše Mts.) is located in northern part of the country, on the border with Poland. This area represents mountain and foothills landscapes. The area is characterized by elevational gradient from 450 m to 1300 m a.s.l. The mountainous part with its specific valuable ecosystems is protected as National Park. The most valuable ecosystems are natural forests and relict arctic tundra. The land cover in the mountainous part is composed mainly by forests, mountain meadows, pastures and alpine treeless areas (tundra). At the foothills landscape mosaics is composed of forests, agriculture land (meadows, pastures and arable land) and settlements (small towns and villages). Orthophotos were used for the validation of this area on the Czech territory, while Google Earth dataset was used for the Polish side.
4 (1620)	**Czech Republic (CZ) study area *Prague metropolis*** contains 224 municipalities of the Central Bohemia Region located in the immediate vicinity of Prague, where elevation ranges from 166 to 492 m a.s.l. The rapid growth of the town since 1990 has brought some negative aspects for the landscape. These are primarily urban sprawl and soil sealing. Suburbanization processes with the new residential development have been strongly concentrated, especially, in the most attractive localities in Prague's surrounding pristine areas where it often occupied very large areas. Agricultural areas have been lost due to the expansion of transport networks and construction accompanying development, as well. A combination of orthophotos and Google Earth dataset were used for the validation.
5 (6848)	**Greece (GR) study area *Central Macedonia*** is located in the northern part of the country in the Region of Central Macedonia, which is one of the thirteen administrative districts of Greece. A maximum elevation of the study area is of 1648 m a.s.l. It comprises of agricultural land, forests, inland waters and artificial surfaces. Agricultural activities involve management of both arable and irrigated crops, with high production of cereal, fruits and industrial plants. The region has a rich biodiversity within various ecosystems and numerous protected areas. A combination of orthophotos and Google Earth dataset were used for the validation.
6 (7060)	**Greece (GR) study area *Thessaly*** is located in the central part of the country and borders the regions of Western and Central Macedonia in the north, Epirus in the west, Central Greece in the south and the Aegean Sea in the east. The landscape is composed of mountainous parts in the perimeter and lowlands in the centre with a maximum elevation of 2917 m a.s.l. (Olympus mountain). It consists of high landscape and land cover diversity, including islands and main land in the same area, mountains and plain areas and mixed land use conditions. Google Earth images and WorldView 2 products [generated by NASA Goddard] were used for the validation.

Table 1. *Cont.*

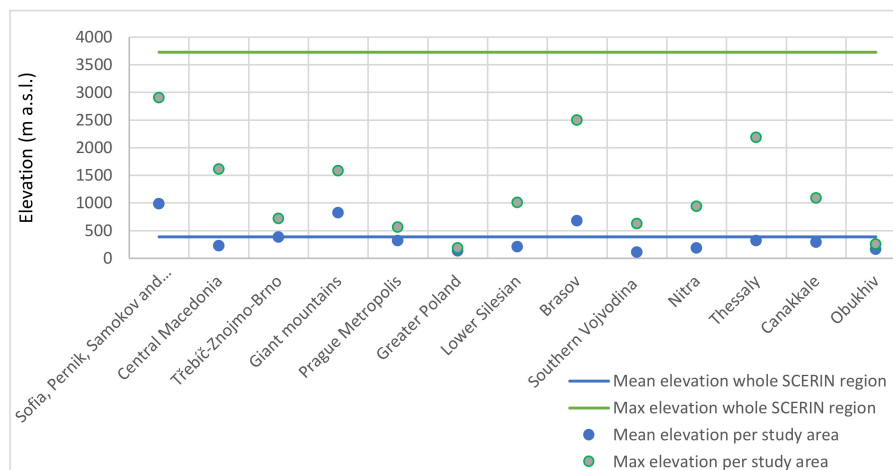| N (Area, km^2)	Study Area Description
7 (1582) & 8 (1786)	Two **Polish (PL)** study areas located in *Greater Poland* and in *Lower Silesian* voivodeships. Greater Poland area is a flat arable region with a maximum elevation of 174 m a.s.l. and large agriculture fields. Lower Silesian area is also a region with a dominant agriculture sector but smaller fields. The elevation is up to 941 m a.s.l in the Owl Mountains, Central Sudetes. Both areas are mainly featured by agricultural landscape (~80% for each) with addition of forest land cover (~15% and 11%, respectively) and artificial surface of 5% coverage each. The smallest land cover extent is the inland water, which occupies circa 1%. These areas were selected based on the criterion of demonstrating minimum CLC Changes between 2006 and 2012 [32]. Google Earth dataset was used to validate both study areas; additionally, for the Lower Silesian study area, the WorldView 2 [generated by NASA Goddard] products were used.
9 (5362)	**Romania (RO)** study area *Braşov* is situated in the centre of the country. It is characterized by a mountainous relief that occupies 40% of the area surface. The rest of the territory (60%) is mostly occupied by hilly areas and in a smaller proportion by plains. The maximum elevation is 2527 m a.s.l. in the Carpathian Mountains and the minimum 400 m a.s.l. in the Olt River floodplain. The land cover is well balanced between agricultural, pastures, forests and urban areas, making Brasov study area a representative area for the central part of SCERIN. Airborne images were used for the validation.
10 (6701)	**Serbia (RS)** study area *Southern Vojvodina* is located in the northern part of the county, along the southern boundary of the Vojvodina autonomous province and the southernmost periphery of the Carpathian basin. The land cover consists of arable land, forest, artificial surfaces, inland waters and urban areas, providing representativeness for larger regions of the Carpathian basin relevant to the SCERIN area. The agricultural lowlands range in elevation between 70 and 120 m a.s.l. These plains surround the low, gently sloping, forest covered isolated hills of Fruška gora National Park (539 m a.s.l.) and Vršac mountain (641 m a.s.l.) and the large, artificially afforested protected natural area of Deliblato sands. Inland waters are represented by wide flows of the Danube and Sava rivers and a number of lakes. Google Earth images were used for the validation.
11 (6404)	**Slovakia (SK)** study area *Nitra* represents the diverse Slovak landscape extending from Danube lowlands in the southern part, along river terraces and highlands up to Carpathian Mountains in the northern part with elevation range from 98 to 936 m a.s.l. Intensive agriculture (arable lands) dominates the study area. Forestry prevails in the mountains. Urban areas represent mainly small centralized villages and one metropolitan city (Nitra). Google Earth images were used for the validation.
12 (6735)	**Turkish (TR)** study area *Canakkale* province is located in the northwest part of the country, covering the survey area, excluding Imbros and Tenedos Islands and Gallipoli Peninsula. Besides the historical and cultural importance, the area serves as one of the two transitional crossroads that combine Europe and Asia. The area has complex topographic structure and the elevation ranges from the sea level at Dardanelles Strait up to 1741 m a.s.l. at mount Ida. The majority of the area is covered by different types of forests. Arable, urban and inland water land covers are also present on the study area. Google Earth dataset was utilized for the validation.
13 (762)	**Ukraine (UA)** study area Obukhiv is in Kyiv region, Obukhiv district, which is a part of the Joint Experiment for Crop Assessment and Monitoring (JECAM) FAO study area in Ukraine. This territory is an intensive agricultural area with moderately continental, mild climate and sufficient moisture and it demonstrates a lot of different land cover types with an elevation up to 252 m a.s.l. The crop calendar lasts from September till July for winter crops and from April to October for spring and summer crops. A typical field size is 30–250 ha. Crop types include winter wheat, winter rapeseed, spring barley, maize, soy beans, sunflower and sugar beet. Due to relatively large number of major crops and other socioeconomic factors there is no typical simple crop rotation in this region. Most producers use different crop rotations depending on specialization. The Google Earth dataset was used for the validation.

Figure 2. Elevation comparison between SCERIN and pilot areas (according to the 25 m European Digital Elevation Model [33].

Figure 3. Comparison of SCERIN mean meteorological conditions against the study areas' ones for the 1981–2010 interval (Latin numbers indicate the month or the year). (The data set used for climatic characterization of SCERIN and study areas is provided by Climatic Research Unit (CRU), University of East Anglia. The data set is a gridded time-series for air temperature and precipitation, for the 1981–2010, version 4.01 on 0.5° × 0.5° grid [34]).

2.2. Selection of Global and Continental Land Cover Products and Classes

The GCLC products, selected for analysis in this study include (Table 2):

- the Global Land Cover (GLC), which has been developed by USGS (The United States Geological Survey) in collaboration with the University of Maryland and the Department of Geographical Sciences. The purpose of the dataset was to register global forest changes [10]. The layers have been derived from Landsat 7 ETM+ data acquired between 2000 and 2012 using image interpretation methods [10], with a spatial resolution of 30 × 30 m (https://landcover.usgs.gov/glc/).
- the GlobeLand30 (GLOB), which is developed and distributed by the National Geomatics Centre of China. The main goal of the GLOB is to provide good quality information (land cover map) covering the entire Earth and complex spectral and textual characterization of global landscapes at medium to high resolution [15]. It has been developed using the pixel

and object-based methods applied on Landsat TM and ETM+ images and the multispectral images of China Environmental Disaster Alleviation Satellite (HJ-1) from 2010 with a 30 × 30 m resolution [15]. The classification system includes ten land cover types: cultivated land, forest, grassland, shrubland, wetland, water bodies, tundra, artificial surfaces, bare land, permanent snow and ice (http://www.globallandcover.com/GLC30Download/index.aspx).

- the Corine Land Cover 2012 (CLC), which is a land cover inventory (in 44 classes) project initiated in 1980s by the European Union, in order to support environmental policy development in Europe. It has been updated in 2000, 2006, 2012 and the latest started in 2016. The CLC dataset is generated at national level under the European Environment Agency (EEA) management and quality control (http://land.copernicus.eu/pan-european/corine-land-cover/clc-2012). Data used to derive the CLC 2012 classes are IRS P6 LISS III and Rapid Eye dual date from 2011 to 2012 with a 25 × 25 m resolution (http://land.copernicus.eu/pan-european/corine-land-cover). Computer assisted photo-interpretation (CAPI) is the mapping methodology used to obtain the dataset. The version of the CLC dataset, 18.5, is used for this study. The incorporation of CLC, although a land cover/ land use product, in the analysis is related with the fact that it is actually the main source of information that many environmental, climate, socioeconomic and so forth, studies are using for the area.

- GMES/Copernicus Initial Operation High Resolution Layers (GIOS), which represent land cover maps of European countries and address both the local component (i.e., the Urban Atlas (https://www.eea.europa.eu/data-and-maps/data/urban-atlas)) and the continental component. The main objectives of the GIOS are to monitor the land cover at a high spatial resolution and continental level and to assist major environmental issues, as soil sealing: imperviousness; and natural cover: forest, grassland, wetland and water bodies [35]. It is implemented by the European Environmental Agency under the Copernicus framework. The GIOS were obtained from the same satellite imagery as CLC (2011 to 2012), by semi - manual interpretation method, with a spatial resolution of 20 × 20 m (http://land.copernicus. eu/pan-european/high-resolution-layers).

Table 2. Main characteristics of used GCLC products.

GCLC Product	Data Source	Time Frame	Spatial Resolution	Classification Method	Provider
CLC	IRS P6 LISS III and Rapid Eye	2011–2012	25 × 25 m	Computer assisted photo-interpretation	European Environment Agency
GLOB	Landsat 5 TM and 7 ETM+	2010	30 × 30 m	pixel and object-based methods	National Geomatics Centre of China
GIOS	IRS P6 LISS III and Rapid Eye	2011–2012	20 × 20 m	semi-manual interpretation method	Environmental Agency under the Copernicus framework
GLC	Landsat 7 ETM+	2000–2012	30 × 30 m	image interpretation methods [10]	The United States Geological Survey and University of Maryland

For the validation and comparison purpose, four thematic LULC classes were determined: 'Agriculture' lands, 'Artificial' areas (e.g., urban, human-made constructions), 'Forest' areas having more than 10% of tree cover density (according to FAO definition [36]), 'Water bodies' and 'Other' areas.

2.3. GCLC Products' Pre-Processing

The four above listed openly available GCLC datasets were downloaded for the extent of SCERIN region and stored at raster format (Figures S1–S4 of the Supplementary Materials). The legends harmonization as an important requirement for the validation [29] was elaborated (see Table 3). Only comparable classes were assessed and the class 'Other' is the result of the merging of the rest of the classes and/or the unclassified areas in each specific GCLC. The importance of class 'Other' lies only in accounting for the possible bias, respectively to the reported accuracy assessment results, that a smaller or bigger percentage of a study area not to be considered might bring along, due to a) the

nature of the GCLC (e.g., the GLC or GIOS), which might not include all examined land cover classes and b) to the amount of the unclassified pixels (please see Section 2.4).

The CLC nomenclature comprises of three levels [37]. In this study Level-3 is not considered. Out of the 15 Level-2 thematic land use classes the ones present within the study area extent were merged to their respective higher hierarchical classes; thus, Level-2 classes were downscaled to Level-1 according to [8]. From the GLOB, four classes of following grid-code values were extracted: 10—'Arable Lands,' 20—'Forest,' 60—'Water,' 80—'Urban Area' and merged as the one layer. From GLC, tree cover and water layers were acquired as separate raster files. Only pixels with tree coverage above 10% were selected and merged with water into the final raster file. From the GIOS dataset, four layers were utilized: forest tree type, tree cover density, imperviousness and permanent water body. Broadleaf and Coniferous Forest types were initially selected, upon which the rule of tree cover density with value equal and higher than 10% was applied (according to [36]). The extracted pixels, forming the new forest layer were merged with the impervious and permanent water body layers into one final raster file. Eventually, four final raster files for the four GCLC products were clipped to each study area extent. The remaining land cover areas for each study region were classified as 'Other' class.

Table 3. The corresponding LC classes between the different employed GCLC products.

General Class	CLC Class	GLOB Class	GIOS Class	GLC Class
Agriculture	2. Agricultural Areas	Arable Lands (code 10)	-	-
Artificial	1. Artificial Surfaces	Urban area (code 80)	Imperviousness	-
Forest	3. Forest and Semi-Natural Areas (only 3.1.)	Forest (code 20)	Broadleaf and coniferous forests with tree cover density of 10% and more	Tree cover with density 10% and more
Water	5. Water Bodies (only 5.1.)	Water (code 60)	Permanent water body	Water
Other	All other areas	All other areas	All other areas	All other areas

2.4. Sampling Methodology

SCERIN region comprises of a very large area with a diverse landscape, climatic and land use variability depending on the location and country. 13 study areas differing in size and landscape type were selected in order to analyse validity and accuracy performance of the GCLCs at the local scale. Thus, a rigorous sampling design was developed. Samples are derived following a comprehensive sampling procedure based on each layer's percentiles of each subset area class, as follows:

1. The **size of the sample** that forms the validation dataset for each study area is designed to satisfy the approach proposed by Foody (2009) for defining the testing set in remote sensing studies. More analytically, this approach is applied using the equation:

$$n = \frac{z_{a/2}^2 P(1 - P)}{h^2} \tag{1}$$

where n is the sample size, $z_{a/2}$ the critical value of the normal distribution for the two-tailed significance level α, P is a planning value for the correctly allocated cases population proportion and h the half width of the desired confidence interval. Here a typically adopted 0.05 significance level giving a $z_{a/2}$ equal to 1.96 considered. A large conservative value for P of 0.5 and a confidence interval between $\pm 4\%$ up to $\pm 5\%$ were used. For a h of 0.04 applying the Equation (1) results to an estimation of sample size of 601 samples and for the value 0.05, 385 samples. On top of this result and in order to account for the size of each subset area, a maximum of 1000 sample points was set for the biggest study area. For smaller areas a percentile of the 1000 points was defined, based on their extent. However, a minimum of 500 points was set as a rule, too. This means that each study area had to provide 500 to 1000 validation points.

2. In relation with the **number of sample points per class and layer**, a stratified random sampling design [16,38,39] was employed based on the area fraction of each Level 1 CLC subclass to the total cover area. In order to address significant low sample sizes, a minimum of 20 sample points per Level 1 CLC class is set (i.e., 2% of the maximum possible 1000 sample points). More specifically, the minimum of 20 sample points is given to each Level 1 CLC category that was attributed with less than twenty

sample points, whereas the additional ones increased the total number of sample points interpreted for the area.

Sample points were randomly selected with the stratified approach for each GCLC, based on each of the other three GCLC layers to be examined; thus, the validation dataset was at the end unique and appropriate for each GCLC. The percentiles of coverage extent of each high-level category ('Water,' 'Forest,' 'Agriculture,' 'Imperviousness' and 'Others') were estimated. Parts of the percentiles coincided at all layers. Those sample points were kept in the database for all GCLC layers to facilitate the interpretation procedure. Parts of the percentiles differed and as a result an additional number of points per land cover layer was introduced (Figure 4). So, some of the validation points were the same across the GCLC classes, while a smaller or bigger percentage of them differed.

In cases that the 'Other' class' area was larger than 50% of the total area, the number of the sample points was increased, so that the rest classes' sample points account for at least 50% of the sample dataset. This way the result was maintained as unbiased as possible. The latter procedure resulted in more sample points in total than shall have been according to the original calculation for the total area of the whole study area (Table 4).
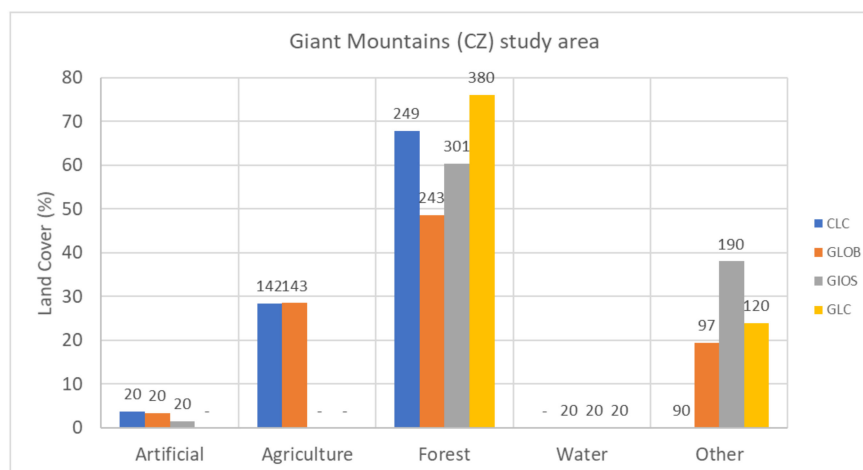

Figure 4. Land Cover % at the Giant Mountains (CZ) study area, as an example of the diverse land cover % present at the various GCLCs (numbers on top of the columns present the number of samples taken for each class validation).

Table 4. Final Number of Sampling Points per study area.

Study Areas	Sample Size (CLC)	Sample Size (GLOB)	Sample Size (GIOS)	Sample Size (GLC)
Giant Mountains (CZ)	501	523	531	520
Třebíč-Znojmo-Brno (CZ)	599	585	848	801
Prague metropolis (CZ)	532	523	912	853
Greater Poland (PL)	539	534	802	840
Lower Silesian (PL)	537	531	828	839
Thessaly (GR)	1010	1019	1730	1790
Central Macedonia (GR)	974	981	1323	1577
Nitra (SK)	903	917	1158	1607
Canakkale (TR)	946	941	1561	942
Obukhiv (UA)	-	500	-	532
Brasov (RO)	751	755	814	796
Sofia, Pernik, Samokov and Dupnitsa (BG)	644	643	815	-
Southern Vojvodina (RS)	925	925	1104	1069
TOTAL	8861	9377	12,426	12,166

2.5. Ground Truth Data and Uncertainty Assessment

The reference data were manually generated based on existing orthophoto material, WorldView 2 very high resolution imagery (HRs) or Google Earth (GEs) from the same year and a date, as close to

the date of the raw image acquisition (DRIA) (from which the GCLC layer at the respective location was generated) as possible (closest DRIA). Multisource data made possible to retrieve information close prior and close after the DRIA and were complementary considered to the closest DRIA, if appropriate (e.g., for water bodies class cases). This way, the possibility of misclassification due to LULC seasonal/temporal changes was reduced. Especially for the HRs, the multispectral images, centred on the required dates were selected from the DigitalGlobe archive and retrieved through the NASA-NGA Commercial Archive data portal (http://cad4nasa.gsfc.nasa.gov/), as L1B radiometrically and sensor corrected imagery. They were stored and processed on the GSFC/ADAPT cloud within the specifically designated environment. To derive validation PDF products, the data was ortho-rectified, using a 30 m digital elevation model (DEM) available from USGS, projected to Universal Transverse Mercator coordinate system (UTM, World Geodetic System 1984). All images were merged into a new false colour raster composite, considering all available images and making a pixel selection to minimize the presence of clouds, shadows and snow.

The decision about the real cover on the ground considered the surrounding area of the sampling point over HRs or GEs, using a 60 m × 60 m buffer zone around the point. In case of 30 × 30 m resolution layers this means ±1 pixel, which shall cover for the georegistration uncertainty observed, evident also in a smaller extent (at the range of a few meters), as reported by [40–42] in most recent studies for the GE images. Especially [43] note for the GE images situation back in 2008 that the horizontal positional accuracy of the GE images is sufficient for assessing remote sensing products at a Landsat relevant spatial resolution across most of the world's peri-urban areas; finding out that accuracy is higher in developed countries (RMSE of 24.1 m). Interpreters' opinion was additionally weighted by the interpreter him/herself. In this context, each interpreter provided a confidence level to handle the uncertainty for each and every annotation during the generation of the ground truth database. Three confidence levels were assigned as #1 for >75% confidence level, #2 for 25–75% confidence level and #3 for confidence level below 25% [8]. For example, #3 would mean that the exact geolocation belongs to A class, while all the surrounding pixels indicate that this is not correct and it shall be registered as B class; however, due to the fact that A is exact at the point, the interpreter assigned class A to it, while indicating a #3 confidence level. The confidence level slicing was used this way, as it is easy to understand and implement by the interpreter, whether he or she are certain (i.e., #1) or not certain (i.e., #2) that this is the case, or rather certain that this is not the case (i.e., #3) of the reality registered on the image due to its lower spatial resolution. Worth to mention that interpreters are experienced personnel working with remote sensing datasets frequently in land cover/ use topics and they were trained following specific jointly developed guidelines through the three years process and development of this study and extensive technical meetings.

2.6. Accuracy Assessment Incorporating Confidence Level Evaluation

A confusion matrix approach, per confidence level, was used to validate the performance of each GCLC map. This method reflects the agreement between each GCLC and the ground truth [17,44–46], using four accuracy measures: the producer's accuracy (PA), the user's accuracy (UA), the overall accuracy (OA) and the kappa coefficient, based on errors of omission and commission on the non-diagonal lines of the confusion matrix (rows and columns). Equation (2) calculates the incorporation of the confidence parameter to the validation process,

$$wA \; = \; \frac{\sum_{i=1}^{3} w_i \, * \, N_i \, * \, A_i}{\sum_{i=1}^{3} w_i \, * \, N_i} \tag{2}$$

where w_i is the given weight for the i confidence level, N_i the number of observations and A_i the achieved accuracy metric rate for the given confidence group. Based on the methodology used in Reference [8] the different weights are calculated using the median of the confidence level, defined based on the percentage range, that is, 87.50 for 75–100% (#1), 50.00 for 25–75% (#2) and 12.50 for

0–25% (#3). Then the corresponding weight w_i for each confidence class was 0.583 for confidence level #1, 0.333 for #2 and 0.083 for #3.

3. Results

3.1. Accuracy Assessment per GCLC

The validation process indicated that the four GCLCs products show a rather good OA at the studied SCERIN areas. In particular, the resulting weighted OA was in most cases over 85%, while in a few cases below but not less than 70% (Figure 5). In most cases, the CLC has the lower scores, while the GLC the higher ones closely with GIOS and GLOB.
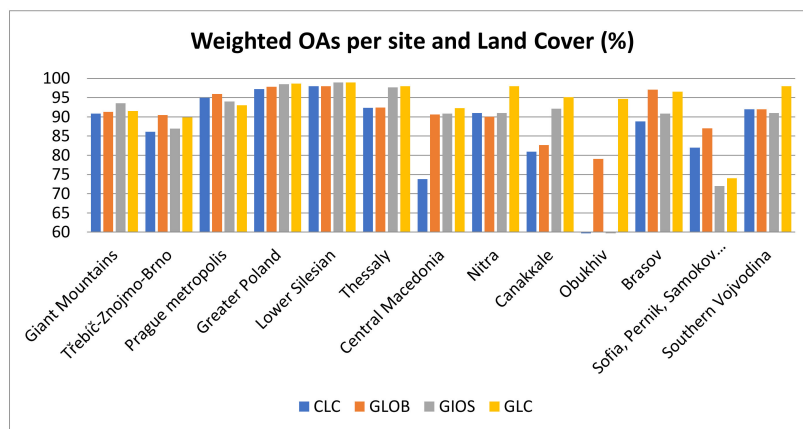

Figure 5. Weighted overall accuracy (OA) rates per area and GCLC layer.

Additional information for each product per LC class is presented in Tables 5–9. In particular, the resulting UAs of CLC (Table 5) indicated a relative low performance (OA below 60%) of 6.39% of all cases for the 'Artificial' and the 'Water' classes, while 10.64% of all cases lower accuracy (60–75%) for the same classes. By GLOB (Table 6) percentages decrease to 3.84% and 7.68%, respectively. GIOS (Table 7) with the 'Agriculture' class missing show lower accuracies in 8.34% of all cases, equally divided to 'Artificial,' 'Forest' and 'Water' classes. Finally, GLC (Table 8) with the 'Artificial' and the 'Agricultural' classes being omitted demonstrates 3.84% with lower accuracy for the 'Water' class (Figure S1).

Table 5. CLC User's Accuracy and Overall accuracy (wOA) metrics following the implementation of Confidence levels, the non-weighted Overall Accuracy (OA) and the percentage difference (Δ) of weighted and non-weighted OAs (in bold numbers the accuracies of the dominant land cover categories of the specific study area).

	CLC						
	Class				OA (in %)	wOA (in %)	Δ (in %)
Study Area	Artificial	Agriculture	Forest	Water			
	Weighted User's | Producer's Accuracy (in Rounded %)						
Giant Mountains (CZ)	73 | 87	**86 | 92**	95 | 93	- | -	86.00	91.00	5.00
Třebíč-Znojmo-Brno (CZ)	88 | 59	**89 | 95**	84 | 86	70 | 100	84.00	86.00	2.00
Prague metropolis (CZ)	94 | 95	**96 | 98**	90 | 90	65 | 75	79.00	95.00	16.00
Greater Poland (PL)	85 | 72	**98 | 98**	95 | 100	100 | 100	97.00	97.00	0.00
Lower Silesian (PL)	100 | 86	**98 | 99**	90 | 95	100 | 95	97.00	98.00	1.00
Thessaly (GR)	62 | 98	**97 | 98**	98 | 72	98 | 99	91.00	92.00	1.00
Central Macedonia (GR)	29 | 45	**84 | 92**	95 | 46	62 | 85	73.00	74.00	1.00
Nitra (SK)	76 | 90	**89 | 97**	98 | 76	94 | 88	85.00	91.00	6.00
Canakkale (TR)	78 | 63	**80 | 66**	89 | 94	93 | 89	79.00	81.00	2.00
Obukhiv (UA)	-	**-**	-	-	-	-	-
Brasov (RO)	81 | 78	**90 | 89**	94 | 90	32 | 100	87.00	89.00	2.00
Sofia, Pernik, Samokov and Dupnitsa (BG)	99 | 95	**91 | 100**	99 | 79	91 | 95	80.00	82.00	2.00
Southern Vojvodina (RS)	57 | 85	**93 | 98**	94 | 77	92 | 96	86.00	92.00	6.00

Table 5. *Cont.*

Study Area	Artificial	Agriculture	Forest	Water	OA (in %)	wOA (in %)	Δ (in %)
	CLC						
	Class						
	Weighted User's | Producer's Accuracy (in Rounded %)						
Cases divided by All Cases					*Sum of Cases (horizontal addition)*		
Cases of lower accuracy (60–75%)	4.26 | 4.26	0.00 | 2.13	0.00 | 2.13	6.38 | 2.13	10.64 | 10.65		
Failures (accuracy <60%)	4.26 | 4.26	0.00 | 0.00	0.00 | 2.13	2.13 | 0.00	6.39 | 6.39		

Table 6. GLOB User's Accuracy and Overall accuracy (wOA) metrics following the implementation of Confidence levels, the non-weighted Overall Accuracy (OA) and the percentage difference (Δ) of weighted and non-weighted OAs (in bold numbers the accuracies of the dominant land cover categories of the specific study area).

Study Area	Artificial	Agriculture	Forest	Water	OA (in %)	wOA (in %)	Δ (in %)
	GLOB						
	Class						
	Weighted User's | Producer's Accuracy (in Rounded %)						
Giant Mountains (CZ)	84 | 83	**86 | 96**	95 | 92	83 | 96	87.00	92.00	5.00
Třebíč-Znojmo-Brno (CZ)	91 | 92	**92 | 96**	89 | 85	60 | 100	89.00	90.00	1.00
Prague metropolis (CZ)	96 | 94	**96 | 99**	96 | 96	97 | 97	81.00	96.00	15.00
Greater Poland (PL)	85 | 59	**99 | 98**	94 | 100	100 | 94	98.00	98.00	0.00
Lower Silesian (PL)	100 | 95	**99 | 100**	93 | 82	87 | 43	97.00	98.00	1.00
Thessaly (GR)	88 | 100	**97 | 96**	98 | 76	100 | 98	91.00	93.00	2.00
Central Macedonia (GR)	57 | 58	**91 | 98**	97 | 84	100 | 100	90.00	91.00	1.00
Nitra (SK)	87 | 91	**82 | 98**	97 | 61	98 | 93	88.00	90.00	2.00
Canakkale (TR)	83 | 76	**92 | 79**	84 | 95	84 | 87	80.00	83.00	3.00
Obukhiv (UA)	54 | 98	**86 | 84**	91 | 74	97 | 96	75.00	79.00	4.00
Brasov (RO)	89 | 19	**91 | 91**	96 | 90	73 | 100	87.00	89.00	2.00
Sofia, Pernik, Samokov and Dupnitsa (BG)	81 | 95	**63 | 100**	98 | 89	97 | 100	83.00	87.00	4.00
Southern Vojvodina (RS)	64 | 16	**94 | 99**	90 | 83	91 | 97	90.00	92.00	2.00
Cases divided by All Cases					*Sum of Cases (horizontal addition)*		
Cases of lower accuracy (60–75%)	1.92 | 0.00	1.92 | 0.00	0.00 | 3.84	3.84 | 0.00	7.68 | 3.84		
Failures (accuracy < 60%)	3.84 | 7.69	0.00 | 0.00	0.00 | 0.00	0.00 | 1.92	3.84 | 9.61		

Table 7. GIOS User's Accuracy and Overall accuracy (wOA) metrics following the implementation of Confidence levels, the non-weighted Overall Accuracy (OA) and the percentage difference (Δ) of weighted and non-weighted OAs (in bold numbers the accuracies of the dominant land cover categories of the specific study area).

Study Area	Artificial	Agriculture	Forest	Water	OA (in %)	wOA (in %)	Δ (in %)
	GIOS						
	Class						
	Weighted User's | Producer's Accuracy (in Rounded %)						
Giant Mountains (CZ)	92 | 100	-	**95 | 94**	84 | 100	87.00	94.00	7.00
Třebíč-Znojmo-Brno (CZ)	96 | 47	-	**91 | 98**	77 | 95	85.00	87.00	2.00
Prague metropolis (CZ)	95 | 94	-	**93 | 96**	70 | 99	83.00	94.00	11.00
Greater Poland (PL)	94 | 92	-	**99 | 100**	100 | 97	99.00	99.00	0.00
Lower Silesian (PL)	99 | 96	-	**98 | 99**	100 | 93	98.00	99.00	1.00
Thessaly (GR)	97 | 99	-	**97 | 98**	100 | 98	95.00	98.00	3.00
Central Macedonia (GR)	78 | 91	-	**89 | 92**	100 | 97	89.00	91.00	2.00
Nitra (SK)	87 | 87	-	**89 | 90**	100 | 97	90.00	91.00	1.00
Canakkale (TR)	95 | 62	-	**94 | 92**	92 | 84	91.00	92.00	1.00
Obukhiv (UA)	-	-	**-**	-	-	-	-
Brasov (RO)	85 | 97	-	**96 | 98**	100 | 100	89.00	91.00	2.00
Sofia, Pernik, Samokov and Dupnitsa (BG)	81 | 97	-	**97 | 100**	99 | 99	58.00	72.00	14.00
Southern Vojvodina (RS)	65 | 46	-	**65 | 100**	96 | 100	91.00	91.00	0.00
Cases divided by All Cases					*Sum of Cases (horizontal addition)*		
Cases of lower accuracy (60–75%)	2.78 | 2.78	-	2.78 | 0.00	2.78 | 0.00	8.34 | 2.78		
Failures (accuracy <60%)	0.00 | 5.56	-	0.00 | 0.00	0.00 | 0.00	0.00 | 5.56		

Table 8. GLC User's Accuracy and Overall accuracy (wOA) metrics following the implementation of Confidence levels, the non-weighted Overall Accuracy (OA) and the percentage difference (Δ) of weighted and non-weighted OAs (in bold numbers the accuracies of the dominant land cover categories of the specific study area).

Study Area	GLC						
	Class				OA (in %)	wOA (in %)	Δ (in %)
	Artificial	Agriculture	Forest	Water			
	Weighted User's | Producer's Accuracy (in Rounded %)						
Giant Mountains (CZ)	-	-	**89 | 97**	97 | 95	90.00	92.00	2.00
Třebíč-Znojmo-Brno (CZ)	-	-	**77 | 94**	79 | 100	87.00	90.00	3.00
Prague metropolis (CZ)	-	-	**90 | 99**	80 | 99	83.00	93.00	10.00
Greater Poland (PL)	-	-	**100 | 98**	100 | 100	99.00	99.00	0.00
Lower Silesian (PL)	-	-	**99 | 93**	100 | 100	96.00	99.00	3.00
Thessaly (GR)	-	-	**98 | 99**	100 | 94	97.00	98.00	1.00
Central Macedonia (GR)	-	-	**93 | 92**	100 | 93	92.00	92.00	0.00
Nitra (SK)	-	-	**96 | 99**	100 | 98	97.00	98.00	1.00
Canakkale (TR)	-	-	**97 | 93**	89 | 84	94.00	95.00	1.00
Obukhiv (UA)	-	-	**97 | 95**	96 | 98	92.00	95.00	3.00
Brasov (RO)	-	-	**96 | 99**	74 | 100	96.00	97.00	1.00
Sofia, Pernik, Samokov and Dupnitsa (BG)	-	-	**100 | 97**	100 | 100	71.00	74.00	3.00
Southern Vojvodina (RS)	-	-	**97 | 68**	100 | 100	92.00	98.00	6.00
Cases divided by All Cases					*Sum of Cases (horizontal addition)*		
Cases of lower accuracy (60–75%)	-	-	0.00 | 3.84	3.84 |0.00	3.84 | 3.84		
Failures (accuracy < 60%)	-	-	0.00 | 0.00	0.00 | 0.00	0.00 | 0.00		

Table 9. GCLC (CLC, GLOB, GIOS or GLC) is presented, which achieves higher accuracy (UA and PA) in mapping the respective land cover per study area. Cases, where more than one GCLCs are performing equally, are presented by listing more than one GCLC at a time.

Study Area	Class			
	Artificial	Agriculture	Forest	Water
	GCLC Achieving Higher Accuracy Based on Weighted User's | Producer's Accuracy			
Giant Mountains (CZ)	GIOS | GIOS	CLC, GLOB | GLOB	CLC, GLOB, GIOS | GLC	GLC | GIOS
Třebíč-Znojmo-Brno (CZ)	GIOS | GLOB	GLOB | GLOB	GIOS | GIOS	GLC | CLC, GLOB, GLC
Prague metropolis (CZ)	GLOB | CLC	CLC, GLOB | GLOB	GLOB | GLC	GLOB | GLC
Greater Poland (PL)	GIOS | GIOS	GLOB | CLC, GLOB	GLC | CLC, GLOB, GIOS	CLC, GLOB, GIOS, GLC | CLC, GLC
Lower Silesian (PL)	CLC, GLOB | GIOS	GLOB | GLOB	GLC | GIOS	CLC, GIOS, GLC | GLC
Thessaly (GR)	GIOS | GLOB	CLC, GLOB | CLC	CLC, GLOB, GLC | GLC	GLOB, GIOS, GLC | CLC
Central Macedonia (GR)	GIOS | GIOS	GLOB | GLOB	GLOB | GIOS, GLC	GLOB, GIOS, GLC | GLOB
Nitra (SK)	GLOB, GIOS | GLOB, GIOS	CLC | GLOB	CLC | GLC	GIOS, GLC | GLC
Canakkale (TR)	GIOS | GLOB	GLOB | GLOB	GLC | GLOB	CLC | CLC
Obukhiv (UA)	GLOB | GLOB	GLOB | GLOB	GLC | GLC	GLOB | GLC
Brasov (RO)	GLOB | GIOS	GLOB | GLOB	GLOB, GIOS, GLC | GLC	GIOS | CLC, GLOB, GIOS, GLC
Sofia, Pernik, Samokov and Dupnitsa (BG)	CLC | GIOS	CLC | CLC, GLOB	GLC | GIOS	GLC | GLOB, GLC
Southern Vojvodina (RS)	GIOS | CLC	GLOB | GLOB	GLC | GIOS	GLC | GIOS, GLC

3.2. Comparison between Weighted and Standard overall Accuracy Metrics

In this section, a comparison between the OA and weighted OA is presented based on the resulting accuracy levels by integrating the confidence levels that were assigned by the experts during the photo-interpretation. In Tables 5–8, the OA, weighted OA and the calculated differences between them are presented. Generally, the wOA increased in all cases by an average 2%. In certain cases, while the confidence level reduced, the OA reduced as well. Representative examples are the cases of Prague and Brasov where this observation is valid for all the GCLC datasets. This is expected, because confidence level 2 and 3 observations refer to difficult photo-interpretation cases. Usually, these were

observed in regions with complex terrain or for points lying on the edge of a class or on the borders of two classes and therefore they are mostly associated with classification errors.

The pattern is similar when the comparison is made between OA and weighted OA per GCLC layer of all studied areas (Figures S2–S4). In Figure 6, one can observe the calculated difference (Δ) between standard OA and weighted OA. For all the cases the metric increased by 3.3–4.7% following the incorporation of the confidence levels in the accuracy assessment. The greater increase occurs for the OA of CLC (by 4.7%) and GIOS (by 4.5%) and the smallest for the GLC and GLOB (by ~3.3%). That variability is due to the fact that a large number of commission errors attributed with a confidence level of #2 or #3, was eliminated when the weighted OA was calculated; because of the lower weight given in the confidence level #2 and #3 observations during the calculations.

Figure 6. Overall Accuracy (OA) and weighted OA (wOA) per land cover map for the selected study areas in SCERIN.

4. Discussion

4.1. CLC

CLC is the flagship land cover mapping product of the European Copernicus program delivered to the public through the Copernicus land services (https://land.copernicus.eu/pan-european). In the case of CLC the accuracy can be influenced by minimal mapping unit that is set on 25 hectares for areal phenomena and a minimum width of 100 m for linear phenomena. The pixel size of IRS P6 LISS III data that is used for CLC 2012 classification is 24 × 24 m. This resolution could enable more precise mapping without the generalization caused by MMU use [47,48]. The programmatic aim for the thematic accuracy of the product was set to 85% OA and this aim was achieved at the European reporting level based on independent validation [14]. Specifically, the OAs obtained for CLC were 83.6% for the blind analysis and 89.7% for the plausibility analysis (double check of the misclassification cases by the experts). In this study, except three cases (Central Macedonia, Canakkale and Sofia, Pernik, Samokov and Dupnitsa), the 85% aim was confirmed in each case study area at the defined level of class aggregation. However, the great variability of OA values is visible in the results and ranges from 73% in Central Macedonia to 97% in Greater Poland. Regional variability of OAs was also reported in the EEA validation [14], in general being the lower in Anatolian and Black Sea region (e.g., Turkey—78.61%, Romania—78.9%) and tends to be higher in the continental region (e.g., Poland—92.06%) [13]. Several reasons could explain these differences in our study. The misclassification reasons refer to the complexity of the CLC nomenclature and class definition what might resulted in several interpretations for a given land unit. Misclassifications of forest are well known and are also reported in the EEA validation report [13], where authors stated that this is mainly because of complicated class definition of 'Transitional Woodland,' which might characterize both the physiognomic state of the vegetation or a dynamic aspect of the vegetation, which may lead to possible confusion with forest according to the forest growing (311 'Broad-Leaved Forest'/312 'Coniferous Forest'/313 'Mixed Forest') or 321 'Natural Grassland'/323 'Sclerophylous Vegetation' in clear cut areas and abandoned lands. In addition, production of CLC and resulted omission and commission error

rates of 324 vary a lot across countries. This was also the case in the Thessaly and Central Macedonia study areas, where high omission rates of forests are registered. Furthermore, landscape complexity described by the fine-grained structure and occurrence of small patches of land units of different land covers and high minimal mapping unit (MMU) of CLC can justify the regional differences of the accuracy performance of CLC. This type of landscape is included in so called "aggregated" classes in CLC (e.g., 242, 243 'Heterogeneous Agricultural Areas,' including the 'Complex Cultivation Pattern' and the land principally occupied by 'Agriculture with Significant Areas of Natural Vegetation'). These classes in general were underestimated in the CLC production [14]. Though they belong to agricultural classes at higher hierarchical level of classification, they might include substantial portion of forests (small forest patches in complex agricultural areas), shrubs (both natural shrubs in Central Macedonia, Sofia, Pernik, Samokov and Dupnitsa or abandoned overgrown pastures, vineyards and orchards in Nitra and Canakkale study areas), artificial surfaces (sparse residential areas within the complex agricultural areas in Central Macedonia, Třebíč-Znojmo-Brno, Greater Poland and Lower Silesian). In general, if proportion of heterogeneous agriculture areas is high in CLC production, the underestimation of forests, shrubs or artificial surfaces might be likely the case.

4.2. GLOB

Contrary to the CLC, GLOB has not been systematically validated at global level, since this is a very challenging task. Instead, different independent validation studies at different scales (reporting levels) and different landscapes had been reported in scientific literature [49]. The study of [15] estimated 80% OA based on 8 selected study areas with differing landscapes at five different continents. Out of these, 2 study areas belong to Europe, namely Sweden and Spain reaching OA of 81.99% and 84.73%, respectively. The authors of [12] reported OA values from 81% to 92% for 8 regions in Italy. Applicability of GLOB for local studies had been analysed in the Thessaly Mediterranean region, where OA reached 90% [8] and South-West Germany with OA of 85.3% [50]. In our study, relatively good results of thematic accuracy were achieved, with OA ranging from 75% (Obukhiv) to 98% (Greater Poland). Furthermore, there was not that big variability of OA values compared to CLC among the study areas. Except Obukhiv and Canakkale, all study areas reached the OA above 80% and wOA greater than 87%. We think that this could be caused by the consistent approach used for the product production in the whole region [15]. Per class assessment revealed lowest PA performance for the class 'Artificial,' followed by 'Forest.' Latter was mainly due to the dominant proportion of 'Shrublands' and 'Natural Grasslands' in the studied areas. Relatively lower values of accuracies are also reported from Thessaly [8] and Ukraine [51]. In Nitra case, these were mainly overgrown vineyards and orchards, abandoned agricultural fields in Sofia, Pernik, Samokov and Dupnitsa and natural shrub lands in Canakkale and Central Macedonia that were mistakenly classified as agricultural areas. This could be explained by two reasons. Firstly, GLOB production method uses specific texture information and regular distribution pattern of cultivated lands for the agricultural land extraction. In fact, overgrown abandoned agricultural lands may still reflect this pattern, though they are not managed anymore and represent shrublands in reality. In Canakkale, however, it could be explained mainly with scale effect and a situation, where small scattered cultivated lands are within the large areas of shrublands. In comparison to the CLC, GLOB does not have specified a MMU but the method used different scaling parameters for image segmentation in the early phase of the classification, which may lead to aggregation of small patches with larger neighbouring objects/parcels. This was also the reason for misclassifications of class 'Artificial' with 'Agriculture' leading to relatively high omission rates and underestimation of residential areas in Třebíč-Znojmo-Brno, Brasov and Greater Poland and oppositely, in high commission error rates and overestimation of residential areas in Obukhiv and Central Macedonia study areas. Compared to CLC there were not that big misclassifications of forests and shrublands even in the Mediterranean region. This might result from the incorporation of NDVI time series bearing a specific phenological pattern for the classification of natural and seminatural vegetation [15].

4.3. GLC and GIOS

GIOS together with GLC 'Tree Cover Layer' were systematically validated by the EEA [52]. Based on the 10% threshold of tree cover values, the GIOS product met the thematic classification accuracy requirements (e.g., 82% PA and 89% UA) at European reporting level, while GLC tree cover layer achieved slightly lower accuracy values (75% PA and 83% UA). In our case studies GIOS 'Forest' class achieved similar accuracy values ranging from 89.5%. to 99.9% PA and 64.5% to 98.9% for UA, while GLC 'Forest' achieved slightly better results, specifically from 67.8%. to 99.6% PA and 77.4% to 99.7% for UA. The EEA validation study demonstrated substantial variability from country to country (or region), with accuracies weaker over southern Europe particularly for GLC data, a fact that authors attributed to increased landscape complexity in these regions. Similar to CLC, accuracy values appeared higher for central Europe [45]. The EEA validation study reported substantially lower values for the Anatolian region (mainly Turkey), for example, 46% PA, 21% UA and Mediterranean region (79% PA, 71% UA). In the present study however, such a big variability of accuracy values for GLC forest layer across different study areas was not identified. In particular, accuracy performance of both GIOS/ GLC forest layers were relatively high in Canakkale (92.4%/93% PA and 94.2%/97.5% UA), Central Macedonia (92.4%/92.5% PA and 89.1%/93.3% UA) and Thessaly (97.7%/99.4% PA and 97.4%/98.4% UA). This could underline the fact that accuracy performance of global products at local scale might vary substantially even at sub region level. In Canakkale case, it is assumed that forests can be easier identified in agricultural landscape than in other parts of diverse Anatolian landscape. Another specific misclassification was identified in Southern Vojvodina and Třebíč-Znojmo-Brno, where high commission error of 'Forest' class was attributed to the misclassification with the 'Artificial' class (Southern Vojvodina). The error of 'Forest' class in Třebíč-Znojmo-Brno appeared mostly in the deciduous forest. This type of forest was misclassified probably as 'Grassland' or as vegetation not defined as 'Forest' (for example, shrubs). 'Water' class seems to be easily identified due to the high spectral contrast with other land cover classes. Both GIOS and GLC products performed well for the 'Water' class, for example, UA ranging from 70% to 100% and PA ranging from 83.5% to 100%. GIOS water layer was systematically validated by the recent EEA validation study [53] that reported similar good performance for GIOS 'Permanent Water' class across Europe (target accuracy of 90%), though they revealed lower accuracy values in southern regions with dry climatic conditions and predominant occurrence of temporary water (e.g., in Canakkale) [46]. Similar to this study's result, they revealed prevailing higher values of PA compared to UA, which might result to slightly overestimation of the water covered areas. In the present study relatively higher commission error values of waters is revealed in Canakkale, which might be attributed to occurrence of temporary dried areas on the reference validation image. Typical commission errors of GIOS 'Water' class were defined based on the systematic validation of EEA report [53] as misclassification with liquid dump areas, temporal water logged areas, burnt areas or coniferous forest stands in topographically influenced areas. When automatic classification approaches are used, as it was in case of GLC water layer, occurrence of snow and clouds on production images can influence the commission errors of waters [54]. This could be also the case in Romania study areas, where relatively high commission errors of water class was identified. GIOS 'Imperviousness Layer' was also systematically validated recently across Europe resulting in slightly lower thematic accuracies than other GIOS classes. Specifically, only one third of countries exceed the minimum accuracy requirement of 85% and a half exceeds an 80% limit [55]. In the present study, thematic accuracies of the 'Urban' class achieved quite good results with UA ranging from 56% to 95% and PA ranging from 54% to 97%; however, visible variability was revealed what is assumed to be caused by local specificity rather than consistent trend across different regions. In EEA study however, the high thematic accuracies tend to be associated with the producer´s rather than user´s accuracy supporting the conclusion that imperviousness layer overestimates urban areas [55]. In contradiction with the aforementioned study, the present study did not reveal this trend and relatively had high omission errors of urban areas (Třebíč-Znojmo-Brno, Canakkale and Southern Vojvodina). In Třebíč-Znojmo-Brno and Greater Poland the misclassification was found

mostly related with small artificial objects (scattered residential settlements, highways and roads), where they were mixed with vegetation types. In Canakkale study area, these misclassifications occurred especially around the areas under development and relatively small settlements around towns, where the differentiation of small artificial surfaces from the surrounding shrub land cover becomes more difficult.

5. Conclusions

This study examined the credibility and validity of commonly used moderate-to-high spatial resolution GCLCs to verify their use for decision support within the area. A jointly approved and internationally recognized approach is followed producing comparably good results in relation with EEA's and literature's targets and findings. Deviations are discussed and attributed to reasons based on particularities of the land use and land cover specificities of the local conditions.

By combining samples from all experts' confidence levels the resulting weighted OA estimation reached rates around 90%, while for most areas the results reached not less than 74%. Further analysis on the PA and UA metrics identified certain classes, that is, 'Agriculture' and 'Forest,' as the most accurate and reliably identified land covers. Lower accuracy rates were recorded for 'Artificial surfaces,' most probably due to local specificities rather than consistent trend across different regions. 'Water' class demonstrates a variable behaviour based on the study area and GCLC examined. For example, using CLC or GLOB one shall expect high producer and low user accuracy, that is, an 'overmapping,' respectively; whereas this is not the case with GIOS or GLC.

Results provide benefit both for the local applications and for the regional and continental environmental or socioeconomic analyses using the GCLC layers, as the credibility is overall high and becomes even higher for specific classes and framework conditions. Users may now choose the most appropriate for one's case freely available GCLC layer and work with it. This work shall repeat itself every few years, as new GCLC layers become available. Of special interest and anticipation are GCLC layers to be produced by Sentinel satellites, as they provide a great opportunity for finer products with an enhanced spatial, spectral and temporal resolution to overcome unfavourable conditions here and there. The need for similarly valuable or even more reliable and spatially detailed decisions is underpinned by increasing human induced pressures coupled with overpopulation and human accelerated ones, such as the climate change. In the same context, research shall expand on usability of GCLCs by including more land cover classes (e.g., shrublands), disaggregated land cover classes (e.g., grasslands) or specific classes of high biodiversity values (e.g., wetlands). The advancement of deep learning and joint multispectral and SAR analysis methods shows promising for the better exploitation of the available non-precedent data thesaurus.

Author Contributions: I.M., K.K., M.T. and I.G. conceived and designed the experiments; M.T., I.G., L.F., G.J., L.K., O.B., P.S., T.K., I.Z.G., D.M., M.M., A.H., T.R., L.G., M.I. and M.L. performed the experiments; I.M., M.T. and I.G. analysed the data; I.M., M.T., I.G., O.B., A.H., L.F., L.K., F.Z., P.S., T.K., M.N., A.I., M.N., L.G., M.I. and M.L. have contributed to manuscript; M.T., I.G., M.N., O.B. and F.Z. prepared the geospatial data; I.M., M.T., K.K., P.C. and J.A. reviewed and edited the manuscript.

Conflicts of Interest: The authors declare no conflict of interest.

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