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Comparing the structural uncertainty and uncertainty management in four common Land Use Cover Change (LUCC) model software packages

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ABSTRACT

Research on the uncertainty of Land Use Cover Change (LUCC) models is still limited. Through this paper, we aim to globally characterize the structural uncertainty of four common software packages (CA_Markov, Dinamica EGO, Land Change Modeler, Metronamica) and analyse the options that they offer for uncertainty management. The models have been compared qualitatively, based on their structures and tools, and quantitatively, through a study case for the city of Cape Town. Results proved how each model conceptualised the modelled system in a different way, which led to different outputs. Statistical or automatic approaches did not provide higher repeatability or validation scores than user-driven approaches. The available options for uncertainty management vary depending on the model. Communication of uncertainties is poor across all models.

1. Introduction

Uncertainty is inherent in spatial analysis because of the need of abstraction to represent any of the earth's characteristics or processes through a map or a GIS procedure. It is also inherent to any analysis that involves human understanding of any real-world process. We understand uncertainty as an indicator of the degree of distrust of the images and concepts of the real world that we are using (Castilla and Hay 2007). This uncertainty must be carefully examined to be aware about the limitations of our analysis and studies.

Land Use Cover Change (LUCC) models have many sources of uncertainty, which are difficult to disentangle (Uusitalo et al., 2015). Altogether, they are known as model output uncertainty (Refsgaard et al., 2007; Klein Goldewijk and Verburg 2013) or the uncertainty cascade (Refsgaard et al., 2013). Notwithstanding, several authors have tried to classify them in different groups (Van Asselt 2000; Walker et al., 2003; Refsgaard et al., 2007, 2013; Matott et al., 2009; Klein Goldewijk and Verburg 2013; García-Álvarez et al., 2019), mainly differentiating the following types of uncertainty:

- Epistemological uncertainty. The uncertainty that comes from the delimitation and conceptualization of the problem to be modelled. When strictly referring to the uncertainty of the way a problem is conceptualized in a model, several authors talk about "structural uncertainty" (Ferchichi et al., 2017). Brown et al. (2021) specifically refer to model paradigms when analysing model structures that lie in a very different conceptualization of the systems to be modelled.
- Model technical uncertainty. The uncertainty arising from the computer implementation of the model, concerning not only the model algorithm, but also the data formats, resolution and other issues. It is related to epistemological uncertainty.
- Process variability uncertainty. The uncertainty that comes from the different ways a system can evolve in the future.
- Input uncertainty. The uncertainty that comes from the data used in the model and its ability to represent the earth surface and/or its characteristics.
- Parameter uncertainty. The uncertainty associated to the values at which the different model parameters are calibrated.

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- Model operation uncertainty. The uncertainty that arises from the accumulation and interaction of uncertainties propagated through the model.

These sources of uncertainty in LUCC modelling exercises have been addressed widely in literature. Many papers assess the output uncertainty of specific exercises (Memarian et al., 2012; Ligmann-Zielinska 2013), whereas others focus on specific sources of uncertainty, like parameter uncertainty (Dietzel and Clarke 2004; Conway 2009; García et al., 2011; Van Vliet et al., 2013; Houet et al., 2015; Confalonieri et al., 2016; Grinblat et al., 2016; Liao et al., 2016) or process variability uncertainty (Kok and Van Delden 2009; Verburg et al., 2013; Alexander et al., 2015; Maier et al., 2016).

Less common is the research about epistemological uncertainties of LUCC models and, specifically, about the models' structural uncertainty (Elsawah et al., 2020). Some studies address specific topics related to this issue, like the different procedures to calculate change potential and change allocation (Riveira and Maseda 2006; Lin et al., 2011; Pérez-Vega et al., 2012; Camacho Olmedo et al., 2013; Shafizadeh-Moghadam et al., 2015). Ferchichi et al. (2017b) propose a framework to quantify structural uncertainty of LUCC models based on probabilistic theory and sensitivity analysis. However, there is a lack of studies that characterize the overall structural uncertainty of available LUCC model software packages and analyse the tools and options that each model offers for uncertainty management and communication.

Today, there is a large availability of standard model software packages to simulate different spatial dynamics (Camacho Olmedo et al., 2018b). Although they are considered too simple by some users to model complex phenomena, their use is ever-increasing (Wickramasuriya et al., 2009; Chaudhuri and Clarke 2013; Leija et al., 2021) and they are tools used in practice for real policy cases (Barredo et al., 2003; Van Delden et al., 2011; Eastman and Toledano 2018b; Guzman et al., 2020). Information about the uncertainty associated to the use of these software packages is not usually widespread and no paper analysing their structural uncertainty and their approaches to uncertainty management has been found in the literature. However, knowledge about these aspects is required to improve their understanding and characterization. In addition, it will help to engage planning agents and spread their use in real-world problems solving (Yeh and Li 2006; Batisani and Yarnal 2009; Sohl et al., 2016).

Through this paper, we aim to fill the previous research gap by characterizing and comparing four standard LUCC model software packages. Model comparison has been proposed by several authors as a way to assess the structural uncertainty (Kelly et al., 2013; Uusitalo et al., 2015; Brown et al., 2021) and has been usually employed as a useful approach to better characterize and understand the available software packages (García et al., 2012; Toro Balbotín 2014; Mas et al., 2014; Aguejdad et al., 2016; Camacho Olmedo et al., 2018b).

Through the comparison, we will answer the following research questions:

- Which are the sources of uncertainty that come from the different model structures?
- How does each model manage and communicates uncertainty?

We will analyse the model structure of each software and the options that they offer for uncertainty management and communication through a qualitative comparative analysis of the models. Additionally, we will assess the potential uncertainty associated to the model structure by applying the four compared models to the same study case. In the following section, we explain the methodological approach of this paper in detail.

2. Materials and methods

2.1. Model software packages

We compared four standard pattern-based LUCC model software packages: CA_Markov, Dinamica EGO, Land Change Modeler, as included in the TerrSet 2018 version, and Metronamica. Below, we provide a short description of each model. A graphic representation of each one is provided in the Annex 1. Annex 2 includes a comparative table to evaluate the differences among models.

The models have been selected based on the authors' deep experience with them (Mas et al., 2010, 2011, 2014; Camacho Olmedo et al., 2018a; García-Álvarez, 2018) and wide use among the LUCC modelling community (Santé et al., 2010; Kamusoko 2012; Eastman and Toledano 2018b; Ferreira et al., 2019). Practical experience with the models is essential to fully understand the model conceptualizations and structures and their limitations in real-case applications. The wide use of these models among the LUCC community guarantees the utility of the results here delivered, as they help to characterize standard tools used by many users for different purposes, either as part of scientific studies or real case applications. In addition, as they rely on common LUCC modelling theories, we can draw general lessons from their analysis and comparison, which can be applied to any LUCC model.

CA_Markov (Eastman and Toledano 2018a) is a modelling tool which makes use of several procedures integrated in TerrSet (previously IDRISI), a software of geospatial analysis and modelling. The quantity of changed pixels is determined by a Markov matrix, whereas the location of those pixels is performed through the combination of a series of suitability layers, a contiguity filter and a multi-objective allocation procedure.

Dinamica EGO (Soares-Filho et al., 2002, 2009; Rodrigues and Soares-Filho 2018) is a free environmental modelling platform that includes LUCC modelling methods. Due to the flexibility that it offers, there is a wide variety of ways to set up a LUCC model. As common practise, Markov chains and Weights of Evidence (WoE) are used for the estimation of the quantities and change potential. Change allocation is performed through a couple of stochastic cellular automata functions: patcher, which produces new patches, and expander, which simulates the growth as expansion of previous patches.

Land Change Modeler (LCM) (Eastman 2015a; Eastman and Toledano 2018b) is a constrained LUCC model which is also integrated in TerrSet. The change potential calculation is empirically obtained through three possible methods: neural networks, logistic regression and a machine learning algorithm (SimWeight). The change allocation is performed through a multi-objective allocation procedure, whereas the quantity of change is estimated by means of a Markov matrix.

Metronamica (RIKS 2012; Van Delden and Vanhout 2018) is a constrained cellular automata model based on the theory developed by White and Engelen in the 90's (White and Engelen 1993; White et al., 1997). Land use is allocated according to a "competition for space" principle based on the following inputs: interaction rules between land uses (human behaviour), accessibility, land suitability (environmental conditions) and zoning (planning). Demands can be defined externally or by means of a regional model simulating job and population dynamics.

2.2. Model comparison

Model structures were compared according to the following aspects: change potential calculation (including the explanatory factors considered by each model), quantity of changes estimation, allocation of changes, pattern simulation, and validation and outputs. Although only the last one specifically relates with uncertainty management and communication, these questions have been reviewed for all other aspects as well, regarding the extent to which the models include tools or allow user intervention for uncertainty management.

The comparison followed a both qualitative and quantitative analysis of each software (Fig. 1). The qualitative analysis complements the limitations of the quantitative analysis to assess sources of uncertainty that are not usually addressed in the literature (Elsawah et al., 2020). Through the qualitative approach (2.2.1) we compared the way in which each model conceptualizes the modelled system and the available options they offer for uncertainty management. Through the quantitative approach (2.2.2), we compared model outputs for the same case study (city of Cape Town) to assess the differences that come from the model structure.

The case study is part of the urban modelling practice. Accordingly, results from our analysis may be affected by the specificities of urban dynamics: urban growth is usually simulated through a common set of driving forces (accessibility, physical suitability, zoning) and neighbour interactions. Nonetheless, general understanding of the models' options for uncertainty management and system conceptualization can be also applied to other types of application.

The study case is explained in detail in annex 3. It consisted of a model set up with a spatial resolution of 100 m grid cells for the city of Cape Town and the period 1990–2013.

2.2.1. *Qualitative model characterization*

We reviewed and characterized the structures and features of the different software packages. This includes, among other items, system conceptualization, available methods for quantity of changes estimation, change potential calculation, change allocation, uncertainty management/validation and communication of results as well as the theory behind those methods. This information was obtained through the model's documentation and based on the deep experience of authors with the analysed software (Mas et al. 2014, 2018; Paegelow et al. 2014, 2018; Camacho Olmedo et al., 2018b; García-Álvarez, 2018).

2.2.2. *Model outputs assessment*

The four models were calibrated for the same case study following the approach described in annex 3. Outputs generated by each model were then analysed and compared. This allowed to analyse which differences between simulations came from the use of different model structures. According to this criterion, the higher the consensus among model outputs, the more certain is the simulation. Simulation success was also measured by comparing each simulation with reference data through common LUCC validation indices and metrics, Kappa Simulation (Van Vliet et al., 2011) and Spatial metrics (Mcgarigal 2018) (see below). The higher the agreement between reference and simulated data, the more successful the simulation is considered.

For the comparison of output maps, we differentiated between soft-classified and hard-classified maps (Camacho Olmedo et al., 2013). The first ones, which we will also refer to as Change Potential (CP) maps, show the probabilities of change to a specific category. Hard-classified maps, which are the final land use maps simulated by the models and we refer to as simulation results, assign every pixel to a specific category and, therefore, show states instead of probabilities.

Agreement between CP maps obtained through different methods of change potential calculation was measured through the Spearman correlation coefficient incorporated in the R package "ENMTools" (Warren et al., 2021). To this end, Transition Potential (TP) maps to the same category in Dinamica and LCM were aggregated and compared to the Land Use Potential (LUP) maps for that category in CA_Markov and Metronamica. LUP maps show the probability of change to a specific category (e.g. B), whereas TP maps show the probability of a specific transition (e.g. A to B) happening. To make both types of maps comparable, areas of CA_Markov and Metronamica LUP maps not considered in the transitions of Dinamica and LCM TP maps were masked.

Hard-classified simulated outputs from different models were compared by means of standard cross-tabulation techniques, Kappa Simulation (Ksim) and a set of spatial metrics calculated at the class level: number of patches, patch mean size and standard deviation and proportion of like adjacencies. Ksim evaluates the agreement between the changes simulated by each model compared to the agreement that is expected by chance (Van Vliet et al., 2011). Spatial metrics characterize the shape and size of patches and the way they are allocated on the map, that is, the maps' patterns. A patch is a group of neighbour pixels with the same value (Botequilha Leitao et al., 2006). The proportion of like adjacencies inform about the aggregation or cohesion between patches of the same class (Mcgarigal 2018). That is, how aggregated or fragmented are the patches that make up a class.

Each model was executed 20 times under the same parameters and conditions to assess the intra-model output variability. Only outputs from the first executions were employed for the previous assessments, whereas outputs from the remaining 19 executions were only employed to assess the agreement between model executions. Outputs from different model executions show low variability and do not significantly alter the pattern logic of the simulated CP areas or LUC changes. Thus, single outputs are enough to compare the output uncertainty caused by different model structures.

Agreement between change potential maps obtained through the same production method for each model was assessed by calculating the average standard deviation of the pixel values across the 20 outputs. Intra-model agreement between simulations was assessed through KSim and cross-tabulation, as in the inter-model comparison.

3. Results

3.1. *Change potential calculation*

Change potential is calculated in the four compared models based on the relation defined or found between a set of factors or drivers of change and the LUC changes. That relation can be defined by the user in the case of expert-driven models (CA_Markov, Metronamica) or calculated through automatic or statistical approaches, as defined by Van Vliet et al. (2016), in the case of data-driven models (Dianmica EGO, LCM). In the second case, models are trained until the best statistical relation between explanatory factors and LUC changes is obtained. In the first case, models are trained based on user criteria, which is usually driven by validation metrics, such as Kappa or Quantity and Allocation (dis)agreement indices.

Although we can obtain the same relation between factors and LUC changes through any of the methods implemented in the four software packages, each method entails a specific workflow for the combination of factors and produces a specific type of change potential map. Depending on the method, there are also some restrictions regarding the number or type of factors that can be taken into account. Accordingly, the selected methods and the way they have been implemented are closely connected with the model conceptualization.

3.1.1. *LUC and LUCC explanatory factors*

Only Metronamica puts restrictions regarding the number and type of factors considered. It only comprises four factors (neighbourhood interactions, accessibility, suitability and zoning), although the user can choose how many base maps he or she likes to include in the different factors and even rule out some of them by modifying the transition potential formula that guides the change potential map creation.

The Metronamica factors may be dynamic. The model also includes a random component in the change potential map creation, which introduces variability between different CP maps produced by the model (yellow cell in Table 1). It is possible to run the model in a deterministic way as well (random factor = 0), although the developers do not recommend this due to the inherent uncertainty in land use dynamics.

CA_Markov is not able to work with dynamic factors, which makes the model more uncertain when simulating processes that are explained by different or variable factors along time. On the other hand, Dinamica EGO and LCM admit any type and number of factors, including the dynamic ones. Notwithstanding, for LCM, when using Logistic

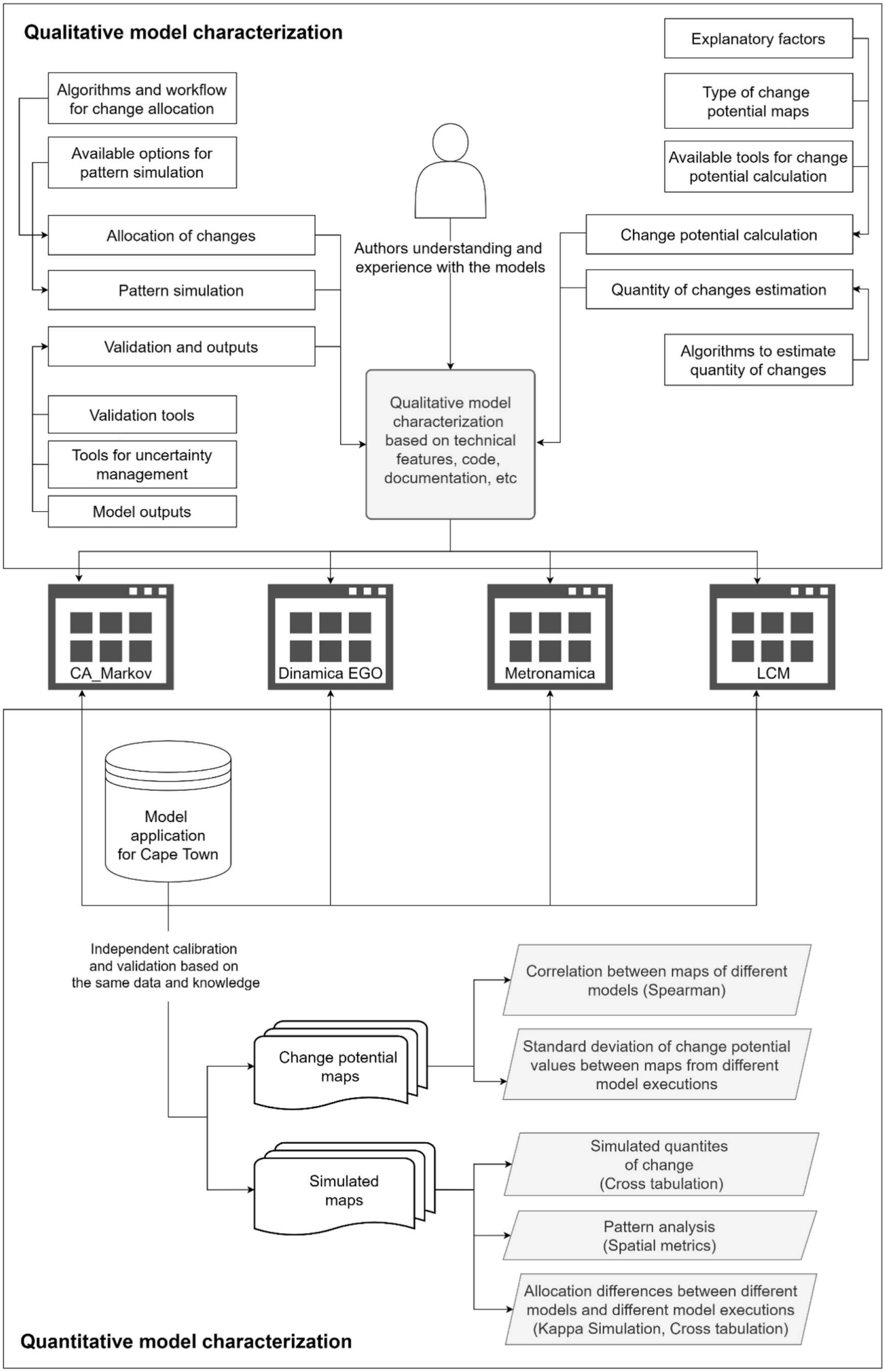

Fig. 1. Conceptual chart of the methods followed to compare the four model software packages.

Table 1
In diagonal and grey, average standard deviation of change potential maps produced through the same method after 20 model executions for the transitions to residential areas. Off-diagonal cells show the Spearman correlation coefficient between change potential maps produced through different methods for the transitions to residential areas. CAM: CA_Markov; Metro 0: Metronamica with random factor = 0; Metro 0.5: Metronamica with random factor = 0.5; LG SY10: Logistic Regression in LCM with a Systematic Sampling = 10%; LG SY100: Logistic Regression in LCM with a Systematic Sampling = 100%; LG ST10: Logistic Regression in LCM with a Stratified Sampling = 10%; LG ST100: Logistic Regression in LCM with a Stratified Sampling = 100%; NN: LCM with Neuronal Networks; SM: LCM with SimWeight; Manual WoE: Dinamica EGO with manual adjustment of Weights of Evidence; Auto WoE: Dinamica EGO with Weights of Evidence automatically calculated.

	CA_Markov	**Metronamica**		**Land Change Modeler**						**Dinamica EGO**	
	CAM	Metro 0	Metro 0.5	LG SY10	LG SY100	LG ST10	LG ST100	NN	SM	Manual WoE	Auto WoE
CAM	0.00										
Metro 0	0.42	0.00									
Metro 0.5	0.41	0.99	0.01								
LG SY10	0,42	**0,52**	**0,51**	0.00							
LG SY100	0,44	**0,50**	**0,49**	0,99	0.00						
LG ST10	0,42	**0,51**	**0,50**	1,00	0,99	0.2					
LG ST100	0,44	**0,50**	**0,49**	0,99	1	0,99	0.00				
NN	0,43	0,29	0,28	0,79	0,80	0,80	0,80	0.02			
SM	**0,50**	0,34	0,33	0,74	0,75	0,74	0,75	0,75	0.03		
Manual WoE	**0,53**	0,00	-0,01	0,14	0,16	0,14	0,16	**0,32**	**0,35**	0.00	
Auto WoE	0,33	-0,41	-0,41	-0,02	0,00	-0,02	0,00	**0,18**	**0,22**	0,44	0.00

Regression as the change potential calculation method, the model requires factors that are linearly related to the potential for transition (Eastman 2015b). To this end, LCM includes tools for factors transformation. However, they transform the factors based on LUC data, assuming a temporal stationarity, i.e. the continuation of past trends to the future, which may not be real.

3.1.2. *Two different types of change potential maps*

Dinamica EGO and LCM produce Transition Potential (TP) maps (Camacho Olmedo et al., 2013), which indicate the potential of a set of defined land uses to transition to another set of land uses. Although transitions can take place from any class to every other class on TP maps, they are usually restricted to the more meaningful, as it is difficult to find statistically significant relationships between a few LUC changes and a set of factors. In these cases, the found relationships may be significantly affected by errors in data or the presence of one-off events.

Through expert-driven approaches, models produce Land Use Potential (LUP) or suitability maps (Camacho Olmedo et al., 2013; 2018a). They indicate the preference of each land use class to occupy any location of a study area based on a set of drivers defined by the user, which in practice allows any transition to happen at any point in time. They do not necessarily require of historical data to be obtained (Aguejdad 2021), although Camacho Olmedo et al. (2013) point out how users create these maps based on the understanding of distribution of the considered land uses in time, which implicitly includes the understanding of previous past changes.

For our study case, correlation between Change Potential (CP) maps is independent of the type of maps compared. The CA_Markov and Metronamica LUP mas show the highest correlation with the TP maps of LCM, whereas TP maps automatically produced by Dinamica EGO show the highest correlalation with Metronamica LUP maps (Table 1).

3.1.3. *Methods for change potential calculation*

Each model calculates the change potential though different procedures (Fig. 2), which are closely related to the way each model has been conceptualized.

LCM offers three methods for transition potential map creation: Neural Networks and SimWeight, based on machine learning techniques, and Logistic Regression. The three methods trust automatic or statistical procedures as defined by Van Vliet et al. (2016) to find out the relation between changes and drivers of change. To this end, they use a sample of pixels as training and then, in the case of Neural Networks and SimWeight, the inferred relations are compared to a set of validation pixels. As far as the analysis sample varies with each model run, the inferred relations change with the sample as well (Kim 2010), although this variation is low (Table 1). The logistic regression procedure allows the user to employ all the pixels in the analysis and, therefore, avoid this possible uncertainty.

Dinamica EGO makes use of the Weights of Evidence (WoE) to calculate the change potential maps, although the model also admits external maps produced through other methods to bypass the incorporated methods. The WoE is a Bayesian method that relates the presence of a given set of factors with the probability of land use change (Eastman et al., 2005). Soares-Filho et al. (2013) developed a Genetic Algorithm that allows the user to refine the change potential calculated through the WoE method. The software also allows the user to manually edit the obtained weights to account for some of the uncertainties that the data, calibrations periods, etc can entail. This manual adjustment may have a great impact on the obtained maps. In our modelling exercise, change potential maps obtained with automatic and adjusted weights showed big differences (Table 1).

CA_Markov does not integrate a specific method for change potential calculation, although the model help advises to employ the Multicriteria Evaluation (MCE) implemented in TerrSet as the standard tool for this purpose. When using this method, the model will rely on user or expert knowledge, becoming very dependent on the uncertainty of that knowledge. In this regard, in this method he decides which factors to use and how they should be transformed and combined. He even assigns a weight to every factor.

In Metronamica, the change potential map is calculated through a formula that combines a series of input data manually adjusted by the user. The user can also edit the formula, which gives him the chance to account for the model structure uncertainty. However, they can also introduce new sources of uncertainty by doing so.

With the exception of Dinamica EGO, CP maps produced through the different methods implemented by each model show very high correlation among them and lower correlation with CP maps produced by other models (Table 1). In addition, there is not a clear correlation between CP maps based on their production method: manual vs automatic/statistical approaches. Accordingly, the Dinamica EGO CP maps automatically produced through the WoE show lower correlations with CP maps of other models than the CP maps obtained after the manual

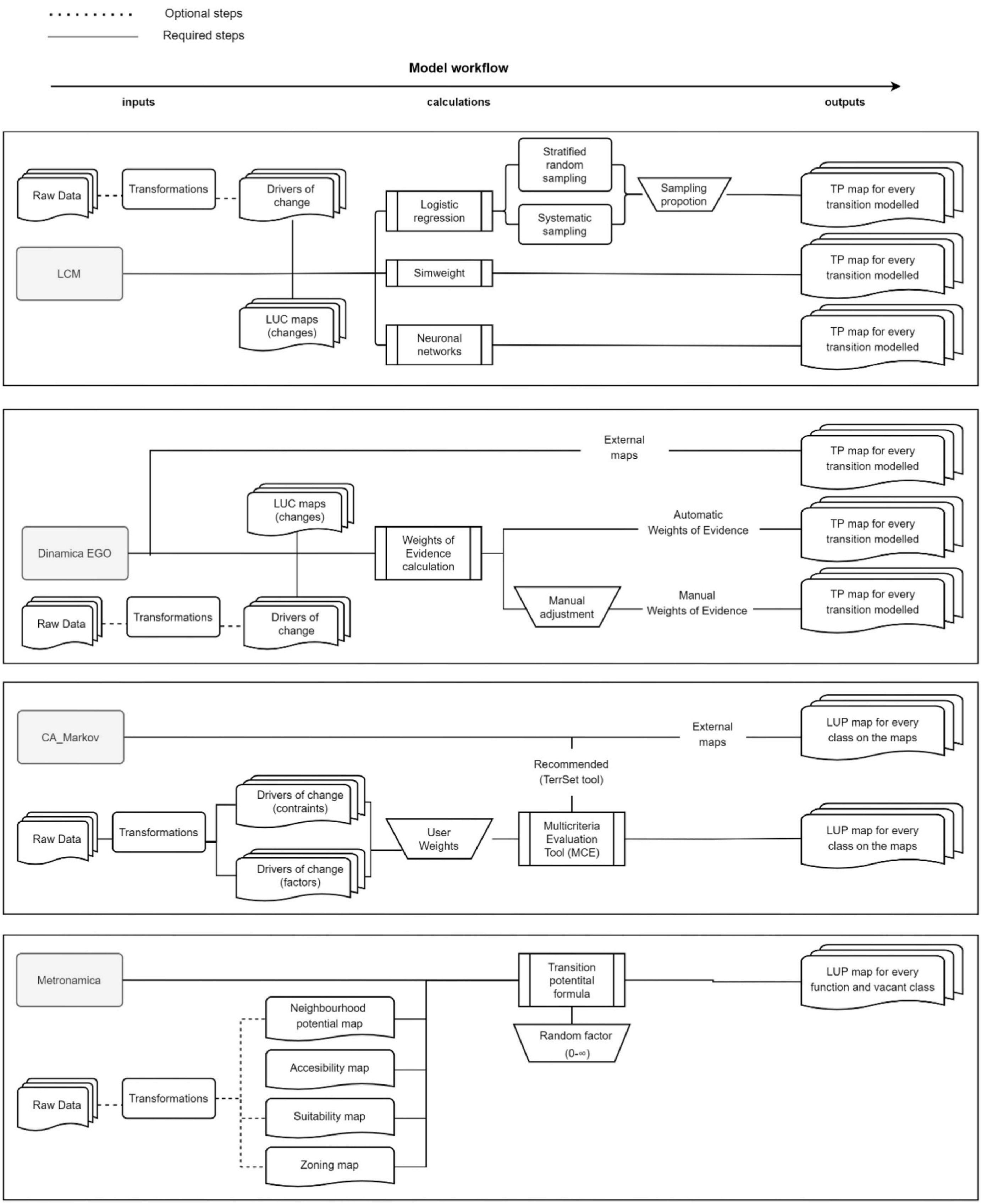

Fig. 2. Methods for change potential maps production offered by each model.

modification of the obtained weights.

3.2. Quantity of changes estimation

CA_Markov, Dinamica EGO and LCM calculate the simulated quantities from Markov chains. They indicate the probability of every category to transition to every other class and to remain the same (Camacho Olmedo and Mas 2018a; Aguejdad 2021). Thence, they make the modelling process to focus on transitions instead of land use states.

Through this approach, it is difficult to model systems where the land use dynamics change frequently and that do not follow historical patterns of growth (Mas et al., 2018; Paegelow 2018; Aguejdad 2021). That is, systems where the transitions between land uses are not always the same and at similar intensities. In addition, Markov chains usually calculate transition probabilities from past changes, extracted by comparing LUC maps at two different time points (Camacho Olmedo and Mas 2018a). In these cases, the uncertainty of input maps will be transferred to the obtained probabilities. Nonetheless, the three models allow the user to manually modify the obtained Markov probabilities from input data, and, therefore, to account for some of the uncertainties associated to input data. However, this step may not be easy for some users.

The Markov probabilities tool implemented in TerrSet and used in the context of CA_Markov allows to consider in the uncertainty of input maps in the quantity of change estimation. However, this introduces important modifications in the calculated quantities of change (Mas et al., 2014). Accordingly, this method can introduce more uncertainty than the one for which it finds an answer.

Metronamica does not include any method for quantity of changes estimation. The user enters the total number of cells (persistence + changes) that will make up each function class. The tool the user employs to decide the total number of cells will determine the uncertainty of this data. In addition, the transitions modelled for every category will rely on the settings of the interaction rules in the CA component. If the user does not introduce high values of inertia for the existent pixels of the function classes, some incongruent transitions can take place. Moreover, since the user cannot enter any information about the quantities of the vacant classes, their final size will also rely on the user calibration. Metronamica is therefore the most flexible model for modelling different types and speeds of change. However, because of this high level of flexibility, the ability of the user to replicate the dynamics of change is critical when calibrating the model and simulating the correct quantities of change.

All four models calculated different quantities of change, despite being based on the same reference data (Table 2). Small differences in the way Markov probabilities are calculated and used to calculate the number of pixels explain the disagreements between CA_Markov, Dinamica EGO and LCM. Metronamica's differences are explained by its specific method and the user calibration.

Table 2
Changes in pixels simulated by every model (2002–2013) for every transition compared to the changes measured in reference maps for the same period.

Modelled transitions	Residential areas			
	Vegegation areas to…	Other cultivated areas to…	Cultivated vine áreas to…	Rural residential to…
Reference	7376	658	232	331
CA_Markov	7139	649	231	330
Dinamica EGO (Manual)	6853	594	NA	297
LCM (Neuronal)	9361	121	NA	497
Metronamica (0.5)	8137	252	17	570

3.3. Allocation of changes

LCM, CA_Markov and Metronamica follow a deterministic procedure for change or land use allocation. On the contrary. Dinamica EGO includes a stochastic algorithm of change allocation that simulates different changes each time that the model is run (Table 3 and Fig. 3).

LCM and CA_Markov make use of a Multi Objective Land Allocation (MOLA) mechanism. It selects those pixels with the highest potential to change, solving conflicts between different objectives based on the minimum-distance-to-ideal-point-rule (Eastman et al., 1995). Metronamica follows a similar procedure. It selects the pixels with the highest potential to change for every category, allocating first the demands of the function classes and, then, the pixels of the vacant classes. Although the process is deterministic, the random factor added to the change potential maps allows transitions to take place in areas less likely to change.

CA_Markov includes a contiguity filter as part of the allocation process, forcing pixels with lower potential values to be simulated as change if located next to previous pixels of the simulated category. In LCM, a zoning layer can be included in the allocation of changes step, multiplying the values of the change potential maps.

The allocation functions of Dinamica EGO (patcher and expander) include a Cellular Automata component, favouring the simulation of pixels adjacent to land use classes of the same category. They also include a stochastic component to account for the unpredictability of human decision-making, which however is not easy to control. It is associated to a specific prune factor, which can be managed by the user, but also to a Monte Carlo approach of land use allocation and the parametrization of the expander and patcher functions (García-Álvarez, 2018). To reduce this stochasticity to a minimum, the user must choose a prune factor of 1, define clear and different transition potential values for the candidate cells and parametrize the expander and patcher functions according to the pixel size. In our case study, the stochasticity was relatively high: in 20 model executions, only 7.6% of the pixels simulated as change were allocated in the same place, with 34% of the changing pixels allocated in the same place less than 10 times (Table 4 and Fig. 3).

Simulated changes from each model usually show more agreement with the outputs from other models than with reference maps (Table 4). CA_Markov and Metronamica are the models that simulate the most similar changes. On the contrary, CA_Markov and Dinamica EGO are the models simulating more different changes. These differences cannot be explained by differences between change potential maps, as there is not a direct relation between correlation of change potential maps and the agreement of simulated changes (Tables 1 and 4).

3.4. Pattern simulation

CA_Markov, Dinamica EGO and Metronamica include a Cellular Automata component to replicate the real LUC pattern. This is lacking in LCM, which however allows to include a dynamic factor of distance to any of the map categories. LCM can infer from this variable the relation between LUC changes and the distance to cells of the other categories. However, this is calculated automatically by the model and therefore dependent on input data uncertainty. Because there is no user intervention possible, there is no direct control of the modelled pattern.

This CA component or attraction factor is especially relevant to simulate urban dynamics, such as the ones of the City of Cape Town, as new urban areas usually grow on the urban edges, usually in the search

Table 3
Number of times that each pixel is allocated in the same place across 20 model executions in Dinamica EGO.

1-5	6–10	11–15	16–19	20 (Deterministic)
15.5%	18.3%	27.1%	31.4%	7.6%

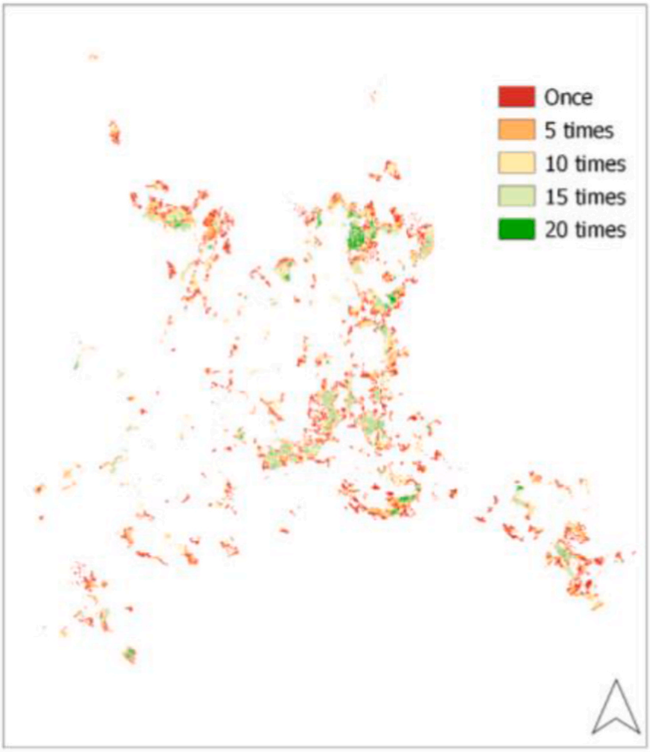

Fig. 3. Map showing the number of times that each pixel is allocated in the same place across 20 model executions in Dinamica EGO.

Table 4
Off-diagonal cells show Kappa simulation scores between simulated changes by the compared models. The higher the KSim (0–1), the higher the agreement between changes simulated by the two simulations diagonal cells show. Diagonal cells show Kappa simulation scores between simulated and observed changes for each model. The higher the KSim (0–1), the higher the agreement between observed and simulated changes.

	CA_Markov	Dinamica EGO (Manual)	LCM (Neuronal networks)	Metronamica (0.5)
CA_Markov	0.23	–	–	–
Dinamica EGO (Manual)	0.274	0.33	–	–
LCM (Neuronal networks)	0.303	0.415	0.41	–
Metronamica (0.5)	0.566	0.374	0.515	0.33

for economies of agglomeration (White et al., 1997).

For our modelling exercise, although LCM simulated a general pattern very similar to the reference landscape, the simulation includes many small and scattered patches that do not fit the common pattern associated with land uses like urban residential. Even if we can check a visual coherent pattern in Fig. 4, the spatial metrics reveal how LCM was the model that simulated the most new patches of urban residential: 120 opposite to 7 new patches of change between the reference maps of 2002 and 2013 (Table 5).

In CA_Markov the user controls the compactness of the simulated pattern through a user-defined contiguity filter. It up-weights the land use potential values of pixels close to pixels of the considered class and down-weights those which are far from this (Camacho Olmedo and Mas 2018b). It applies the same compactness logic to all modelled classes. In our study case, urban residential and urban informal changes were simulated according to the same pattern: patches of both classes became more compact, with a reduction in the total number of patches and a bigger mean path size (Table 5). However, urban informal pattern is more scattered (large increment of the number of patches and a lower mean patch size) than the urban residential one.

Metronamica allows to define neighbourhood interactions between all classes of the map and each function class, making it possible to get a specific pattern for each class, solving the previous limitation of CA_Markov. The user can also play with the weight of self-attraction rules and the random factor to facilitate the production of new patches in Metronamica. However, both CA_Markov and Metronamica faced difficulties when trying to simulate changes as new patches. In the two models, all changes were simulated as infill of existing patches or as an organic halo from them (Fig. 4).

Dinamica EGO simulates the desired pattern through two different functions: expander and patcher, which can be used together or independently. The expander function simulates changes as expansion of previous patches of the same use, whereas the patcher function simulates changes as new patches, disconnected from previous pixels of the same use. The user must indicate to the model the size and shape of the new patches for each modelled transition through three parameters: mean, variance and isometry. Accordingly, Dinamica EGO is the model that gives more control to the user regarding pattern simulation. For our study, the simulated landscape of Dinamica resembled quite well the reference landscape (Table 5), being maybe the best model when it comes to this point.

3.5. Tools for validation, uncertainty management and communication

Directly or indirectly, all four models offer the user a wide range of tools to test the accuracy and uncertainty of the simulation results. This is possible in Metronamica through the complementary Map Comparison Kit software and in CA_Markov and LCM through TerrSet, the software where these models are included. The Dinamica EGO platform is directly able to calculate a wide range of validation measures.

Metronamica is the only model that explicitly includes a tool for scenario management. It also allows to inform about the stochasticity associated to single run simulations. Dinamica EGO, because of its flexibility, can be designed to produce similar results. CA_Markov and LCM are more constrained to this end. LCM is only able to simulate business-as-usual scenarios (Eastman and Toledano 2018b). In CA_Markov, different model applications must be set up to account for different scenarios.

All four models provide manuals and tutorials that describe the models' methods and explain how to use them properly (Soares-Filho et al., 2009; RIKS 2012; Eastman 2015b). However, information about how to validate or assess the uncertainty of the modelling exercises is usually lacking. In addition, none of the four models is open source, which limits the user development and understanding of the software. Nonetheless, Metronamica foundations are deeply addressed in the literature (White and Engelen 1993; White et al., 1997) and described in detail in the model documentation (RIKS 2012), facilitating the replication of the model by other users.

4. Discussion

Each of the four model software packages compared conceptualized the systems and processes to be modelled in a different way, which resulted in different outputs. These sources of structural uncertainty are discussed in detail in section 4.1. In addition, all models provide different methods or tools to deal, manage and communicate the possible uncertainties of the modelling exercise. They are discussed in section 4.2.

Part of the results here discussed are limited by the study case selected for the model comparison. Model outputs were only compared for one specific case and one historic period. Analyses making use of different historic periods and study areas could provide complementary results. In addition, we have only judged the models' success based on

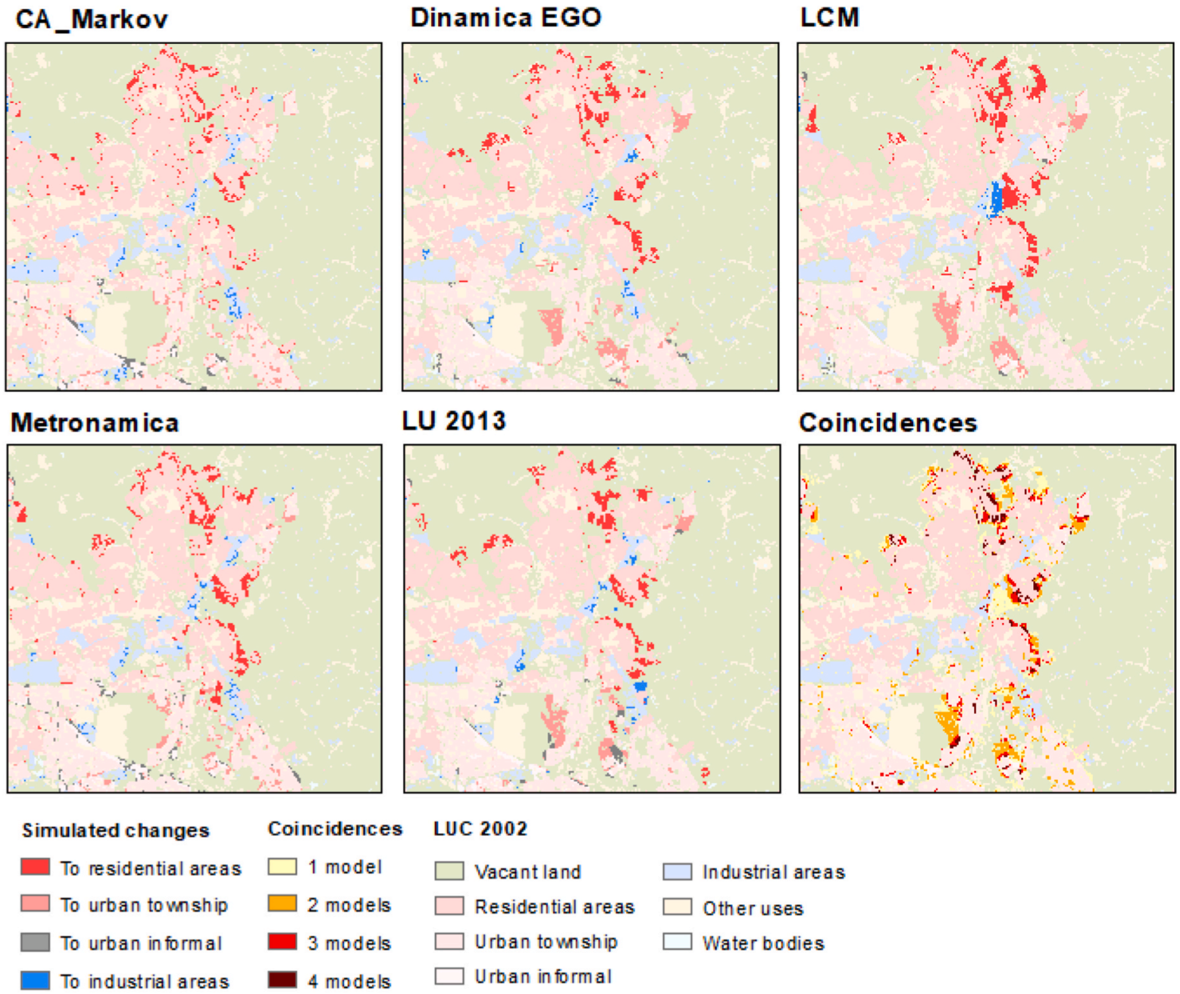

Fig. 4. Changes simulated by every model (2002–2013) for an example area of Cape Town compared to the changes that the reference map show. The last map in the lower right corner shows the coincidences between the simulated changes by the four models.

Table 5
Spatial metrics difference between 2002 and 2013 for the reference map and the four simulations for the categories urban residential (R) and urban informal (I). NP: Number of patches; Mean; Patch mean size; SD: Patch standard deviation; PLAJD: Proportion of like adjacencies. *E.g. 7 means that the reference map of 2013 has 7 more patches than the land use map of 2002.

	NP		MEAN		SD		PLAJD	
	R	I	R	I	R	I	R	I
Reference map	7*	25	4.97	2.09	53.92	5.86	0.17	4.02
CA_Markov	−35	−8	19.44	5.23	88.03	13.62	1.67	8.39
Dinamica EGO	7	9	4.08	3.08	62.57	6.57	0.23	−0.69
LCM (Neuronal networks)	120	47	−20.18	−0.10	−1.87	7.65	0.25	−0.10
Metronamica	22	65	0.55	−0.25	87.88	5.35	0.63	3.16

their quantitative performance with respect to a historic period of reference. Assessing the plausibility of model parameters and results, based on expert judgment or other strategies, could also provide complementary conclusions.

4.1. *Structural uncertainty*

How a system is conceptualized in a model comes with an important source of epistemological uncertainty, which may depend to a great extent on the purpose or objective for which the model was initially developed. Models developed for a specific purpose and application can include a structure that suit the simulated processes best. For standard models, like the ones assessed in our application, the sources of structural uncertainty can be bigger. The models assessed in our study have all developed towards generic modelling frameworks. Although they might have been developed for a specific purpose originally, over time they have been adapted to be able to simulate a wider range of dynamics.

LCM and Dinamica EGO were initially developed to simulate deforestation dynamics (Soares-Filho et al., 2002; Eastman 2015a), but successfully simulated urban processes in our study case and have been applied with success in other domains (Eastman and Toledano 2018b; Rodrigues and Soares-Filho 2018). In this regard, they do not limit the number or nature of the factors considered, which makes them very flexible tools. That is also the case of CA_Markov, that was not specifically developed for any application, but has been successfully applied to many domains (Eastman and Toledano 2018a).

Metronamica, based on the model proposed by White and Engelen to simulate urban dynamics (White and Engelen 1993; White et al., 1997), has been also applied to simulate non-urban dynamics (Van Delden and Vanhout 2018; Navarro Cerrillo et al., 2020). However, the model has been specifically designed to simulate urban and regional processes in detail, as revealed by the four factors that model considers: accessibility, neighbourhood, suitability and zoning. They are the common drivers of urban change, but may be limited to simulate dynamics related with farming or natural vegetation.

In CA models, such as CA_Markov, Dinamica EGO or Metronamica, the behaviour of a complex system is explained by the relation between every of its components (conceptualized as cells) and their neighbourhoods. If this assumption does not lie on the base of the dynamics of the modelled system, these models will probably fail when modelling the intended dynamics. This logic fits well with urban processes, like the ones of Cape Town, as well as with other ones, such as deforestation (Barredo et al., 2003; White et al., 2015; Kura and Beyene 2020). However, even in urban environments, not all dynamics can be explained following the same CA theory. In our study case, model's fit was poor for informal settlements (Annex 3), as this class usually grows scattered and cannot be easily explained by common CA rules (Ibrahim et al., 2019). Liu et al. (2019) point out at the limited capabilities of CA models to simulate novel urban processes, such as urban regeneration, gentrification, or urban shrinkage. Nonetheless, Lauf et al. (2016) simulated with success urban shrinkage processes for Berlin in a Metronamica-based model.

Even if relying on the same CA theory, models can implement it in a different way, leading to variable model structures and sources of uncertainty. Simple approaches, such as the contiguity filter of CA_Markov, may be less suited for complex applications where several categories or dynamics are modelled. Thus, the CA component in CA_Markov only allows the user to tune the compactness of the entire simulated landscape, without distinctions at the class level. In our application, this hampered the correct simulation of informal settlements, whose pattern did not adapt to the general compactness logic applied by the model.

Pontius Jr. and Malanson (2005) considered the ability to control the modelled pattern as an important feature of a modelling exercise. CA models allowing the definition of complex interactions (attraction and repulsion rules) between land uses, such as Metronamica, give an answer to this question. However, only through the implementation of more complex methods, such as the Expander and Patcher algorithms of Dinamica EGO, the model can simulate different dynamics than the infill or growth from the patch edges. In this regard, García et al. (2011) and Hewitt and Díaz-Pacheco (2017) point out at the model's ability to simulate emergent growth isolated from previous developments when analysing the complexity of CA models.

In our study case, Dinamica EGO was the only CA model able to replicate the full complexity of the land use change pattern. Soares-Filho et al. (2003) and Mas et al. (2014) proved the high control that this model offers for pattern simulation. Notwithstanding, this flexibility is dependent on the stochasticity introduced in the model, which may hamper the user understanding and the model stability (García-Álvarez, 2018).

The simulation of dynamics by means of contiguity rules is also possible through non-CA approaches, such as LCM. A dynamic factor of attraction/repulsion between one land use and the others can account for those contiguity patterns. For our study case, the parametrization of this factor in LCM contributed to the generation of a similar simulation in CA and non-CA models.

The correct or uncertain simulation of the studied dynamics may be also caused by other model characteristics, such as the assumption of temporal stationarity of LUC change (Feng et al., 2019). Markov-based models, like CA_markov, Dinamica EGO and LCM, reproduce past processes into the future, which makes difficult to simulate turning points in the modelled systems when different land use transitions take place (Mas et al., 2018; Paegelow 2018). In addition, quantities of change in Markov-based models are usually calculated from historical data, making the models very dependent on input data representativeness and accuracy (Paegelow 2018; Aguejdad 2021). Verburg et al. (2019) recommend the development of models able to simulate the LUC demands explicitly, which can link demand and supply.

Models based on TP maps, like Dinamica EGO and LCM, also find difficult to simulate different transitions through time and usually trust their calibration in recent changes, which may be not enough to represent the system's future variability. To account for this process variability, models should be also able to handle dynamic factors. This is a common feature in the three of the models compared, with CA_Markov as the only software not able to handle these type of factors.

There is a wide variety of non-CA modelling approaches (National Research Council 2014; Camacho Olmedo et al., 2018b). Many of them, like LCM, rely on machine learning and statistical procedures. Through these methods, the model studies the relation between past changes and drivers of change and apply it to the future. However, if not allowing for user intervention, the model may become very dependent on input uncertainties from data, short calibration periods, etc. LCM does not offer any room for user intervention to this end, which hampered the correction of some pattern inconsistencies in our study case. Thus, in LCM, model success entirely depends on the ability of the chosen evaluation method to correctly find the relation between drivers of change and past changes.

When models relying on automatic or statistical procedures allow for user intervention, the users should be aware of the impact of their intervention and the uncertainties that it may bring. In Dinamica EGO, the change potential can be calculated through the Weights of Evidence or a Genetic algorithm and the obtained result later modified by the user. In our study case, this modification produced very different change potential maps to the ones automatically generated by the model.

Models relying on user understanding, such as Metronamica and CA_Markov, avoid the uncertainties that come from the method, but become dependent on the user input's uncertainty (Botterweg 1995; Sohl et al., 2016; Li et al., 2017). They may be even bigger than the ones associated to the selected method for change potential calculation.

In automatic or statistical approaches, the model's success will depend a lot on the data and, specifically, on the number and statistical representativity of observed changes. If these are not large or representative enough, the relation that the model finds between changes and drivers of change may be biased. However, this may be a common feature in those models trusting user knowledge if s/he heavily relies on historic dynamics to manually calibrate the models, such as in the studies of Guzman et al. (2020) and Tamuka Moyo et al. (2021). In these cases, expert judgment could be a solution, as experts can inform about the plausibility of the user's parameters and the simulation results (Hewitt et al., 2014).

According to Botterweg (1995), user's calibrations are only valid for those users or experts who made the calibration, limiting the repeatability of the model application. However, in our exercise, expert-based calibrations showed high correlation, even with change potential maps obtained through statistical or automatic approaches. On the contrary, change potential maps obtained through different statistical or automatic approaches showed high variability. These findings are similar to the ones obtained by Krueger et al. (2012). Thus, although the repeatability and easiness of calculation are usually some of the common advantages pointed out to choose automatic or statistical approaches, this is not always the case.

Expert or user knowledge has been pointed out as a useful tool for uncertainty assessment (Uusitalo et al., 2015). Nevertheless, total user control, like in Metronamica, has important limitations. The modeller needs to understand how hundreds of parameters work at the same time. Accordingly, he can struggle during the calibration, especially if he does not have the expertise or experience required (Elsawah et al., 2017). A mixture of both data-driven and knowledge-driven approaches can be considered an adequate solution (Pérez-Vega et al., 2012). This is already implemented in Dinamica EGO and has already been tested in CA_Markov and Metronamica (Ghosh et al., 2017; Newland et al., 2018).

4.2. Uncertainty management

4.2.1. Managing the structural uncertainty

Models can offer different strategies to deal with the structural uncertainties they may convey. One of the most common is the provision of different methods in each of the modelling steps, among which the users can choose the most suitable. It connects with the models' need to provide multiple process representation suggested by Verburg et al. (2019). Another approach is the possibility of direct user intervention. The availability of models' code is maybe the option that would offer the users more room to deal with the models' structural uncertainty, although it would require a high level of expertise and user understanding of the model. In addition, it has been considered a required step by Verburg et al. (2019) to progress on LUCC modelling and the management of uncertainty. However, none of the four models assessed are open source.

For the production of change potential maps, offering the possibility to use external maps created through other methods is a good solution, which has been applied in practice in Metronamica and is already implemented in Dinamica EGO and CA_Markov. In the last case, this option is extensively used (Cai and Wang 2020; Arora et al., 2021). Offering a range of methods for change potential calculation is another approach. However, the different methods should be complementary, providing a similar utility.

Dinamica EGO provides two different complementary methods (Weights of Evidence, Genetic Algorithm) to calculate the change potential. This, in addition to the admission of external maps, gives the user a wide range of chances to deal with the model's structural uncertainty. LCM supplies three different methods for change potential calculation plus two extra machine learning techniques that have been included in the last release of the model (Eastman and Toledano 2018b). However, logistic regression is just provided for pedagogic purposes (Eastman and Toledano 2018b) and not recommend by the developers (Eastman 2015a). In addition, machine learnings behave like a black boxes (Kim 2010; Mozumder et al., 2016), hampering the user understanding of the model. If s/he cannot understand why one method produces different results than the other, s/he will not be able to effectively manage the model's structural uncertainty by selecting among the different methods that are available.

For change allocation, models can also offer different algorithms or methods. However, this is less common than in the change potential calculation. All four models compared offer a single method of change or land use allocation, which cannot be modified in CA_Markov and LCM. Through the provision of flexible frameworks, like in Dinamica EGO, models can allow the user to develop their own land allocation algorithms. Other approach is allowing the user modification of the specific method or algorithm implemented in the model. Metronamica, for example, allows the user to modify the transition potential formula that the model uses to allocate land uses.

For the quantity of changes estimation, user intervention is the most common approach for uncertainty management. The four models assessed allow users to modify the quantities of simulated changes, which give them the chance to employ different methods to calculate those quantities. However, depending on the format that these quantities must be provided, the room for user intervention may be more limited. In this regard, LCM only allow to introduce markov probabilities. CA_Markov and Dinamica EGO offer options for the implementation of dynamic methods of quantity of changes estimation. In a similar vein, Metronamica allows the dynamic computation of quantities of change through a regional model that can be parametrized by the user.

4.2.2. Stochasticity as a means to account for the model allocation uncertainty

Stochasticity is considered as an important feature by several authors to replicate real phenomena (García et al., 2011; Van Vliet et al., 2012; Renard et al., 2013). It accounts for the uncertainty of the real world, where decisions are dependent on uncertain human actions. For a given set of changes, there are usually large available areas for development with similar potential to change. Uncertain human action is the factor that can explain why a change took place in one place or another.

By including a stochastic component, models can account for this uncertainty. García et al. (2011) reviewed two main approaches for the inclusion of randomness in LUCC models: a stochastic perturbation, included in Metronamica as part of the change potential calculation, and Monte Carlo methods of change allocation, as included in Dinamica EGO. The first approach allows less likely changes to happen and has been pointed out as useful when communicating the uncertainty of the change allocation step (White et al., 2015). The second approach allows cells with similar potential to change to be simulated at each model execution, although may produce important output variability, as in our study case.

4.2.3. Process variability uncertainty

At the regional or global levels, the aggregation of uncertain local human decisions brings about new drivers or processes of change, which finally change the foundations of the systems. Accordingly, real systems are far from equilibrium systems, which can evolve to new stages governed by new rules and processes (White et al., 2015). Usually, models deal with this process variability uncertainty by accounting for randomness in the modelling process (Hewitt and Díaz-Pacheco 2017) or by means of the definition of scenarios (Van Asselt 2000; Maier et al., 2016). Some tools have been also proposed to deal with this uncertainty, like the self-modification algorithm in SLEUTH (Clarke 2004).

Stochasticity facilities those tipping points to happen, allowing to replicate more complex systems. However, changing the foundations of a system is only possible by means of entering a large randomness, which at the same time may hamper the user comprehension of the model. The stochastic perturbation approach included in Metronamica produces limited stochasticity, at least when staying between the ranges indicated by the developers, as proved in our simulation and other studies (Wu 2002; García et al., 2011; Hewitt and Díaz-Pacheco 2017). The Monte Carlo method for change allocation implemented in Dinámica EGO can produce very stochastic simulations, accounting for the process variability uncertainty mentioned above (Mustafa et al., 2018). However, the uncertainty that this method introduces in the user comprehension of the performed calibration can be higher than the one for which it finds an answer, as the model can show different results every time that it is run, making the model parametrization and understanding uncertain. Accordingly, the user must find a balance between the stochasticity of his/her model and its stability.

Scenarios allow to manage the process variability uncertainty by providing a range of possible system evolutions, under different drivers and processes of change. They allow the user to explore future system uncertainties in a transparent way: the user knows what is being tested. However, only those uncertainties that can be thought of will be included, while a more black box approach also has the potential to capture the unknown unknowns.

Models only able to produce business-as-usual scenarios or that offer options for parameter variation, like LCM (Pérez-Vega et al., 2012; Eastman and Toledano 2018b), cannot deal with this source of uncertainty. When different scenarios can be produced, such as in the other three compared models, the provision of specific tools for the management and creation of scenarios, like in Metronamica, may be a very useful tool to manage this source of uncertainty (Van Delden and Hagen-Zanker 2009; Riddell et al., 2020).

Caution should be paid regarding the uncertainty that scenarios capture. Studies show that there are often larger differences between results of a baseline scenario simulated with different model software packages than between different scenarios run with the same model (Van Delden et al., 2012; Prestele et al., 2016; Sohl et al., 2016). This uncertainty, mostly structural, should be therefore carefully evaluated. To this end, model comparison has been repeatedly pointed out as a tool for model validation and characterization of their uncertainty (Pérez-Vega et al., 2012; Sohl et al., 2016; Paegelow et al., 2018). In this regard, this study proves how the same model application calibrated through very similar parameters for four different model software packages may deliver different results.

4.2.4. Validation and uncertainty analysis

Models usually include specific tools to validate and assess the uncertainty of their outputs. However, if this is not possible, the generation of outputs that can be easily exported to other validation software, or even the connection between the models and these software, is equally effective. In this regard, Metronamica, CA_Markov and LCM give the user a wide range of options for model validation through the Map Comparison Kit and TerrSet. The provision of flexible GIS frameworks, where users can design and implement their own validation methods, like in Dinamica EGO, is another valid option for the provision of validation and uncertainty management tools.

It is important that the model developers provide the users guide and assistance when making these validation exercises or generally assessing the model uncertainty. In this regard, Elsawah et al. (2020) pointed out a gap between theory and practice in the implementation of uncertainty assessment exercises. It is common the availability of model manuals and tutorials that give some tips to this end, like in the four models compared. However, specific guidelines about validation and, above all, about uncertainty analysis, are usually lacking and have been not found for any of the compared models. When available, they focus on one or a few analyses and do not make the user aware of the complexity that a full validation and uncertainty analysis may entail.

4.2.5. Communication of uncertainty

There is still a lack of attention in the provision of tools to communicate the uncertainty that the models provide, which is especially important for their correct use among decision makers and stakeholders (Elsawah et al., 2020). None of the analysed models provides enough tools to communicate most of the uncertainties of the analysis to the audience, from the problem conceptualization to the model validation. Models just focus on specific sources of uncertainty, but not on the whole uncertainty of the modelling exercise. This can be related with the lack of an agreed framework for uncertainty assessment in LUCC modelling. The development of external tools, easily connected with the models, that fulfil that need could be an alternative solution.

The generation of probability outputs, which account for the model stochasticity and variability among model runs, is a useful approach to communicate the uncertainty of single outputs. However, only Metronamica includes a tool to produce these outputs, which could be especially useful in Dinamica EGO, due to the important stochasticity that the model can convey. Notwithstanding, this result could be inconvenient if it is not properly used. It can give the audience a false perspective about the uncertainty of the simulation. It just accounts for the system's uncertainty that the models try to replicate through a stochastic component. However, it does not account for all the other sources of uncertainty which we have addressed in this paper.

5. Conclusions

Each model software package conceptualized the modelled system in a different way, which led to differences in the way the LUC dynamics and changes were simulated. Despite of these differences, there is not a best modelling approach. Each model entails different uncertainties and limitations, which must be carefully considered by their potential users. In this regard, comparing different model outputs for the same application is a good approach to account for the structural uncertainty of our modelling exercises.

The less automatic the model workflow is, the more options the user has to control the model structural uncertainty. In this regard, constrained approaches that offer little room for user intervention, like LCM, can be associated to important sources of structural uncertainty if the model structure does not perfectly fit with the modelled processes. Nonetheless, very flexible approaches, which rely a lot on user or expert knowledge, may become very dependent on the uncertainties introduced by them. Thus, mixed approaches, like Dinamica EGO, are considered preferable. Nonetheless, statistical or automatic modelling approaches did not provide in our study case more repeatability or better simulation scores than models relying on user knowledge, which proved that user intervention is not necessarily associated with more uncertain simulations.

Offering several options or methods for change potential calculation, quantity of changes estimation and change allocation allows user intervention in the modelled process, but does not leave all decisions in the user. However, when offering several options or methods, these should be complementary and provide different approaches. In this regard, the different options for change potential calculation offered by LCM provided similar results.

Randomness and scenario management were identified as two important elements to account for the uncertainty of the modelled processes, but are not usually included in all models. In our case, only Dinamica EGO and Metronamica were able to both simulate stochastic simulations and generate different scenarios. In addition, we have identified a lack of attention in models to important aspects related with uncertainty management, such as the communication of model uncertainties and the provision of tools and guidance for uncertainty analysis.

Declaration of competing interest

The third author of the paper (Hedwig Van Delden) is the director of the Research Institute for Knowledge Systems (RIKS), which develops, commercializes and promotes the Metronamica software. There is not any conflict of interest between the rest of the authors and the models assessed.

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Appendix A. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.envsoft.2022.105411.

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