A Comparative Analysis of "Urban Expansion" using Remotely Sensed Data of CORINE Land Cover and Global Human Settlement Layer in Estonia

Najmeh Mozaffaree Pour[1][a] and Tõnu Oja[2][b]

[1]*Department of Geography, University of Tartu, Tartu, Vanemuise 46, Tartu, Estonia*

[2]*Department of Geography, University of Tartu, Tartu, Estonia*

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Abstract: Monitoring urban expansion is important because the policy makers in cities must detect the changes to provide services and manage resources for urban dwellers. In this study we analyse the built-up areas extracted from very high-resolution images of two important databases of CORINE land cover and GHSL; Built-Up Grid to map urban expansion at local level of cities of Tallinn and Tartu in their context (County) in Estonia. The reason for selecting these datasets was the representation of an available temporal data in many timespans which allowed extracting urban expansion in our case studies. The analysis was carried out over a subset of these datasets in ArcGIS environment and the data of GHSL- Built-Up Grid was extracted from Google Earth Engine platform. Therefore, the results showed that there was an increase in the amounts of built-up areas and its rate in these two counties while based on these two databases the results were not similar in areas and cells but similar in rate and growth patterns.

1 INTRODUCTION

Monitoring urban expansion is important because the policy makers in cities must detect the changes to provide services and manage resources for urban dwellers. While urbanization is universal, changes in land cover and landscape pattern around the globe are irrevocable. Therefore, the spatial and temporal characteristics and consequences of urbanization must be scientifically understood. A widely used technique for detecting the urban expansion is remotely sensed data. Remote sensing (RS) technology enhances the availability of spatially explicit and temporally consistent land use and land cover change information (Herold et al., 2002; Michishita et al., 2012).

Satellite remote sensing offers a tremendous advantage over historical maps or air photos, as it provides recurrent and consistent observations over a large geographical area, reveals explicit patterns of land cover and land use, and presents a synoptic view of the landscape (Jensen et al., 1999). Increased availability of very high-resolution remotely sensed images in recent years, coupled with advancements in high-performance computing resources and efficient image processing algorithms have fostered the development of high-resolution human settlement datasets (Cheriyadat et al., 2007, Vijayaraj et al., 2007, Patlolla et al., 2012).

The availability of regional and global land cover products, provides us with a wide variety of options to utilize for our own respective research. However, these products differ on the basis of the methodology used to create them and the classification systems used to generate the several land use partitions (Defries et al., 1994; Fritz et al., 2010).

Starting with the GHS-BUILT product, it was the result of a large scale experiment conducted by the European Commission in 2014 aimed at extracting information on built-up areas from Landsat (Pesaresi et al., 2016), producing the first multi-temporal explicit description of the evolution of built-up presence in the past 40 years. The Landsat product contains a set of multi-temporal and multi-resolution

[a] https://orcid.org/ 0000-0001-9969-6631

[b] https://orcid.org/0000-0001-7603-220X

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grids. The main product is the multi-temporal classification layer on built-up presence derived from the Global Land Survey (GLS) Landsat image collections (GHSL homepage).

In particular, the GHSL project is focused on innovative automatic image information extraction processes, using metric and decametric scale satellite data input (Pesaresi et al., 2013) and making the information gathering is independent from any rural/urban prior abstract definition (Pesaresi et al.,2015). As Florczyk et al., 2016 mentioned "The main characteristics of the developed methodology for GHSL are a scene-based processing and a multiscale learning paradigm that combines auxiliary datasets with the extraction of textural and morphological image features".

Turning to the CORINE land cover database, the project inventory was initiated in 1985 (reference year 1990). Updates have been produced in 2000, 2006, 2012, and 2018. It consists of an inventory of land cover in 44 classes. The CORINE uses a Minimum Mapping Unit (MMU) of 25 hectares (ha) for areal phenomena and a minimum width of 100 m for linear phenomena. The CORINE is produced by the majority of countries by visual interpretation of high resolution satellite imagery. In a few countries semi-automatic solutions are applied, using national in-situ data, satellite image processing, GIS integration and generalisation (CORINE Land Cover homepage). The CORINE is recognized by decision-makers as an essential reference dataset for spatial and territorial analysis on different territorial levels (Büttner, 2002).To provide more information about the methodology used for the final products of these two databases, as follows in Table 1.

In this study the built-up areas data extracted from very high-resolution images will provide unique understanding in the mapping of urban expansion and further the knowledge of human signatures at local levels. Therefore, we evaluated a set of two datasets,

Table 1: Conceptual Frameworks for overview of COTINE and GHSL databases (CORINE Land Cover homepage, GHSL - Global Human Settlement Layer homepage).

Subjects	CORINE LAND COVER PROGRAMME	GHSL PROGRAMME
Classification of Urban area	The artificial surfaces shape the urban areas main classes of which are Continuous urban fabric, Discontinuous urban fabric, Industrial or commercial units, Port areas, Airports, Mineral extraction sites, Dump sites, Construction sites, Road and rail networks and associated lands, Green urban areas and Sport and leisure facilities.	The built-up area class is defined as the union of all the spatial units collected by the specific sensor and containing a building or part of it. Buildings are enclosed constructions above ground which are intended or used for the shelter of humans, animals, things or for the production of economic goods and that refer to any structure constructed or erected on its site.
Satellite data and sensor used	CORINE Land Cover from Copernicus Land Monitoring Service of European Nations Website for years 1990, 2000, 2006, 2012 and 2018.	The RS data used are the Landsat programme, which used of 32808 scenes organized in four collections corresponding to the epochs 1975, 1990, 2000, and 2014.
Scale	The scale chosen for the project was 1:100 000 The surface area of the smallest unit mapped in the project is 25 hectares.	The scale chosen for the project was 1:50 000 The capacity to discriminate built-up areas was demonstrated with optical sensors in the spatial resolution range of 0.5m-10m.
Innovation	At Community level, in the CORINE system, information on land cover and changing land cover is directly useful for determining and implementing environment policy and can be used with other data (on climate, inclines, soil, etc.) to make complex assessments (e.g. mapping erosion risks).	The new method generalizes the single-variable single-training set optimization techniques in the machine learning phase, to the scenario where the combination of multiple variables in input are taken into consideration with a combination of multiple training set collections.
Access to the data	Free access for all users	Fully open and free data and methods access
Coordinate Systems	EPSG:3035, ETRS89 / LAEA Europe	Spherical Mercator (EPSG:3857), World Mollweide (EPSG:54009)
Temporal extent	CLC1990, CLC2000, CLC2006, CLC2012, CLC2018	1975-1990-2000-2014
Spatial extent	Europe: 1990: 26 (27 with late implementation) countries 2000: 30 (35 with late implementation) countries 2006: 38 countries 2012: 39 countries 2018: 39 countries	Global

consisting of GHSL alongside CORINE land cover. While GHSL dataset is available as global coverage, CORINE land cover dataset is a continental program for Europe. The reason for selecting these datasets relies on the fact that they represent in temporal and in many timespans which allowed extracting urban expansion in our case studies. The analysis was carried out over a subset of these datasets in ArcGIS environment and the data of GHSL- Built-Up Grid were extracted from GEE platform.

2 METHODS

2.1 Study Area

Estonia is located in Northern Europe, on the eastern coast of the Baltic Sea. Estonia’s neighbours are Russia in the East, Latvia in the South, Sweden in the West and Finland in the North. Its land border is 645 km long, with half of it running along rivers and lakes. It lies between 57.3 and 59.5 latitude and 21.5 and 28.1 longitude (ESTONICA; Encyclopaedia about Estonia). In this study we selected two major counties of Estonia (Figure 1). Harju County which is located in northern Estonia and the capital and largest city of Estonia, Tallinn, is situated there. Tartu County which is located in eastern Estonia and covers 6.9% of its territory, whereas the city of Tartu is the centre of the county located at a distance of 186 km from Tallinn.

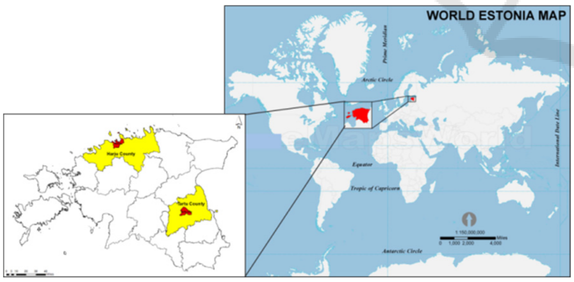

Figure 1: Study area.

2.2 Data and Data Processing

In this research spatial data includes raster format of GHSL, Built-Up Grid 1975-1990-2000-2015 (P2016) with Image ID: JRC/GHSL/P2016/BUILT_LDSMT_GLOBE_V1 at GEE platform code editor and raster data of CORINE land cover dataset from Copernicus Land Monitoring Service of European Nations Website (CORINE Land Cover webpage). GIS vector data was county boundary shapefiles obtained from Estonian Land Board Geoportal of Estonia (Maa-amet webpage).

To employ geostatistical analysis methods to compare and determine the urban expansion, projection conversion and resolution resetting were performed. The coordinate system of two datasets was projected to Lambert Conformal Conic (Estonia_1997_Estonia_National_Grid) provided by the World Geodetic System 1984 (WGS84) reference system. The spatial resolutions of these two datasets were unified after the grid unit was determined and data were prepared in the same grid unit size.

Raster data of CORINE land cover were 100-meter resolution which was resampled to 30 meters’ resolution using nearest-neighbour interpolation to match the pixel size of both extracted databases. GIS (ArcMap from the products of ArcGIS Desktop 10.6) was used to generate and analyze the data. We also used built-up areas as the “artificial surface” layers of CORINE land cover database (Table 2).

Table 2: The vector data from CORINE land cover database reclass to built-up in this study.

CORINE class	Reclass Name	CORINE code	Land cover names
Artificial Surfaces	Built-up	111	Continuous urban fabric
		112	Discontinuous urban fabric
		121	Industrial or commercial units
		123	Port areas
		124	Airports
		131	Mineral extraction sites
		132	Dump sites
		133	Construction sites
		122	Road and rail networks and associated land
		141	Green urban areas
		142	Sport and leisure facilities

2.3 Data Analysis

2.3.1 Spatial Distribution of Built-up Areas using Annual Growth Rate (AGR)

To monitor the spatial distribution of urban expansion density, in this research we used two indicators, one was annual growth of urban land (AGU: equation 1) to quantify the increasing urban land areas every year and the other one was annual growth rate of urban land (AGR: equation 2) to quantify the urban land's growth rate every year (He et al., 2017). These two indicators' calculating formulas can be expressed as,

$$AGU = (Ur_{t+n} - Ur_t)/n \quad (1)$$

Where, Ur_{t+n} and Ur_t are the urban land area in year $t + n$ and t and n is the interval of the calculating period (in years). Annual growth rate of urban land can be calculated as:

$$AGR = (\sqrt[n]{\frac{Ur_{t+n}}{Ur_t}} - 1) \times 100\% \quad (2)$$

Where, Ur_{t+n} and Ur_t are the urban land area in year $t + n$ and t, respectively. Generally, the target calculating unit is set to the administrative districts of two counties.

2.3.2 Built-up Density Analysis

Following Sabo et al., (2018), the analysis of built-up density in a grid as cell size analysis; we used a cell size of 30×30 m. It is suitable for understanding the capabilities of mapping of GHSL and CORINE land cover built-up density and their spatial characteristics. Thus to derive the built-up density, the total sum of built-up pixels in a cell is divided by the total area of the cell. The formula is as follows in equation 3:

$$dens_i = \frac{\sum_{K=1}^{N} bu_k}{w_i \times h_i} \quad (3)$$

Where $dens_i$ is the density for cell i, bu_k is the kth built-up pixel in the specific cell i, N is the maximum number of built-up pixels in one cell, w_i and h_i are the width and height of the cell, respectively.

3 RESULTS

3.1 Results of Spatial Distribution of Built-up Areas

Table 3 displays AGU and AGR for the Tartu County and the Harju County. The results of the two datasets of GHSL and CORINE land cover showed that the most common trend in the built-up area was the consistent increase during the years. The area of built-up based on GHSL database in the Harju County increased from 7415.73 ha in 1990 to a peak of 8741.16 ha in 2014 which forms average annual growth of 54.69 ha between 1990 and 2000 and 55.61 ha between 2000 and 2014. Similarly, there was an increase in built-up area from 22710.96 ha in 1990 to 29879.19 ha in 2012 and 30480.57 ha in 2018 which means 1.15% annual growth rate between 1990 and 2000 and 1.90% from 2012 to 2018. It was also apparent trend in Tartu County.

The area built-up extracted from GHSL database in Tartu County slightly grow from 1299.15 ha in 1990 to 1583.91 ha in 2014 with a smaller annual growth rate of 0.44% from 2000 to 2014 compared to AGR growth (0.59%) between 1990 to 2000. Likewise, the built-up area extracted from CORINE land cover database showed a rise from 6988.23 ha in 1990 and 7981.65 ha in 2012 and 8353.17 in 2018.

Respectively the annual growth was in the highest level between 2000 and 2012 at 80.40 ha and the annual growth of rate was in its peak at 1.68% between 2012 and 2018.

Table 3: Annual Growth Of Urban Land and Annual Growth Rate in Harju County and Tartu County.

AREA OF BUILT-UP/AGU/AGR		AREA OF BUILT-UP(ha)				AGU(ha)			AGR (%)		
		TO 1990	2000	2012/ 2014	2018	1990-2000	2000-2012/ 2014	2012-2018	1990-2000	2000-2012/ 2014	2012-2018
Harju County	GHSL	7415	7962	8741		54	55		0.87	0.60	
	CORINE	22710	24814	29879	30480	210	422	100	1.15	1.03	1.90
Tartu County	GHSL	1299	1403	1583		10	12		0.59	0.44	
	CORINE	6988	7016	7981	8353	2	80	61	0.39	0.77	1.68

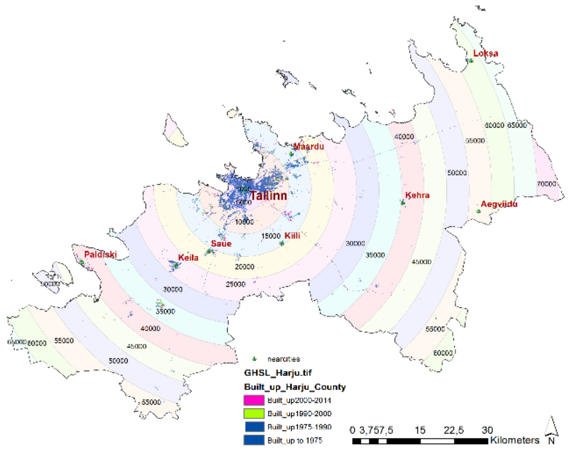

Figure 2: Built-up areas in Harju County extracted from GHSL databases.

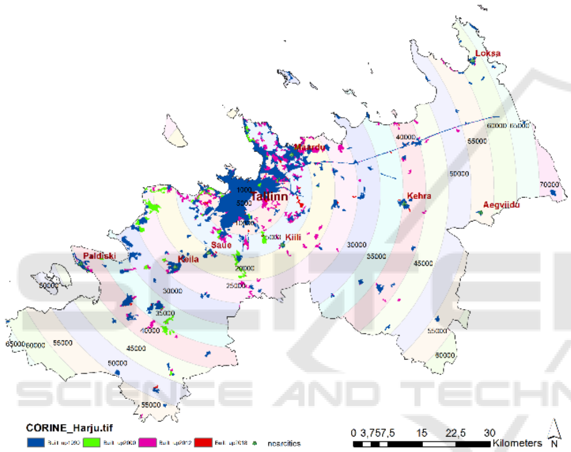

Figure 3: Built-up areas in Harju County extracted from CORINE databases.

Figure 2, 3, 4 and 5 show the built-up area in both counties extracted from GHSL database and CORINE land cover database. Figure 2 and 3 represent the urban expansion in constant rings of 5km buffer from Tallinn. While the expansion happened mostly in the third ring (15km) based on the GHSL, the expansion of built-up areas significantly occurred in the 8th ring (40km) from Tallinn.

Respectively the expansion of built-up area in Tartu County took place mostly in the first ring (5km) from Tartu based on GHSL database (Figure 4) and continued in the 6th ring (30km) from Tartu based on the CORINE land cover database (Figure 5).

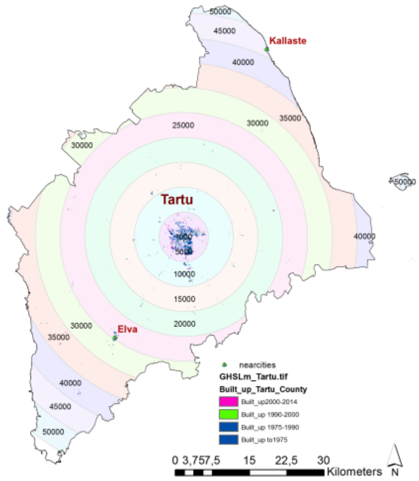

Figure 4: Built-up areas in Tartu County extracted from GHSL databases.

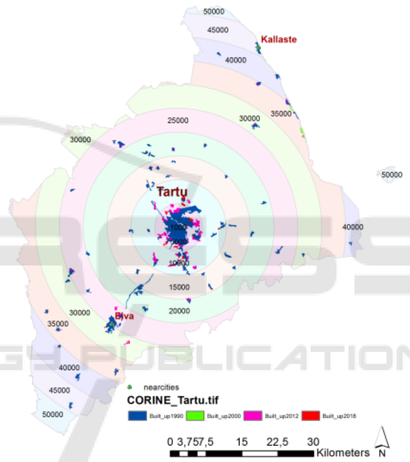

Figure 5: Built-up areas in Tartu County extracted from CORINE databases.

3.2 Built-up Density Analysis Results

The results of the built-up area density analysis are presented in Table 4 and Figures 6 and 7. The densities are calculated per grid cells of 30×30m for both counties. Regarding the ratio of built-up cells in Harju County, the GHSL showed a rise from 82397 built-up cells to 97124 cells. The cell density also increased from 0.017 (1.7%) to 0.020 (2.0%) from year 1990 to 2014. Respectively the CORINE built-up cells increased from 252344 to 338673 cells from 1990 to 2018 which expressed a density of 0.052 (5.2%) in 1990 developed to 0.070 (7.0%) in 2018.

Table 4: Cell Density Analysis Results.

Cell Density Analysis		CELL OF BUILT-UP	AREA OF BUILT-UP(ha)	CELL OF BUILT-UP	AREA OF BUILT-UP(ha)	CELL OF BUILT-UP	AREA OF BUILT-UP(ha)	CELL OF BUILT-UP	AREA OF BUILT-UP(ha)
		TO 1990		2000		2012/2014		2018	
Harju County	GHSL	82397	7415	88474	7962	97124	8741		
	CORINE	252344	22710	275718	24814	331991	29879	338673	30480
Tartu County	GHSL	14435	1299	15599	1403	17599	1583		
	CORINE	77647	6988	77965	7016	88685	7981	92813	8353

Similar growth pattern in Tartu County was found. Based on the GHSL the density of built-up cells was 0.3% in 1990 raised to 0.5 % in 2014. According to CORINE there was a rise in cell density from 2.1% in 1990 to 2.5% in 2018.

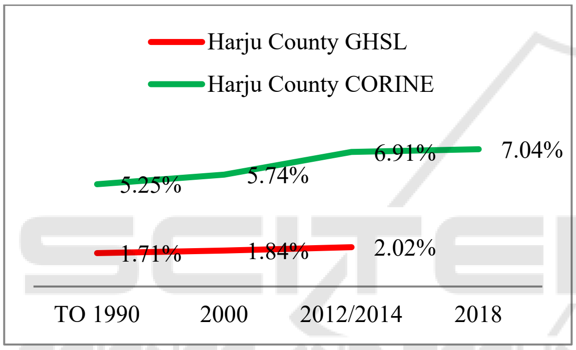

Figure 6: Built-up Cell Density (in %) in Harju County.

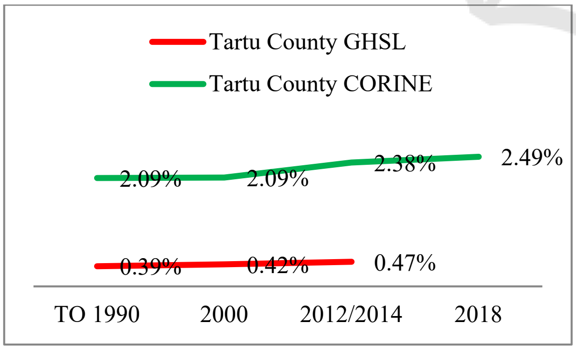

Figure 7: Built-up Cell Density (in %) in Tartu County.

4 DISCUSSION

The results provide evidence that the general trend of urban expansion slightly increased in the built-up area from 1990–2014 (extracted maps from GHSL-built-up layer database) and from 1990- 2018 (extracted maps from CORINE land cover database) in both counties (Figures 8, 9, 10 and 11).

In terms of spatial distribution of built-up areas, the two indicators of AGU and AGR were used. While these two indicators showed increase in built-up areas and its rate, there was a clear difference between the data extracted from GHSL and CORINE land cover databases.

The largest difference was related to AGU in the Harju County from 2000 - 2014 (GHSL) / 2012 (CORINE). While 55.61 hectares added to urban lands based on the GHSL, data of CORINE showed increase by 422.05 hectares. Although the data extracted from the GHSL showed less built-up areas as compared to the CORINE during the study period, there was a higher degree of AGU and AGR in the GHSL in Tartu County between 1990 and 2000.

There are two main reasons for these differences. First, it could be the difference in definition and classification of built-up area by these two datasets. In line with the ideas of Florczyk et al., (2016), in this study the “artificial surface” layers of CORINE land cover database were classified to built-up. These consist of continuous and discontinuous urban fabric, industrial or commercial units, port and airport areas, construction sites, roads and even green urban areas which are tightly related to built-up structures.

While in GHSL, as Pesaresi et al., (2013) have mentioned, the built-up area consisted of buildings and built-up areas. GHSL definition was based on INSPIRE (Infrastructure for Spatial Information in Europe) definition for buildings, but did not take into accounts the underground buildings. Also classification schema of the GHSL is more general not assuming any embedded urban/rural dichotomy (Pesaresi et al., 2009).

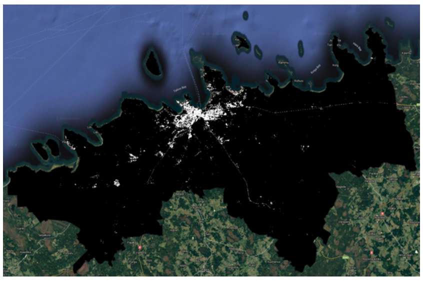

Figure 8: Urban extend maps of Harju County from GHSL.

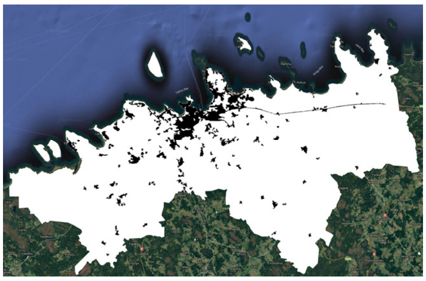

Figure 9: Urban extend maps of Harju County from CORINE.

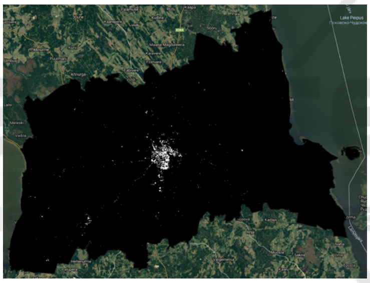

Figure 10: Urban extend maps of Tartu County from GHSL.

Figure 11: Urban extend maps of Tartu County from CORINE.

The results of Figures 12 and 13 also represented the urban expansion in concentric rings from the cities of Tallinn and Tartu. While the results of urban expansion indicated that the GHSL-built-up were mostly in the third ring (15km) in the Harju County, the expansion of built-up areas occurred even in the 8th ring (40km) from Tallinn. Respectively the results of expansion of built-up in Tartu County showed similar differences. Based on GHSL database the expansion took place in the first ring (5km) from Tartu while CORINE land cover database showed the expansion in the 6th rings (30km) from Tartu.

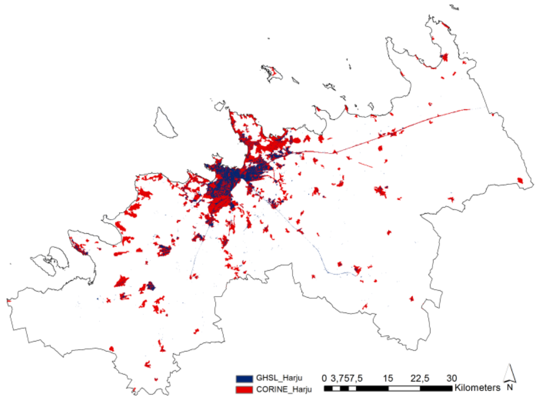

Figure 12: Map of Built-up area difference between GHSL and CORINE in Harju County.

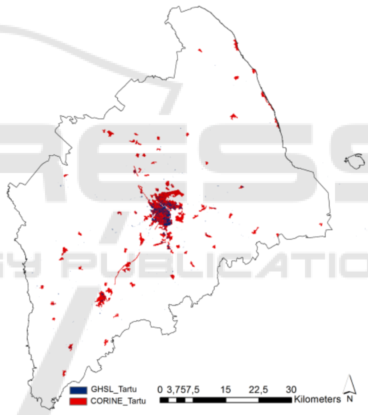

Figure 13: Map of difference between GHSL and CORINE in Tartu County.

5 CONCLUSIONS

This work presents spatial data extracted from two important databases of CORINE land cover and GHSL; Built-Up Grid to determine urban expansion in two major cities of Estonia. We used temporal data of the GHSL for 1975, 1990, 2000, and 2014 and timespans of the CORINE data was 1990, 2000, 2012 and 2018 and the analysis was based on the last product (2014 for GHSL and 2018 for CORINE). We analysed the built-up areas and cells which represent the physical dimension of human settlements and definitely define the urban expansion of cities using AGU, AGR and built-up density analysis.

The results indicated the increase in the amounts of built-up areas and its rate while in these two databases the results were not similar in areas and cells but similar in rate and growth patterns. We demonstrated that the differences could be due to the definition of built-up or as explained in conceptual frameworks of CORINE and GHSL databases, it could be the results of different satellite data and sensor used for the final products, the scale of the two datasets and the temporal extent of the data.

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