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Cadastral land-use data generalisation for the creation of large scale maps

Mikeli Paraskevi [a,*], Skopeliti Andriani [a], Nakos Byron [a]

[a] *Cartography Laboratory, School of Rural and Surveying Engineering, National Technical University of Athens, Greece, mikeli_evi@hotmail.com, askop@survey.ntua.gr, bnakos@central.ntua.gr*

* Corresponding author

Abstract: Land-use maps are necessary for planning at the neighbourhood and municipal level as well as at the regional and country level. However, each scale requires different level of detail. Generalisation is a fundamental cartographic procedure used in map production, which allows the transition from a larger scale to a smaller one. In this research, Hellenic Cadastre parcel data at reference scale 1:2500 with land-use attributes are generalized, to produce maps in scales 1:5K, 1:10K, 1:25K. Two different approaches star and ladder generalisation were applied. The method uses a cartographic rule (the minimum map element) for the selection operator and semantic and geometric (Longest Common Boundary and Best Neighbour) criteria for the aggregation operator. The results were evaluated by estimating the changes of land-uses area after generalisation. The generalisation of the cadastral land-use data was implemented utilizing commercial software (ArcGIS) tools within Python using the ArcPy library.

Keywords: land-use, generalisation, cadastral data, polygons, rules

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1. Introduction

Regardless of the nature of spatial data, the generalisation objective is always the same: reduction of the unnecessary detail, according to map scale level and to map purpose, in order to better communicate the information to the user/map reader [ICA] (Weibel & Dutton, 1995). Although the different applications of generalisation have a common purpose, the operators / transformations differ depending on the data to be generalized and the needs of the user/ map reader.

Before the widespread of spatial databases and GIS, the generalisation of a map was considered to consist of two stages: the generalisation of the cartographic/ geographical model (*model-oriented generalisation*) and the *cartographic generalisation* (Muller, 1995b in Cheng and Li, 2006). These two procedures can be applied either autonomously or in combination (Cheng and Li, 2006).

Generalisation can be applied to both geometry and semantics of a cartographic/geographic entity. The method is characterized geometry-based when generalisation is applied according to geometric accuracy criteria, while if the criteria are related to the semantic relevance of entities, the process is characterize as theme-based (Cheng and Li, 2006). In this research both geometric and semantic generalisation are investigated for land-use polygons generalisation. Geometry generalisation is implemented with appropriate operators, while semantic generalisation is applied based on a "land-use classification schema (ontologies)" across scales.

The main purpose of this research is to examine the use of cadastral land-use data (reference scale 1:2500) generalisation in the production of large scale maps (e.g. scales 1:5K, 1:10K, 1:25K), with the minimum user involvement, utilizing ArcGIS tools within Python (ArcPy library). The work aims to answer the following questions:

- Is it possible to produce large-scale maps from cadastral data utilizing generalisation?
- Can generalisation be applied to the geometric and the semantic features of the parcels?
- How can the generalisation procedure be applied?
- Can the same generalisation workflow be applied for the production of a number of different map in various (smaller) scales (ladder generalisation vs. star generalisation)?
- Are the land-use changes produced by generalisation in harmony with map scale?

The paper is organized as follows: Section 2 provides background material on generalisation; Section 3 describes the proposed generalisation method, the case study and the results and Section 4 discusses the results and presents the future plans.

2. Related Work

Generalisation is a fundamental cartographic procedure, although its automation is difficult to be accomplished due to complexity and its holistic character (Cheng and Li, 2006; Monmonier, 1982 in Cebrykow, 2017). As early as 1988, Brassel and Weibel proposed a conceptual approach to holistic automatic generalisation. That approach was extended by McMaster and Sea in 1992, while Perkal in early 1958 (in Cebrykow, 2017) introduced a number of objective rules to the generalisation process trying to change its subjective character.

Generalisation, and more precisely its automation, is crucial for NMAs (National Mapping Agencies) and private mapping companies in the framework of map production. Automation results to the minimization of users involvement and therefore to production cost, which also leads to better data management and compliance with other demands (Stoter et al., 2011). Generalisation can also facilitate the provision of open data to society, as it achieves cost and data volume reduction (Stoter et al., 2016). At the same time, it supports the integration of heterogeneous data from different sources in a GIS (van Smaalen, 2003).

Over the last two decades, significant efforts have been made to conceptually approach generalisation automation and to design processes with the minimum user involvement. The differences between various generalisation approaches depend on: the data to be generalised (e.g. generalisation of a topographic or categorical map), the desired product (e.g. cartographic representation or cartographic model) and the implementation tools (e.g. open source software, commercial software, GIS tools, integrated programming).

A number of researchers have focused on generalization of cadastral and land-use maps. Van Smaalen (2003), presented a generalisation workflow for a categorical map (e.g. maps of entities with geometry and semantics which indicate categories). He proposed an object-oriented conceptual approach whose implementation is done by the aggregation of adjacent geometries. Cheng and Li (2006) tested the effects of two different generalisation processes (geometry-based and theme-based) and proposed qualitative and quantitative measures for assessing the generalisation product. They generalised a land-use map based on the MMU (Minimum Map Unit), which depends on the source and target scale. Alves et al. (2010) suggested a workflow for the generalisation of cadastral topographic map. Haunert and Wolf (2010) proposed a mixed integer-programming method for areal features generalisation, where the minimum area is selected and merged with the most similar neighbor. Park and Yu (2011) developed a generalisation model for spatial cadastral data. Initially, the road network is isolated and generalized, then the land-use polygons are generalized through aggregation based on rules. Dimov et al. (2014) proposed an automatic generalization process for land-use data (vector and raster) of a non-urban area, using programming tools and GIS. The purpose of that research was the production of a generalised map (scale 1:25K) from 1:1K data. In the proposed procedure algorithms for both vector and raster data were applied, such as the Euclidean distance and the Delaunay triangulation. Geometry, semantics and topology rules were utilized and the change of geometric and thematic properties of polygons were evaluated. Yadav (2015) used raster data to create land-use maps at scales 1:10K, 1:25K and 1:50K. A generalisation process is used for the creation of the maps at different scale, which is based on a polygon similarity model. Hidayat and Susetyo (2019) examined the generalisation of buildings polygons (1:5K) in order to map them in smaller scales (1:25K, 1:250K).

Spatial data generalisation is a fundamental transformation that is implemented with a wide range of operators (Cheng and Li, 2006). The choice of operators depends on the type of generalisation (model-oriented or cartographic), on the feature type to which it is applied (geometry or semantics), on the nature of the data (e.g. dimensions), on the purpose of generalisation (at what level of detail/scale). The *aggregation* operator is mostly used in polygon maps generalisation (van Smaalen, 2003; Cheng and Li, 2006; Haunert and Wolff, 2010; Park and Yu, 2011; Dimov al., 2014; Yadav, 2015; Peng et al., 2017; Susetyo and Hidayat, 2019; Li et al,. 2020; Shen et al., 2020). Moreover, *selection* (of the smallest of the elements to be generalized/aggregated) is a common operator (van Smaalen, 2013; Dimov et al., 2014; Susetyo and Hidayat, 2019; Shen et al., 2019). Stoter et al. (2013) used specific operators for map generalisation (eg *displacement, simplification*), while for model generalisation data-driven operators according to constraints are used according to constraints. Regarding to semantic feature generalisation, the most common technique is the use of a classification schema and the *reclassification* operator (Yadav, 2015; Peng et al., 2017).

The complex and subjective character of generalisation impedes its optimization, however there are a few objective measures to describe the quality of generalisation products (Haunert and Wolf, 2010). Van Smaalen (2003) evaluated both visually and quantitatively his method results. A common way to validate generalisation performance is the user/expert who evaluates product data consistency and the preservation of initial data basic features (in Stoter et al., 2013). Cheng and Li (2006) provided a set of qualitative and quantitative objective measures for the evaluation of the product of generalisation, in order to compare two different algorithms (geometry-based and a theme-based).

Frank and Ester (2006) proposed a set of similarity measures through which changes of local entities are calculated. Stoter et al. (2009) proposed three evaluation procedures, using commercial software, which include: cartographers-expert evaluation, automated constraint-based evaluation and visual quality comparison. Alves et al. (2010) measured generalisation product quality with rules about change in geometric features and accuracy, the preservation of patterns and quantity information. Dimov et al. (2014) used the product's compactness (through measuring area change for each class) and evaluated semantic consistency by measuring the thematic change from initial data (through raster algebra by subtracting raster product super-class from initial raster super-classes). Haunert and Wolf (2010) suggested optimization approaches through mathematical programming. In their research, they modelled the generalisation process with graphs, as an optimization problem.

In literature, there have been others studies related to generalisation of polygons with semantics features. Van Oosterom (2005) introduced the first data structure for multi-scale area data. Peng et al. (2017) implemented a similar to generalisation process, as they proposed an optimal workflow of polygon aggregation sequences in order to transform a given large scale land cover map (source map) to a given smaller scale land-cover map (target map). The purpose of this algorithm is the creation of maps with scales between the large (start) and the smaller one (goal).

From the above analysis, it is obvious that land-use generalisation is a crucial topic in generalisation for map production. The use of specific operators such as aggregation and selection dominates. Additionally, the evaluation of the generalisation results is highly recommended. These findings will guide this study as well.

3. Cadastral data generalization for the production of large scale maps

In the present research, it was investigated whether cadastral spatial data, that collect land-use information at parcel level, can be used for the production of large scale maps.

3.1 Data

Hellenic Cadastre provides a spatial database of reference scale 1:2500 that uses parcel as level of detail (Figure 1). The spatial database consists of thematic polygons. Each entity represents a parcel and records the land-use value. The main topological constraints of such a spatial database is the absence of gaps and overlaps.

The study area is Larissa, a city in central Greece. The basic criterion for selecting this city is the existence of an urban and a non-urban area. In the urban sub-area the land-uses show high diversity (even in neighbouring parcels) and the parcels are quite small, whereas in the non-urban sub-area the parcels are larger and the land-uses show little variation. The differences between the two sub-areas play a decisive role in the outcome of the proposed generalisation process. For example, the larger the area of a polygon, the probability to need generalization gets smaller. In contrast, the smaller the polygon in a neighbourhood with polygons with many different land-uses, the greater are the changes in the semantics after generalisation. Moreover, the parcels in the urban sub-area are organized in building blocks separated by the road network, while in the non-urban sub-area the road network is sparse. Finally, in Larissa there are important entities such as the road network, the river, the riparian zone and the railway network, that are not considered for generalisation in the framework of this work.

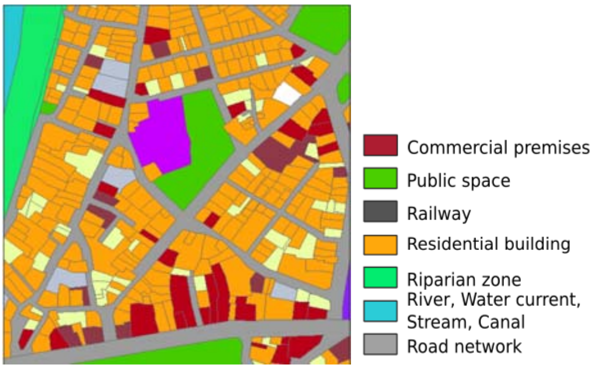

Figure 1. Initial data visualization.

3.2 Methodology

A data-driven and cartographic oriented approach for the generalisation of land-use cadastral data is adopted. The selected operators, criteria, rules, parameter values and constraints depend on the data features (e.g. polygons with categorical semantics). Generalisation is applied with the polygon aggregation operator based on cartographic, geometric and semantics rules (van Smaalen, 2003; Cheng and Li, 2006; Haunert and Wolff, 2010; Park and Yu, 2011; Dimov et al., 2014; Peng et al., 2017; Susetyo and Hidayat, 2019; Li et al., 2020; Shen et al., 2020). The proposed method is implemented with ArcGIS basic geoprocessing tools customized with Python and the ArcPy library. Moreover generalisation results are evaluated with quantitative measures that assess the global changes in map geometry and semantics (Cheng and Li, 2006; Alves et al., 2010; Dimov et al., 2014).

The proposed method applies a cartographic generalisation constraint to the cartographic/geographic model entities, which is used for the selection of "small" polygons (Mikeli, 2019).

To the best of the authors' knowledge this is the first generalisation research for land-use data at parcel level collected by the Hellenic Cadastre. For the purpose of the research a classification schema/ontology is created to handle changes in classification schema across scales (Figure 2). The suggested workflow does not require any user involvement during the processing and the evaluation stage.

3.2.1 *Minimum Map Element definition*

An important factor in the proposed method is the definition of Minimum Map Element. The desired product of the generalisation, is the map. A map is a graphic visualization of the spatial database. For this reason it was decided to apply a cartographic constraint to the size of polygons in each map scale. Thus, it was considered that any polygon on the map after generalisation should be greater than the *Minimum Map Element (MME)*. *MME* is defined in this case study as a polygon with area 3mm x 3mm at the map scale. *MME* differentiates for each target scale as it is directly related to the visual accuracy of the graphical visualization and as consequence with the scale (Cheng and Li, 2006). Application of specific values can be set in a future work as well.

(a)

(b)

Figure 2. (a) Land-use Classification Schemas across scales (b) Land-uses that do not change (The translation from Greek has been done by the authors for the purpose of this research).

3.2.2 *Classification schema*

In order to apply parcel generalisation across scales, the definition of a land-use *classification schema* is needed**.** The generalisation is applied to entities geometry and semantics. Regarding the semantics, during generalisation, the land-use of a small polygon might change due to aggregation with a larger polygon. At the same time the land-use classification changes for each target scale according to the classification schema across scales.

A custom classification schema across scales is created for this research, (Figure 2) since to the best of the authors' knowledge no inter scale schema is provided by any official Hellenic source. In order to decide on the number of classes for each scale, the Topfer – Pillweizer Principle of Selection was utilized in combination with the area values of the land-use categories. As shown in Figure 2, at each scale the level of detail for land-use classes changes. The smaller the scale, the more general become the land-use classes. By introducing generality to each level the semantic scale is also reduced. Moreover, in smaller scales there are fewer land-uses classes, which are the result of merging similar land-uses classes of a more detailed scale level. A number of land-uses (e.g. river and riparian zone, road network, railway) are retained at all scale levels, since they do not appear in parcels and cover a large area in relation to the target map scales.

The generalization methodology includes two main phases selection and aggregation.

3.2.3 *Selection phase*

The selection operator is used to specify the polygons to be generalized. All polygons which are smaller than MME in the target scale are selected to undergo generalisation.

3.2.4 *Aggregation phase – Best Neighbour Definition*

The aggregation operator is used to merge the geometry of a small polygon to the most appropriate adjacent polygon (*Best Neighbor* Polygon) and possibly change the semantics. The *Best Neighbour Polygon (BNP)* is determined by semantic and geometric criteria, which cover the following cases:

1) If there is only one neighbour the small polygon aggregates with it.

2) If there are more than one neighbours and one of them has the same land-use value (at source scale) with the small polygon, the small polygon aggregates with that neighbour.

3) If there are more than one neighbours with the same land-use at source scale with the small polygon, the small polygon merges with the neighbour with the *longest common boundary.*

4) If there are no neighbours with the same land-use value with the small polygon at source scale schema, and there is only one neighbour with the same land-use value

at the target scale schema the small polygon merges with it.

5) If there are no neighbour with the same land-use value with the small polygon at source scale, and there are more than one neighbours with the same land-use value at the target scale the small polygon merges with the neighbour with and the *longest common boundary*.

6) If the small polygon has no neighbours, it merges with the land-uses polygons which do not take part in generalisation (e.g. river, riparian zone, road network, railway) taking into account *longest common boundary*.

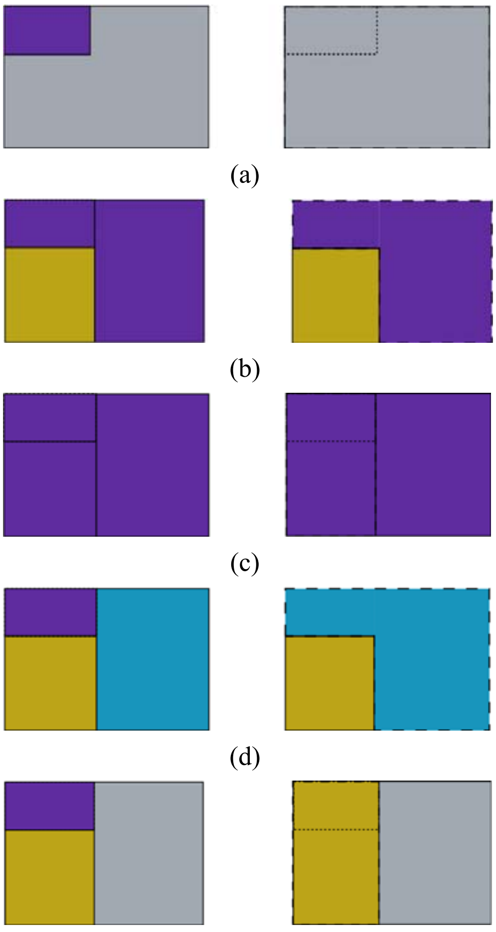
(a)
(b)
(c)
(d)
(e)

Figure 3. Aggregation criteria – implementation examples. To the left are the parcels before aggregation and to the right after aggregation. In each example the small purple polygon is selected to be generalized (a) only one neighbor (b) only one neighbor with same land-use value (c) more than one neighbors with same land-use value (d) no neighbor with same land-use value at source scale and one neighbor with same land-use value at target scale (e) no neighbor with same land-use value.

To summarize the aggregation criteria, when choosing the *best neighbour polygon* the semantic similarity is emphasized. A neighbour with the same land-use value at the source scale is considered inherently better than the others for merging and a neighbour with the same land-use value at the target scale is inherently better for merging than the one with which the small polygon has a *longest common boundary*.

At this point it should be mentioned that instead of comparing the length of the small polygon common boundary to each neighbour, the Neighbors Common Length Rate (NCLR) index is utilized in order to normalize the adjacency criterion to be independent of the polygon size.

$$NCLR = \frac{commonboundarylength}{smallpolygonperimeter} \tag{1}$$

Finally, at each aggregation the newly created polygon inherits the land-use value of the larger original polygon (Figure 3).

Generalisation Algorithm	
Input	Spatial table with polygon geometry recoding the parcels and the land-use values for the area of interest
1:	Identification of building blocks
2:	Calculation of Minimum Map Element at target scale
3:	**For** each building block:
4:	Find the polygon with the **minimum area** (min_polygon)
5:	**If** (min_polygon > Minimum Map Element) → **Next** building block
6:	**Else**: **find** min_polygon Best Neighbor according to above criteria, **merge**, **aggregate**, **update** building block data
7:	Find the polygon with the **minimum area** (min_polygon) on the updated building block
8:	**If** (min_polygon > Minimum Map Element) → **Next** building block
9;	**Else**: repeat the process for this building block
Output	Generalized data at selected scale for the area of interest

Table 1. Proposed method generalisation workflow.

3.3 Implementation

The proposed method is implemented using simple ArcGIS geoprocessing tools (e.g. calculate area, find adjacent polygons for a specific polygon, spatial merge, aggregate, update, dissolve etc) in the Python framework in conjunction with the ArcPy library. The generalisation method is presented in Table 1. A common generalisation process is applied to the spatial data in two ways: star and ladder generalisation (Mikeli, 2019).

3.3.1 *Star generalisation*

The method is applied to the source spatial data (reference scale 1:2500) to create maps at scale 1:5K, 1:10K and 1:25K.

3.3.2 *Ladder generalisation*

The method is applied to the source spatial data (reference scale 1:2500) to create the 1:5K map. The 1:5K map data are generalized for the production of 1:10K map and the 1:10K map data are generalized for the production of 1:25K map.

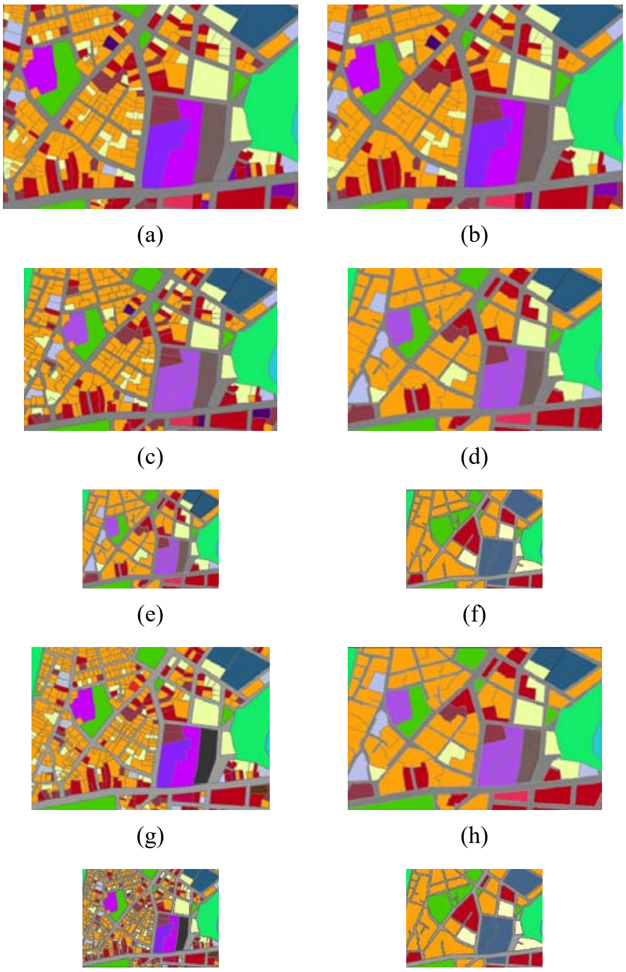
(a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

Figure 4: Generalisation implementation (due to template limitations images have been downsized). On the left, source data are portrayed at the target scale without generalisation and on the right the generalisation results are portrayed at target scale: (a) urban area source scale 1:2500 (b) urban area generalized data at target scale 1:5K (c) urban area source scale 1:5K (d) urban area generalized data at target scale 1:10K (source 1:5000) (e) urban area source scale 1:10K (f) urban area generalized data at target scale 1:25K (g) urban area source scale 1:2500 (h) urban area generalized data at target scale 1:10K (i) urban area source scale 1:2500 (j) urban area generalized data at target scale 1:25K.

3.4 Results & Evaluation

The method was applied to the initial data, for the urban and non urban sub-area, in order to produce maps of scales 1:5K, 1:10K and 1:25K. Moreover the method was applied with the same aggregation criteria and the same *Minimum Map Element* to both urban and non-urban sub areas.

The results for both procedures (star and ladder generalisation) are presented in Figure 4 for the urban subarea and in Figure 5 for the non-urban subarea.

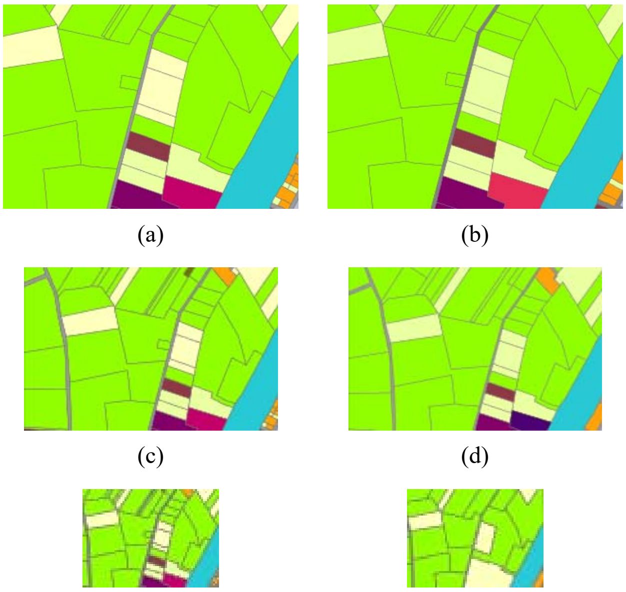
(a) (b) (c) (d) (e) (f)

Figure 5: Generalisation implementation (due to template limitations images have been downsized). On the left, source data are portrayed at the target scale without generalisation and on the right the generalisation results are portrayed at target scale: (a) non urban area source scale 1:2500 (b) generalized non urban data at scale 1:5K (c) non urban data source scale 1:2500 (d) generalized non urban data target scale 1:10K (e) non urban area data source scale 1:2500 (f) non urban area data generalized target scale 1:25K.

Maps created by ladder and star generalization are considered successful as the legibility and semantic criteria are satisfied based on the management of "small polygons" and the adoption of a scale specific classification schema. In order to evaluate the proposed method, the changes in land the uses were assessed. The change in the percentage coverage of each land-use (Table 2) was computed utilizing the average and the total (sum) value while applying the classification of the target scale. Changes in non urban subareas are smaller than in the urban subarea. This is in accordance with the larger size of parcels which results to smaller degree of generalisation. Average change percentages in ladder generalisation are smaller than in star generalisation due to the scalar application. Total change percentages are also smaller in star generalization since aggregation is guided by "small polygons" in relation to target scale whereas in ladder generalization aggregation is applied multiple times resulting to greater changes. However, results are influenced by the parcel size, the land-use distribution and the classification schemas.

Mean & Sum of land-use change (%)					
		Urban Area		Non-Urban Area	
Source	Target	Mean	Sum	Mean	Sum
1:2500	1:5K	0.22	2.61	0.04	0.35
1:2500	1:10K	0.86	6.25	0.06	0.39
1:2500	1:25K	2.02	12.14	1.79	10.78
1:5000	1:10K	0.74	8.17 (10.78*)	Not applied	Not applied
1:10K	1:25K	1.42	7.32 (18.1*)	Not applied	Not applied

Table 2. Evaluation of results (* cumulative values in relation to 1:2500)

4. Conclusion

Generalisation is an important procedure in map production. The exponential growth of spatial data created an urgent need to organize them into functional structures, such as spatial databases. In order to use spatial data in different spatial analysis scenarios (such as planning), visualize them at different scales or even maintain them in an efficient way, spatial data generalisation is an essential process. Generalisation can influence the semantic and geometric aspect of spatial data, although the used operators and the aim of each is different.

In this paper, cadastral parcels with land-use attributes were generalised to produce large scale maps. Generalisation is applied with the polygon aggregation operator based on cartographic (Minimum Map Element), geometric (Best Neighbour Polygon*)* and semantics rules (scale dependent classification schema).The proposed methodology was applied in a case study for cadastral data provided by the Hellenic Cadastre. It is implemented in ArcGIS environment by a custom developed routine using the ArcPy library methods and basic geoprocessing tools. The proposed method can be used for land-use as well for land-cover polygon generalisation. It can be used to generalise any polygon database with semantic features that can be schematized in different conceptual levels. Finally, it is considered to be useful for multiscale mapping and multiscale spatial databases. Although the results of the proposed algorithm are very promising, there are always improvements to be done. The first of our aims is to implement the proposed algorithm in an open-source environment such as PostgreSQL/PostGIS. This is possible since the method uses OGC Simple Feature Model and is based on basic GIS functions such as finding neighbour polygons, computing common border, aggregation etc. An interesting extension could be for the user to set critical values depending on target scale and entities area or different weights to specific land-uses. Moreover, the method should be applied to larger and different areas in order to check the rules completeness and possibly alter or even state different rules. Finally, the method could be slightly altered (e.g. utilizing more generalisation operators such as collapse) and applied for the creation of medium scale maps (e.g. 1:50K, 1:100K etc) as well.

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