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Combining a land parcel cellular automata (LP-CA) model with participatory approaches in the simulation of disruptive future scenarios of urban land use change

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A B S T R A C T

Urban development is a process that becomes increasingly complex as the city evolves and in which unexpected events can happen which may alter the envisaged trend over time. To anticipate and examine the sudden emergence of processes that are difficult to predict over long-term future timelines, prospective methodologies are required to manage and implement disruptive narrative storylines in future scenario planning. In this research, a method that combines Land Parcel Cellular Automata (LP-CA) and participatory approaches was developed in order to generate land use trajectories that are spatially consistent with disruptive narrative storylines. The urban-industrial corridor of Henares (Spain), which has undergone important urban transformations in recent decades, was chosen as the study area to test the model. In a preliminary validation of the LP-CA model, a Figure of Merit (FOM) value of 0.2817 indicated satisfactory performance. The results demonstrated the usefulness of the participatory scenario-building and the workshop in supporting the configuration of the model parameters and the spatial representation of complex urban dynamics. In conclusion, this methodology can be used to generate simulations of urban land use change in disruptive future scenarios and to spatially observe the propagation of the uncertainty associated with future events across different urban land uses.

1. Introduction

Cities are becoming increasingly more complex. As they evolve, the interactions between their constituent parts increase (Batty, 2020), which makes it even more difficult for researchers to study them. This complexity is further accentuated by uncertainty, due to the impossibility of understanding and quantifying all the exogenous factors that influence urbanisation processes (Mustafa, Saadi, Cools, & Teller, 2015).

In order to face a complex and uncertain future, scenario planning emerges as an alternative that provides a wider range of expectations about the future, identifying possible directions to achieve a more suitable framework for consistent decision-making (Lyons & Davidson, 2016; Peterson, Cumming, & Carpenter, 2003; Zapata & Kaza, 2015). However, the effectiveness of scenario planning may be limited if all the scenarios remain very close to the business-as-usual (BAU) projection. Unexpected events such as the housing bubble crisis in Spain (Burriel, 2011), the migration crisis in Europe (Hampshire, 2015), the SARS-CoV-2 pandemic (Antipova, 2021) or the recent Ukrainian war undermine linear planning, and are difficult to envisage without imaginative and flexible future scenarios (Houet et al., 2016). This means that for the best possible management of (un)desired future urban developments, disruptive thinking must be part of the envisioning process, so breaking with the linearity of current events to encompass the unexpected (Soria-Lara et al., 2021).

As part of the urban planning process, urban simulation models attempt to represent the future development of cities to ensure that they can develop in a reasonable planned way. Of these, cellular automata (CA) models are the most commonly used in support of urban management, especially in local or regional studies (Aburas, Ho, Ramli, & Ash'aari, 2016; Santé, García, Miranda, & Crecente, 2010; Triantakonstantis & Mountrakis, 2012). In particular, irregular CA models have emerged in a context of urban land use change at a local scale (Benenson & Torrens, 2004; O'Sullivan, 2001; Pinto & Antunes, 2010; Stevens & Dragićević, 2007). Most of these models focus on simulating urban growth using land parcels as the best base unit for their analysis (Abolhasani, Taleai, Karimi, & Rezaee Node, 2016; Barreira-González,

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Aguilera-Benavente, & Gómez-Delgado, 2019; Barreira-González, Aguilera-Benavente, & Gómez-Delgado, 2015; Stevens, Dragicevic, & Rothley, 2007; Yao et al., 2017; Zhai et al., 2020). However, it is difficult for these models to consider the wide range of factors involved in the future evolution of urban areas by themselves, especially when imaginative, disruptive scenarios are depicted. Many parameters implemented in CA models require critical and social thinking in order for them to be successfully adapted into future simulation. With this in mind, an increasing number of studies are linking narratives with modelling tasks in a participatory way, so as to obtain better, more realistic results (Hewitt, van Delden, & Escobar, 2014; Houet et al., 2016; Kok & van Delden, 2009, 2013).

This paper takes the *intimately coupled narratives & models* approach, a combination of the *model-based approach* and the *narrative-based approach* (Houet et al., 2016). It is well-adapted to enable the active participation of stakeholders and facilitates the integration of both qualitative and quantitative information when linking narrative storylines with urban land use models (Houet et al., 2016). This combined approach, integrated into participatory scenario planning, involves three key steps mentioned below:

- Create a narrative storyline by engaging researchers and citizens, contributing ideas from a wide range of imaginative futures (including disruptive ones).
- Work on the narratives in a participatory workshop involving experts and stakeholders to transform qualitative insights into input for the model.
- Provide a map of future urban land uses in such a way as to enhance the value of the narrative storyline itself.

The aim of this research is to propose an integrated methodology to simulate imaginative, disruptive scenarios by combining land use modelling techniques with participatory approaches. This methodology implies the use of a new land parcel cellular automata (LP-CA) model which uses well-defined boundaries and real dimensions of land parcels to make the mapped scenarios more easily understandable for the actors involved in the participatory scenario planning process. We believe this integrated approach will be helpful to support the simulation of multiple, structurally distinct futures and to reproduce complex urban dynamics, such as land use conversion and abandonment included in disruptive narrative storylines. The proposed methodology has already been tested on a dynamic urban-industrial corridor in the Madrid Metropolitan Area (Spain).

This paper is divided into seven sections. After this introduction, the concept of disruptive scenarios and their usefulness in future simulation is explored. This is followed by a description of the study area. The next section sets out the methodology, introducing the LP-CA model and assessing its performance. The participatory process of scenario building is then explained together with its link to modelling tasks, and the section concludes with a partial validation of the future scenario. This is followed by the results and the discussion. The paper ends with brief concluding remarks and suggestions as to possible future lines of research.

2. Disruptive scenarios to face the future

The *disruptive* concept is an increasingly important feature of research into future scenarios. Christensen (1997) employs the term *disruptive* to indicate a change in a pre-existing trend due to innovation. Millar, Lockett, and Ladd (2018) define *disruptive change* as sudden change that renders the processes that preceded the change invalid as bases for predictive models. Within the urban planning context, *disruptive* is used to refer to possible events that can positively or negatively affect the dynamics of the city (Molinero-Parejo, Aguilera-Benavente, & Gómez-Delgado, 2021). Unexpected *disruptive* events can sometimes alter the path outlined by urban plans and, even if they have a contingency plan, they may not be prepared for disruptive changes. Urban planners and decision-makers must therefore expand the range of possible future scenarios envisaged in their plans.

To simulate disruptive scenarios, it is crucial to engage citizens, experts and stakeholders in city planning during the visioning step as they can add to the process *outside the box* thinking (Soria-Lara et al., 2021) and help to generate disruptive narratives. It is also necessary to redevelop simulation models to enable them to complement the maps of future urban land uses changes in line with the disruptive narrative storylines, where new urban processes and patterns may emerge. Although previous researchers have simulated off-trend scenarios (crisis, innovation, sustainability, etc.) (Domingo, Palka, & Hersperger, 2021; Kok & van Delden, 2009; Plata Rocha, Gómez-Delgado, & Bosque-Sendra, 2011; Vaz, Nijkamp, Painho, & Caetano, 2012), there is still a lot of work to do, since most of the scenarios simulated using CA models cannot be considered disruptive in the terms evaluated by Soria-Lara et al. (2021), as they have not been generated through barely imaginable (but plausible) processes (see Table 1). The keywords "as usual", "baseline", "trend" or "natural" are used in Table 1 to refer to traditional thinking in scenario planning.

Many of these scenarios fall within a narrow divergence range within the BAU zone (Fig. 1). This limits the ability of the integrated scenario-model approach to simulate unexpected events, such as gentrification or the abandonment of certain areas. In Western Europe, many city centres have undergone transformations from predominantly commercial and industrial uses to residential housing (Hamnett & Whitelegg, 2007). A reverse, but more recent process, is the adaptative reuse of old residential buildings as office buildings (Rodrigues & Freire, 2017). In the same way, urban regeneration necessarily involves the possibility of properties being used for new purposes. The renovation of abandoned buildings in city centres often involves a change of use (Lami, 2020), for example, from residential to commercial use. Another disruptive urban process that has affected many European cities in the last decade is urban shrinkage (Haase, Athanasopoulou, & Rink, 2016). As previously stated, models should re-adapt to simulate the abovementioned

Table 1
Urban scenarios simulated by CA models.

Author(s)	Purpose	Scenarios
(Yang, Zhang, Nan, Liu, & Zheng, 2019)	Modelling urban expansion	• Sustainable development • Dynamics as usual • Fragmented development • Unequal development • Conventional development
(Liu et al., 2017)	Simulating multiple land use scenarios	• Baseline development • Fast development • Slow development • Harmonious development
(Vaz et al., 2012)	Forecast of urban change	• Ecological interest • Business as usual • Economic interest
(Feng et al., 2018)	Urban growth modelling and future scenario projection	• Business as usual • COUNTY-dominated • ROAD-dominated • POP-dominated
(Zhou, Dang, Sun, & Wang, 2020)	Multi-scenario simulation of urban land change	• Natural development • Planning constraint
(Yao et al., 2017)	Simulating urban land-use changes	• Disorganized urban development with no restrictions • Sustainable urban development with ecology control • Sustainable urban development with ecology control and "job-housing balance"
(Jia et al., 2020)	Urban modelling for streets	• Trend development • CBD-based development • TOD promotion
(Chen, Liu, & Li, 2017)	Urban growth simulation	• Business-as-usual

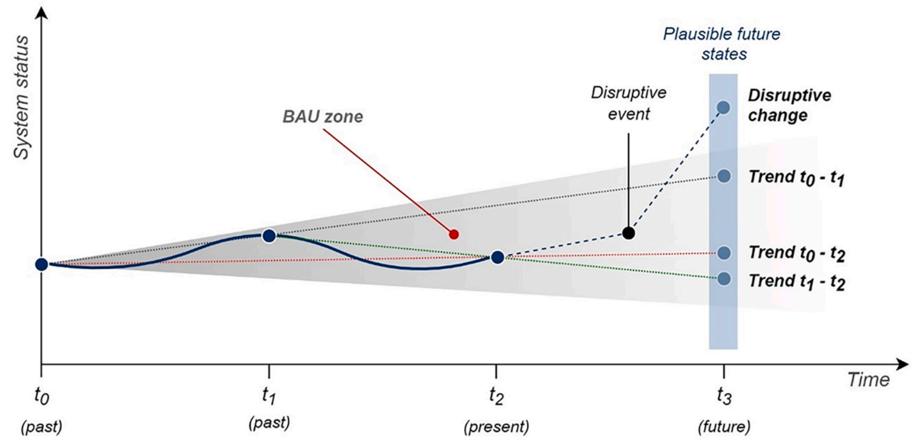

Fig. 1. Conceptual diagram of changes in scenario planning due to disruptive events that cause an abrupt divergence in the envisaged trend.

processes, after which the integrated use of disruptive scenarios and LP-CA models - the objective of this research - could help create more resilient plans to deal with disruptive changes (Laird, 2014).

3. Study area and data

As a study area for this research, we focused on part of the Henares Corridor, Madrid - Guadalajara (Spain) (Fig. 2). The study area covers several municipalities with a total population of 419,791 inhabitants (National Statistics Institute, 2018). It is characterised by small and medium-sized towns with significant industrial fabric and a variety of territorial and social dynamics (Barreira-González et al., 2019; Cantergiani & Gómez Delgado, 2020).

As regards the input data, cadastral parcels were obtained from the *General Directorate of the Cadastre* of Spain (https://www.sedecatastro.gob.es/). These parcels were then classified into 5 active urban land use categories: (1) commercial and utilities, (2) industrial, (3) single-family residential, (4) multi-family residential, and (5) mixed (residential and commercial), obtaining the 2018 reference map. For the calibration, simulation, and validation of the LP-CA model, reference maps were generated for 1986 and 2002 from the development date of the land parcels.

According to these historical data, annual area growth and the cumulative area growth in these land uses in the study area were analysed (Fig. 3) and significant fluctuations of varying intensity were identified. These involved a marked increase or decrease in the built-up area due to

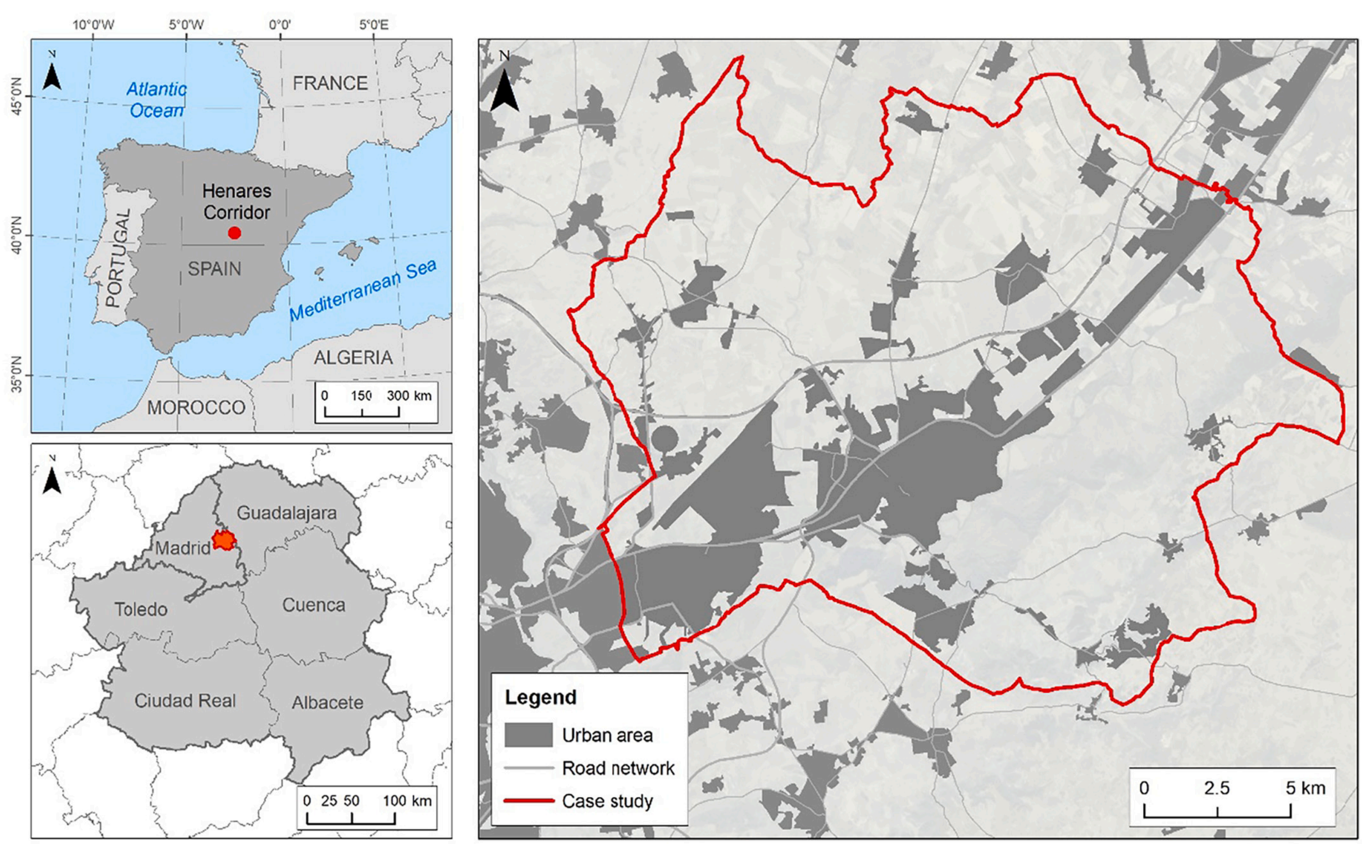

Fig. 2. Study area.

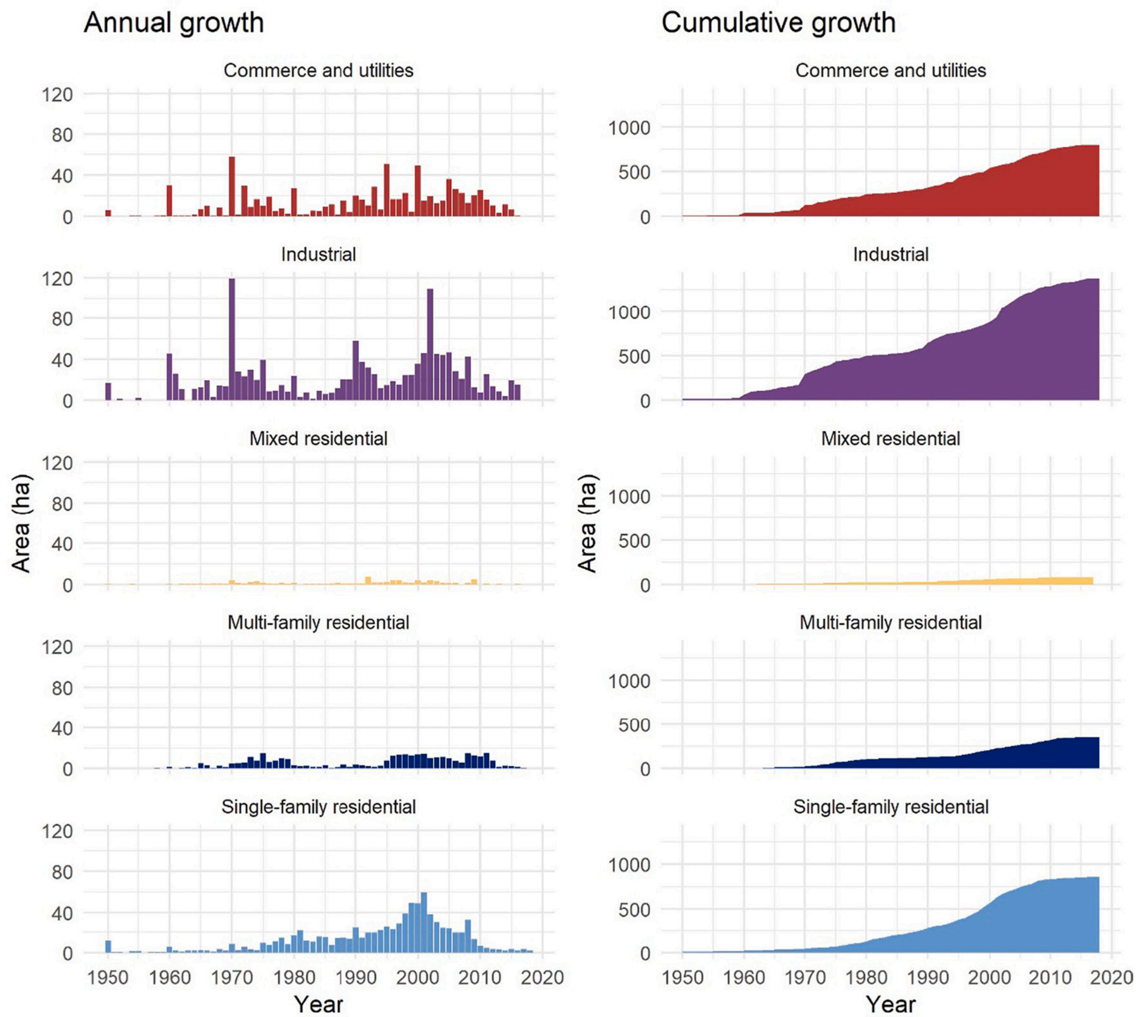

Fig. 3. Annual and cumulative growth in the five urban land uses in the study area.

disruptive events. For example, sharp changes can be observed in the early 1970s and 2000s, especially due to new urban developments (single-family residential growth starting in 1990) and the slowdown in the development of new industrial areas due to the oil crisis (early 1970s). The impact of the global economic crisis of 2008 can also be observed, as the upward curve flattens out.

4. Methodology

The methodology is divided into five sections. In the first section, the LP-CA model is introduced and the parameters are described, as is the calculation of the transition potential. This is followed by an explanation of the process of evaluation of the LP-CA model and the metrics applied in the validation of its overall performance. Next, the scenario building process based on participatory approaches is explained. The fourth section presents new advances in the adaptation of the LP-CA model in combination with participatory approaches to simulate disruptive scenarios, while in the final part, the validation of the results of simulating future scenarios is described.

4.1. The LP-CA model

This study applied a LP-CA model derived from well-established models based on the work of White, Engelen, and Uljee (1997), which had been adapted to an irregular parcel environment (Barreira-González, Gómez-Delgado, & Aguilera-Benavente, 2015; Chen et al., 2017). The transition potential of a land parcel to change its current state is primarily determined by a combination of several factors. The probabilistic formula is represented in Eq. 1 as follows:

$$P_{i,k}^{t} = v \cdot A_i \cdot S_{i,k} \cdot Z_i \cdot N_{i,k,d}^{t} \quad (1)$$

where $P_{i,k}^{t}$ is the potential for parcel i to undergo a transition to an urban land use k in a time t, v is the stochastic perturbation term, A_i is the accessibility in parcel i, $S_{i,k}$ is the suitability in parcel i for land use k, Z_i is the zoning in parcel i and $N_{i,k,d}^{t}$ is the neighbourhood effect between parcel i for urban land use k within a time t and the adjacent parcels within a buffer at a distance d.

Stochastic perturbation. The real world is full of human decisions and actions that are difficult to quantify by deterministic models since many of them exhibit a certain degree of randomness. With this assumption in mind, stochastic perturbation was introduced into the calculation of transition potential (White & Engelen, 1993). This factor is computed using Eq. 2:

$$v = 1 + (-\ln(rand))^{\alpha} \quad (2)$$

where $rand$ is a random number ($0 < rand < 1$) and α is a number ($0 < \alpha < 1$) that controls the size of the disturbance. As White and Engelen (1993) points out, a low α value implies simpler and more compact growth forms, while a high α value reports a more random structure of the city, higher fragmentation, and higher entropy.

Accessibility. This is defined as the ease with which people can travel to a desired location, usually for leisure, study, or work purposes. This parameter is assessed by measuring the distance from the centroid of each parcel to the nearest edge of the road network (streets, roads, highways, and toll roads).

Suitability. This study adopted Geographically Weighted Logistic Regression (GWLR) to obtain the development suitability for each urban land use on each parcel (Molinero-Parejo, Aguilera-Benavente, & Gómez-Delgado, 2021). This method is a modified GWR in its logistic version, adapted for its application with binary dependent variables (urban - nonurban). Mirbagheri and Alimohammadi (2017) showed that GWLR improves simulation performance in urban CA. In short, it allows us to investigate spatial variations in regression coefficients and the spatial, non-stationary relationships that are not visible in global models (Fotheringham, Brunsdon, & Charlton, 2002). The suitability value ($S_{i,k}$) for a parcel i with an urban land use k was calculated as follows in Eq. 3:

$$S_{i,k} = \beta_0(u_i, v_i) + \sum_n \beta_n(u_i, v_i)x_n + \varepsilon_i \tag{3}$$

where β_0 is the intercept, β_n the regression coefficient and x_n the value of the explanatory variable n. (u_i, v_i) stand for the coordinates at point i and ε_i is the random error.

Zoning. In this study, the zoning classification established by each town plan has been condensed into the following three categories: urban land, undeveloped land and protected nonurban land. This factor controls the weighting assigned to each parcel based on its suitability for development according to the legal planning framework.

Neighbourhood. There is no consensus among researchers on how to implement the neighbourhood factor (Chen et al., 2017). In this research, the *vector Enrichment Factor* (*vF*) was implemented in the model (van Vliet et al., 2013; Verburg et al., 2004). This index is calculated using a boundary buffer intersect traced at a specified distance around the spatial feature due to the irregular shape and size of the land parcels in the study area. All the parcels that intersect with this buffer zone are considered as neighbours.

The *vector Enrichment Factor* (Eq. 4) calculates the proportion of a given urban land use within a specific distance from the target parcel with respect to the proportion of said urban land use within the entire study area.

$$vF_{i,k,d} = \frac{1}{N}\sum_{i \in I}\frac{a_{k,d,i}/a_{d,i}}{A_k/A} \tag{4}$$

where I indicates the set of all the parcels in the study area, i each of them and N their sum, $a_{i,\,k,\,d}$ is the sum of the total area of the parcels with urban land use k within the distance buffer d, $a_{i,\,d}$ is the sum of the total area of the parcels within the distance buffer d, A_k is the total area occupied by an urban land use k in the study area and A is the total area of the study area. Applying this formula, a total of 25 attraction-repulsion functions were generated for all possible combinations of each pair of land uses, capturing possible effects of land use segregation/mixing and distance-dependent processes. These functions were calculated using a distance range of 50 to 800 m, in steps of 50.

4.2. Model calibration and validation

The three-step modelling approach (calibration, simulation and validation) was employed to ensure that the model was operating correctly (Camacho Olmedo, Paegelow, Mas, & Escobar, 2018) before disruptive scenario simulation. Since the horizon for future simulation is 32 years (2018–2050), it was decided to use the same time looking backwards for the training period. This was divided into calibration (1986–2002) and simulation (2002–2018), with the last year used for validation (2018). This period was considered long enough to minimise the impact of non-representative characteristics.

In order to assess the results obtained in the calibration and validation processes, *Figure of Merit* (FOM) and its complements *Producer Accuracy* (PA) and *User Accuracy* (UA) were used (Eqs. 5, 6 and 7 respectively) (Pontius et al., 2008). The proportion of area that has changed with respect to the total of the study area is low, justifying the use of FOM instead of *Overall Accuracy* (Pontius et al., 2008). FOM is a ratio between 0 and 1 that compares the simulated change with the reference change in the analysed period. 0 indicates no overlap between simulated and reference changes and 1 indicates 100% agreement between them.

$$FOM = \frac{Hits}{Misses + Hits + Wrong\ Hits + False\ Alarms} \tag{5}$$

$$PA = \frac{Hits}{Misses + Hits + Wrong\ Hits} \tag{6}$$

$$UA = \frac{Hits}{Hits + Wrong\ Hits + False\ Alarms} \tag{7}$$

The model was calibrated using the period 1986–2002. For this purpose, neighbourhood and stochastic perturbation parameters were analysed. First, the neighbourhood was fitted independently for the model, using it as a single factor. For this purpose, buffer sizes between 50 m and 800 m (in intervals of 50 m) were tested. After selecting the best performing buffer size, 30 simulations were run for each α value between 0 and 1 (in intervals of 0.1).

After that, a simulation was carried out for the period 2002–2018 using the parameters that best fitted the model to the study area. Model validation attempts to indicate the goodness of fit, on which the credibility of the model will depend (Camacho Olmedo et al., 2018). Thus, once calibration and simulation had been completed, the next stage was to validate the model by assessing the accuracy of the results of the simulation step with the metrics described above. This was done by comparing the 2018 simulated map with the 2018 reference map.

4.3. Participatory scenario-building

During the course of this research, seven narrative storylines on the evolution of land use and transport by 2050 were created by conducting semi-structured interviews with a sample of 129 local people in the study area, incorporating *wild cards* to stimulate more disruptive thinking (Soria-Lara et al., 2021). *Wild cards* are defined as turning points in the trend, caused by sudden incidents (Mendonça, Pina e Cunha, Kaivo-oja, & Ruff, 2004). This methodology allowed us to envision imaginable and unimaginable, but plausible, futures. The most disruptive narrative according to Soria-Lara et al. (2021), *High levels of lack of security in urban areas*, was chosen to test the model. During the narrative assessment process, 71% of the experts indicated that this narrative was very disruptive, and 10% described it as highly disruptive. A summary of this narrative is described below:

The 2050 future is characterised by a high level of lack of security in the population as a consequence of increasing social inequalities. Public green areas would be converted into private spaces, with some of them used for additional car infrastructures. There would be a preference among high-income families for living in the periphery of the city in private residential communities because the city centres have become unsafe. Consequently, the modal split would be drastically altered, with the private car being by far the most popular option for all daily trips. As a result, urban land uses would be highly segregated into homogenous areas connected by motorised infrastructures. Lack of security in the city centres would lead to their abandonment, with just a few specific economic activities (retail, restaurants, offices, etc.*) and low-income families remaining in these areas.*

The information provided by narrative storylines is mainly qualitative, and it is a challenge to obtain quantitative information as inputs for modelling scenarios (Hewitt et al., 2014; van Delden & Hagen-Zanker, 2009; White, Straatman, & Engelen, 2004). This issue was addressed by combining a participatory workshop with narrative storylines. In the first part of the workshop (Molinero-Parejo, Aguilera-Benavente, Gómez-Delgado, & Soria-Lara, 2021), stakeholders (urban planners, transport planners, real estate developers, civil engineering lecturers and environmental consultants) quantified the growth of each urban land use for the selected scenario, basing themselves on their knowledge of its past trajectory in order to establish consistent and plausible values. They also assessed the degree of land use mixing and urban sprawl scored on a 5-point Likert scale. Land use mixing was evaluated as low (2), while urban sprawl was evaluated as very high (5). Later, stakeholders created an overview and dynamic map (represented by markers) of the narrative storyline to spatially represent its main characteristics in a general overview, considering new urban developments and drawing new transport infrastructures (Fig. 4). This map, besides serving as input for some factors of the model, is an essential piece of the scenario evaluation process, as it allows to compare and evaluate the consistency of the results under combined methods.

4.4. Linking participatory approaches with LP-CA to simulate disruptive processes

There is insufficient information to fit the model to simulations of disruptive futures. In order to overcome this problem, the workshop results, derived from the interaction between participants, were semi-quantified and linked to the parameters of the LP-CA model, which therefore processed both land use quantity and allocation information. The neighbourhood and stochastic perturbation factors were calibrated using a past time period and multiple model runs, however, the accessibility, suitability and zoning factors have been fitted based on the expert knowledge obtained from the participatory workshop. The participants began by indicating the quantity of growth for each urban land use, taking urban growth over the period 1986–2018 as a reference, and were free to indicate the quantity of loss if they considered it, according to the narrative. The proportions were adapted as percentages to make it easier for participants to understand them. Raw quantities were avoided. The percentages were as follows:

- (−) [1986–2018 growth] - (25% of [1986–2018 growth])
- (=) [1986–2018 growth]
- (+) [1986–2018 growth] + (25% of [1986–2018 growth])
- (++) [1986–2018 growth] + (50% of [1986–2018 growth])
- (+++) [1986–2018 growth] + (75% of [1986–2018 growth])

These percentages were converted into quantitative values as inputs for the LP-CA model, establishing the gains and losses for the selected period (Table 2).

Another key component addressed during the workshop was accessibility. When making simulations, only the transport infrastructures already existing in the reference year are taken into consideration.

Fig. 4. Participants discussing the *High levels of lack of security in urban areas* scenario during the participatory workshop.

Table 2
Gains and losses in each urban land use over the period 2018–2050.

Land use	Growth rate	Gain (ha)	Loss (ha)
Commerce & utilities	=	1141.17	81.30
Industrial	–	717.66	113.27
Single-family residential	+++	1163.55	88.26
Multi-family residential	=	67.77	52.31
Mixed (Residential & commercial)	–	0.00	18.44

*These quantities were estimated in line with expert opinion, bearing in mind the changes over the period 1986–2018.

However, any new infrastructures constructed during the selected period will inevitably influence future urban growth. The experts were therefore asked to draw possible new transport infrastructures on the map, which were included in the accessibility calculations.

In terms of spatial allocation, markers were used to allocate different land uses to different places on the overview map. This provided an important input for calculating suitability maps. The growth hotspots identified by the experts were selected as a dependent variable for the GWLR. To obtain a suitability value for each urban land use on each parcel, we used factors such as elevation, slope, distance to parks, distance to interurban bus stops or distance to facilities or amenities, as applied in similar studies on simulating large-scale urban land use change (Abolhasani et al., 2016; White et al., 1997).

If the envisioned futures are disruptive, zoning also has to be adjusted in line with the selected scenario. For example, users could establish a weighting value for each zoning category so as to prioritize new urban development on undeveloped land. Similarly, building on protected land could be completely restricted by giving such areas a zero weighting. Alternatively, users could give protected areas a slightly higher weighting, so allowing for a scenario in which some illegal development of protected land occurs. Based on the overview map created by the experts, values of 0.95, 0.03 and 0.02 were established for urban land, undeveloped land and protected nonurban land respectively.

It should also be noted that most buildings require a significant initial investment, and in some cases, such as commercial or industrial uses, it may take several years for them to become profitable. This makes a short-term change in land use unlikely (van Vliet et al., 2013). For this reason, the model also takes into account the conversion inertia of those parcels that already have a particular urban land use. For this purpose, the percentage of markers in which the land use exchanged (as denoted in the overview map created during the workshop) was considered. It is also important to remember that land use can also change from urban to nonurban. This is often due to the abandonment of buildings or the reclamation of natural areas. The ability to simulate this transition was also integrated into the model as part of its adaptation to disruptive scenarios. For the selected scenario, a loss probability map was calculated based on the distance to the centre of the medium-sized cities (as reflected in the narrative storyline) and the markers removed from each urban land use. A summary of the overall operation and adaptation of the model can be seen in Fig. 5.

4.5. Partial validation of simulated future scenarios

To evaluate the results of the simulated future scenario, a partial validation was carried out. First, a detailed visual analysis was conducted, identifying and linking most characteristic urban processes with the narrative storyline. A frequency map for each urban land use was also obtained, representing the number of times the model has allocated a particular use to each parcel, bearing in mind the stochastic perturbation. To this end, a total of 30 simulations were run with the alpha value for stochastic perturbation set to 0.2. In addition to their spatial representation on the frequency map, the percentage of land parcels in which land use changed was statistically analysed. In previous research,

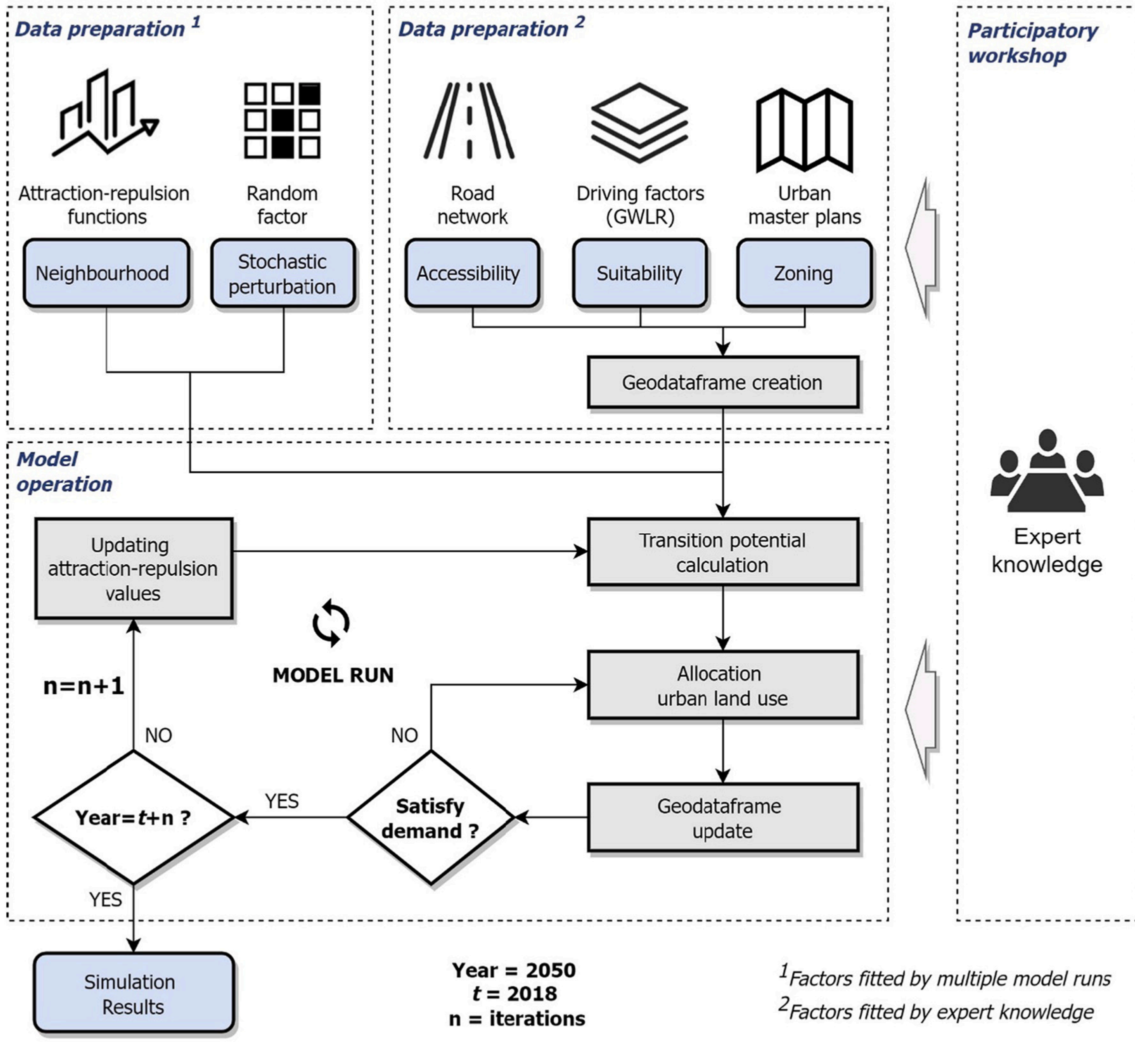

Fig. 5. Flowchart of the adapted LP-CA model.

methods like these have been used to validate simulation results and to observe the propagation of error due to uncertainty (Barreira-González, Gómez-Delgado, & Aguilera-Benavente, 2015).

5. Results

5.1. Model calibration and validation results

The calibration results for the period 1986–2002 report a maximum FOM value of 0.2617 using a neighbourhood size of 200 m for the calculation of the attraction-repulsion effects. As illustrated in Fig. 6, the

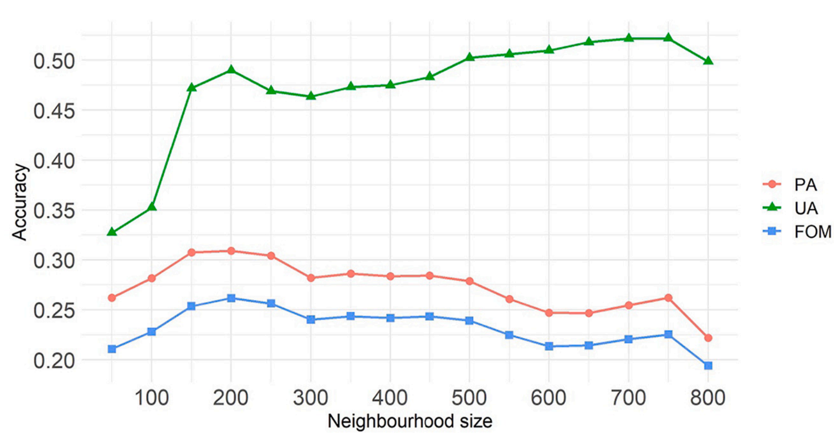

Fig. 6. Accuracy assessments for different neighbourhood sizes.

LP-CA model is sensitive to neighbourhood size, showing a variation in FOM of up to 0.067. PA and UA accuracy metrics have a greater range of variation. However, although PA values show a similar trend to FOM values, UA values reach their maximum value at 750 m. Over this distance, a significant decrease in accuracy can be observed in the three metrics. In this case, an excessively large neighbourhood size can cause the capture of too many land parcels, so producing an overestimation of the attraction-repulsion effects.

Once the neighbourhood factor had been fitted, 30 simulations were carried out to identify the most suitable α value for stochastic perturbation. An analysis of the mean values for the distribution derived from the results for each α value showed that the best results were achieved with $\alpha = 0.2$, with a mean FOM value of 0.2666 (Fig. 7).

The model validation results indicate a satisfactory performance of the model (FOM = 0.2817), with an accuracy value in the general range reported in other studies that simulate urban land uses with vector-based or land parcel CA models (Yao et al., 2017; Zhai et al., 2020; Zhu, Sun, Song, Yang, & Ding, 2020). In the research conducted by Pontius et al. (2008), regions with net changes of <10% of the total area did not exceed FOM values of 0.15. This means that simulating large areas and periods with few changes can result in low FOM values.

Therefore, we can conclude that the results obtained in the calibration and validation of the model (FOM values of 0.26 and 0.28 respectively) are good enough for their main purpose, since they exceed the range of 0.15, indicating a higher value than expected in other applications with net changes of <10% of the total study area. It should be noted that the changes that occurred in the period 2002–2018 affected 3.42% of the total area.

5.2. Results for the simulation of disruptive future scenarios

Fig. 8 shows the future scenario simulated in the Henares Corridor, Madrid - Guadalajara (Spain) for the period 2018–2050. Several urban processes can be identified. In the first zoomed-in area (1), significant changes can be observed from multi-family residential to single-family residential. This conversion phenomenon is also found in several other urban centres in the study area, leading to a process of homogenisation of the urban landscape. This is linked to the segregation of urban land uses, one of the characteristics highlighted in the narrative. In the second zoomed-in area (2), urban land has been lost as a result of the abandonment of built-up areas in city centres. This is a typical characteristic of shrinking cities. In fact, during the past decade, the municipality of Alcalá de Henares has suffered a significant decline in population. Finally, in the third zoomed-in area (3) in a peripheral municipality, dramatic growth can be observed in single-family residential. Thus, if we analyse the overall spatial configuration, major urban growth can be observed in the peripheral areas. This results in significant urban sprawl within the metropolitan areas.

If the results are analysed in quantitative terms, with the given parameters, the model reports that 0.61% of the study area would be abandoned during the study period (2018–2050). It also found, by contrast, that 6.64% of the total area would be developed (nonurban to urban). In addition, 1304 land parcels - just 0.2% of the total area - would undergo a change of use. This means that, in total, 7.45% of the study area would experience changes, while the other 92.54% would remain stable over this period. Table 3 shows the area and the number of parcels covered by each urban land use in the reference map and the simulated map.

If the total area by 2050 (far right-hand column) is compared with the total area in 2018 (bottom row), there is growth in all urban land uses, apart from mixed residential which has declined slightly. The number of parcels covered by multi-family residential use has also fallen slightly despite an increase in the total area. This is due to the process of urban land use conversion, and the use of irregular land parcels. The highlighted values on the diagonal show the stable land that did not change in each category, while the off-diagonal values show the transitions from one urban land use to another. The largest transition is from multi-family residential to single-family residential.

5.3. Mapping of the most frequently developed land parcels

By integrating stochastic perturbation into the simulation, it is possible to get some idea of the possible directions in which the different urban land uses may grow under the selected scenario and consider the possible associated errors. On the basis of 30 model executions, frequency maps were generated showing the number of times the same land use was allocated to the same land parcel (Fig. 9).

In this regard, Table 3 offers a detailed picture of how the model performs with the integration of stochastic perturbation. The industrial and single-family residential uses are quite consistent, with around 90% of the simulated land parcels being allocated in the same location. However, commerce and utilities and multi-family residential uses show more variability. For both these land uses, about 30% of all the land parcels that changed across the 30 model executions were allocated in the same location (see Table 4). The fact that commerce and utilities, and multi-family residential uses show greater variability in parcel allocation is linked to the fact that both are under-represented in the study area.

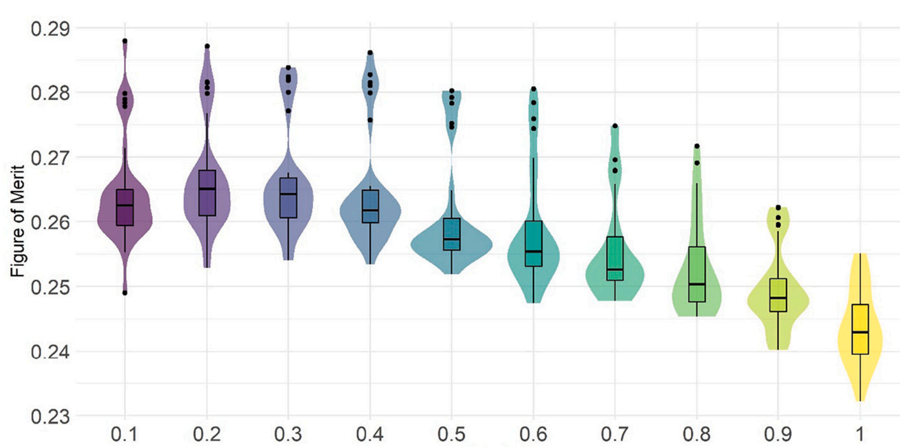

Fig. 7. Accuracy assessments (FOM) for the different α values used in the calibration of stochastic perturbation.

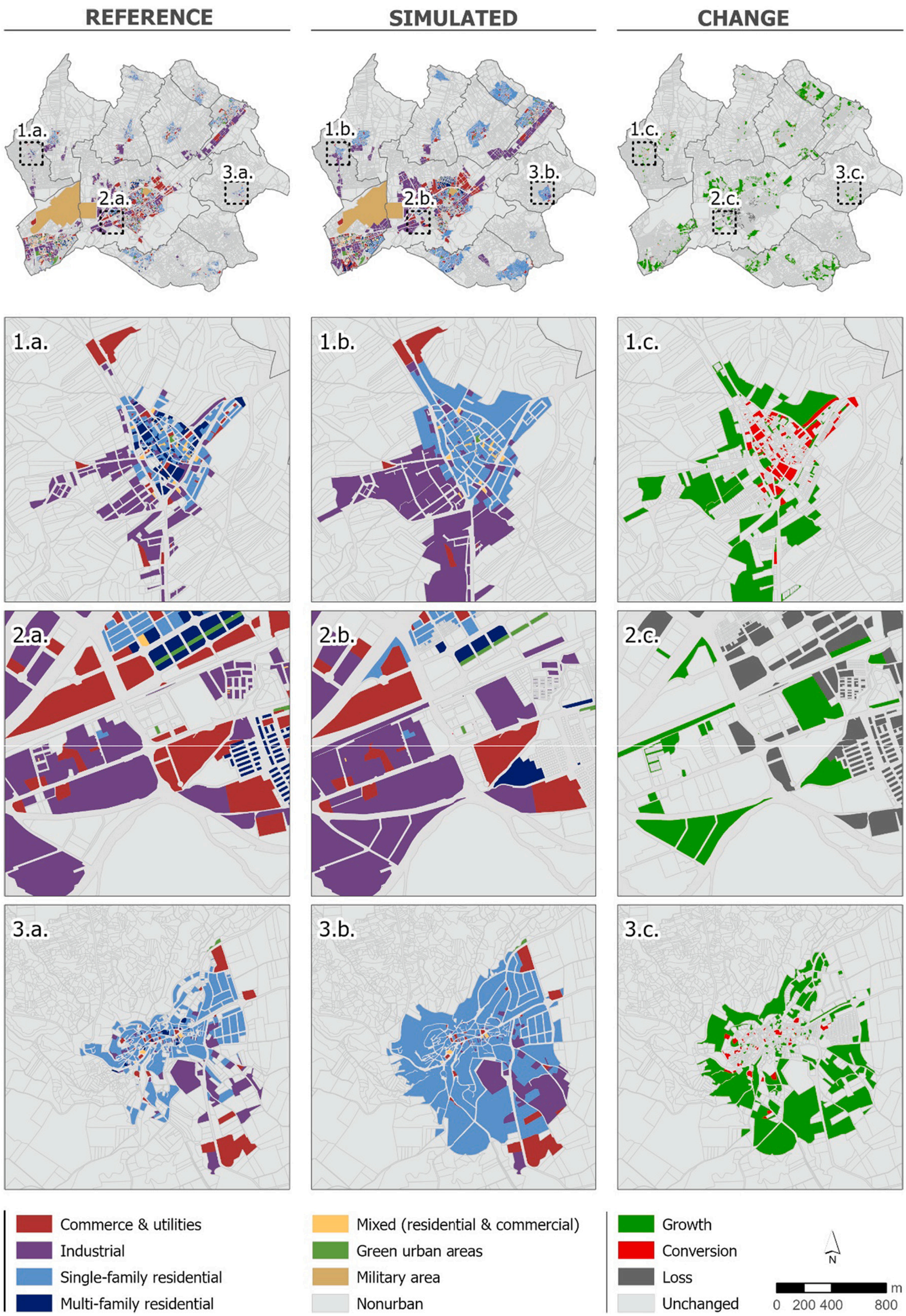

Fig. 8. Reference map (2018), simulated map (2050), and change map (land use changes 2018–2050) of the study area. The zoomed windows show detailed views of the urban areas of (1) Ajalvir, (2) Alcalá de Henares and (3) Los Santos de la Humosa.

Table 3
Area-based matrix for the transitions between different urban land use categories for the simulated period (2018–2050) in hectares. Values in brackets denote the number of parcels.

	2018						
2050	Commerce & utilities	Industrial	Single-family	Multi-family	Mixed	Nonurban	Total in 2050
Commerce & utilities	805.37 (1470)	0 (0)	5.47 (302)	0 (0)	0 (0)	185.46 (340)	996.29 (2112)
Industrial	0.43 (6)	1379.74 (4344)	0.01 (1)	0 (0)	0 (0)	794.13 (1189)	2174.33 (5540)
Single-family	14.57 (83)	18.38 (312)	847.24 (24100)	26.78 (399)	0.04 (1)	1143.70 (4892)	2050.75 (29787)
Multi-family	0 (0)	0.03 (7)	3.25 (193)	281.49 (3130)	0 (0)	138.97 (375)	423.77 (3705)
Mixed	0 (0)	0 (0)	0 (0)	0 (0)	75.06 (1002)	0 (0)	75.07 (1002)
Nonurban	62.84 (191)	58.78 (355)	32.43 (1441)	48.26 (782)	6.32 (111)	26,552.47 (10194)	26,761.14 (13074)
Total in 2018	883.22 (1750)	1456.95 (5018)	888.41 (26037)	356.56 (4311)	81.44 (1114)	28,814.76 (16990)	32,481.34 (55220)

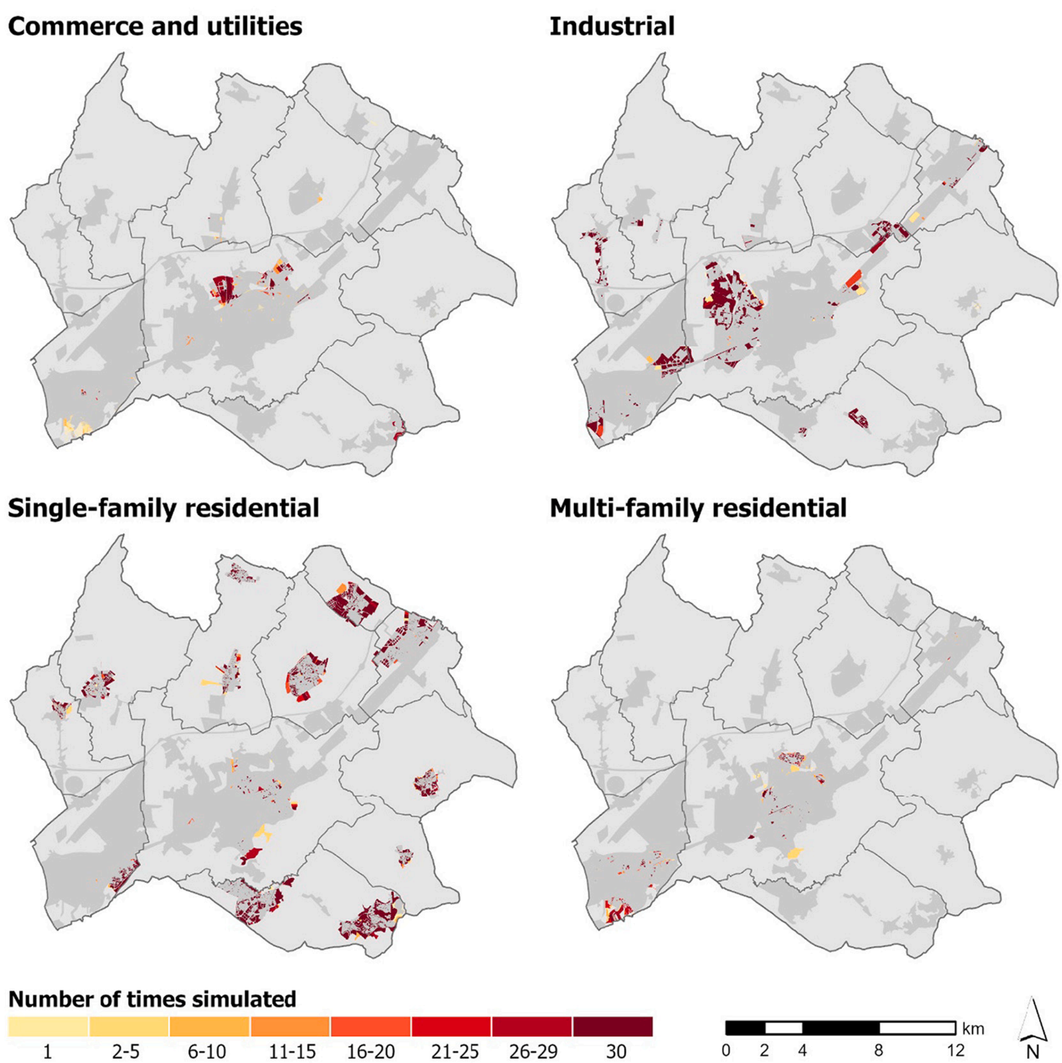

Fig. 9. Frequency maps showing the number of times the same land use was allocated to the same land parcel in 30 model executions with stochastic perturbation (α = 0.2). Dark grey represents urban areas in the reference year.

Table 4
Percentage of land parcels that have been allocated to the same location and category of all the land parcels that changed across 30 model executions.

Times simulated	Commerce and utilities	Industrial	Single-family	Multi-family
1	12.01%	1.90%	0.69%	8.03%
2–5	41.22%	4.44%	1.84%	15.78%
6–10	4.97%	0.95%	0.74%	5.41%
11–15	3.46%	0.71%	0.64%	3.34%
16–20	2.19%	1.27%	0.59%	6.85%
21–25	2.89%	1.03%	0.61%	8.03%
26–29	11.89%	2.38%	1.78%	31.47%
30	33.37%	89.22%	93.79%	29.13%

6. Discussion

6.1. Integrating modelling and participation to envision disruptive futures

Uncertainty arising from the occurrence of sudden unexpected events is one of the major challenges facing urban planning (Goodspeed, 2020). This has become particularly clear during the SARS-CoV-2 pandemic, one of whose side effects was the huge increase in people working from home. It also led to changes in people's lifestyles (Belzunegui-Eraso & Erro-Garcés, 2020) with short journeys (to work, school, shops, etc.) falling by 50% compared to the pre-pandemic period (Fatmi, 2020). These changes may result in a spatial redistribution of urban land uses. Therefore, the use of multiple disruptive scenarios and the inclusion of stakeholders in urban and regional planning practices would assist in minimising uncertainty and managing such complex phenomena in a comprehensive manner.

The importance of participation in urban and regional planning has been emphasised in the literature (Brown & Wei Chin, 2013), however, engaging the general public in processes of this kind is a complicated task that requires a major two-way collaborative effort between researchers and the public. In this context, the ideas provided through semi-structured interviews allowed for the creation of multiple narrative storylines. The use of *wild cards* as conditioners or breakpoints proved a crucial factor in inspiring more disruptive thinking (Soria-Lara et al., 2021). Some of these narratives were subsequently used in a workshop in which a range of experts in this field were invited to participate. These experts collaborated in the analysis, design, and discussion tasks in relation to the spatial configuration of urban land uses and the transport network, so generating inputs for the LP-CA model.

Another challenge is to explain to stakeholders how the CA models work. Even the simplest of these models are primarily designed for use by a specialised research audience. By holding the workshop, this gap between stakeholders and researchers was minimized, the necessary *know-how* was collected and converted into inputs for the LP-CA model, and the quality of the information was improved by integrating the human component. The quantity of growth for each urban land use was added at the discretion of experts and stakeholders, while the accessibility, suitability and zoning maps were generated later with the support of the information obtained from the overview map. It should also be noted that both the workshop map and the simulated map are complementary, providing under-recognized aspects or gaps not visible one-sidedly, and checking the entire process of modelling future scenarios for greater consistency of the outcomes.

This participatory process made it possible to configure several parameters of the model by providing a critical and objective perspective of the spatial configuration of urban land use as reflected in the narrative storyline. The use of land parcels also offers the stakeholders a much clearer picture of the outcomes, so facilitating the interpretation process. It is also necessary to explore other possible methods for validating and/or evaluating future disruptive scenarios, as the future by its very nature is unknown and we have no on-the-ground evidence with which to compare it. A crucial step in successfully completing this participatory planning process through disruptive future scenarios is to hold a new workshop, in which citizens, experts and stakeholders collaborate to visualise, analyse, and evaluate the outcomes of the simulated urban land use maps that they themselves helped generate.

6.2. Practical considerations of LP-CA model in simulating disruptive scenarios

The main purpose of the LP-CA model is to generate land use trajectories that are spatially consistent with the disruptive narrative storylines. The accuracy metrics used to assess the model indicated that it was operating correctly. In this respect, it is worth remembering that the FOM values are not only affected by the size of the study area or by the percentage of the total area in which land use changes, and that simulating separate urban areas makes it even more difficult to allocate new urban land uses. Another problem that can complicate the simulation of large study areas is the competition between different urban areas, which can lead to the expected quantity of growth being concentrated in a single municipality, so preventing the others from growing.

The results of the disruptive scenario simulation were consistent with the description of the selected narrative storyline. Processes described in the scenario narrative (segregation of urban land uses, significant expansion of single-family residential on the periphery, and the abandonment of city centres) were identified in simulated maps, as shown in Fig. 8. Moreover, the use of land parcels as the spatial unit enabled the model to reproduce more realistic urban dynamics, which adapted to the spatial boundaries defined by legislative planning.

In addition, internal transitions between the urban land uses of already developed parcels, and transitions from urban to nonurban, have been critical components in the simulation of disruptive future scenarios. Although these urban dynamics are integrated into most of the simulation models based on regular CA, they are not normally found in irregular models, especially in those that use land parcels as the spatial unit (Barreira-González et al., 2019; Zhai et al., 2020). This is a significant step forward.

The influence of stochastic perturbation was also spatially represented for each urban land use. In this family of CA-models, it is particularly important to reflect the impact of randomness as a way of measuring those urban processes that do not respond to deterministic causes (Barreira-González et al., 2019). Single-family residential and industrial uses were allocated in the same places in around 90% of the runs, so indicating that stochastic perturbation has little influence. This suggests a greater robustness of both urban land uses in terms of their spatial distribution. In the Spanish case, the industrial fabric and single-family housing developments have well-defined locations, tending to grow in a compact and segregated manner. By contrast, multi-family residential and commercial and utilities uses were strongly affected by this parameter, as manifested in greater spatial variation in the places allocated to these uses. The development of these two urban land uses is more scattered and heterogeneous, which makes it more difficult to establish rules or factors that explain their spatial distribution.

7. Concluding remarks and further research

The authors consider that the methodology developed in this study makes an important contribution to research in this field, in that it complements the multi-scenario approach as a tool for supporting local urban management and decision-making processes, by allowing a better understanding of uncertainty in urban environments. It prepares planners to act in a wide range of situations, enabling them to make more informed decisions. It is particularly relevant today in a period of strong uncertainty, as can be observed in the growing trend of publications focusing on disruption in the anticipation of future events.

The results show that this model successfully simulates urban expansion (growth), the change from one urban land use to another (conversion), and the abandonment of urban areas (loss) at parcel level as relevant processes in the mapping of disruptive scenarios. Furthermore, the improvement from previous versions of the model in terms of the number of simulated land uses and urban dynamics (Barreira-González et al., 2019; Barreira-González, Gómez-Delgado, & Aguilera-Benavente, 2015) provides a better picture of the general distribution of city functions, so allowing a more accurate spatial simulation of multi-future scenario narratives. This approach contributes to the exploration of imaginable and unimaginable futures (that may or may not happen) and the envisioning of spatial consequences they may have on urban environments, providing support in anticipatory decision-making in land use planning.

Lastly, to complete the cycle of prospective scenario planning, a final step focusing on scenario evaluation and the identification of associated impacts is required. A new method for validating future disruptive scenarios through a participatory workshop, in which stakeholders and experts collaborate to analyse the outcomes of the simulation is being explored. However, it is important that the process in which urban land uses are allocated to the different parcels provides easily interpretable, clear outcomes for the actors who assess and analyse the scenarios, so assisting in the decision-making process and in the design of policy packages.

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CRediT authorship contribution statement

Ramón Molinero-Parejo: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Data curation, Writing – original draft, Writing – review & editing, Visualization. **Francisco Aguilera-Benavente:** Conceptualization, Resources, Supervision, Project administration, Funding acquisition, Writing - original draft, Writing - review & editing. **Montserrat Gómez-Delgado:** Conceptualization, Resources, Supervision, Project administration, Funding acquisition, Writing - original draft, Writing - review & editing. **Nikolai Shurupov:** Conceptualization, Methodology, Software, Data curation, Writing – original draft.

Declaration of Competing Interest

None.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://github.com/TransUrban-UAH/LP-CA-Model

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