This paper has been published online in the journal *Computers, Environment and Urban Systems*. Readers may find the edited version of this manuscript through the following link: https://doi.org/10.1016/j.compenvurbsys.2019.101375

Thematic resolution influence in spatial analysis. An application to Land Use Cover Change (LUCC) modelling calibration

Abstract

Understanding the uncertainty of every spatial analysis is a required step to be aware of its usefulness and limitations. The chosen scale of analysis determines part of this uncertainty. Thematic resolution refers to the grain component of scale, regarding the thematic detail at which categorical maps are made. The higher the thematic detail or resolution, the larger the amount of information we have and the more complex the analysis will be. Through this paper, we aim to assess how the calibration of a Land Use Cover Change (LUCC) model differs according to variation of the thematic resolution of input Land Use Land Cover (LULC) maps. To achieve this objective, we have set up four modelling exercises in Metronamica, each one calibrated with maps at different thematic resolutions. Obtained simulations were compared in terms of allocation of changes, modelled quantities, explanatory power of the model and pattern of simulated changes. Results show that the model behaves differently depending on the selected thematic resolution. Lower thematic resolution led to simpler simulations that, however, get better validation scores. High thematic resolution maps introduce more complexity and information in the analysis. If not correctly managed, this complexity and information can translate to model noise, worsening the model performance. The paper ends with a proposal of criteria to follow to aid modellers and researchers in the selection of the proper thematic resolution for their analyses.

Key words

Thematic Resolution, Scale, Uncertainty, Land Use Cover Change Modelling, Metronamica

1. Introduction

Given the impossibility of representing the complexity of the real world in a map, geographical data always imply some level of generalization, which is dependent on the selected scale. We understand scale "as a continuum through which entities, patterns, and processes can be observed and linked" (Marceau 1999), that is, a window of perception of a system at a given level of detail. At each scale, we deal with a different degree of detail and we are also able to study different processes or dynamics. In addition, depending on the selected scale and, accordingly, on the level of generalization, the analyses are subject to greater or lesser uncertainty. To effectively manage this uncertainty, we need to fully understand how our variables are spatially structured and then select the proper scale and level of generalization for their study. Therefore, a full understanding of how scale affects our data and analyses is needed, as pointed out by Lam and Quattrochi (1992) and Verburg and Veldkamp (2005), among others.

This paper contributes to a body of research which seeks to understand the effects that the selection of a specific spatial scale has in any geographical analysis. Notwithstanding, scale is a wide term that can refer to different aspects of data: as extent of the study space, level of spatial detail (spatial resolution) or level of thematic detail (defined as thematic resolution by Castilla et al. (2009) and Van Delden et al. (2011)). It can also refer to dimensions other than the spatial one; for example, temporal scale. To resolve the complexity of research about scale we follow the conceptual framework designed by Wu (2007), who distinguishes between dimensions (time, space and organizational hierarchy), kinds (intrinsic, observation, experimental, modelling and policy scale) and components of scale (grain, extent, coverage, spacing and cartographic scale).

We focus our attention on the grain component defined by Wu (2007), which can be analysed spatially or temporally, as well as thematically. Specifically, we aim to analyse the thematic resolution or grain. We consider it one of the most important components of scale, which, however, has not, to date, received a great deal of attention in the literature. A full understanding of the effects caused by every dimension, kind and component of scale is out of the scope of this paper and also a task that cannot be completed by a single piece of research or in only one investigation.

The thematic resolution, also called class resolution (Conway 2009), categorical or thematic scale (Ju et al. 2005; Aldwaik et al. 2015), and taxonomic scale (Lowell 2008), can be understood as the level of detail at which a variable is thematically defined. It mainly refers to discrete or qualitative variables, which have known and definable boundaries. In the case of land use mapping and modelling, the higher the number of land uses mapped, the higher the thematic or class resolution (Castilla et al. 2009; Van Delden et al. 2011).

In geographical analysis, the level of thematic resolution relates to the complexity of the analysis one carries out. The higher the thematic resolution of the variable to be analysed, the larger the number of components that will be utilised in the analysis and, therefore, the more complex the analysis will be. When undertaking, for example, land use change analysis, studying deforestation using binary maps (forest-non forest) is not as complex as when employing higher resolution maps that consider other categories such as crop fields, pastures, or urban areas. Therefore, we must well reason the selection of the proper thematic resolution for the analysis. It is a key decision with large implications.

In this investigation, we seek to aid researchers in making these decisions by studying the effect that the selection of a different thematic resolution has in a specific geographical analysis: Land Use Cover Change (LUCC) modelling. With LUCC modelling, the aim is to replicate the behaviour of a given system through the analysis of its land use cover change. The model represents this change using a pair of Land Use Land Cover (LULC) maps and the researcher attempts to explain it using a series of independent variables, such as proximity to other uses, accessibility, slope, planning, or other social drivers. The thematic or class resolution of the LULC maps is one of the key drivers of the complexity of the modelling exercise. Accordingly, this paper aims to show how changing the thematic resolution of those maps affects the results of a modelling exercise.

Most of the LUCC modelling exercises found in the literature do not explicitly justify the use of a specific thematic resolution for the LULC maps. Usually, the data sources or the constraints imposed by the model employed determine the chosen resolution. According to the study provided by Van Vliet et al. (2016), LUCC modelling applications show a wide range of thematic resolutions. They range from maps distinguishing 30 classes to binary maps, differentiating only two classes: presence or absence of one use. The most common are lower resolutions. Differentiation of several passive and static land use classes only happen in a few cases (Fig. 1). Dietzel and Clarke (2006), when talking about Cellular Automata modelling, differentiate primarily between binary approaches and those which consider more than two classes in the modelling exercise. Van Delden et al. (2011) discuss the number of land use classes as one of the elements to investigate model complexity through scale and scaling issues, and provide examples across a set of model applications around the world.

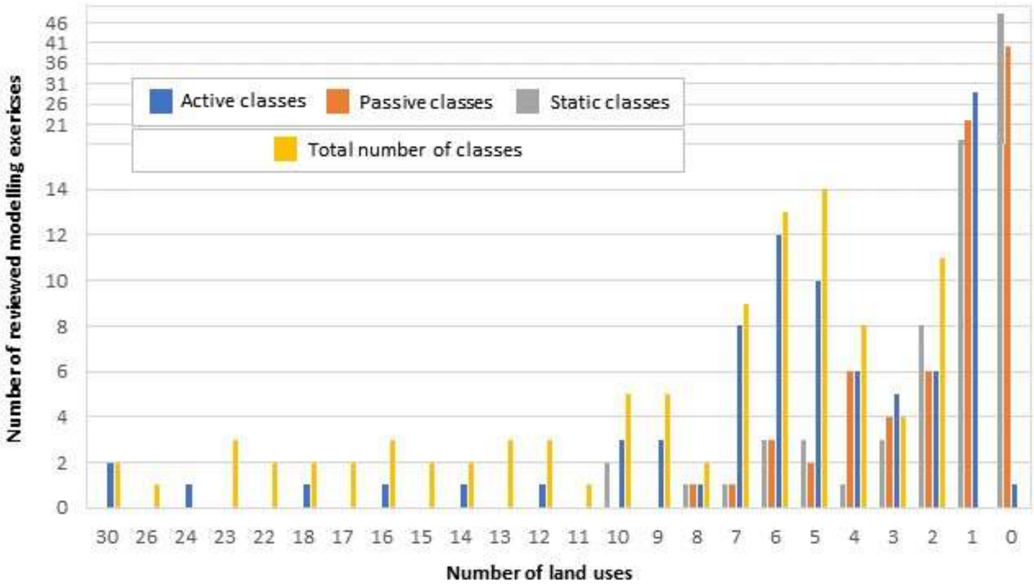

Figure 1. Common practice regarding thematic resolution of LULC maps in LUCC modelling reviewed by Van Vliet et al. (2016) from a total of 98 LUCC modelling exercises. Active classes refer to those categories that are actively simulated. Passive classes refer to those categories that are simulated passively as a consequence of the function classes changes. Static classes are those categories that remain invariant in the simulation. Total number of classes refer to the sum of active, passive and static classes. The minimum thematic resolution is therefore two classes, with 48 exercises that do not have any static class and 40 without any passive class. Source: review made by Van Vliet et al. (2016)

There are only a few studies which include sensitivity analysis of the impact that the change of thematic resolution has on a specific LUCC modelling exercise (Dietzel and Clarke 2004, 2006; Conway 2009; Hasbani et al. 2011; Zhao 2011). These studies, however, refer to exercises with specific modelling environments, and they are difficult to extrapolate to other software. Furthermore, they do not consider input maps with a wide range of thematic resolutions, comparable to the wide range of class resolutions one can find in the literature (Fig. 1). In addition, the analyses carried out are usually partial, not considering all types of (dis)agreement, such as the quantity, allocation and pattern (dis)agreement.

This research aims to fill these gaps by calibrating the same LUCC model using the Metronamica software package at four different thematic resolutions, which range from a very detailed distinction of land uses to a very general perspective. We consider the lowest thematic resolution chosen (4 categories) simple enough so as to avoid binary approaches. In this regard, the simplicity of the lowest thematic resolution exercise calibrated gives sufficient insight about the consequences of excessive simplification of LUCC modelling applications. On the other hand, Metronamica allows for the definition of neighbourhood rules between every category of the input LULC maps and the active modelled classes. Hence, the modelling approach allows for assessment of the full influence of the thematic resolution on the calibration of the model.

Finally, with the results obtained by the above-described exercises we aim to answer the following research questions: What is the influence of thematic resolution in any analysis? and how should we choose the best thematic resolution for a specific analysis?

3. Study area, materials and methods

3.1 Study Area

The modelled region is the Asturias Central Area, in north Spain (Fig. 2). This space groups together the main residential and industrial developments of Asturias. It is, therefore, the most dynamic space in the region in terms of changes of artificial uses. There are also other LUCC dynamics, such as forestation-deforestation or agricultural abandonment. However, they are more difficult to study and they are of less interest than urban dynamics from a planning perspective.

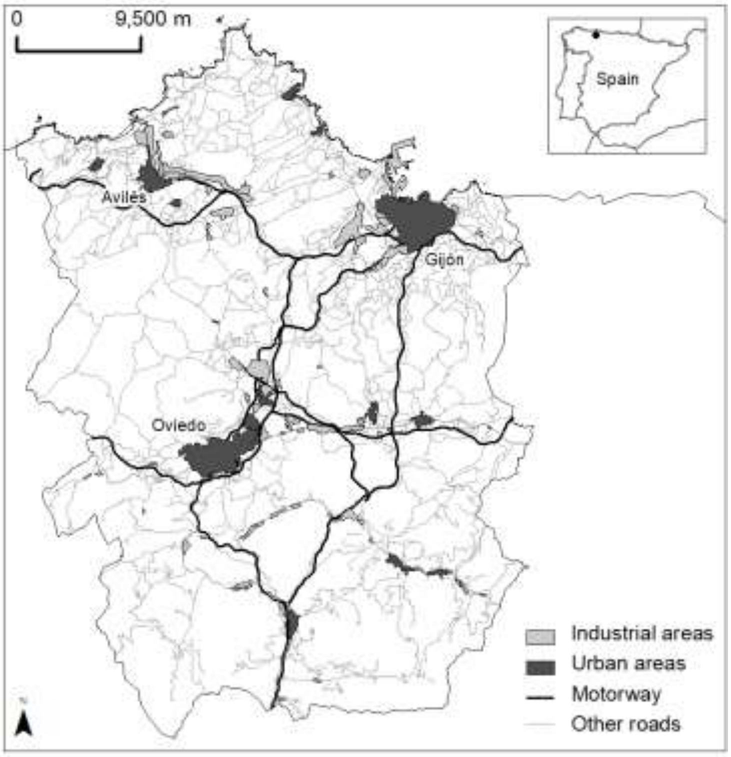

Figure 2. Asturias Central Area location map

3.2 Materials

We obtained four LULC maps at different levels of thematic resolution from the SIOSE database (Fig. 3). SIOSE (Sistema de Información sobre Ocupación del Suelo de España – Information System about Land Cover in Spain) is a LULC database obtained by photointerpretation at a scale of 1:25.000 for the years 2005 and 2011 (Equipo Técnico Nacional SIOSE 2015). SIOSE is comprised of a map, where visually coherent land cover polygons are drawn at the specified scale, and a database that registers the proportions of the land covers that make up every polygon. For example, a polygon can be made up of 50% pastures and 50% arable land. Generally, to draw a polygon it must be bigger than 0-5 to 2ha and wider than 15m (Valcárcel Sanz and Castaño Fernández 2012).

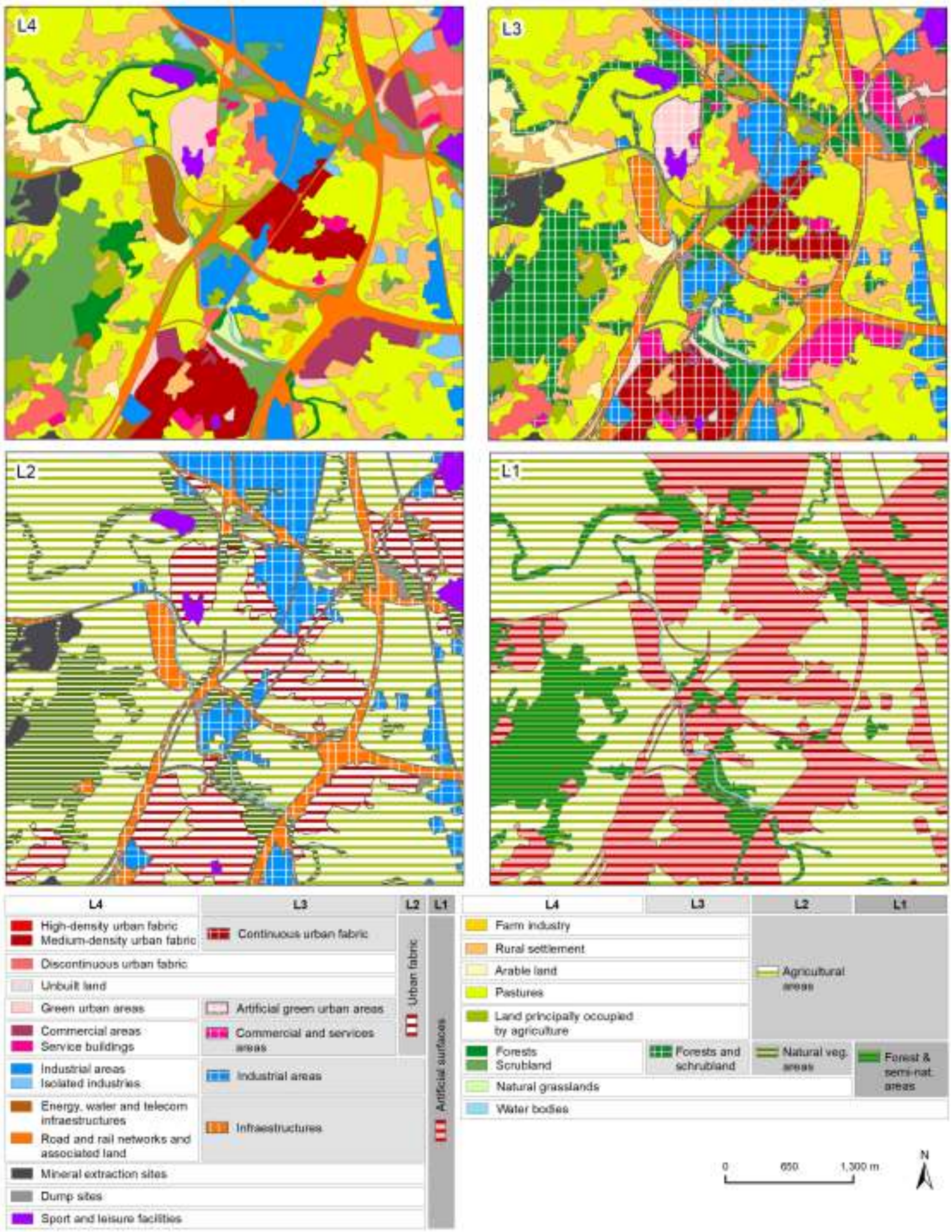

Figure 3. Land Use and Land Cover (LULC) maps at four different levels of thematic resolution obtained from SIOSE and used as input to the modelling exercises. Source: SIOSE 2005

Because of the characteristics of SIOSE, one polygon can be defined by more than just one land cover (e.g. 50% Industrial unit / 50% Roads). Whereas in some cases those compounds of land covers are defined (e.g. rural settlement, that can be made up of arable land, buildings or other natural vegetation classes), in other cases this information is not available. It is therefore the user who must establish the rules to determine a single land cover for each polygon. This is a required step to perform the modelling exercise. In this regard, most of the common available LULC models, including the one used in this study, only work with hard-classified maps. That is, maps where each pixel belongs to exactly one category (Camacho Olmedo et al. 2018).

The criteria to make this generalization was based in the deep authors' knowledge of the study area. In addition, authors have qualitatively assessed and validated the generalized map. Although it comes with more uncertainties than the original dataset, because of the generalization carried out, they are not of specific concern for the validity of the analysis. The original dataset is a very detailed one which must be generalized to perform the modelling exercise. Doing the generalization by means of coherent criteria, according to good understanding of the study area and its land cover characteristics, guarantees the solvency of these operations.

The highest resolution map does not preserve the thematic resolution of the original database, as we grouped those classes that were not of interest for our modelling purposes. Accordingly, we have focused our attention on those artificial and vacant categories than can help to explain the industrial and urban land use change dynamics of the Asturias Central Area (Table 1).

L4	L3	L2	L1
High-density urban fabric	**Continuous urban fabric**	**Urban fabric**	**Artificial surfaces**
Medium-density urban fabric			
Discontinuous urban fabric	**Discontinuous urban fabric**		
Unbuilt land	**Unbuilt land**		
Green urban areas	*Green urban areas*		
Cemetery			
Commercial areas	**Commercial and services áreas**		
Service buildings			
Industrial areas	**Industrial areas**	**Industrial areas**	
Isolated industries			
Energy, water and telecom infrastructures	*Infrastructures*	*Infrastructures*	
Road and rail networks and associated land			
Port areas			
Airports			
Mineral extraction sites	*Mineral extraction sites*	*Mineral extraction sites*	
Dump sites	*Dump sites*	*Dump sites*	
Sport and leisure facilities	*Sport and leisure facilities*	*Sport and leisure facilities*	
Farm industry	*Farm industry*	Agricultural areas	Agricultural areas
Rural settlement	**Rural settlement**		
Arable land	Arable land		
Pastures	Pastures		
Land principally occupied by agriculture, with significant areas of natural vegetation	Land principally occupied by agriculture, with significant areas of natural vegetation		
Forests	Forests and scrubland	Natural vegetation areas	Forest and semi-natural areas
Scrubland			
Natural grassland	Natural grassland		
Beaches, dunes, sands	*Beaches, dunes, sands*	*Open spaces with little or no vegetation*	
Open spaces with little or no vegetation	*Open spaces with little or no vegetation*		
Water bodies	*Water bodies*	*Water bodies*	*Water bodies*

Table 1. Defined legends for the reclassification of the SIOSE dataset. In bold are the classes modelled actively (**functions**), underlined are the categories modelled passively (vacants), and finally, in italics are those classes that remain static during the simulation (*features*). For more on this distinction and its meaning, see section 3.3.

The original vector maps were rasterized at a spatial resolution of 50m. This resolution was selected according to data detail, characteristics of the dynamics of the modelled area and considering the conclusions of the study carried out by Díaz-Pacheco et al. (2018) for a similar application. It also fits with the recommendations given by Hengl (2006) when selecting a specific spatial resolution for a given dataset.

Readers are directed to specific literature about spatial resolution influence in LUCC modelling to understand the effects that this decision could have had in the results of our study (Jantz and Goetz 2005; Ménard and Marceau 2005; Pan et al. 2010; Kim 2013; Blanchard et al. 2015). Finer spatial resolutions reduce the modelled quantities (Ménard and Marceau 2005; Blanchard et al.

2015) and increase the complexity of the modelled pattern (Ménard and Marceau 2005) and, in general, the complexity of the whole exercise (Kim 2013). Because of that, model performance indices are usually better at coarser spatial resolutions (Jantz and Goetz 2005). Changes in the spatial resolution also vary the way different variables, such as land use neighbourhood, explain the change (Pan et al. 2010).

To create the driving forces that explain the change predicted by the model we employed vector layers showing the roads, train stations and ports of the Asturias Central Area, as well as raster layers of the slope and zoning of the area. This last source was obtained from the Asturias government, whereas the other data was downloaded from the information provided by the Spanish National Geographic Institute.

3.3 Methods

To test the impact that changing the thematic resolution has on the calibration of a LUCC model, we ran the same application of the Asturias Central Area for each of the four LULC maps obtained (Fig. 3). Whereas the driving forces and the theory explaining the change were kept constant, we changed the input LULC maps for each exercise. Therefore, differences among all four exercises are due only to the different maps employed, at distinct levels of thematic resolution.

Metronamica is the software selected for carrying out the modelling exercises. It is a constrained Cellular Automata (CA) LUCC model built on the theory proposed by White and Engelen (1993, 1997) and White et al. (1997). An important part of the LUCC modelling research of the last decades relies on this theory (Santé et al. 2010), which ensures the meaningfulness of the selected modelling approach. Metronamica distinguishes three types of classes to be modelled: those classes that are modelled actively (functions), those which are modelled passively (vacants) and those which remain static during the simulation period (features) (Van Delden and Hurkens 2011).

The user specifies the demands of every function class. Then, the model allocates these demands to those cells which have the highest transition potentials, which is the result of combining all driving forces that, according to the user, explain the allocation of these categories. They are the neighbourhood of a cell to other classes, the accessibility, the environmental suitability and the planning areas. Additionally, a random factor accounts for the uncertainty of human action in the transition potential formula of function classes. Vacant classes are allocated after the function classes also according to their transition potential values, which are just defined by their environmental suitability and an inertia/conversion factor. A full description of the Metronamica model can be found in its official documentation (RIKS 2012).

We calibrated the application for the timeframe 2005-2011, a period during which the most important changes in the study area took place (Gobierno del Principado de Asturias 2016). Changes after this period, because of the economic crisis of 2008, are scarce and more dependent on political decisions, which would make the model calibration less reliable. Demands for the calibration period were directly extrapolated from map differences (2011 - 2005). However, to test in detail the allocation differences caused by changing the thematic resolutions, we ran another simulation employing in all exercises the demands measured by the input maps at the higher levels of thematic resolution (L4 and L3). We aggregated the changes measured by each function class at these levels of thematic resolution into the corresponding function class at the lower levels of thematic resolution, according to the thematic aggregation logic shown in Table 1.

We carried out an initial calibration for every exercise according to expert knowledge (Fig. 4). Then, the calibration was manually improved on a trial and error basis, according to the information given by the different validation indices: Kappa (K), Fuzzy Kappa (FK), Kappa Simulation (KS), Fuzzy Kappa Simulation (FKS) and a two spatial metrics (clumpiness and fractal dimension index). The information provided by these indices was complemented by visual inspection. We also used a neutral model that randomly allocates the simulated changes (Hagen-Zanker and Lajoie 2008) as a reference to test the goodness of the simulation.

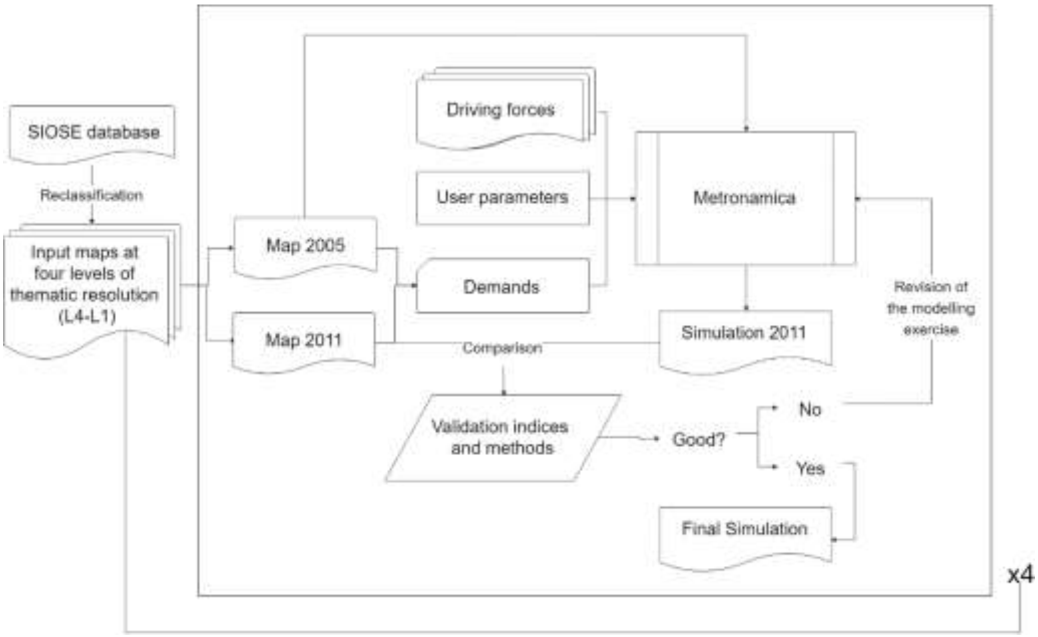

Figure 4. Scheme of the procedure followed to calibrate the four modelling exercises

Once we fully calibrated the four exercises, we compared the simulations obtained through a series of metrics and indices to analyse the impact that the change of the thematic resolution has on the modelling practice.

Quantity and allocation (dis)agreements between pairs of simulations were calculated through the matrix proposed by Pontius Jr. (2018). We progressively aggregated the maps at higher thematic resolutions to make the comparison between all outputs possible. We also performed a crosstabulation between the four simulations, aggregated to the lowest level of thematic resolution, to visually test the spatial coincidences between the four maps obtained. We compared the pattern generated by means of the Moran's *I* spatial autocorrelation index. It allows us to see how aggregated the cells of the same category in a map are with respect to other maps with the same categories.

We also employed for the comparison Kappa indices obtained in the calibration and the demands introduced as inputs. Kappa Simulation (KS) expresses the agreement between the changes of two categorical maps with respect to a third one which is used as reference, corrected by the agreement expected by chance (Van Vliet et al. 2011). Fuzzy Kappa Simulation (FKS) expresses the same agreement, but considering fuzzy set theory to account for the degree of spatial mismatch (Van Vliet et al. 2013). Fuzzy Kappa (FK) expresses the agreement observed between two categorical maps, corrected for the agreement expected by chance, and including fuzzy set theory to account for the degree of spatial mismatch (Hagen 2003).

Finally, we calculated the LUCC Budget built on the theory proposed by Pontius Jr. et al. (2004) for each temporal pair of maps (2005-2011) used as input. It shows the type and quantity of changes measured by each pair of maps, differentiating between total gross change (gains + losses), total net change (gains – losses) and swap (gross chain – net chain for a specific category, or group of categories). We calculated the LUCC budget for whole maps, but also differentiating the types of categories defined by Metronamica (functions, vacants and features).

4. Results

Like previous studies in the field, we have confirmed how changes in the thematic resolution of a geospatial analysis (e.g. simulation of Land Use Cover Change (LUCC)) have an impact on the obtained results. This impact is notorious and unavoidable, even if we manually calibrate the exercise to avoid that influence. It does not steadily increase when changing the thematic resolution, but is more evident at the finest and coarsest levels of thematic resolution.

The four simulations we carried out show important disagreements between them. They are disagreements in terms of the allocation of changes (Section 4.1), the modelled quantities (Section 4.2), the explanatory power of the model (Section 4.3) and the pattern of the allocated changes (Section 4.4).

4.1 Allocation (dis)agreement

When comparing the simulations obtained at each level of thematic resolution, the allocation agreement differs according to the function class considered. While it is high for the industrial areas modelled in the simulations L4, L3 and L2, it is low for all urban classes (Fig. 5).

We could interpret the stronger agreement between the simulated industrial areas at all levels of thematic detail as a consequence of the low uncertainty associated with the modelling of this class, that is, to a correct interpretation of the class behaviour and the drivers that explain its change. However, this class remains almost the same in all four exercises, whereas the urban classes are first thematically very disaggregated and then several classes are aggregated with each other at each level of thematic resolution (Table 1). Hence, that higher agreement is mainly a consequence of the absence, except for the L4 simulation, of thematic (dis)aggregation at each level of class resolution for the industrial areas case.

The allocation agreement is always higher between simulations at similar levels of thematic detail. Accordingly, the agreement between simulations L1 and L2 for artificial surfaces is higher than the agreement between simulations L1 and L3 and between simulations L1 and L4 (Fig. 5). We can therefore conclude that the bigger the difference in terms of thematic detail between two simulations, the more different are the simulations obtained. However, at very detailed levels of thematic resolution this is not true. In these cases, some classes, such as discontinuous urban fabric or unbuilt land, are too detailed and not very dynamic: changes from and to these classes are scarce. It is difficult to interpret and consequently replicate those dynamics of change. Accordingly, the modelling of these categories is very uncertain and the allocation agreement between different simulations for the same class is very low (Fig. 5).

4.2 The demands

The initial demands are different for part of the modelling exercises (Fig. 6). When lowering the thematic resolution of the LULC maps, some categories that previously we did not model, because they acted as features, were aggregated into one function class (Table 1), increasing the number of cells to be modelled. E.g. the urban fabric at the level 3 aggregates the green urban areas of level 2. We did not model the changes from vacant classes to green urban areas in the higher thematic resolution modelling exercises, but we modelled them in the other exercises once that class and, therefore, its changes, were aggregated with the function class.

These differences in the initial modelled demands increase the probability of simulating the changes of those categories correctly. The driving forces explaining changes are almost the same in all exercises, as it is the theory that we have built to explain those changes. However, the instances the model has to assign changes are not, as the model at lower thematic resolution has more cells to allocate, that is, bigger demands. Accordingly, the kappa indices that show the performance of the model increase at lower thematic resolutions because of the greater demands

(Table 2). Kappa Simulation (KS) already corrects for the quantity of change, but it increases because the bigger demands serve to correctly allocate some of the observed LUC changes. When we run all exercises according to the same quantities of change, the kappa scores were very similar for simulations at levels of thematic resolution 1, 2 and 3 (Table 2). In fact, instead of improving the performance of the model, when using the same quantities of change, that performance gets even worse when lowering the class resolution.

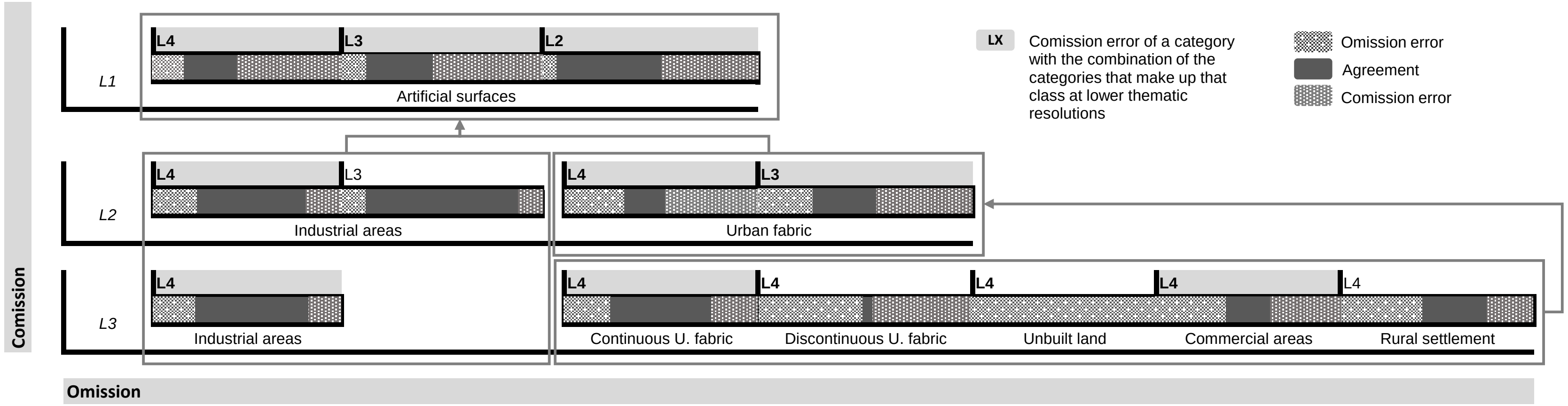

Figure 5. Allocation (dis)agreement between each pair of simulations for each function class. The agreement refers to the proportion of cells that correspond to the same category or their equivalent in both simulations. Omission error refers to those cells that are simulated as the function category in the simulation of the horizontal axis (**LX**), but are not simulated according to the same category in the simulation of the vertical axis (*LX*). Conversely, commission error refers to those cells which are simulated as the function category in the simulation of the vertical axis (*LX*), but are not simulated according to the same category in the simulation of the horizontal axis (**LX**).

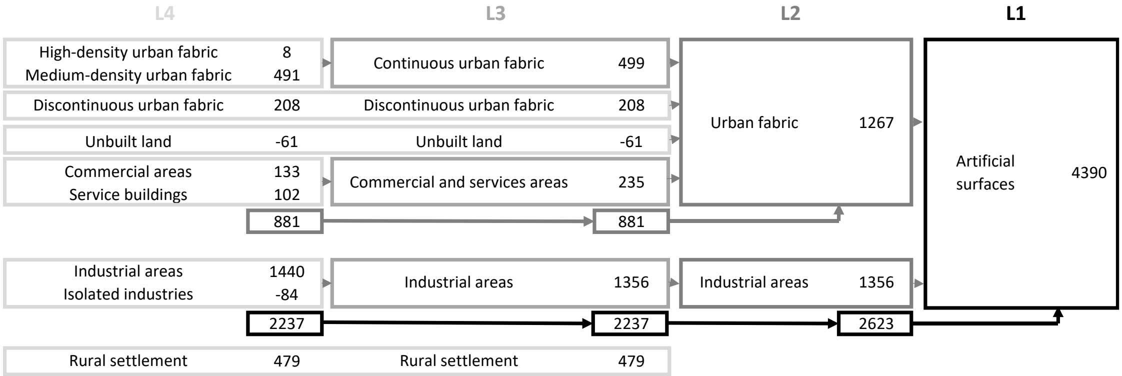

Figure 6. Quantities (cells) modelled for each function class at each level (L) of thematic resolution according to map differences between 2011 and 2005

In general, when working with the same demands, kappa scores do not vary to a large degree when changing the thematic resolution. Conversely, they tend to remain constant. The Kappa Simulation (KS) of urban fabric in the simulation at level 2 is similar to the KS score of continuous urban fabric in the simulation at level 3 and to the scores of medium-density and high-density urban fabric in the simulation at level 4 (Table 2). This shows that the changes we are able to simulate correctly are always the same, independent of the level of thematic resolution considered.

	L4	L3	L2		L1	
Demands	=	=	≠	=	≠	=
Overall statistics						
FKS	0.178	0.088	0.131		0.182	
FK	0.908	0.964	0.97		0.974	
Vacant Classes						
Arable land	-0.002 (0.23%)[1]	0.022 (0.23%)	0.157 (0.62%)	**0.143** (0.62%)	0.200 (1.57%)	**0.140** (1.57%)
Pastures	**0.158** (1.18%)	**0.141** (1.18%)				
Land principally occupied by agriculture	0.034 (0.95%)	0.039 (0.95%)				
Forests	0.219 (2.52%)	0.039 (1.16%)	0.036 (0.98%)	0.032 (0.98%)	0.038 (1.27%)	0.011 (1.27%)
Scrubland	0.197 (2.69%)					
Natural grassland	0.001 (0.5%)	-0.000 (0.5%)				
Function classes						
High-density urban fabric	0.133 (0.003%)	**0.188** (0.18%)	0.231 (0.34%)	**0.183** (0.34%)	0.254 (1.24%)	**0.177** (1.24%)
Medium-density urban fabric	**0.217** (0.18%)					
Discontinuous urban fabric	0.018 (0.15%)	0.021 (0.15%)				
Unbuilt land	0.098 (0.03%)	0.122 (0.03%)				
Commercial areas	0.178 (0.03%)	0.048 (0.06%)				
Service buildings	0.073 (0.03%)					
Industrial areas	**0.396** (0.24%)	**0.447** (0.27%)	**0.435** (0.26%)	0.441 (0.26%)		
Isolated industries	0.104 (0.10%)					
Rural settlement	0.055 (0.27%)	0.059 (0.27%)				

[1]The percentage refers to the proportion that the change of that class represents with respect to the whole map, including changes and permanence

Table 2. Fuzzy Kappa Simulation (FKS) and Fuzzy Kappa (FK) scores for each modelling exercise at each level of thematic resolution. Kappa Simulation (KS) scores are also provided at the class level for each vacant and function category. For the L2 and L1 exercises, kappa scores

are provided for those exercises that were set up with the same demands as the exercises L3 and L4 (=), and also for those exercises where the demands were extracted from map differences between 2005 and 2011 (≠). In parentheses, a percentage shows the proportion that the changes of the considered category represent with respect to the whole landscape, to indicate the relative importance of each kappa score relative to the full modelling exercise.

4.3 Model explanatory power

According to the kappa scores used as reference, we could explain correctly the changes or transitions from some vacant to other function classes. E.g., the transition from pastures to continuous urban fabric in the L3 simulation. However, they represent a small proportion of all changes shown in the input maps.

The total gross change of the vacant, and even of the feature classes, is in most of the cases bigger than the total gross change of the function classes. Specifically, the total gross change in the function classes in the highest thematic resolution maps (L4) is around 1%, whereas the swap between vacant classes represents for the same case 3.75% of the total studied area (Table 3).

We did not have the data, nor the knowledge and tools needed so as to correctly model the interactions between vacant classes. Accordingly, the kappa scores are low when keeping the thematic detail of these classes, except for the simulation L4 (Table 2). For this case, the FKS of the L4 model is very high due to the high scores achieved when modelling the vacant categories "Forests" and "Scrubland".

	L4	L3	L2	L1
Total net change (gains – losses)	**4.71%**	2.19%	1.80%	1.63%
Total gross change (gains + losses)	**10.43%**	**6.30%**	4.78%	4.26%
Total gross change of vacant classes	**8.06%**	**4.02%**	2.90%	2.84%
Change as swap of vacant classes	**3.75%**	**1.90%**	1.10%	1.14%
Total gross change of function classes	1.04%	0.97%	0.65%	**1.24%**
Change as swap of function classes	**0.17%**	**0.17%**	0.02%	0.00%
Total gross change of feature classes	1.32%	1.32%	1.23%	**0.18%**

Table 3. Changes according to the type of category considered (vacant, function or feature) measured by the LULC maps employed as inputs for each modelling exercise (SIOSE 2005 - 2011). The percentages refer to the proportion that the changes represent with respect to the whole map

The exchanges between forests and scrubland are more numerous than the changes of all remaining vacant and function categories together (5.21% vs 3.89%) (Table 3), which explains the strong influence that the simulation of these categories has on the global FKS scores. However, these classes were not properly simulated, as the low FK index demonstrates. FKS expresses a high agreement between simulated changes and changes shown by the reference maps (2005-2011). However, in contrast to FK, it does not give particular importance to the modelled persistence, which explains why high FKS scores do not always correspond with better simulations.

4.4 The Modelled pattern

The modelled pattern is simpler at lower thematic resolutions (Fig. 7). The lower the class resolution, the more grouped are the simulated cells of the same class, as shown by the Moran's I correlation coefficient (Table 4). For the reference maps, autocorrelation between changes is similar at all levels of thematic resolution. Changes measured by input maps show high spatial autocorrelation, like the one simulated at the lowest levels of thematic resolution in the modelling exercises (Table 4).

For the L4 simulation, the Moran's I coefficient shows the largest correlation coefficient for the simulation of scrubland and forest patches in the analysis. We did not correctly simulate these classes, as pointed out in the previous section. In addition, we did not model these classes in the other exercises, when we lowered thematic resolution of input maps. When considering the correlation of changes of the L4 simulation without scrubland and forests changes, to make it comparable with the other three exercises, we confirm behaviour identified previously: at higher thematic resolutions, the cells are more scattered. That is, simulated cells are commonly part of small or tiny patches, at a certain distance one from another, and it is more common to find isolated cells between them.

Although in all cases the influence of the Cellular Automata component in the simulated landscape is apparent, at lower thematic resolutions most of the allocated change follows a very simple contiguity logic (Fig. 7). Simulated cells are located next to previously simulated cells of the same category, showing a pattern of growth which, visually, makes the simulation appear very simple.

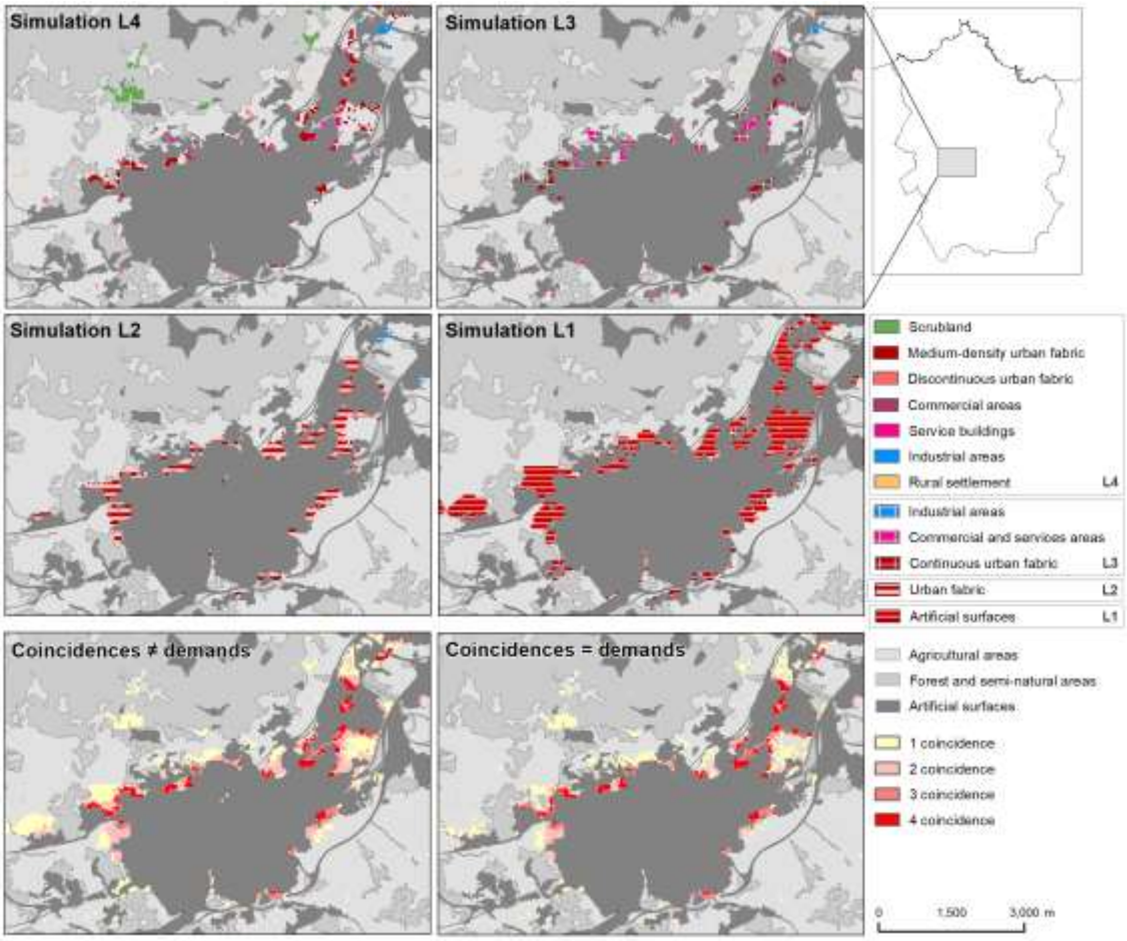

Figure 7. Top, maps of the simulated changes at each level of thematic resolution in the modelling exercises run with different demands for an example area of the modelled region (Oviedo city and surroundings). Bottom, maps showing the coincidences between the four simulations for the modelling exercises run with the same demands (right) and those set up with different demands (left).

L4		L3	L2	L1
With schrubland-forest transition	Without scrubland-forest transition			
0.715878 (0.591352)	0.312031 (0.532884)	0.381907 (0.533799)	0.564368 (0.545607)	0.592156 (0.585642)

Table 4. Coefficients of Moran's I spatial autocorrelation for the changes simulated at each level of thematic resolution. In brackets are included coefficients of autocorrelation for the changes showed by reference input maps. Values range from -1 to 1, meaning negative values that the changes are disaggregated and positive values aggregation of LUC changes.

5. Discussion

5.1 What is the influence of the thematic resolution in any analysis?

Depending on the chosen level of thematic resolution, the results of our study will vary to a great extent, as supported by the results of the analyses and the conclusions of other studies carried out in different research fields (Strand et al. 2002; Buyantuyev and Wu 2007; Liang et al. 2013; Aldwaik et al. 2015). At each specific resolution, the variation will be different, being the highest and lowest levels of thematic resolution the ones that show more differences and specificities.

The impact that changing the level of thematic resolution has in a specific geospatial analysis is also dependent on the other dimensions, kinds and components of the scale of the analysis and the underlying data. Very detailed datasets, such as SIOSE, produced at a scale of 1:25.000 with a Minimum Mapping Unit between 0.5 and 2ha, are more sensitive to changes in the chosen scale of representation than are coarser datasets. With the latter, the scope for generalisation is limited since much spatial information has been removed by using a comparatively small number of classes. Therefore, the influence of the thematic resolution in our analysis has been especially important because of the detailed dataset employed. Studies employing simpler datasets will provide different results. In any case, we always need to consider that, when adapting the scale, the quantity of information managed changes exponentially depending on the level of detail of the data.

Drawing on the results of our analysis, we consider different ways in which the thematic resolution can influence our study: the complexity of the analysis (Section 5.1.1), the validation scores achieved (Section 5.1.2) and the modelled pattern (Section 5.1.3).

5.1.1 Complexity

Higher thematic resolutions mean more thematic information and, therefore, more complex analyses. The larger the number of categories considered, the more variable are the interactions between these categories. In binary approaches, there are only two types of transitions: from one category to the other and vice versa. However, in maps with higher thematic resolutions, the number of possible transitions or interactions between classes increase exponentially. For our study case, the change measured as swaps between vacant classes remained almost constant at the L1 and L2 levels of thematic resolution, and then grew exponentially: from 1.10% to 1.90% (L3) and 3.75% (L4).

When dealing with multiple class interactions, as in the L4 simulation, we may not be able to understand all complex dynamics the model is able to simulate, which impacts negatively on our model understanding. As the relations between categories are more numerous and complex, they are more difficult to comprehend. This reduces the quality of the modelling exercise, as revealed in our study case by the validation indices and metrics we have employed.

Relations and differences between classes are usually easier to interpret at lower thematic resolutions. This explains why in land use mapping the agreement between datasets is usually higher at lower levels of thematic resolution (Bach et al. 2006; Pérez-Hoyos and García-Haro 2013). Notwithstanding, some complexity will always be needed. If not provided, modelling exercises may be an oversimplification of real systems. At very low thematic resolutions, relations between classes are very simple. One cannot discern the different types of conversions or attractions between categories, which explain the complexity of a real system and the way it evolves in its different parts.

In addition, when dealing with higher thematic resolution maps we may not have the information, nor the tools, to correctly model the new interactions between categories. In our case, we were not able to correctly model the vacant classes in the exercises with higher thematic resolution exercises. In this regard, the simulation of vacant classes in Metronamica is very simple, determined only by the multiplication of a suitability map with an inertia/conversion factor (RIKS 2012). Modelling these classes as functions could fix the problem. However, we did not count with the knowledge nor information to properly explain their change. Data is for that purpose essential. If the new modelled classes at higher levels of thematic resolution do not show enough quantity of changes, we may not be able to understand the processes that explain those changes. Thus, modellers usually trust data to understand how a system works and its dynamism (Messina et al. 2008; Chang-Martínez et al. 2015; Van Vliet et al. 2016).

For modelling exercises, too much complexity, due to very high thematic resolutions, can be counter-productive, as models themselves are just a simplification of a real system. Models usually focus on the most important processes of change and ignore the less important ones (Heuvelink 1998). Therefore, levels of thematic resolution that give us information about a lot of small important processes of change will not be correctly managed by most of the available model software. On the contrary, excessive generalization may lead to oversimplification of modelled systems and the loss of their realism. If employing complex modelling tools, there may be a disconnection between the complexity of the tool and the simplicity of the chosen resolution. Thus, modellers must find a balance between the complexity they are able to manage and the realism of the modelled system.

5.1.2 Validation indices

The different performance of the model because of changes in the thematic resolution was not caused by working with mixed categories difficult to interpret (e.g. forest and semi-natural areas), the higher chance of errors in maps at higher resolutions or by the confusion that the interaction between a lot of categories (multiple transitions of change) provoke. Instead, it was due to the omission of the changes we could not explain at higher thematic resolutions and to the variation of the demands, that increased the chances the model had to correctly simulate those changes.

Usually, the higher the thematic resolution, the more demands on the person doing the calibration. If the modeller does not know how to deal with that higher resolution, simpler exercises are then preferred. Therefore, the class resolution can be seen as a tool to avoid those details or processes we cannot explain, improving the validation indices of our simulation and, consequently, the confidence of the audience and stakeholders in our results. Notwithstanding, to get full confidence in our results, we also need to provide reliable and complete validation studies in order to assess bias.

In our case, basing judgement on the information provided by the Kappa Simulation (KS) index led to incorrect conclusions in the L4 simulation. KS and Fuzzy Kappa Simulation (FKS) must be always used together with Kappa and Fuzzy Kappa (FK); whereas (F)KS accounts for the percentage of correctly predicted change, the (F)Kappa indices account for the percentage of predicted persistence. However, many studies make use only of the (F)KS indices (Hewitt et al. 2014; Altartouri et al. 2015; Blecic et al. 2015) or the (F)Kappa indices (Van Delden et al. 2010; Ding et al. 2013; Zhang et al. 2016). Thence, modellers must evaluate the goodness of fit of their exercises with a wide range of metrics and indices, as the ones previously mentioned, together with visual inspection.

The classes we could model correctly were the same at all levels of thematic resolution: the two types of urban fabric and industrial areas. This supports the conclusions of Conway (2009). We did not correctly model the other classes, but different values of goodness of fit according to the employed metrics were obtained because of the omission of changes alluded to and variation of demands. Dietzel and Clarke (2006) and Conway (2009) also demonstrated for other software, study cases and data, this relation between the different levels of thematic resolution, the variation of the modelled demands and the different performance of the modelling exercises.

This must be carefully considered in the case of those software environments that can automatically extract the demands from input maps, as does CA_Markov (Eastman and Toledano 2018a) or Land Change Modeler (LCM) (Eastman and Toledano 2018b). They employ second-order Markov Chains, which determine the probabilities to change from the changes measured from two past times point (Van Schrojenstein Lantman et al. 2011). If not manually edited, the Markov probability matrix would influence to a great degree the results of the analysis, depending on the chosen level of thematic resolution.

5.1.3 The modelled pattern

The complexity of the modelled pattern is also a consequence of the thematic resolution. Common binary approaches (urban / not urban, forest / not forest) can lead in Cellular Automata (CA) models to the simulation of very simple patterns (Dietzel and Clarke 2006; Zhao 2011), where newly simulated cells are frequently located next to previously simulated cells of the same class. The L1 simulation in our analyses also showed this behaviour.

Abolhasani et al. (2016) have established three types of neighbourhood interactions modelled by CA models: compactness, compatibility and dependency. When working with binary approaches, the only possible interaction is the compactness. In a similar vein, at low thematic resolutions the complexity of the compatibility and dependency relations is not particularly meaningful. That is why low levels of thematic resolution generate a very simple pattern of growth, determined only by compactness rules, as in the L1 simulation. This pattern approximates to an oil stain that progressively spills over a surface, which does not seem realistic. In the real world, some classes are more resistant to change than other ones and, therefore, a very simplistic organic growth is not expected. Conversely, the landscape presents a higher fragmentation, like the one obtained by increasing the thematic resolution.

A high importance of zoning when allocating land uses can play a role in avoiding the simulation of very simplistic patterns, also increasing the allocation agreement between simulations at different levels of thematic resolution. For our study case, the higher agreement between industrial areas in the different simulations can be explained by this factor. Industrial areas did not show an organic pattern of growth like urban fabric, but one mostly affected by zoning rules. Notwithstanding, we should consider to what extent this strategy improves the correct simulation of future land use dynamics, which is the main purpose of most LUCC models. Thus, spatial zoning weight should not be used in a way that the models become very deterministic.

5.2 How should we choose the best thematic resolution for a specific analysis?

There is not an ideal level of thematic resolution for all analyses, nor for each study. This decision will always bring uncertainty. However, we can understand it as a tool to deal with that unavoidable uncertainty.

The selection of the thematic resolution must be well reasoned, based on the following aspects: objectives of the proposed analysis, information and knowledge of the studied processes and variables, the tools employed and the audience' needs. In the next lines, we address in detail how each of these aspects must be considered when selecting the thematic resolution of a study.

Firstly, we need to make the **objectives** clear, that is, what we want to study and why. Thematic detail for all the other classes apart from those ones that are responsible of the dynamics to be modelled should be only provided when it helps to better explain these dynamics. Models like Metronamica enable the definition of neighbourhood interactions between the class of interest and the other classes. The new interactions made possible by higher resolution maps may improve the simulation.

Secondly, we need to consider the **information and knowledge** we have to explain the variables or processes to be studied. When the categorical maps are just used in an informative way, to provide information, there is no limit in the thematic resolution to be employed, as it will only mean that we can get more detailed information. Notwithstanding, the larger the quantity of information, the more difficult the interpretation will be (Wang and Marceau 2013).

When the data are employed, together with other sources, in some analysis, the chosen thematic resolution must be linked to the complexity level of the whole study. Higher thematic resolutions should only be chosen if the new information this extra resolution provides is explained by forces for which we have data. Different to previous research, we have proved how the thematic resolution impact on the analysis is more a consequence of our ability to deal with or explain this bigger detail than because of the change of resolution itself.

Thirdly, the information we are able to use is also dependent on the **tool** employed. The chosen thematic detail and, accordingly, the desired complexity, must be linked to the sophistication and characteristics of the selected tools. Previous studies which have only focused on the sensitivity of a specific LUCC model software package to thematic resolution changes have not specifically addressed the way the software chosen has affected the conclusions they got. Most of these studies have only worked with data-driven models, where changes in the input maps will unavoidably affect the way the model behaves.

For CA models, the simulation of categories that do not show a compacted pattern can be problematic, as the patterns simulated by these models tend to be quite simple. Accordingly, the user must consider the simplification of the input maps to avoid these categories when making use of CA models. In addition, the thematic resolution will play a more important role in CA models where a full specification of interactions between categories is possible (e.g. Metronamica), than in other modelling approaches where there is no or limited interaction between categories.

Fourthly, the selected level of thematic resolution must also consider the **audience needs**. Despite their importance, they have not been considered in previous studies about sensitivity of LUCC models to class resolution changes. As stated by Van Delden et al. (2011), those using the model results usually require a minimum complexity. Accordingly, analyses at very low thematic resolutions can be seen as too simplistic. On the other hand, higher thematic resolutions can lead to a false sense of accuracy (Van Delden et al. 2011), which could result in the loss of the audience and stakeholder engagement.

In summary, before selecting a specific level of thematic resolution we need first to understand the data we are working with and the information and tools we have to explain it. To this end, conducting sensitivity analysis with different resolutions is the ideal solution. In this way the user can fully understand how changing the thematic resolution affects the results of their analysis, building the knowledge required as to take the correct decision. Conway (2009) advises for LUCC modelling practise to undertake calibration exercises that proceed from simpler approaches, at low levels of thematic detail, to more complex ones, until the desired outcome is obtained.

6. Conclusions

The selected thematic resolution and, therefore, the chosen scale, clearly has an impact on the results of a geospatial analysis. We should therefore pay more attention to these initial decisions, as the utility and reliability of our analyses depend on them.

There is not an ideal solution for the selection of the best thematic resolution for each analysis. The user must carefully consider the objectives of their study, the knowledge and data available, the tools which will be used and the audience' needs. Nevertheless, sensitivity analyses are always recommended to assess the influence of the thematic resolution in our studies and, therefore, to consider the uncertainty that this decision brings. Only after this step can a reasoned decision be taken.

This research has shown how the chosen thematic resolution can affect the modelled quantities and pattern, the validation indices obtained or the degree of complexity of the analysis. However, these effects can be different when employing other data, tools or calibration approaches. Therefore, further research should explore how changing the thematic resolution affects the results of a modelling exercise when using less detailed datasets, non-CA models or calibration methods different to the manual one.

References

Abolhasani S, Taleai M, Karimi M, Rezaee Node A (2016) Simulating urban growth under planning policies through parcel-based cellular automata (ParCA) model. Int J Geogr Inf Sci 8816:1–26 . doi: 10.1080/13658816.2016.1184271

Aldwaik SZ, Onsted JA, Pontius Jr. RG (2015) Behavior-based aggregation of land categories for temporal change analysis. Int J Appl Earth Obs Geoinf 35:229–238 . doi: 10.1016/j.jag.2014.09.007

Altartouri A, Nurminen L, Jolma A (2015) Spatial neighborhood effect and scale issues in the calibration and validation of a dynamic model of Phragmites australis distribution - A cellular automata and machine learning approach. Environ Model Softw 71:15–29 . doi: 10.1016/j.envsoft.2015.04.010

Bach M, Breuer L, Frede HG, et al (2006) Accuracy and congruency of three different digital land-use maps. Landsc Urban Plan 78:289–299 . doi: 10.1016/j.landurbplan.2005.09.004

Blanchard SD, Pontius Jr. RG, Urban KM (2015) Implications of Using 2 m versus 30 m Spatial Resolution Data for Suburban Residential Land Change Modeling. J Environ Informatics 25:1–13 . doi: 10.3808/jei.201400284

Blecic I, Cecchini A, Trunfio G a. (2015) How much past to see the future: a computational study in calibrating urban cellular automata. Int J Geogr Inf Sci 29:349–374 . doi: 10.1080/13658816.2014.970190

Buyantuyev A, Wu J (2007) Effects of thematic resolution on landscape pattern analysis. Landsc Ecol 22:7–13 . doi: 10.1007/s10980-006-9010-5

Camacho Olmedo MT, Mas J-F, Paegelow M (2018) The simulation stage in LUCC modeling. In: Camacho Olmedo MT, Paegelow M, Mas J-F, Escobar F (eds) Geomatic Approaches for Modeling Land Change Scenarios. Springer, Cham, Switzerland, pp 27–51

Castilla G, Larkin K, Linke J, Hay GJ (2009) The impact of thematic resolution on the patch-mosaic model of natural landscapes. Landsc Ecol 24:15–23 . doi: 10.1007/s10980-008-9310-z

Chang-Martínez L, Mas J-F, Valle N, et al (2015) Modeling Historical Land Cover and Land Use: A Review from Contemporary Modeling. ISPRS Int J Geo-Information 4:1791–1812

. doi: 10.3390/ijgi4041791

Conway TM (2009) The impact of class resolution in land use change models. Comput Environ Urban Syst 33:269–277 . doi: 10.1016/j.compenvurbsys.2009.02.001

Díaz-Pacheco J, Van Delden H, Hewitt R (2018) The importance of scale in land use models: experiments in data conversion, data resampling, resolution and neighbourhood extent. In: Camacho Olmedo MT, Paegelow M, Mas J-F, Escobar F (eds) Geomatic Approaches for Modeling Land Change Scenarios. Springer, Cham, Switzerland, pp 163–186

Dietzel C, Clarke KC (2006) The effect of disaggregating land use categories in cellular automata during model calibration and forecasting. Comput Environ Urban Syst 30:78–101 . doi: 10.1016/j.compenvurbsys.2005.04.001

Dietzel C, Clarke KC (2004) Replication of Spatio-temporal Land Use Patterns at Three Levels of Aggregation by an Urban Cellular Automata. In: Sloot PMA, Chopard B, Hoekstra AG (eds) 6th International Conference on Cellular Automata for Research and Industry, ACRI 2004. Springer, Amsterdam, pp 523–532

Ding WJ, Wang RQ, Wu DQ, Liu J (2013) Cellular automata model as an intuitive approach to simulate complex land-use changes: An evaluation of two multi-state land-use models in the Yellow River Delta. Stoch Environ Res Risk Assess 27:899–907 . doi: 10.1007/s00477-012-0624-7

Eastman JR, Toledano J (2018a) A Short Presentation of CA_MARKOV. In: Camacho Olmedo MT, Paegelow M, Mas J-F, Escobar F (eds) Geomatic Approaches for Modeling Land Change Scenarios. Springer, Cham, Switzerland, pp 481–484

Eastman JR, Toledano J (2018b) A Short Presentation of the Land Change Modeler (LCM). In: Camacho Olmedo MT, Paegelow M, Mas J-F, Escobar F (eds) Geomatic Approaches for Modeling Land Change Scenarios. Springer, Cham, Switzerland, pp 499–505

Equipo Técnico Nacional SIOSE (2015) Documento Técnico SIOSE 2011. Versión 1.1

Gobierno del Principado de Asturias (2016) Directrices subregionales de ordenación del Área Central de Asturias. Avance: objetivos y criterios

Hagen-Zanker A, Lajoie G (2008) Neutral models of landscape change as benchmarks in the assessment of model performance. Landsc Urban Plan 86:284–296 . doi: 10.1016/j.landurbplan.2008.04.002

Hagen A (2003) Fuzzy set approach to assessing similarity of categorical maps. Int J Geogr Inf Sci 17:235–249 . doi: 10.1080/13658810210157822

Hasbani, G. J, Wijesekara N, Marceau DJ (2011) An Interactive Method to Dynamically Create Transition Rules in a Land-use Cellular Automata Model. In: Salcido A (ed) Cellular Automata - Simplicity Behind Complexity. InTech, pp 3–22

Hengl T (2006) Finding the right pixel size. Comput Geosci 32:1283–1298 . doi: 10.1016/j.cageo.2005.11.008

Heuvelink GBM (1998) Uncertainty analysis in environmental modelling under a change of spatial scale. Nutr Cycl Agroecosystems 50:255–264 . doi: 10.1023/A:1009700614041

Hewitt R, Van Delden H, Escobar F (2014) Participatory land use modelling, pathways to an integrated approach. Environ Model Softw 52:149–165 . doi: 10.1016/j.envsoft.2013.10.019

Jantz CA, Goetz SJ (2005) Analysis of scale dependencies in an urban land-use-change model. Int J Geogr Inf Sci 19:217–241 . doi: 10.1080/13658810410001713425

Ju J, Gopal S, Kolaczyk ED (2005) On the choice of spatial and categorical scale in remote sensing land cover classification. Remote Sens Environ 96:62–77 . doi: 10.1016/j.rse.2005.01.016

Kim JH (2013) Spatiotemporal scale dependency and other sensitivities in dynamic land-use change simulations. Int J Geogr Inf Sci 27:1782–1803 . doi: 10.1080/13658816.2013.787145

Lam NS-N, Quattrochi D (1992) On the Issues of Scale, Resolution, and Fractal Analysis in the Mapping Sciences. Prof Geogr 44:88–98 . doi: 10.1111/j.0033-0124.1992.00088.x

Liang Y, He HS, Fraser JS, Wu ZW (2013) Thematic and Spatial Resolutions Affect Model-Based Predictions of Tree Species Distribution. PLoS One 8:1–10 . doi: 10.1371/journal.pone.0067889

Lowell KE (2008) Uncertainty in Landscape Models: Sources, Impacts and Decision Making. In: Pettit C, Cartwright W, Bishop I, et al. (eds) Landscape Analysis and Visualisation. Berlin, Heidelberg, pp 367–382

Marceau DJ (1999) The scale issue in social and natural sciences. Can J Remote Sens 25:347–356 . doi: 10.1080/07038992.1999.10874734

Ménard A, Marceau DJ (2005) Exploration of spatial scale sensitivity in geographic cellular automata. Environ Plan B Plan Des 32:693–714 . doi: 10.1068/b31163

Messina JP, Evans TP, Manson SM, et al (2008) Complex systems models and the management of error and uncertainty. J Land Use Sci 3:11–25

Pan Y, Roth A, Yu Z, Doluschitz R (2010) The impact of variation in scale on the behavior of a cellular automata used for land use change modeling. Comput Environ Urban Syst 34:400–408 . doi: 10.1016/j.compenvurbsys.2010.03.003

Pérez-Hoyos A, García-Haro FJ (2013) Evaluación de productos de cubiertas del suelo en la península ibérica. Rev Teledetección 40:22–40

Pontius Jr. RG (2018) Pontius Matrix

Pontius Jr. RG, Shusas E, McEachern M (2004) Detecting important categorical land changes while accounting for persistence. Agric Ecosyst Environ 101:251–268 . doi: 10.1016/j.agee.2003.09.008

RIKS (2012) Metronamica Documentation. Maastricht

Santé I, García AM, Miranda D, Crecente R (2010) Cellular automata models for the simulation of real-world urban processes: A review and analysis. Landsc Urban Plan 96:108–122 . doi: 10.1016/j.landurbplan.2010.03.001

Strand GH, Dramstad W, Engan G (2002) The effect of field experience on the accuracy of identifying land cover types in aerial photographs. Int J Appl Earth Obs Geoinf 4:137–146 . doi: 10.1016/S0303-2434(02)00011-9

Valcárcel Sanz N, Castaño Fernández S (2012) Cartografía de ocupación del suelo en España. Proyecto SIOSE. CNIG, Madrid

Van Delden H, Hurkens J (2011) A generic Integrated Spatial Decision Support System for urban and regional planning. In: Chan F, Marinova D, Anderssen RS (eds) 19th International Congress on Modelling and Simulation. Perth, pp 127–139

Van Delden H, Stuczynski T, Ciaian P, et al (2010) Integrated assessment of agricultural policies with dynamic land use change modelling. Ecol Modell 221:2153–2166 . doi: 10.1016/j.ecolmodel.2010.03.023

Van Delden H, Van Vliet J, Rutledge DT, Kirkby MJ (2011) Comparison of scale and scaling issues in integrated land-use models for policy support. Agric Ecosyst Environ 142:18–28 . doi: 10.1016/j.agee.2011.03.005

Van Schrojenstein Lantman J, Verburg PH, Bregt A, Geertman S (2011) Core Principles and Concepts in Land-Use Modelling: A Literature Review. In: Koomen E, Borsboom-Van Beurden J (eds) Land-Use Modelling in Planning Practice. Springer, Dordrecht, Heidelberg, London, New York, pp 35–57

Van Vliet J, Bregt AK, Brown DG, et al (2016) A review of current calibration and validation practices in land-change modeling. Environ Model Softw 82:174–182 . doi: 10.1016/j.envsoft.2016.04.017

Van Vliet J, Bregt AK, Hagen-Zanker A (2011) Revisiting Kappa to account for change in the accuracy assessment of land-use change models. Ecol Modell 222:1367–1375 . doi: 10.1016/j.ecolmodel.2011.01.017

Van Vliet J, Hagen-Zanker A, Hurkens J, Van Delden H (2013) A fuzzy set approach to assess the predictive accuracy of land use simulations. Ecol Modell 261–262:32–42 . doi: 10.1016/j.ecolmodel.2013.03.019

Verburg PH, Veldkamp A (2005) Introduction to the Special Issue on Spatial modeling to explore land use dynamics. Int J Geogr Inf Sci 19:99–102 . doi: 10.1080/13658810410001713362

Wang F, Marceau DJ (2013) A patch-based cellular automaton for simulating land-use changes at fine spatial resolution. Trans GIS 17:828–846 . doi: 10.1111/tgis.12009

White R, Engelen G (1993) Cellular automata and fractal urban form: a cellular modelling approach to the evolution of urban land-use patterns. Environ Plan A 25:1175–1199 . doi: 10.1068/a251175

White R, Engelen G (1997) Cellular automata as the basis of integrated dynamic regional modelling. Environ Plan B Plan Des 24:235–246 . doi: https://doi.org/10.1068/b240235

White R, Engelen G, Uljee I (1997) The use of constrained cellular automata for high-resolution modelling of urban land-use dynamics. Environ Plan B Plan Des 24:323–343 . doi: 10.1068/b240323

Zhang P, Liu Y, Pan Y, et al (2016) Land use pattern optimization based on CLUE-S and SWAT models for agricultural non-point source pollution control. Remote Sens Environ 58:230–244 . doi: 10.1007/s12665-016-6058-7

Zhao G (2011) The effect of land use categories resolution on geography cellular automata model. In: 2011 International Conference on Multimedia Technology, ICMT. IEEE, Hangzhou, China, pp 5614–5617