Spatial Statistics 2015: Emerging Patterns

Multidimensional Land Cover Change Analysis using Change Vector and Land Cover Taxonomies

Helbert Arenas[1], Benjamin Harbelot, Christophe Cruz

Checksem Team, Le2i, UMR CNRS 5158, University of Burgundy
Dijon, 21000, France

Abstract

Around the world, land cover changes occur due to natural and anthropogenic factors. In many cases, the consequences of anthropogenic interventions are unexpected. In order for scientists and policy makers to identify land cover change processes of interest, it is necessary suitable tools for early and efficient analysis of land cover data. In our research, we present a data model that makes use of semantic web technologies to manage a hierarchical structure of land cover types. Using this approach, it is possible to manage the land cover information at different levels of abstraction. In our research, we use a Change Vector Analysis approach to represent the land cover change. The number and semantics of the axes in the resulting multidimensional space depend on the level of abstraction decided by the researcher and can be modified on the fly. Using this approach, it is possible to detect processes allowing the researcher to have quantitative change measurements. In this work, we present our research using data from the CORINE land cover program, corresponding to the years 1990, 2000 and 2006. As our study area, we have selected ten countries in Eastern Europe, that became members of the EU between 2005 and 2007. Our results suggest that our method is efficient, reliable and scalable.

Peer-review under responsibility of Spatial Statistics 2015: Emerging Patterns committee.

Keywords: spatio-temporal; description logics; land cover;

1. Introduction

Currently researchers have access to large amounts of data related to land cover. By analyzing this information it is possible to detect dynamic processes that involve land cover changes. However due to the large amounts of information it is possible that certain processes might be hidden behind irrelevant data. In order to tackle this problem we introduce a data model designed to analyze multi-temporal data using hierarchically structured land cover types.

In Section 2, we describe related research in this domain. In Section 3 we provide an overview of the datasets we use in this study. In Section 4 we describe our methodology. Finally, in Section 5 we present our conclusions and future work.

2. Related Research

The change vector approach was first introduced in [1], here the author aims to use periodic remote sensing imagery to detect the evolution of forests. In order to achieve this, the author creates spectral change vectors between datasets of different temporal points. Then the author evaluates the magnitude of the vector against an arbitrary threshold. If the magnitude is higher than the threshold there has been some change, otherwise the unit has

1 * Corresponding author. Tel.: +33-068-892-5338 ; *E-mail address:* helbert.arenas@checksem.fr

remained static. By analyzing the directions of the vectors it is possible to differentiate between different types of changes [1].

The vector change approach has been used by different researchers to study land cover dynamics. For instance in [2] the authors use the vector change analysis method to identify land cover changes in rural-urban fringe areas. This study takes into consideration spectral as well as texture information to identify changes using satellite imagery from Landsat TM, CBERS/CCD and ALOS/AVNIR.

A more recent example is [3]. Here, the authors use the Change Vector Analysis technique to study soil degradation in sandy areas involving aeolian erosion in Northern China. In this work, the authors use several consecutive Landsat images to measure the changes along time. The authors process the spectral information from the satellite imagery in order to obtain NDVI and albedo measurements. The authors claim that by using this technique, it is possible to differentiate the magnitude and the direction of the changes [3].

In [4], the authors use corine land cover information of 1990 and 2000 in vector format to identify geometrical changes in parcels represented as polygons in Slovakia and Netherlands. This work is then further expanded in [5], here the researchers identify different types of land cover evolution by comparing Corine datasets of 1990 and 2000 for the whole Europe using an arbitrary regular unit of analysis.

The study area of our research is defined by former communist countries that became members of the European Union between 2004 and 2007. The evolution from a central planned economy to a market oriented has been found as a relevant factor in land cover changes by previous researchers such as [6].

The abandonment of agricultural land in European Union countries has occurred along 20th. century, particularly after the Second World War. In most of the cases this process occurs in unfavorable environmental conditions, for instance, parcels located in steep slopes, with poor soils, or with high elevation. However these type of evolution seems to occur at a much accelerated pace in countries that in a short period of time change from a socialist system to a market oriented one.

In [6], the authors study the agricultural land abandonment in European Russia, using Landsat TM/ETM+ satellite imagery. The study area of [6] comprised most of the Kaluga, Vladimir, Rjazan, Smolensk and Tula provinces. After the fall of the Soviet Union agricultural regulation and subsidies were eliminated. Land and property of collective and state farms was distributed among workers. National statistics indicate that agricultural production suffer an important decrease during the 1990s. In [6] the authors use two sets of images, the first for the period 1985 to 1999, and the second for the period 1999 to 2002. The results of the analysis indicate that that 31% of the agricultural land in use in 1990 was abandoned by 2000, which translates into 1.7 million ha. However the agricultural loss was not even among the provinces: 46% of the agricultural land in the Smolensk province was abandoned, 30% in Kaluga, 26% in Tula , 28% in Rjazan and 27% in Vladimir. In [6] the authors conclude that in the absence of government support, market forces determine which agricultural lands remain and which are abandoned, being the main principles, profitability and accessibility.

3. Study area and Datasets

After 1994, a number of former communist countries submitted their application to become part of the European Union. Most of these countries became members in a period between 2004 and 2007, making it the greatest expansion of the EU in terms of population and area. Thanks to environmental surveillance funded by the EU, there is a great wealth of standardize information regarding the land cover of former communist countries that became members of the EU. The study area of our research includes eleven former socialist countries admitted in the European Union after 2004: Hungary (2004/05/01), Poland(2004/05/01), Romania(2007/01/01), Slovakia(2004/05/01), Latvia(2004/05/01), Estonia(2004/05/01), Lithuania(2004/05/01), Bulgaria(2007/01/01), Czech Republic(2004/05/01), Slovenia(2004/05/01) and Croatia(2013/07/01) (See Figure 1b).

The analysis units of our study are subnational divisions obtained from the GADM database of Global Administrative Areas [7]. In total our study area comprises 6538 subnational units. Each analysis unit has defined, well established boundaries.

The land cover information we use comes from the CORINE program. This is a European Union program designed to coordinate environmental information for the countries in the Union. The available information depicts the land cover status for the years 1990, 2000 and 2006. CORINE data uses a hierarchical land cover classification with three taxonomic levels. In the most detailed level, it has 44 classes. In the second level the taxonomy has 15 classes, while in the first and coarser level it has 5 classes [8]. The land cover classes at the first level are: “Artificial Surfaces”, “Agricultural areas”,”Forest and semi natural areas”,”Wetlands” and “Water bodies”.

The land cover information is provided as vector and as raster. In the case of raster it is possible to obtain thematic datasets with pixel size of 100x100m and 250x250m. The pixel value is an integer in the range [1,44], representing the land cover classes at level 3 [8]. In our research we use raster datasets with spatial resolution of 100 x 100m. for the three available time points, 1990,2000 and 2006.

4. Methods

We overlap the geometry of the analysis units with the land cover information provided by CORINE. To perform the overlap, we use a technique called Zonal Statistics. To accomplish this task we use a python library called “rasterstats” [9].

The result of the zonal statistics calculation is a table in which for each subnational unit, we have the count of pixels for each land cover type at Level 3 for each of the three time points (1990, 2000, 2006). Later, we proceed to transform the counts into percentages in order to be able to compare administrative units of different sizes.

We can conceptualize each land cover category as a dimension. Then the status of an administrative unit at any given point of time is a point in the multidimensional land cover space. The evolution of land cover is defined by the vector between two temporal points. The magnitude of the vector would indicate whether there is a big or small land cover change. The direction of the vector would indicate different types of land cover evolution.

By using the hierarchical relations between land cover classes, it is possible to conceptualize the land cover composition at different detail levels. Figure 1a depicts the boxplots for the magnitude of change for the 2 time periods and the three taxonomic levels.

The result of the zonal statistic analysis is a pixel count for land cover categories at CORINE Level 3. However, the number of categories at this level is 44, which makes the analysis of the results a complex task. In our approach, we propose the use of the land cover taxonomy to reduce the complexity of the analysis. Using the taxonomy, we can collapse categories at Level 3 into the corresponding land cover superclasses at Level 2. The resulting dataset has 15 dimensions instead of 44, facilitating the analysis.

All our information is modeled with Description Logics and stored in a triplestore. The relations between taxonomic levels are explicit. Then it is a straightforward process to move from the land cover taxonomic level 3 to level 2. This process is implemented as a simple SPARQL query.

In this research, we are interested in units that have experienced change. We consider dynamic units as the ones that have an aggregated magnitude of vectorial change higher than 6.875 (the third quartile of the aggregated values distribution). By applying a classification method to the change vectors, we can identify different land cover types of evolution. To accomplish this task we use a hierarchical clustering algorithm. Using this technique the members of low level clusters become members of a larger one. The resulting clusters are non-overlapping. The tool we use is “hclust” based on a contribution by F. Murtagh to the R project [10].

By observing the centers of each cluster we could identify the type of evolution they represent. For instance L2_7 represents an intensification of land use: increase of urban fabric and arable land, while a decrease on pastures and scrub and herbaceous vegetation. the increase of farm land with a decrease in Pastures. L2_4 is comprised by vector representing afforestation processes. While L2_5 represents another type of land use intensification, with a decrease in pastures and an increase of heterogeneous agricultural areas (See figure 1d and 1e).

6. Conclusions

The use of the vector change approach working in tandem with a taxonomic land cover classification enables us analyze the land cover evolution, taking into consideration the magnitude of the change as well as the direction of the change. Thanks to the use of semantics and description logics, it is easy to move between land cover taxonomic levels, being necessary only a simple SPARQL query.

Our approach when coupled with statistic classification methods allows us to discover specific patterns of change.

Acknowledgements

We thank Direction Generale de l'Armement (DGA) and the Conseil Regional de Bourgogne for the financial support for developing our work.

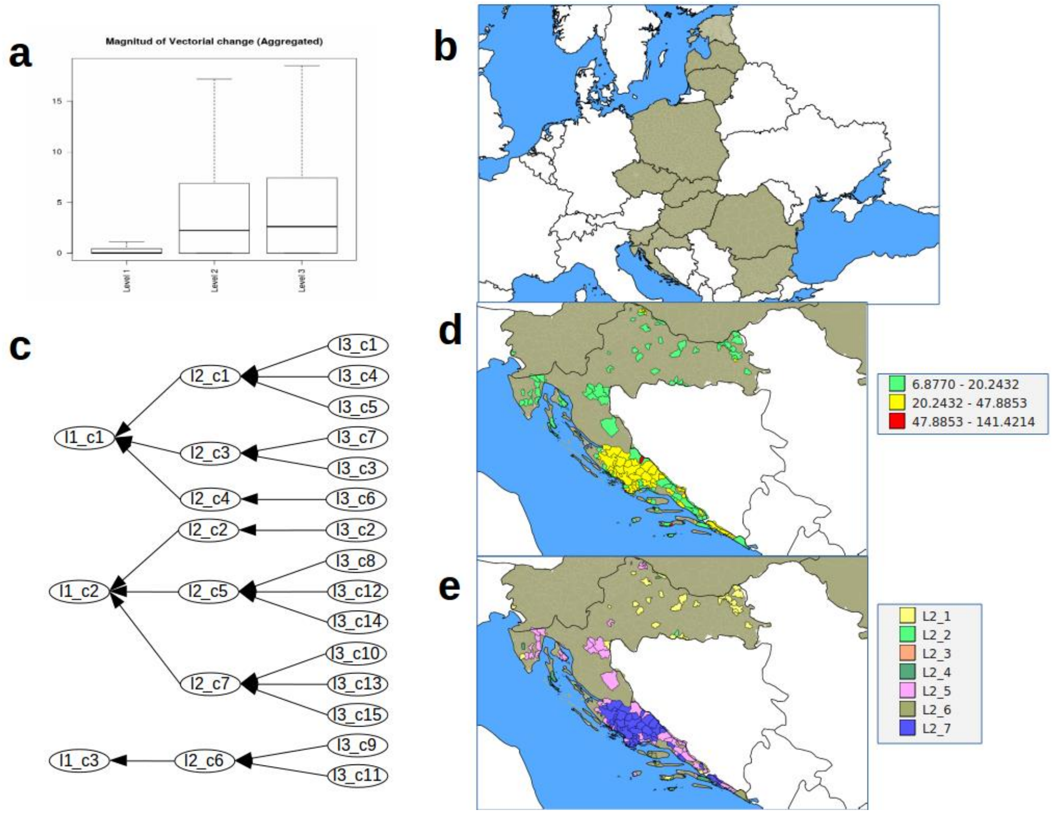

Fig. 1. (a) Boxplots of the aggregated magnitudes of vectorial change (1990-2000)+(2000-2006). (b) Study Area, comprised by post-socialist countries. (c) Hierarchical classification of change vectors. (d) Detail of the map, showing magnitude of change in Croatia between 2000-2006. (e) Detailed map showing the classification of change vectors for Croatia for the period 2000-2006.

References

[1] W. Malila, Change Vector Analysis : An Approach for Detecting Forest Changes with Landsat, LARS Symposia (1980) 326–335.

[2] C. He, A. Wei, P. Shi, Q. Zhang, Y. Zhao, Detecting land-use/land-cover change in rural-urban fringe areas using extended change-vector analysis, International Journal of Applied Earth Observation and Geoin-formation 13 (4) (2011) 572–585.doi:10.1016/j.jag.2011.03.002.

[3] A. Karnieli, Z. Qin, B. Wu, N. Panov, F. Yan, Spatio-Temporal Dynamics of Land-Use and Land-Cover in the Mu Us Sandy Land, China,Using the Change Vector Analysis Technique, Remote Sensing 6 (2014)9316–9339. doi:10.3390/rs6109316.

[4] J. Feranec, G. Hazeu, S. Christensen, G. Jaffrain, Corine land cover change detection in Europe (case studies of the Netherlands and Slovakia), Land Use Policy 24 (2007) 234–247.doi:10.1016/j.landusepol.2006.02.002.

[5] J. Feranec, G. Jaffrain, T. Soukup, G. Hazeu, Determining changes and flows in European landscapes 1990-2000 using CORINE land cover data, Applied Geography 30 (1) (2010) 19–35.doi:10.1016/j.apgeog.2009.07.003.

[6] A. Prishchepov, D. Muller, M. Dubinin, M. Baumann, V. C.Radeloff, Determinants of agricultural land abandonment in post-Soviet European Russia, Land Use Policy 30 (1) (2013) 873–884.doi:10.1016/j.landusepol.2012.06.011.

[7] GADM, GADM database of Global Administrative Areas (2012).

[8] EEA, CORINE Land Cover (2014).URL http://www.eea.europa.eu/publications/COR0-landcover

[9] M. Perry, GitHub python-raster-stats (2015).

[10] F. Murtagh, Hierarchical Clustering, hclust (1996).URL https://stat.ethz.ch/R-manual/R-patched/library/stats/html/hclust.html