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Sensitivity of a common Land Use Cover Change (LUCC) model to the scale (Minimum Mapping Unit and Minimum Mapping Width) of input vector maps

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Maria Teresa CAMACHO OLMEDO

Abstract

Input maps are one of the main sources of uncertainty in Land Use Cover Change (LUCC) models. Such models are usually raster-based. Although extensive research has assessed the impact of the scale of input raster data in the modelling exercise, few studies have focused on the scale of input vector maps. This paper aims to investigate the effect that the Minimum Mapping Unit (MMU) and Minimum Mapping Width (MMW) of input vector maps have on a specific modelling application. To this end, we have set up different exercises with two input maps (SIOSE and CORINE) that have different MMU and MMW. Results prove the influence of these components of the scale on the simulations produced by the models. Modelled changes and quantities vary depending on the input maps. The modelled pattern is, however, very similar, despite the big differences between the reference maps.

Keywords

Uncertainty, Minimum Mapping Unit, Minimum Mapping Width, Scale, Land Use Cover Change Modelling

1. Introduction

Models are just abstractions of the real world (Clarke 2004) and as abstractions, they inevitably come with uncertainty, understood as the difference between the world as it really is and the world as represented through geospatial data or tools (García-Álvarez et al. 2019). We need to deal with and communicate this uncertainty in a way that offers the best possible results, while making users aware of the limits of our analysis.

In spatial analysis, the degree of abstraction is closely related to the scale. Scale is a wide term that has no consistent, standard definition (Fassnacht et al. 2006). Generally speaking, scale can be understood as a window of perception through which we view the world or some specific process (Marceau 1999). This window reflects the limitations within which that world or process can be studied (Quattrochi and Goodchild 1997) and therefore constitutes part of the uncertainties of our analysis (Lloyd 2014). A study of the sensitivity of Land Use Cover Change (LUCC) models to changes in the scale is therefore a key step towards improving our understanding of these tools and gaining the confidence required to encourage their use.

There is extensive research on the sensitivity of LUCC models to changes in scale. However, scale is differently understood in each case. Some papers study the sensitivity of LUCC models to changes in the spatial (Veldkamp and Fresco 1997) and temporal (Rosa et al. 2015; Paegelow 2018) extent, while others focus on the thematic detail of the maps (Dietzel and Clarke 2004b; Conway 2009; Gallardo 2014). Most of the literature analyses the sensitivity of these models to changes in the spatial resolution, i.e. the degree of spatial detail of a raster map (Dietzel and Clarke 2004a; Evans and Kelley 2004; Jantz and Goetz 2005; Blanchard et al. 2015). In the case of Cellular Automata models, these studies usually consider the type and extent of the neighbourhood as part of the sensitivity analysis (Kocabas and Dragicevic 2006; Pan et al. 2010; Morais Viana 2014).

Relatively few studies have considered the scale problem of vector data when calibrating a LUCC model. The spatial detail of vector data depends on its Minimum Mapping Unit (MMU) and Minimum Mapping Width (MMW). MMU is the size of the smallest feature to be drawn in a map, whereas MMW is the width of the narrowest feature to be drawn in this map (Manakos and Braun 2014). In raster data, MMU and MMW are usually equal to the pixel size, although larger MMU and MMW may be decided by the map-maker on the basis of other factors. In vector data, their value varies according to the cartographic scale of the map and the decision of the map-makers.

Most of the available LUCC models are raster-based (Barreira-González et al. 2015). If vector data is used in these models, the original dataset must be rasterized. The influence of the MMU and MMW of the input data on the simulation will depend on how this rasterization is carried out. Rasterizations at coarser spatial resolutions using methods that generalize the landscape being rasterized (e.g. majority rule) will simplify most of the detail of vector maps at small MMU and MMW. By contrast, rasterizations at finer spatial resolutions using methods that preserve the landscape pattern will keep the different level of detail provided by each source.

Dendoncker et al. (2008) found that the differences in outputs between the datasets rasterized at different resolutions and through different methods were bigger than the differences between several scenarios produced by a research project for the same area. Díaz-Pacheco et al. (2018) also found that rasterization techniques at certain spatial resolutions produced closer results to the original dataset than others. García-Álvarez (2018b) assessed how a model simulated different changes when varying the scale of input maps (MMU and MMW). However, these results were due in part to important differences between the input maps, stochasticity of the model and the different spatial resolution selected when rasterizing each pair of input maps.

None of the previous studies have therefore fully answered the research question regarding the impact of the MMU and MMW of the input maps on LUCC modelling. In this paper, we aim to fill this research gap by specifically assessing how the different degrees of detail provided by changes in the MMU and MMW of the input vector maps affect the calibration and performance of the model concerned. Although the evaluation of the influence of the rasterization process on LUCC modelling practice is very much part of the problem, it is beyond the scope of this paper and must be addressed in future research.

With that objective in mind, we set up the same LUCC model with two input LUC maps at different scales: CORINE Land Cover (MMU: 25ha, MMW: 100m) and SIOSE (MMU: 0.5-2ha, MMW: 15m). MMU and MMW are therefore related consistently in our analysis. They vary at the same time: bigger MMU correspond with wider MMW and smaller MMU correspond with narrower MMW.

Although testing the sensitivity of a model to different datasets with different MMU and MMW would be closer to real practice, it would prevent us from achieving our objective, in that the differences between the datasets would not only be due to scale, but also to the different methods of production, classifications, etc. In this regard, the only difference between our input maps was their scale, as CORINE was obtained from a generalization of SIOSE (García-Álvarez and Camacho Olmedo 2017).

The two input maps were rasterized at the same spatial resolution (50m) so as to make sure that the rasterization process did not interfere with the analysis. In addition, we opted for the Metronamica LUCC modelling software package to carry out the analysis. It reflects common practice in LUCC modelling (Santé et al. 2010). Moreover, user may control the randomness in this model, so preventing it from influencing the analysis.

According to the calibration approaches defined by Van Vliet et al. (2016), the calibration of Metronamica can be either manual or based on expert knowledge. This makes calibration more dependent on user decisions (and their related uncertainties), so making it unrepeatable (Botterweg 1995; Clarke 2018). The conclusions of this study may therefore be considered case-specific. However, they provide a general guide to the effects and implications that these decisions can have on the simulated landscape to those users that opt for similar modelling approaches.

The paper is structured as follows: we begin by describing the study area we modelled and the materials we used. We also outline the method for conducting the sensitivity analysis. This is followed by the presentation and discussion of the results of our analysis.

2. Study area

The Asturias Central Area (ACA) is the most dynamic space in the Spanish region of Asturias and is located in its geographical heart (Fig. 1). According to the boundaries defined by the Asturias Territorial Plan (Gobierno del Principado de Asturias 1991), it encompasses the main urban centres and the main industrial and commercial clusters in Asturias.

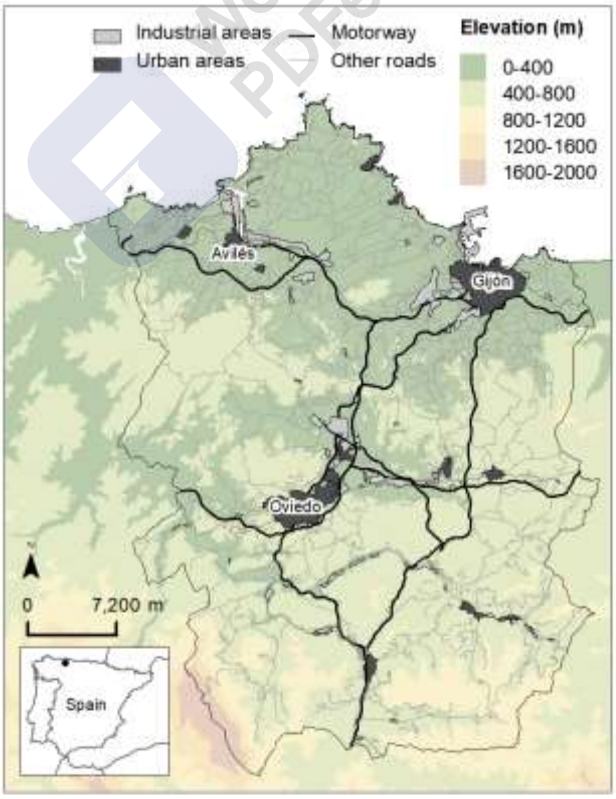

Figure 1. Map showing the location of the Asturias Central Area (ACA). Source: National Topographic Map 1:200.000; Digital Elevation Map 25m

Whereas the south of the ACA suffers sharp economic and demographic decline, most recent industrial and commercial development locates in the north, around Oviedo and Gijón and on either side of the highway that connects them. The area to the east of Oviedo is also increasingly attracting new developments. Nonetheless, changes in Asturias, even in the ACA, are scarce and mostly driven by public investment and, therefore, political decisions (García-Álvarez 2018b). Accordingly, zoning plays a key role in the allocation of new land uses. This makes modelling of the changes in this region less organic and more uncertain, as they mainly depend on single decisions made by politicians or civil servants.

3. Materials

3.1 Metronamica

Metronamica (RIKS 2012) is a constrained Cellular Automata model built on the theory and model proposed by White and Engelen (1993, 1997) and White et al. (1997), which provided a practical application of the theoretical approaches of Ulam (1950), Couclelis (1985) and Tobler (2011). The model distinguishes three types of classes: vacants, functions and features. Features are not modelled because they remain invariant. Function classes are modelled actively and vacants are modelled passively, after all function classes have been allocated.

The allocation of land to the function and vacant classes at each time stage is made on the basis of the values of their transition potential maps (RIKS 2012). The pixels with the highest transition potential values are allocated to the function classes and, the remaining space is then allocated to the vacant classes according to the same procedure. The transition potential of the function classes is the result of a multiplication of the neighbourhood, accessibility, suitability and zoning factors, plus a random component. The transition potential of vacant categories is defined more simply by multiplying their suitability by an inertia/conversion factor.

For function classes, neighbourhood is manually defined by the user as a combination of the inertia of a particular cell to maintain the same land use and the neighbourhood influence on that cell of all the other categories. When the neighbourhood factor has a strong weight, most of the changes are allocated next to cells of the same category. Notwithstanding, reducing the importance of this factor and by means of the random component, the model can simulate isolated new patches, far from existing ones. In our exercises, neighbourhood factor plays a similar role to the other factors and a random component was considered to allow to model to simulate the leapfrogging.

Calibration is undertaken manually in Metronamica, according to the calibration approaches defined by Van Vliet et al. (2016). Demands for the quantities of different land uses are also introduced manually.

3.2 LUC maps

We selected two maps at two different cartographic scales and with different MMU and MMW (Fig. 2): CORINE Land Cover (CLC), from now on referred to simply as CORINE, and SIOSE. These maps are the most important input into the LUC model.

They set out the initial land use composition and configuration of the landscape to be modelled.

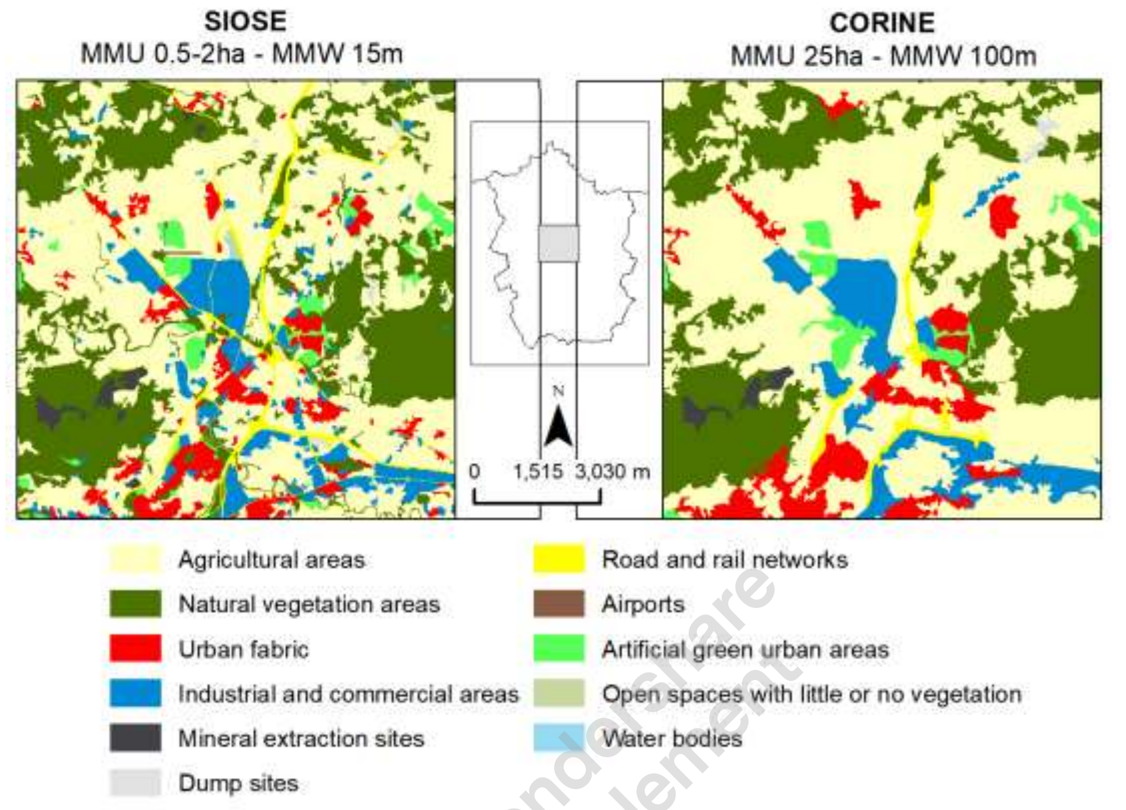

Figure 2. Comparison between the two LUC maps for an example area (Lugones-Llanera) in the centre of the ACA. Source: CORINE and SIOSE 2005

SIOSE is a land use map of Spain produced at the regional level (Equipo Técnico Nacional SIOSE 2015). It is made by photointerpretation at a scale of 1:25.000 or by generalization of more detailed maps (Gil et al. 2010). Its MMU is variable depending on the particular land cover being considered (between 0.5 and 2ha). Its MMW is 15m, although some exceptions below this threshold are accepted (Equipo Técnico Nacional SIOSE 2015). When updating the map to a new time point, only LUC changes affecting areas of more than 0.4ha are drawn.

CORINE is the European reference LUC map. At a national level this map is obtained by generalization of more detailed national maps or by photointerpretation at a scale of 1:100.000 (Büttner 2014). The MMU is 25ha and the MMW 100m. Only LUC changes affecting areas of more than 5ha are included on the maps' updates. Since 2011, CORINE has been obtained in Spain via the generalization of SIOSE (García-Álvarez and Camacho Olmedo 2017), which ensures the compatibility of both maps for the analysis we will be conducting. Nonetheless, this change has led to many uncertainties when using the historical series of CORINE maps (García-Álvarez and Camacho Olmedo 2017).

A pair of maps for the years 2005 and 2011 were chosen from each source. Although the CORINE years of reference are 2006 and 2012, the data refers to the same years as SIOSE (2005, 2011), as in both cases CORINE was obtained by generalization of SIOSE. The dates were chosen according to the dynamism of the study area. Most changes happened before the crisis of 2008, that brought most of the development of the area to a halt (Gobierno del Principado de Asturias 2016; García-Álvarez 2018b).

A common legend was agreed for both maps according to the their compatibility and disagreements detected by previous studies (García-Álvarez 2018a) (Table 1). In this way we ensured that any differences between the two maps were due above all to the different scale and not to other factors. The fine scale profile of the two maps confirms their similarities and limited uncertainty (see appendix A).

Table 1. Selected common legend for SIOSE and CORINE input maps.

Vacant classes	**Features**
Agricultural areas	Mineral extraction sites
Natural vegetation areas	Dump sites
	Road and rail networks
Function classes	Port areas
Urban fabric	Airports
Industrial and commercial areas	Artificial green urban areas
	Open spaces with little or no vegetation
	Water bodies

Both vector maps were rasterized using the same spatial resolution so as to ensure that this component of scale did not influence our comparison of the maps. The selected spatial resolution (50m) was chosen in the light of the authors' previous experience with the same application and in line with the conclusions of other studies for similar models and datasets (Díaz-Pacheco et al. 2018). Large interference is not expected because of the spatial resolution chosen. The MMU of SIOSE and CORINE fitted the pixel size of the rasterized maps. The smallest polygons in SIOSE (5000m^2) and CORINE (5ha for changes) were at least twice the smallest cell to be drawn (2500m^2).

3.3 Driving forces of change

Variables for the LUCC model were chosen according to the input provided by experts in the area being analysed and according to common practice in urban modelling for similar environments and models. The expert opinions were collected in unstructured interviews of a selection of researchers and stakeholders who work in the analysis and planning of the Asturias Central Area. Common practice in urban modelling was obtained through a review of international research on urban land use change modelling. The selected variables were grouped into three categories: accessibility, suitability and zoning.

Accessibility to residential and industrial uses was defined by closeness to national and regional roads, highways, port areas, urban centres and train stations. Areas closer to these features were considered more accessible and, therefore, more prone to change. Layers of these features were obtained from the National Topographic Map of Spain, provided by the Spanish National Geographic Institute (IGN). The layers for urban centres and train stations were manually edited to classify urban centres and train stations according to their population and train frequency respectively.

A slope map calculated from a Digital Elevation model provided by the IGN was the suitability driver. Finally, the zoning drivers were the different planning maps provided by the Regional Government of Asturias.

Accessibility, suitability and zoning maps for the first year of the modelling exercise are provided as supplementary material to this paper.

4. Methods

4.1 Model calibration

One exercise for each pair of input maps (CORINE and SIOSE) was calibrated for the period 2005-2011 following the standard calibration procedure of Metronamica (Hewitt et al. 2014; Van Delden et al. 2018). Location agreement was tested through Kappa indices and pattern agreement by means of two spatial metrics (clumpiness and fractal dimension). Qualitative validation was also performed through visual inspection.

Kappa Simulation (KSim) shows the agreement between the changes in two categorical maps as compared to a third one used as a reference, corrected by the agreement expected by chance (Van Vliet et al. 2011). Fuzzy Kappa Simulation (FKSim) calculates the same agreement, but uses the fuzzy set theory to account for the degree of spatial mismatch (Van Vliet et al. 2013). Kappa shows the agreement between two categorical maps, based on the proportions of their classes and corrected by the agreement expected by chance (Cohen 1960). Kappa accounts well for persistence, whereas Ksim accounts well for change (García-Álvarez et al. 2019). Clumpiness measures the (dis)aggregation between patches, whereas fractal dimension measures the complexity of the patches' shape (Botequilha Leitao et al. 2006).

Initial parameters for the two exercises were set up according to expert knowledge and previous modeller experience on the same application. Then, based on the metrics and methods described above, the model was manually calibrated on a trial-and-error basis by comparing the simulated maps with the reference maps for the year 2011.

Demands were extracted from the changes measured by each pair of input maps (SIOSE 2011 – 2005, CORINE 2011 – 2005). This means that demands will vary depending on the input maps used. Calibration is also dependent on the particular input map used: each exercise has been calibrated to fit its corresponding reference map.

4.2 Model testing

Once the initial exercises were fully calibrated, we set up four extra ones (Fig. 3). Two for each pair of maps: one with the demands for the other exercise (SIOSE CDemands, CORINE SDemands), and one with the parameters for the other exercise and the demands for CORINE maps (SIOSE CParameters, CORINE SParameters). These four exercises were not calibrated any further, as they were set up purely for comparison and analysis purposes.

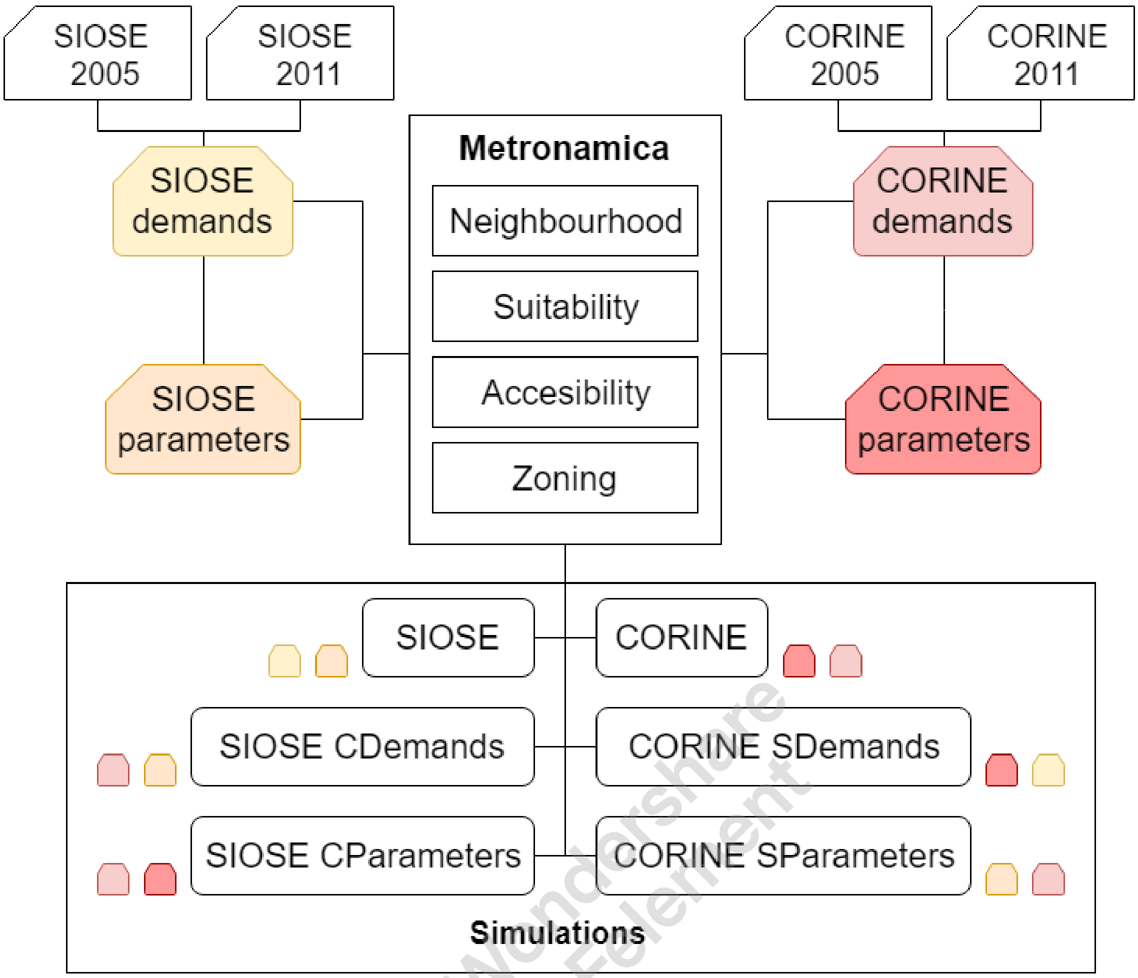

Figure 3. Flowchart for the modelling exercises. SIOSE refers to the modelling exercise set up with SIOSE input maps, demands and parameters. CORINE refers to the modelling exercise set up with CORINE input maps, demands and parameters. SIOSE CDemands refers to the modelling exercise set up with SIOSE input maps and parameters and CORINE demands. CORINE SDemands refers to the modelling exercise set up with CORINE input maps and parameters and SIOSE demands. SIOSE CParameters refers to the modelling exercise set up with SIOSE input maps and CORINE demands and parameters. CORINE SParameters refers to the modelling exercise set up with SIOSE parameters and CORINE input maps and demands.

The two calibrated exercises allow us to assess whether the model is capable of replicating the quantity and pattern of the LUC changes measured by each pair of input maps, while the other four exercises allow us to assess the sensitivity of the model to changes in the MMU and MMW of the input maps.

4.3 Analysis of results

We began by comparing the information provided by each pair of input maps (CORINE and SIOSE). This comparison was made globally and only considering the changes measured by these maps (2011 – 2005). Maps were compared in terms of their pattern, quantity and allocation (dis)agreement and qualitatively through visual inspection. This comparison highlighted the initial differences between the input maps and gave us a reference to assess the model simulations.

Simulated landscapes and changes (simulation – reference map) were also compared to check for differences between them (pattern, quantity and allocation (dis)agreement, visual inspection). To avoid the influence of randomness in the allocation (dis)agreement analysis, compared changes were in this case obtained from simulations run with a random factor of 0. In all other cases, compared simulations were obtained from models considering a random component. In addition, we calculated the Ksim for each simulation with respect to the reference maps to assess their goodness of fit.

Pattern and Ksim, together with visual inspection, inform us about the ability of the model to simulate the landscape composition and configuration. These methods, together with the quantity and allocation (dis)agreement, also allow us to test the sensitivity of the model to changes in the scale of input maps.

Quantity and allocation (dis)agreement was calculated using the matrix proposed by Pontius Jr. (2019). Quantity (dis)agreement is the difference between the quantities or proportions of the categories that make up two maps. Allocation (dis)agreement refers to the difference in the allocation of the categories that make up two maps. It is divided into two components: exchange and shift, the first referring to pairwise confusions and the second to nonpairwise confusions (Pontius Jr. and Santacruz 2014).

The pattern of maps was evaluated through a series of spatial metrics at the class level calculated with Fragstats 4.0. An initial range of metrics was selected to assess the area, edge, shape and aggregation of the patches. This selection was based on the particular aspect being compared and the meaningfulness of the metrics for evaluating this aspect, as evidenced by Li et al. (2005) and Šímová and Gdulová (2012). As all indicated the same pattern differences, we just included in this paper those ones that gave us more information about pattern variability (Table 2).

Table 2. Spatial metrics used in the comparative analyses

Spatial metric	Acronym	Description
Percentage of Landscape	PLAND	Percentage of each class with respect to the whole map
Number of patches	NP	Number of different patches (4 cell neighbourhood, 4cN) in each class
Largest patch index	LPI	Proportion of the whole map taken up by the largest patch (4cN) in each class
Patch cohesion index	COHESION	Estimate of the cohesion of the patches (4cN) in each class, measured as the relation between the area and perimeter of the patches and the map area

5. Results

Section 5.1 describes the differences between input maps because of their different MMU and MMW. The differences are first considered by comparing the maps as a whole (CORINE 2005 vs SIOSE 2005) and then by focusing only on the changes measured by each pair of maps (CORINE 2011-2005 vs SIOSE 2011-2005). Section 5.2 describes the differences between simulations when calibrating the model with each pair of maps. Full input maps, changes and simulations are provided as supplementary material.

5.1 Input maps

Overall, there was a high level of agreement between the maps used as input for the calibration of the models (87%) (Fig. 4). At the category level, the agreement is high for the vacant categories (agricultural and natural vegetation areas), lower for the ones actively modelled (urban fabric and industrial and commercial areas) and very low in the case of the road and rail networks, dump sites and open spaces with little or no vegetation (Fig. 5).

Only a very small part of the road and rail networks is wider than 100m, which means that a lot of these features are not drawn in CORINE because they not fit with its MMW. Due to its narrower MMW, almost all of them appear in SIOSE. Dump sites and open spaces with little or no vegetation are made up of a great deal of small patches and, therefore, deeply generalized when changing the scale. Nevertheless, all categories are affected by this generalization. E.g. the urban fabric category is made up of just 89 patches in CORINE but has 955 patches in SIOSE. Industrial and commercial areas show a similar behaviour: 63 vs 590 patches. These differences can be checked visually in Figure 6.

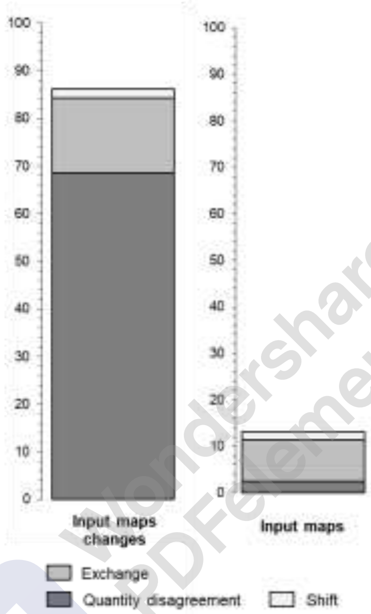

Figure 4. Components of disagreement of the input maps and the changes they measure

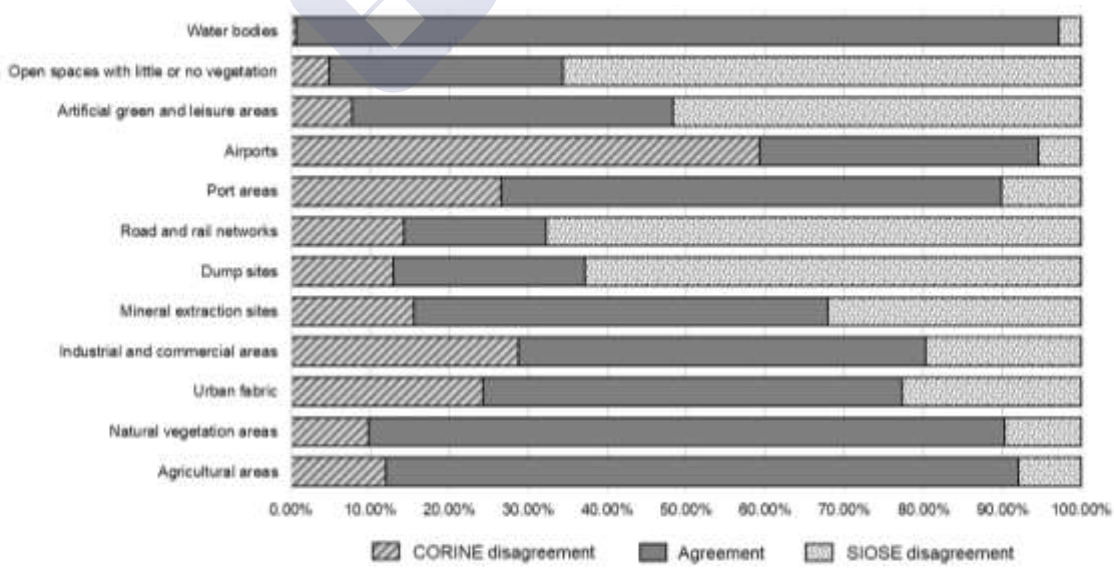

Figure 5. (Dis)agreement bars at the category level between CORINE and SIOSE maps. CORINE and SIOSE disagreement refer to the pixels in one particular category on one map that appear in a different category on the other map

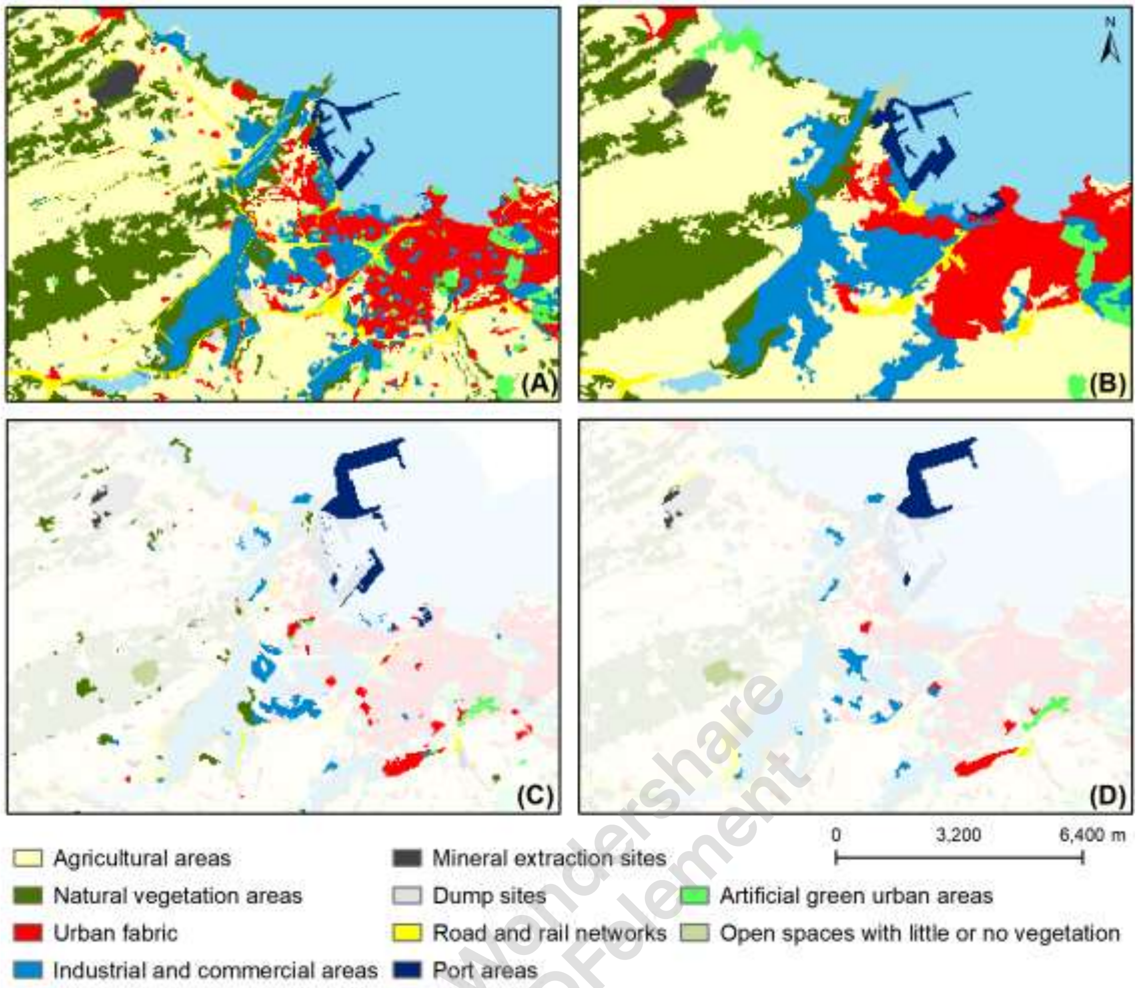

Figure 6. CORINE (B, D) and SIOSE (A, C) maps and changes in an example area within the Asturias Central Area (Gijón). Above, input maps for the year 2005. Below, changes measured by each pair of input maps for the period 2005-2011. Source: CORINE and SIOSE (2005, 2011)

As a rule, SIOSE maps, because of their smaller MMU, are much more fragmented than CORINE . Despite these differences, shape complexity is similar in both cases. CORINE is generalized from SIOSE, which means that the perimeters remain the same. Changes measured by each pair of input maps (CORINE 2011-2005 vs SIOSE 2011-2005) also show this pattern: higher fragmentation in SIOSE and similar complexity (Fig. 6).

Regarding those changes, there was little agreement (14%) between them (Fig. 4). The most important disagreement was in terms of quantity. SIOSE maps detected more changes for all categories because of their smaller MMU. At the category level, there was very little or no agreement at all between CORINE and SIOSE in terms of the changes in vacant classes (Fig. 7). Although higher, the agreement of changes in the function classes is also low (24% for the urban fabric and 14% for the industrial and commercial areas).

There are important differences between the maps in terms of the change in each category as a proportion of all measured changes. Most of the changes in the SIOSE maps (47.4%) refer to one specific category: natural vegetation areas. The remaining 52.6% of the changes correspond to other categories in relative proportions similar to those identified in CORINE. In CORINE, by contrast, the changes at category level are more equally shared between the different categories, with no single dominant category.

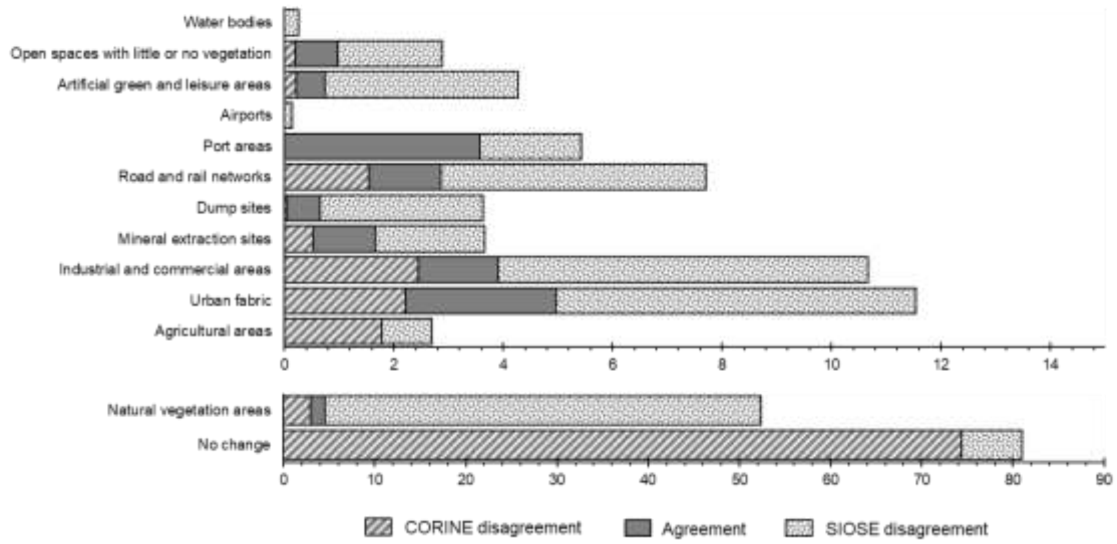

Figure 7. (Dis)agreement bars at the category level between changes measured by CORINE and SIOSE maps. CORINE and SIOSE disagreement refer to the pixels that appear in one particular category on one map and a different category on the other map.

5.2 Simulated maps

According to Kappa Simulation (KSim) values, Metronamica was better able to simulate changes in CORINE than changes in SIOSE (Table 4). Nevertheless, some differences can be observed at the class level. Generally, the CORINE exercises obtained better Ksim values for the urban fabric simulation, whereas the SIOSE exercises modelled the industrial and commercial areas better than CORINE. Poor Ksim values were obtained for the natural vegetation areas in all the exercises regardless of the maps used, which means that this class was not properly modelled in either case.

Table 4. Performance of the model in each of the six modelling exercises set up according to the Ksim values. Ksim is calculated globally and at the class level for function and vacant categories. S11 refers to simulations run with SIOSE as input maps. C11 refers to simulations run with CORINE as input maps.

	Global	Urban fabric	Industrial and commercial areas	Agricultural areas	Natural vegetation areas
			SIOSE demands		
S11	0.087	0.229	0.192	0.137	0.034
C11 SDemands	0.148	0.266	0.177	0.218	0.025
			CORINE demands		
S11 CDemands	0.057	0.155	0.177	0.087	0.023
C11	0.111	0.213	0.189	0.175	0.013
S11 CParameters	0.055	0.180	0.123	0.095	0.013
C11 SParameters	0.106	0.180	0.189	0.161	0.045

When we exchanged the parameters for the exercises using SIOSE and CORINE maps, the Ksim showed opposite results at the class level to those obtained previously. The SIOSE exercise (S11 CParameters) simulated better the urban fabric (0.180 vs 0.155) and worse the industrial and commercial areas (0.177 vs 0.123). For the CORINE exercise

(C11 SParameters) the trend is inverse. The pattern assessed by the spatial metrics is also the opposite when changing the parameters (Table 5). Nevertheless, when the demands and parameters were changed, the CORINE simulation of industrial and commercial areas did not behave in the same expected way as in the other categories and exercises. When the demands were reduced, instead of the Ksim increasing, it fell. When using the SIOSE parameters, the Ksim remained constant.

On the other hand, the modelled pattern of the simulated changes is similar (fragmented) in all cases regardless of the input maps employed. The degree of fragmentation is similar or even greater than that observed in the changes measured by the SIOSE maps (SIOSE 2011 - SIOSE 2005) (Fig. 6 and 8).

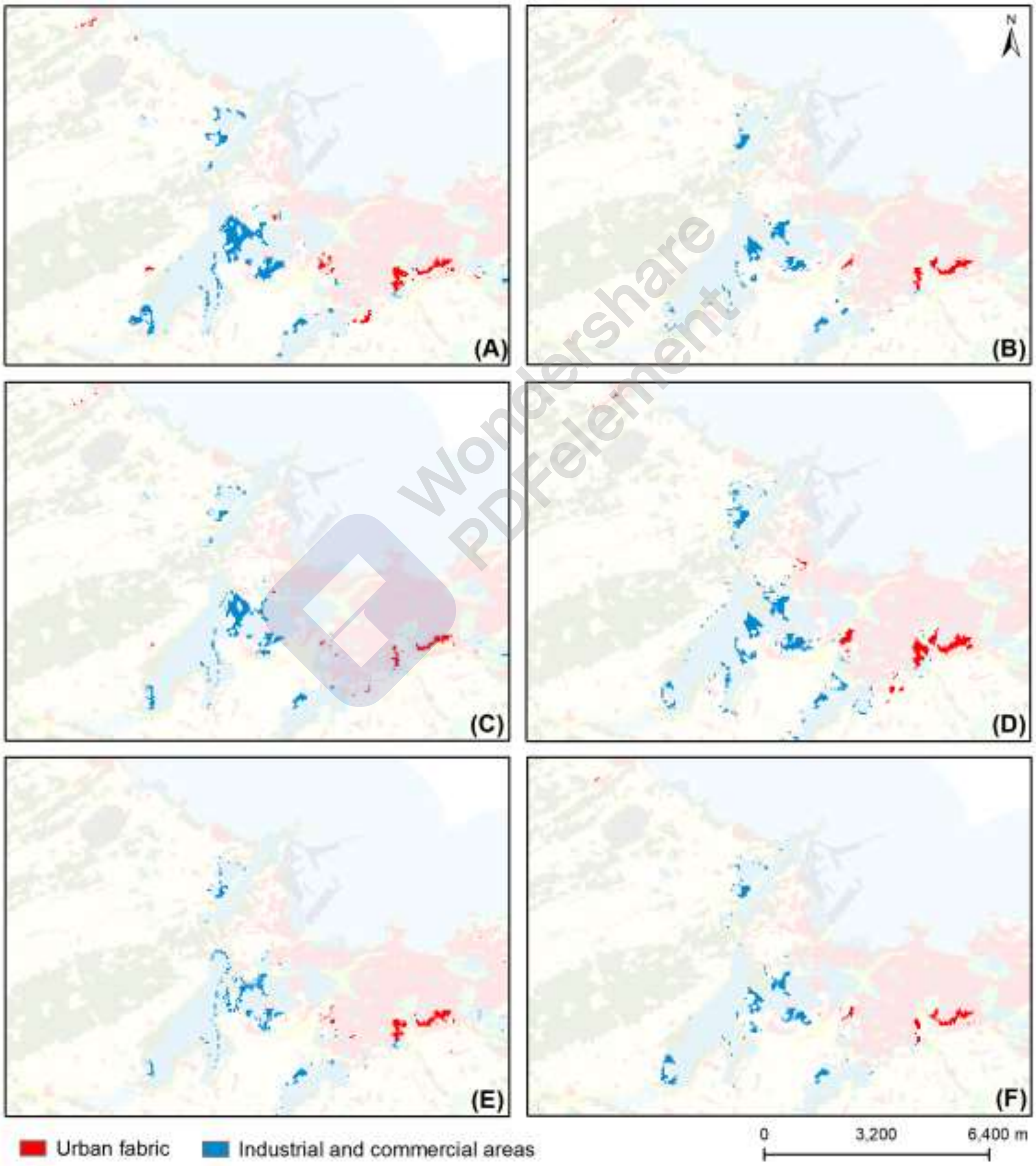

Figure 8. Simulated changes (2011) for an example area within the Asturias Central Area (Gijón): SIOSE (A), CORINE (B), SIOSE CDemands (C), CORINE SDemands (D), SIOSE CParameters (E) and CORINE SParameters (F). Source: CORINE and SIOSE 2005

Table 5. Spatial metrics of the changes modelled by each of the six modelling exercises. For a description of the metrics, see Table 2

	NP		LPI		COHESION	
	Urban fabric	Industrial commercial areas	Urban fabric	Industrial commercial areas	Urban fabric	Industrial commercial areas
S11	183	275	0.020	0.028	82.95	79.58
C11 SDemands	154	303	0.021	0.010	83.52	72.40
S11 CDemands	156	143	0.006	0.018	71.44	77.17
C11	121	172	0.008	0.008	78.48	70.32
S11 CParameters*	156	180	0.016	0.008	80.16	70.40
C11 SParameters*	147	158	0.007	0.007	72.71	72.71

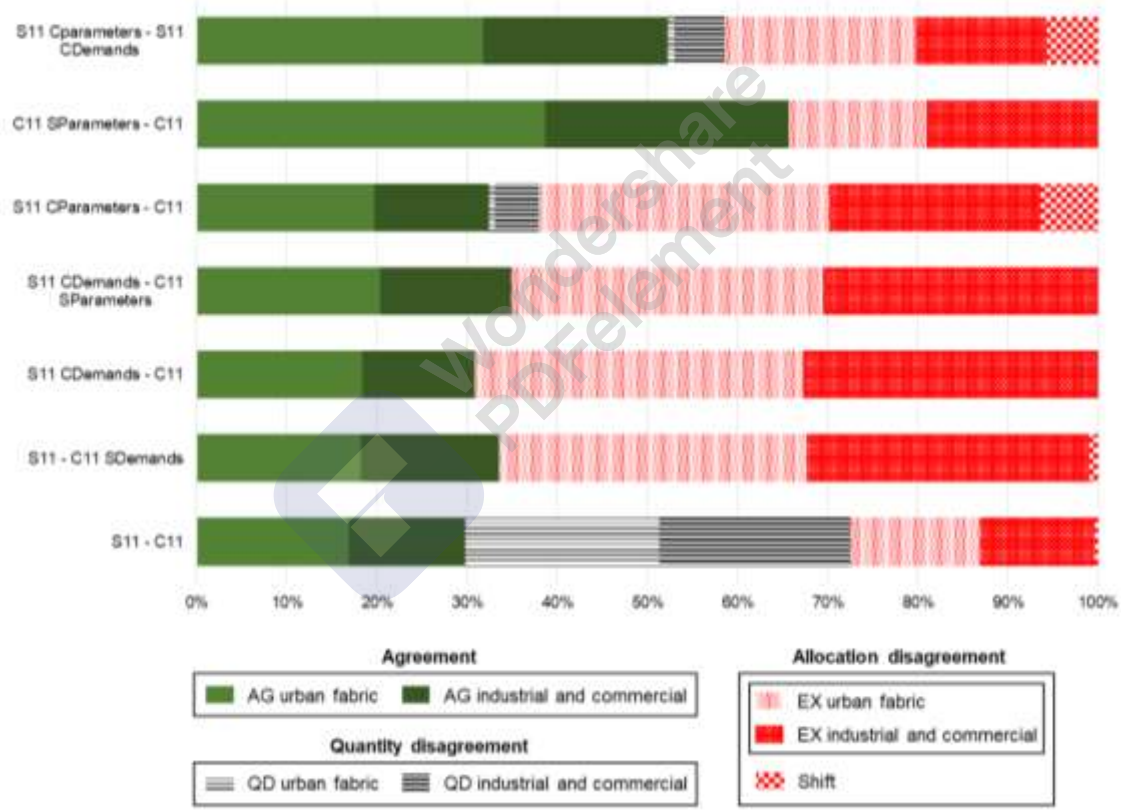

Figure 9. (Dis)agreement bars for each pair of simulations. S11 and C11 refer to simulations made respectively with SIOSE and CORINE as input maps. AG refers to agreement between maps; QD to quantity disagreement; and EX to exchange.

The agreement between simulations is very similar in all cases (30-35%), regardless of the demands considered or even of the parameters used in the exercise (Fig. 9). This agreement is only higher when comparing exercises conducted using the same input maps, but with different parameters.

The exercises run with the original SIOSE and CORINE demands showed an important disagreement in terms of quantity (43%) (Fig. 9). As each pair of maps measured a different quantity of changes, they also simulated different quantities. There was also a small quantity disagreement between the exercise run with SIOSE maps and CORINE parameters and the exercises run with CORINE and SIOSE maps with CORINE demands. This is because of the simulation of unwanted transitions from function categories to vacant categories (e.g. urban fabric to agricultural areas). The modeller did not define a sufficiently high level of inertia for these classes which meant that the model allocated the demands of these function categories to other cells with a higher transition potential to change.

6. Discussion and conclusions

The analysis carried out has revealed important differences between simulations when using input maps with different Minimum Mapping Unit (MMU) and Minimum Mapping Width (MMW). We have grouped these differences into three blocks, according to their nature: differences in the modelled landscape and changes (6.1), differences in the pattern (6.2), and differences in the performance of the model (6.3).

6.1 Modelled landscape and changes

Variations in the MMU and MMW of the maps do not vary the landscape shown by the input maps to any great extent. However, the agreement between the areas that changed in each pair of maps was low, with each map measuring a very different quantity of changes. Changes measured by input maps are therefore scale-dependent, like processes of change (O'Sullivan and Perry 2013).

Maps at finer scales always detect more changes, as proved by Conway (2009) and Blanchard et al. (2015) for other components of scale (thematic and spatial resolution). If we extract the simulated quantities from input maps, like in our exercise or when using Markov-based models, the chosen scale of input maps will affect the modelled quantities. It will also affect the model performance. The knowledge we have to explain and replicate these changes is usually the same when working at similar regional scales, like the ones of CORINE and SIOSE maps. Accordingly, the bigger demands because of the different MMU mostly increase the chances the model has to guess to right location of the modelled changes, as showed in our exercises and pointed out by Conway (2009) when changing the thematic resolution of the employed maps.

When choosing between maps with different MMU and MMW, we must pay special attention to the changes these maps show. A coarser or more detailed scale should be selected depending on how many of these changes we are able to explain and which ones best reflect the dynamics we want to model. Maps at finer scales are better for the study and modelling of the details, whereas maps at coarser scales are more suitable for the study and modelling of macro-structure and macro-changes (Wu and Li 2009).

When working at similar regional scales, as in our case, those differences are subtler. Carefully studying the changes each pair of maps show and making sensitivity analysis with each source is then advisable. E.g. in our case, changes measured by maps at a finer scale did not refer to the categories we want to model actively (natural vegetation areas in SIOSE maps represent 47.4% of all measured changes).

As a general rule, the generalization process due to MMU and MMU variation ends with dominant classes prevailing over the rest of the categories (Nol et al. 2008). If we want to model these dominant categories, a generalized map (large MMU), is a good option. In other cases, maps at finer scales are advisable. Selecting finer or coarser spatial resolutions when rasterizing the input vector maps may be another way of dealing with this issue and obtaining the desired level of generalization.

Notwithstanding, when making use of fine-scale maps, we must consider that they are more likely to be affected by mapping mistakes (Blanchard et al. 2015). On the other hand, coarse-scale maps will more likely make use of mixed categories (Castilla and Hay 2007), which are usually more difficult to interpret (Villa et al. 2008). In addition, some categories are more affected by changes in the MMU and MMW than others (e.g. rail and road networks). Depending on the relative importance of these categories in explaining the pattern or dynamics of the classes of interest, one or other scale should also be selected.

Finally, we must consider the needs and requirements of both stakeholders and audience as well (Van Delden et al. 2011). Excessively simple approaches, in which just a few important changes are modelled, as in CORINE, may not satisfy the requirements and needs of agents and audience.

<u>6.2 Modelled pattern</u>

The simulated pattern was similar in all the simulations, despite the different patterns shown by each pair of input maps. Modelled changes were in all exercises very fragmented, in a similar level of fragmentation to the one of the changes measured by input SIOSE maps. Thus, there is a disassociation between the scale and by extension the pattern of the input maps and the modelled pattern, as pointed out by García-Álvarez (2018).

The pattern of the input maps and the changes they measure (CORINE 2011-2005, SIOSE 2011-2005) is affected by the MMU and MMW of the input maps. However, the pattern of the simulated changes is determined by the neighbourhood rules and the spatial resolution of the model. Although specific for each case, neighbourhood rules were similar in CORINE and SIOSE exercises, especially regarding the self-attraction of land use functions. In addition, both maps were rasterized at the same resolution. As a result, the simulated changes show a comparable pattern in all exercises.

<u>6.3 Model performance</u>

In our exercises, the maps at a coarser scale provided better modelling results than those at a finer scale. Metronamica was therefore better able to simulate the CORINE reference landscape than the SIOSE one. This is due to the simplicity of CORINE maps and the changes they show, which fit better with the simple rules that govern a system in a modelling environment. This agrees with the conclusions of previous sensitivity analysis of other components of the scale (Kok and Veldkamp 2001; Kocabas and Dragicevic 2006; Chen and Pontius Jr. 2011; Blanchard et al. 2015).

The aforementioned simplicity of CORINE maps is mainly the result of the smaller number of changes we need to correctly simulate. Although fewer changes may be easier to replicate, sometimes they are not enough to understand the dynamics of the class of interest. This was the case of the industrial and commercial areas in the exercises run with CORINE. Increasing the demands did not improve the simulation of this class, whereas changing the parameters did not affect the simulated landscape. The unsensitivity of the class to the model tuning reveals that the model was just able to replicate the allocation of a few patches, but not the real dynamics of this category.

The allocation agreement between the different simulations is very similar in all cases, even when comparing the exercises that were run with the parameters employed for the other input maps. It is a low agreement: 30-35%. This means that changes in the input maps result in very different simulations, with bigger differences than those that occur when changing the parameters of the calibrated exercises. That makes sense in a context in which the inertia of land uses to maintain the same cells is assumed, which is a common assumption in LUCC modelling (Van Vliet et al. 2011). In the other cases, input maps would play a minor role, and other factors would be the main drivers behind agreement between simulations. Nonetheless, part of the agreement detected in our simulations (30-35%) is also a consequence of the importance of zoning in our model.

All in all, input maps are one of the main decisive factors in the drawing of the simulation, which also agrees with the conclusions of Syphard et al. (2011) and Prestele et al. (2016). Therefore, simulations for the same area run with different maps may not be directly comparable. When compared, modellers must provide additional information about the uncertainty of the input data and the general uncertainty of the modelling exercises.

Finally, we must also consider the uncertainties in the validation process produced by scale issues when assessing the performance of the model. Most of the commonly used validation indices are based on comparisons between the simulated map of changes and the reference map of changes for the same date (Van Vliet et al. 2016). Because of the lack of connection between the scale (MMU, MMW) of the input maps and the one used for the simulated changes, these validation approaches may not be valid. In these cases, qualitative validation approaches, like visual inspection, may be preferable.

Appendix A. Fine scale profile of input LUC maps

In order to assess the uncertainty of input LUC data, we carried out a fine scale profile of the different categories within the dataset (Table 1). This meant assessing the composition of the categories of a map using highly detailed, accurate data (Gallego 2001). We used the raw SIOSE database for these purposes.

In SIOSE, land cover homogeneous polygons are photointerpreted at a 1:25.000 scale, with a MMU of between 0.5 and 2ha, depending on the considered land cover, and a MMW of 15m. The SIOSE database provides, without limitations, the proportions of the different land covers that make up each polygon (Fig. A.1). In this case, the real detail of land cover information is maintained and generalization is kept to a minimum. We therefore used the information from the SIOSE database to carry out the proposed analysis.

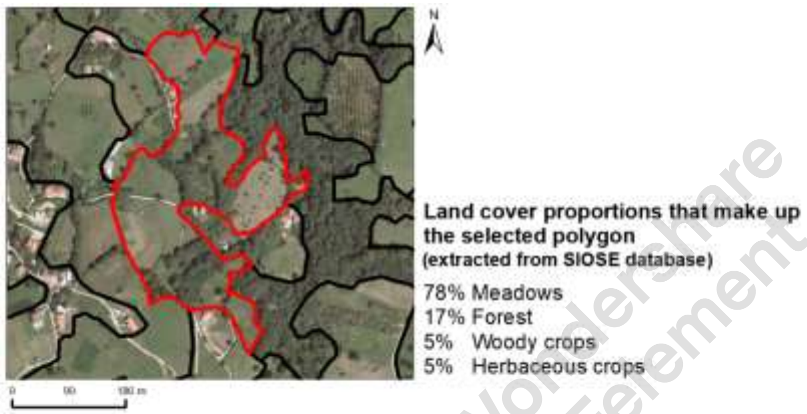

Figure A1. Example of the thematic information provided by the SIOSE database to characterize a polygon (perimeter marked in red) in the Asturias Central Area. Sources: SIOSE 2005; PNOA historical images.

We began by combining the CORINE and SIOSE maps for the year 2005 in vector format together with raw SIOSE polygons with land use proportions. We then calculated the area of the different land uses in each polygon in the CORINE and SIOSE maps, according to the information provided by the SIOSE database. Finally, for each map, we summed up the total area of the land use categories that make up each category in the CORINE and SIOSE maps. A flowchart of the method we followed for making the fine-scale profile for the SIOSE and CORINE input maps classes can be found in Figure A2. Results are presented as a percentage of the total area (Table A).

The categories show a similar composition in both maps (Table A1). This is especially true for the most important categories in both maps, which together represent more than 95% of the surface area of the maps: agricultural areas (around 40% of the area), natural vegetation areas (≈38%), water bodies (≈10%), urban fabric (≈4%) and industrial and commercial areas (≈3%). The only significant differences are in the categories for artificial uses (urban fabric and industrial and commercial areas). The urban fabric is made up of a higher proportion of buildings in SIOSE than in CORINE (Table A1). On the other hand, up to 10% of the industrial and commercial areas of CORINE are made up of natural vegetation and agricultural areas, which are residual for this category in SIOSE.

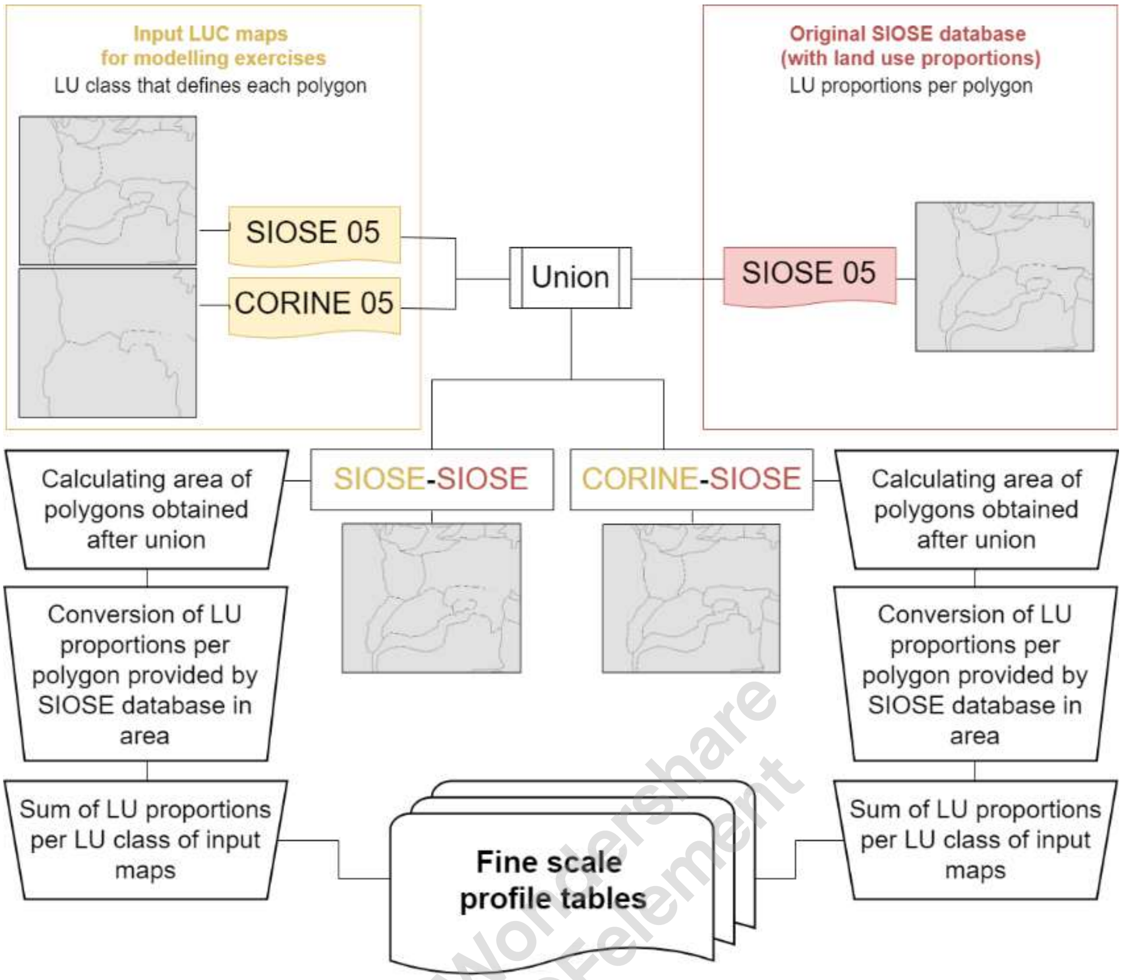

Figure A2. Flowchart of the methodology we followed to make the fine-scale profile of CORINE and SIOSE input maps classes

Larger differences between the composition of the categories in CORINE and SIOSE can be observed in those classes that represent just a small proportion of the two maps. In SIOSE these classes are usually made up of land uses with greater affinity to that of the class being considered. e.g. 61.7% of the road and rail network maps in SIOSE is made up of big avenues, car parks and pedestrian areas without vegetation. In CORINE this proportion is much lower at 36.7% (Table A1).

As CORINE is more generalized, class composition is more heterogeneous. It is more likely to find a mixture of different land uses within the same land use polygon in CORINE than SIOSE. Usually, agricultural and natural vegetation areas, like forests, shrubland and meadows, occupy a small proportion (≥ 10%) of class composition in CORINE (Table A1). At the same time, these classes are non-significative for defining the class composition of SIOSE.

Because of its greater detail, SIOSE enables us to define more homogeneous patches of land use. Even so, there is some level of generalization in all cases. Thus, although SIOSE classes are usually more homogeneous, they also cover a mixture of land uses. This means there is uncertainty in the land use and cover representation of both maps. However, this uncertainty is low. As shown by Table A1, the classes in the two maps are mostly composed of land uses and covers that match the definition of the class being considered.

Table A1. Fine scale profile of CORINE (C) and SIOSE (S) classes (rows). The columns show the land covers defined by the SIOSE database: PST: pastures, FRT: forest, SHR: shrubland, BDS: beaches, dunes and sandy areas; RCK: rocky areas; BSL: bare soil; AGR: artificial green area and urban woodland; AVE: big avenues, parking or pedestrian area without vegetation; NBG: non-built ground, OCT: other constructions; MED: mining, extractive or dumps; HCP: herbaceous crops; WCP: woody crops, MDW: meadows; BLD: buldings; WTR: water bodies. Results are shown in percentages. e.g. CORINE agricultural areas are made up of 3.8% of pastures.

	PST		**FRT**		**SHR**		**BDS**		**RCK**		**BSL**		**AGR**		**AVE**	
	C	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**
Agricultural areas	3.8	3.5	7.1	4.3	4.7	3.0	0.0	0.0	0.1	0.0	0.2	0.1	0.3	0.0	1.5	0.3
Natural vegetation areas	11.1	11.5	46.4	50.3	32.3	34.6	0.1	0.0	1.0	0.8	1.0	0.5	0.1	0.0	0.6	0.2
Urban fabric	0.5	0.2	2.0	1.3	0.9	0.8	0.2	0.0	0.1	0.0	0.0	0.1	15.1	13.9	23.6	20.8
Industrial and commercial areas	0.6	0.0	3.1	0.1	1.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	5.6	7.8	25.4	24.9
Mineral extraction sites	1.2	0.0	3.3	0.0	2.4	0.0	0.0	0.0	1.0	0.0	0.2	0.0	0.8	1.3	3.5	5.8
Dump sites	1.5	0.0	2.6	0.5	4.0	2.0	0.0	0.0	0.0	0.0	1.3	0.1	1.4	0.2	**14.3**	4.0
Road and rail networks	1.7	0.0	4.2	0.0	2.3	0.0	0.4	0.0	0.0	0.0	0.0	0.0	2.8	0.3	36.7	**61.7**
Port areas	0.1	0.0	0.2	0.0	0.4	0.0	2.3	0.0	0.4	0.0	0.0	0.0	0.1	0.3	36.7	**46.0**
Airports	**52.8**	0.0	1.0	0.0	2.7	0.0	0.0	0.0	0.0	0.0	**5.9**	0.0	1.7	**4.4**	31.7	**90.0**
Artificial green and leisure areas	2.5	0.0	**7.9**	0.0	**5.2**	0.0	0.4	0.0	0.2	0.0	0.1	0.0	39.6	**57.1**	11.3	**17.7**
Open spaces with little or no vegetation	14.9	**19.7**	1.0	2.0	**19.1**	13.5	**18.0**	11.9	**41.3**	28.2	0.6	**24.1**	0.2	0.0	0.4	0.3
Water bodies	0.0	0.0	0.1	0.0	0.1	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0

	NBG		**OCT**		**MED**		**HCP**		**WCP**		**MDW**		**BLD**		**WTR**	
	C	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**	**C**	**S**
Agricultural areas	0.6	0.1	0.3	0.0	0.5	0.3	9.7	10.4	4.4	4.8	62.8	69.9	3.8	3.3	0.1	0.0
Natural vegetation areas	0.2	0.0	0.1	0.0	0.4	0.1	0.3	0.1	0.2	0.1	5.6	1.8	0.2	0.0	0.3	0.0
Urban fabric	9.8	9.8	2.3	0.6	4.2	3.1	1.2	1.7	0.8	0.9	8.2	8.6	30.6	**37.9**	0.3	0.0
Industrial and commercial areas	14.4	**18.5**	7.0	6.1	10.3	10.6	0.4	0.0	0.3	0.0	**4.0**	0.1	24.8	**31.5**	2.2	0.0
Mineral extraction sites	6.4	7.2	0.5	1.8	71.2	79.6	0.5	0.0	0.1	0.0	**4.8**	0.0	3.6	3.9	0.0	0.0
Dump sites	8.4	5.6	0.0	0.0	53.2	**82.3**	0.4	0.0	0.4	0.0	**5.1**	0.5	**5.8**	1.6	1.6	0.0
Road and rail networks	20.9	19.3	2.3	**13.8**	7.8	4.1	0.8	0.0	0.8	0.0	**10.0**	0.0	**6.6**	0.8	2.5	0.0
Port areas	13.0	**17.1**	5.9	6.4	16.8	18.4	0.0	0.0	0.0	0.0	0.0	0.0	4.7	5.7	**14.4**	0.0
Airports	1.7	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.8	0.0	1.8	**5.6**	0.0	0.0
Artificial green and leisure areas	5.7	7.3	3.9	**9.9**	**6.5**	1.3	0.9	0.0	0.5	0.0	**7.8**	0.0	6.1	5.6	0.7	0.0
Open spaces with little or no vegetation	0.7	0.0	0.1	0.1	0.1	0.1	0.0	0.0	0.0	0.0	1.4	0.1	0.2	0.0	1.8	0.1
Water bodies	0.0	0.0	0.0	0.0	0.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	99.4	99.8

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