Science of the Total Environment 687 (2019) 104–117

Contents lists available at ScienceDirect

Science of the Total Environment

journal homepage: www.elsevier.com/locate/scitotenv

Spatiotemporal analysis of the housing bubble's contribution to the proliferation of illegal landfills – The case of Gran Canaria

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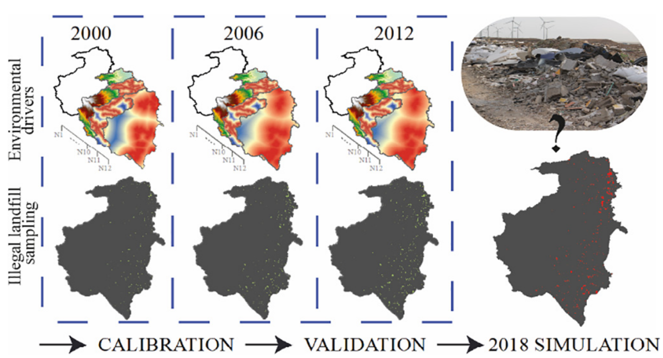
HIGHLIGHTS

- Housing bubble's impacts on illegal landfill (IL) proliferation in Gran Canaria (GC)
- IL proliferation was higher in urban areas during the housing bubble.
- Assessing cellular automata to forecast the proliferation of IL
- Simulations predicted a 133.8 ha increase in ILs for 2018.

GRAPHICAL ABSTRACT



ARTICLE INFO

Article history:
Received 6 March 2019
Received in revised form 23 May 2019
Accepted 5 June 2019
Available online 7 June 2019

Editor: Daniel CW Tsang

Keywords:
Cellular automata
Logistic regression
Markov models
Land change modelling
Illegal landfill occurrence

ABSTRACT

Illegal landfills are the source of many impacts that can alter the environment and represent a public health risk. This study investigates their spatiotemporal distribution in two representative areas of Gran Canaria: northwest (Zone A) and east (Zone B). Illegal landfill occurrence was simulated between 2000 and 2018, to estimate and spatially locate the surface growth of illegal landfills based on cellular automata, cellular automata-Markov and multiobjective land allocation models. The proliferation of illegal landfills in 2018 was simulated following the calibration and validation of the proposed models. Models' accuracy was assessed using Kappa index and landscape metrics. The cellular automata-Markov model had the best performance. The model simulations predicted an increase of 52.3 ha and 81.5 ha affected by illegal landfills in Zone A and Zone B for 2018, respectively. The interannual growth rate of surfaces affected by illegal landfills for the period between 2000 and 2006 was 4.5% and 9.5% and between 2006 and 2012 it was 6.6% and 6.7%, for Zone A and Zone B respectively. The growth of illegal landfills between 2000 and 2006 was higher in urban areas, construction sites, and industrial zones, and may be closely related to the process of urban expansion linked to the real estate boom. The latter would have a deep impact on the landscape due to the proliferation of illegal construction and demolition waste. The growth rate of illegal landfills in urban environments fell during the later period of urban expansion. Overall, simulation outputs showed the model's ability to correctly reproduce the distribution patterns for illegal landfill proliferation. Even though the simulated spatial location of illegal landfills was not highly accurate, the models built in this study provide an informative tool to policy makers to aid the process creating policies for environmental protection as well as territorial planning.

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https://doi.org/10.1016/j.scitotenv.2019.06.079
0048-9697/

1. Introduction

In the last 50 years, European cities have developed different morphological, demographic, and socioeconomic models (Turok and Mykhnenko, 2007), with urbanisation and urban expansion being in many cases the major driving force and a potential source of environmental impacts (Turner et al., 1990). Areas designated for residential construction have been disproportional to declining population trends (Chaline, 2001; Salvati and Sabbi, 2011). The rise of single-family homes has also generalised patterns of urban sprawl (Salvati, 2013), especially in areas with low levels of human activity that affect the conversion of open spaces and natural environments (Colantoni et al., 2016). This continuous urban expansion has generated negative impacts for urban and environmental sustainability, particularly in Mediterranean Europe (European Environment Agency, 2006b; Catalán et al., 2008). It was especially notable in Spain and Greece during the 1990s and early 2000s, with the occurrence of accelerated construction cycles that consolidated a scattered and discontinuous model of urban expansion dominated by low densities of expanding settlements (Dura-Guimera, 2003; Chorianopoulos et al., 2010; Salvati and De Rosa, 2014). The decentralisation of inner cities and suburbanisation led to the development of medium and low density settlements, a predominant trend in Mediterranean urban regions (Salvati et al., 2012). In this regard, a higher rate of population growth and distribution in the 2000–2007 period was identified compared to 2008–2014; although in the latter period there is a tendency to densify and recompact urban spaces (Salvati et al., 2016, 2018).

Unlike Italian or Greek cities, Spanish cities were more exposed to the housing bubble (Cuadrado-Ciuraneta et al., 2017). Around 600,000 homes were built annually from 2000 to 2006 in Spain (INE, 2017b), 30,000 in the Canary Islands (see Supplementary material: Fig. 1s). Home construction was lower but sustained during the period from 2006 to 2012, with 167,000 and 9000 homes built in Spain and the Canary Islands respectively (INE, 2017b). According to the European Environment Agency (2006b), in Spain various factors were decisive for the increase of urban areas during the period of 2000 and 2006: i) economic growth based on sectors with high demand for land consumption, including construction, transportation and tourism; ii) higher domestic and foreign demand for second homes driven by higher living standards along with favourable mortgages with low interest rates, leading to an increase in urban speculation; and iii) substantial investment in public transportation and infrastructures by public authorities in the last two decades (Hortas-Rico, 2014). The 'housing bubble', as a precursor of land cover changes, strongly impacted the natural environment and the landscape (Potschin and Haines-Young, 2006). The high amount of cadastral parcel rezoning from rural to urban caused important changes in the production system, leading to a process of farm and pasture abandonment ahead of expanding tourism and urbanisation (Balabanis et al., 2000; Bonet, 2004; Burke and Thornes, 2004; Sluiter and De Jong, 2007). New urban landscapes were generated as a result of increasing urban population settlement in agricultural and forest areas and along coasts (Salvati et al., 2012). The growth of urban areas favoured the proliferation of paved land, leading to changes in ground cover composition and a subsequent loss of biodiversity in semi-natural areas, agricultural zones, and suburban terrain (Bajocco et al., 2012; Hrenovic et al., 2017). The European Commission reported that soil degradation, referring to limited humidity infiltration in the ground, could cost up to US $56 billion per year (European Environment Agency, 2006b). Even though the impacts associated to urban expansion and their influence on losses of environmental assets have been extensively studied (Marull et al., 2010), the specific impacts associated to waste generation and its effect on dynamics of landscape change may have not been studied until recently (Quesada-Ruiz et al., 2019). Those specific impacts may be associated with processes of landscape conversion resulting from mining and extraction activities (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019). Furthermore, the demolition of old buildings to generate new construction, the suspension of urban projects, and the increase of interior renovation work may have contributed to the generation and illegal deposition of construction and demolition waste in illegal landfills (ILs) (Quesada et al., 2013; Díaz-Parra and Romano, 2016). Considering the aforementioned, a better understanding of the specific components that influence IL patterns in a region could improve the effectiveness of waste management and reduce the impacts derived from their appearance (Tasaki et al., 2007; Biotto et al., 2009; Glanville and Chang, 2015a; Quesada-Ruiz et al., 2019).

Until now, the generation of waste and ILs has been approached using techniques for locating affected areas such as: i) remote sensing (Silvestri and Omri, 2008; Uricchio et al., 2010; Glanville and Chang, 2015b; Mohee et al., 2015); ii) identifying the main physical and socioeconomics drivers of the IL occurrence (Bridges et al., 2000; Tasaki, 2004; Santos et al., 2006; Biotto et al., 2009; Ichinose and Yamamoto, 2011; Jordá-Borrell et al., 2014; Quesada-Ruiz et al., 2018); and iii) prediction of potential areas of IL occurrence (Tasaki et al., 2007; Biotto et al., 2009; Chu et al., 2013; Glanville and Chang, 2015a; Lucendo-Monedero et al., 2015; Quesada-Ruiz et al., 2019). These respective studies agree on the determinant factors: identification of population, accessibility of communication routes, and distance to elements of interest such as distance to industrial zones and urban areas (Quesada-Ruiz et al., 2019). Yet none of the studies cited above considered the possible implications of land use changes on waste generation and IL occurrence by analysing their spatial and temporal aspect. In a previous study conducted on the islands of Gran Canaria (GC) and La Palma it was found that 52% and 43% of the ILs mostly contained construction and demolition waste (Quesada-Ruiz et al., 2018); hence, the importance of understanding the relationship between IL proliferation and the land-use changes caused by phenomena such as the housing bubble.

This paper evaluates novel methodologies, such as cellular automata – Markov (CAM) and multi-objective land allocation (MOLA) (see Section 2.2), to study the interactions of IL occurrence with the natural and human environment. Particularly, this study examines the impact of land-use changes and the housing bubble on IL proliferation processes in GC. A series of partial objectives were defined as follows: i) to analyse the occurrence of ILs for the periods 2000–2006 and 2006–2012; ii) to evaluate different methodological approaches for the modelling and simulation of IL proliferation such as CAM, applying multicriteria analysis and logistic regression, and land change modeller with MOLA, applying logistic regression and neuronal networks; iii) to asses and discuss the accuracy of the simulation models through the use of Kappa indices, Quantity Disagreement (QD) and Allocation Disagreement (AD) indices, and two indices of landscape metrics; and iv) to simulate the extent of areas affected by ILs in 2018. In view of the absence of 2018 orthophotos and considering a fixed range period of 6 years between training and validation and between validation and prediction, we have opted to select 2018 as a prediction year, but with more recent validation data it would be possible estimate the IL occurrence for the future.

2. Methods and materials

2.1. Complex systems theory to study land use changes

Land-use change processes are governed by multiple factors such as: uses of land; responses to social, economic, political, climatic and ecological changes; spatial and temporal scales in the causes of and responses to change; connections in social and geographical space; and ties between people and land (Geist et al., 2006). Causes and consequences of land-use change depend on the social, geographic and historical context. All these processes and the complexities emerging therefrom can be studied by the development and implementation of integrated models with the goal of improving territorial planning. Considering that real-life experiments in land-use systems are difficult, computer models can be used as a computational laboratory in which the hypotheses about the processes of land-use change are tested (Verburg et al., 2015). The science of land-use cover and change (LUCC) has found in computer models a tool to study complex processes that take place at different spatial and temporal scales (Parker et al., 2003; Green and Sadedin, 2005; Van Schrojenstein Lantman et al., 2011). Although a large amount of research presents methods and applications to study LUCC, to the authors' knowledge, there are no scientific publications that approach the matter of illegal landfills. For over two decades, the study of LUCC has found through complex systems theory a way to conceptualise and analyse the dynamic processes involved in land use transformation (Irwin and Geoghegan, 2001; Parker et al., 2003; Verburg, 2006; Santé et al., 2010; Van Schrojenstein Lantman et al., 2011; Yang et al., 2016; Mas et al., 2018; Saeedi, 2018). Complex systems theory incorporates a number of characteristics inherent to land-use change processes, for example self-organisation, emergence, path-dependence and feedbacks (O'Sullivan, 2004; Verburg, 2006). Likewise, complex systems theory takes into account the non-linear characteristics of processes and feedbacks with the environment and within the environment (Torrens and Benenson, 2005; Batty, 2009; Gaudreau et al., 2016) allowing the design and exploration of scenarios to better understand the dynamics and interactions inside a system (Gaudreau et al., 2016; Tiné et al., 2018). Therefore, the use of complex systems modelling approaches permits an explicit focus on system feedbacks that result in an adequate description of land-use dynamics (Geist et al., 2006; Verburg, 2006; Verburg et al., 2015). In view of the goals of this study, the transitions from different types of LUC to ILs were considered as a complex process where there are multiple relationships between the location of a new IL and land-use changes in spaces close to new ILs. Such changes in land use correspond in turn to processes in the change of production model (e.g. agrarian activity) or in the changes of model of territorial or city organisation (e.g. transition from agrarian uses to urban and residential uses). In this sense, the proliferation and location of ILs may be a complex process due to the link between the generation and deposit of waste and the system for territorial organisation of land uses. This consideration of ILs therefore transcends the mere analysis of their specific placement (Cilliers, 1998) and aims to address the study of the dependence relationships of ILs and land uses.

2.2. Complex systems modelling: cellular automata and hybrid approaches

Complex behaviours can be replicated by using simulation approaches that allow the integration of stochasticity and spatiotemporal fluctuations. Cellular automata (CA) models are one such approach, and they have been widely used to mimic and study land-use cover and change dynamics, due to their capability to reproduce non-linear processes (Wolfram, 1984; White and Engelen, 2000; Engelen, 2002; Vliet et al., 2009). CA were developed by the mathematicians Alan Turing and John von Neumann in the 1940s (Batty, 2005; Langlois, 2008). These approaches have been widely used to create simulations of future scenarios (Langlois and Phipps, 1997; Engelen, 2002; Syphard et al., 2005; Di Traglia et al., 2011; Yu et al., 2011 Liu et al., 2014), to study land-use changes (Pontius et al., 2004; Nurwanda et al., 2016; Feng and Tong, 2017), as well as for understanding complex processes that have high levels of uncertainty, such as the appearance of ILs. CAs are composed by a matrix of cells that represent the spatial environment under study. Each cell has a state or value that can change in time depending on the previous state and according to the set of rules applied at a discrete time within a specific neighbourhood (Green and Sadedin, 2005). The transition rules are thus applied homogeneously to all cells for each discreet time step. Although powerful, one of the main issues of using CA to simulate changes is the deterministic nature of the rule creation. To overcome this limitation, alternative hybrid approaches can be implemented. The combination of CA with a Markov decision process adds stochasticity to the model, while the combination of CA with Logistic Regression (LR), or Multicriteria Analysis (MA) provide an alternative way to eliminate the determinism in transition rule creation.

As subtypes of CA models, cellular automata – Markov (CAM) and multi-objective land allocation (MOLA) enable the analysis of changes in terrestrial covers, detecting and locating their future tendencies for change (Pontius et al., 2004). CAM is a combination between CA and Markov chains (MCs). CAM recognises the spatial contiguity of each cell as well as its spatial distribution probability based on MC analysis. This allows a transition area matrix and a transition probability matrix to be obtained for a certain time interval. The former enables total area (in pixels) to be obtained, which includes changes between any land cover class pair. The latter indicates the probability of change for each land cover class determined for all other categories. Hence, use of the transition probability matrix makes it possible to obtain information about the influence of neighbouring cells on those transitions (Eastman, 2015). Both matrixes in CAM can be used to implicitly insert the necessary suitability maps to develop a simulation. Suitability maps in CAM can be generated by using LR or MA approaches. On the other hand, the multi-objective land allocation (MOLA) algorithm can be used to assign new land-use transitions and predict changes (Clark Labs, 2016). MOLA allows the use of suitability maps based on LR and Multi-Layer Perceptron Artificial Neural Network (ANN) to help divide the amount of change predicted by MC in the different land cover classes. The partition and assignment of land covers in MOLA is an iterative process, which also allows unequal weighting of the different sub-objectives (Eastman et al., 1995; Eastman, 2015). MOLA supplies a procedure to resolve multi-object land allocation problems for cases with conflicting objectives (Hajehforooshnia et al., 2011). It also determines a trade-off that attempts to maximise suitability of lands for each objective with respect to their assigned weights (Hajehforooshnia et al., 2011). MOLA thus permits conversion of the simulation into a dynamic process, by recalculating in each time step (discrete simulation) certain conditions such as the modification of distances to land uses or to protected spaces. MOLA therefore includes not just dynamic variables but also recognises the changes produced in the characteristics.

2.3. Study area

This paper focuses on the north-western (Zone A) and south-eastern (Zone B) sectors of Gran Canaria (GC), one of the Canary Islands, coinciding with the areas most affected by ILs (Fig. 1). The Canary Islands comprise one of Spain's 17 autonomous regions and are recognised as an outermost region of the European Union. The Canary Islands comprise a small and fragmented territory where space is a scarce resource (Quesada-Ruiz et al., 2019). This limits the availability of land to set up authorised landfills and other management infrastructures (GOBCAN, 2008, 2015). The distance to the principal centres for processing and valuing collected material increases costs and makes it difficult to manage whatever waste cannot be processed in the islands. However, GC is home to two environmental complexes, two transfer plants, and eight waste facilities. Despite the availability of these facilities for waste management and processing, they are not sufficient to meet the deposit demand (Quesada-Ruiz et al., 2019). On the other hand, it has been verified that the island supports a large number of illegal landfills, as reported by the European Union and disclosed in other studies (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019).

GC has an area of 1560 km^2, being the third largest of the Canary islands. GC has been catalogued as a World Biosphere Reserve by UNESCO, covering 40% of its territory. GC was the island chain's second most populated island in 2016 (845,195 inhabitants), after Tenerife (892,111 inhabitants) (INE, 2016a). GC's population density is very high compared to the rest of Spain: 543.45 inhab./km^2 versus 91.95 inhab./km^2. Its population is concentrated in coastal areas, where its capital is likewise situated, while the interior is less populated. The Canary Islands are the eighth-ranking Spanish region in terms of gross domestic product. It is nevertheless one of the regions with the highest unemployment rates (25%; INE, 2016a) and is the antepenultimate region in terms of least income per capita (€19,900; INE, 2016a). The

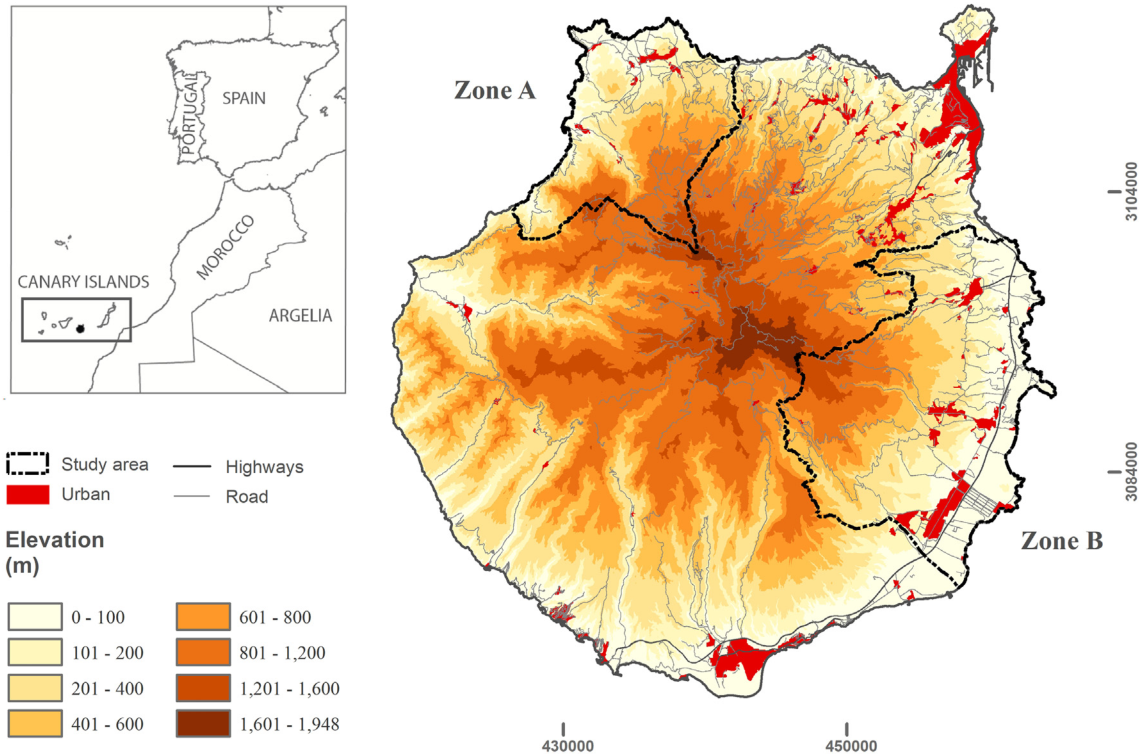

Fig. 1. Study sites on Gran Canaria island.

major economic driver of GC's economic activity is tourism (Cruz et al., 2011), which has given a strong boost to the construction sector. Tourism on GC is basically beach-related (Cruz et al., 2011) and concentrated in the southern part of the island, which received 4,223,679 visitors in 2016 (INE, 2016b). Trade activity is likewise important on GC, particularly around the port area. There is an industrial sector in south-eastern GC, focusing on agro-food production, light manufacturing, and cement (Hernández Torres, 2003; Quesada-Ruiz et al., 2019). Agriculture remains important in some north-eastern and eastern districts of GC, though less so than in years past. Notable is the intensively irrigated cultivation of bananas and tomatoes in greenhouses for export (Morales-Matos and Macias-Hernández, 2003). The general exported goods of the region totalled 3643 M (€), representing the 8.24% of 44,206 M (€) of the regional GDP (INE, 2017a).

2.4. Datasets

The location of ILs was obtained by means of photointerpretation of orthophotos with 0.5 m spatial resolution from the years 2000, 2006 and 2012. A total of 6556 surfaces with waste in the north-western and south-eastern district of GC for 2000, 2006, and 2012 were digitized. Locations with an area greater than 1000 m^2 were categorized as ILs, resulting in 2129 ILs (see Supplementary material: Fig. 2s). The database for each area was complemented with physiographic and socioeconomic characteristics as well as characteristics derived from the analysis of land uses. Each group of characteristics was extracted from datasets available from the “Instituto Geográfico Nacional” of the Spanish Government and the Corine Land Cover program. Due to the lack of disaggregated data for each period, socioeconomic characteristics were indirectly obtained by the application of Euclidean distance (ED) criteria between the location of the IL and the features of interest such as distance to urban areas, agricultural area or industrial areas from the rest of the territory, (Tasaki et al., 2007; Biotto et al., 2009; Jordá-Borrell et al., 2014). Several characteristics were considered as time invariant, such as Euclidean distances to elements of interest such as the coast, protected natural spaces, ravines, and road network. Additionally, physiographic characteristics such as the terrain and slope were also considered invariant over time. Furthermore, the dynamic characteristics such as distances to LUC were computed for each period using the Corine Land Cover maps (European Environment Agency, 2002, 2006a, 2006b, 2012). Euclidian distances to urban, industrial and construction areas and to agricultural land were computed considering the cell centre (Table 1). Each characteristic was standardised, rasterised and resampled to a spatial resolution of 10 m (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019), thus matching the spatial resolution of the original data and allowing us to recognise significant extensions of waste deposits. The characteristic space was created based on expert knowledge, previous research works (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019), review of the literature, and interviews with stakeholders during 2016 and 2017.

Table 1
Characteristics in models.

Characteristic	Short name	Unit of measure	Zone
Altitude	ALTITU	m	A, B
Slope	SLOPE	%	A, B
Distance to coastline	E_COAS	m	A, B
Distance to cliff	E_CLIFF	m	A, B
Distance to natural protected areas	E_PRAR	m	A, B
Distance to highways	E_HIGH	m	B
Distance to roads	E_CARR	m	A, B
Distance to ways	E_WAYS	m	A, B
Distance to forest areas	E_FOAR	m	A, B
Distance to continuous urban fabric	E_CUAR	m	A, B
Distance to discontinuous urban fabric	E_DUAR	m	A, B
Distance to industrial areas	E_INAR	m	A, B
Distance to construction sites	E_COSI	m	A, B
Distance to dry agricultural areas	E_DAAR	m	A, B
Distance to irrigated agricultural areas	E_IAAR	m	A, B
Distance to grass areas	E_GAAR	m	A, B
Distance to transitional woodland-shrub areas	E_TSAR	m	A, B
Distance to spaces with sparse vegetation or without vegetation	E_WVAR	m	A, B

2.5. Model implementation

The modelling of IL occurrence was based on the generation of transition rules, the simulation of future scenarios and validation of the predicted maps. The modelling process was in turn sustained by the use of synchronic data series that ensured: i) equal time intervals between study periods; ii) equal number of characteristics per period; iii) values specific to the characteristics for each period. This enabled the study of the dynamic behaviour of the characteristics and generation of the transition rules. The latter encompassed and described the set of decisions that direct the change of values of the characteristics involved in development of a phenomenon for a given time interval (Nakicenovic and Swart, 2000; Peterson, 2003; Swart et al., 2004). Additionally, transitions rules enabled the application of increments to the characteristics' values and simulation of the dynamic changes of the systems (Lambin and Meyfroidt, 2010). The generation of transition rules required an initial period (t_0), final period (t_1) and validation period (t_2). The transition rules between t_0 and t_1 were used to validate the degree of success in simulating the behaviour of the phenomenon studied in t_2 and the transition rules between t_1 and t_2 were used to obtain the simulation of the future scenario. The transition rule generation procedure between CAM and MOLA were different. In CAM, the transition rules were obtained based on the grouping of transition potential maps for the periods t_0 and t_1. For MOLA, the transition rules related the involvement of the characteristics in t_0 and t_1 to the change of values for a same pixel, using a single transition potential map for the simulation.

Four models were generated (see Supplementary material: Table 1s): i) CAM with LR (Model 1); ii) CAM with MCE (Model 2); iii) MOLA with LR (Model 3); and iv) MOLA with ANN (Model 4). The spatiotemporal modelling of the ILs was divided into three steps for the four models (Fig. 2): calibration, validation and generation of future scenarios (Ngo and See, 2012). All the models used the consecutive periods of 2000–2006 for the calibration and the periods 2006–2012 for the simulation of 2018.

2.6. Model calibration

The calibration of Models 1 and 2 was based on the IL occurrence potential analyses that established the relationship between the drivers and IL occurrence for the years 2000 and 2006. Transition rules were

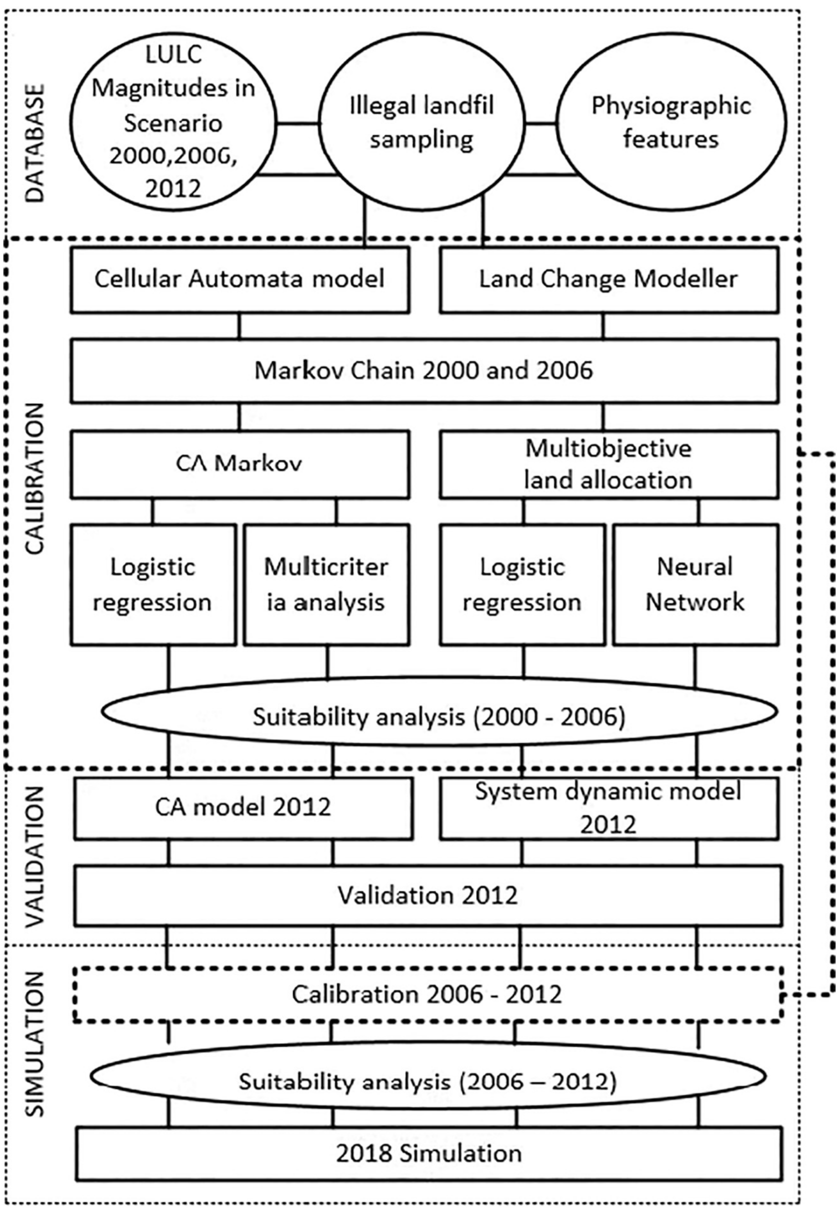

Fig. 2. The flowchart describes the process of modelling IL proliferation: database creation, calibration, validation and simulation in the future scenario of 2018.

thus generated based on the consecutive set of IL occurrence potential maps for each year. Both models used proximity filters of 5 × 5 cells, enabling homogenisation of the simulated map by spatial aggregation, thereby avoiding the pixelated aspect. Six iterations of cellular automata model were applied, one for each year. The transition potential maps provide the changes of the characteristics' values between the years of each period.

The results of all simulation models were the soft prediction models or maps of vulnerability to change, and the model of prediction (Clark Labs, 2016). The soft prediction models selected the cells with highest potential for IL occurrence in the case of Models 1 and 2, and the pixels with greater relationship between the transition of the values of the characteristics considered and IL occurrence in Models 3 and 4. Finally, the model of prediction, as a consequence of applying the soft prediction models, provides the result of the simulation for the future.

Parallel to the calibration and simulation phase, the transition probability matrix was calculated for Model 1 and Model 2 and the transition area matrix for Model 3 and Model 4. The former were generated to learn the probabilities of spatial changes from non-affected zones to IL-affected zones, considering the influence of the changes produced in covers adjacent to the zones of positive IL occurrence. Conversely, the latter only included the probability of change of the pixel values without taking the values of the closest neighbours into account. Also, to facilitate future policies for environmental remediation of ILs, the surface (ha) affected by ILs was estimated for all the models using MC (Metropolis and Ulam, 1949; Coquillard and Hill, 1997).

2.7. Model validation

The accuracy of simulation outputs and generalisation error of the models were evaluated by comparing the predicted changes versus real changes in the study area (Tiné et al., 2018). The validation of the models was carried out by running a simulation of illegal landfill occurrence changes from 2000 to 2012, and comparing its output with the observed change from the 2000 to 2012 illegal landfill occurrence samples. The accuracy of the predictive models were validated by considering the Kappa $K_{standard}$, K_{no} and $K_{location}$ indices, the Quantity Disagreement (QD) and Allocation Disagreement (AD) indices, and the indices for landscape metrics – the Agglomeration Index (AI) and Path Cohesion Index (PCI). The Kappa indices defined by Pontius (2000) are linear functions and have values on a 0 to 1 scale, where 1 indicates perfect agreement and 0 total disagreement. $K_{standard}$ measures the ability of a simulation to achieve a perfect classification given a fixed marginal distribution of cells in a category in the simulation map (Cohen, 1960). K_{no} shows the proportion of agreement without specifying the location. $K_{location}$ is a spatial precision measurement that indicates the correct assignment of values. The Kappa indices were applied to both categories, the presence of IL occurrence and IL absence. The models' predictive ability was further evaluated based on exclusive analysis of positive IL occurrence using the fuzzy Kappa statistic. The models' precision was thus considered to be fair for values between 0.41 and 0.60, good for values in the interval from 0.61 and 0.8 and very good for values above 0.80 (Watson and Petrie, 2010). Due to the models' high success rates in the Kappa indices, resulting from the majority presence of the IL absence class, and to the low results in the $K_{location}$ indicator of the fuzzy Kappa statistics, alternative indicators were proposed: QD, AD, AI and PCI. The first two were proposed as an alternative to the Kappa indices (Pontius and Millones, 2011). The QD index measured the quantity of disagreement between numbers of cells in each category without taking spatial location into account, while the AD index evaluated the quantity of disagreement between the reference map and the comparison map with respect to the spatial location of cells in each category (Tiné et al., 2018). The QD and AD indices are calculated using a contingency table for categoric variables and vary between 0 and 1, respectively indicating perfect agreement and perfect disagreement. Landscape metrics were also obtained to indicate the models' ability to reproduce similar patterns of dispersed or concentrated IL proliferation. Metrics for influence and connectivity appropriate for the study of landscape fragmentation were thus calculated, such as AI and PCI (McGarigal and Marks, 1995). Two different metrics of landscape fragmentation (Agglomeration Index and Path Cohesion Index), which report for influence and connectivity, were calculated within the software environment Fragstats v4.2.1 (McGarigal and Marks, 1995). The former shows the general agglomeration of the ILs, i.e. a tendency to occur in large, aggregate or dispersed distributions. These indicators vary from 0 to 1; AI values close to 0 indicate no adjacency between ILs, i.e. maximum disaggregation, while AI values close to 1 consist of a continuous pattern. PCI refers to the degree to which the ILs can attract or repel the presence of new ILs around existing ones. PCI values close to 0 would indicate that the proportion of landscape composed by the objective class (IL presence) is transformed and increasingly subdivided and is less physically connected. PCI thus quantifies the connectivity between ILs as perceived by the bodies dispersed in binary landscapes. Although the aim of using the landscape metrics was to compare similarities between real IL patterns and simulated ones, they were also applied separately to all the study years (2000, 2006 and 2012) to evaluate the IL dispersion patterns (Tiné et al., 2018). The choice of best simulation model depended on the consideration of all statistics previously examined and on results obtained by gains and losses of the simulated future scenarios.

3. Results and discussion

3.1. Analysis of IL growth according to land uses

The annual growth rate of surface affected by ILs for the period between 2000 and 2006 was 4.5% and 9.5% in Zone A and Zone B, respectively. For the period between 2006 and 2012, the annual growth rate was 6.6% and 6.7%. Those changes represent an increase in absolute terms in the year 2006 of 20.5 ha and 97.8 ha, and in 2012 of 97.8 ha and 111.6 ha for Zone A and Zone B, respectively (see Supplementary material: Table 2s). The ILs of the two zones are mainly located in agro-livestock areas and areas of sparse vegetation, away from urban areas and where there is less monitoring and control. The highest growths nevertheless occurred in areas close to urban uses, construction zones, and industrial zones. Interannual growth of ILs in a radius of 250 m from urban areas for the period between 2000 and 2006 was 21.1% and 13.1% in Zone A and Zone B, respectively. For the period between 2006 and 2012 that IL growth was less in both zones, with an interannual growth rate of 9.4% and 7.7% in Zone A and Zone B, respectively (see Supplementary material: Tables 3s and 4s). Interannual IL growth in a radius of 250 m from construction zones between 2000 and 2006 was 14.0% in Zone A and 23.3% in Zone B. That IL growth was much less between 2006 and 2012, with an interannual growth rate of 4.1% in Zone A and 6.9% in Zone B. The highest IL growth rates in urban areas and construction zones coincided with the period of most urban growth amid the real estate boom. Even though the absolute increment of IL-affected surface less than 250 m from industrial zones was negligible for both zones, high IL surface growth rates occurred between 2000 and 2006, with 47.3% in Zone A and 16.9% in Zone B. That growth could be associated to the creation of new industrial areas on the outskirts of built-up areas. During the period between 2006 and 2012, the IL surface growth rate less than 250 m from industrial zones fell to 15.7% in Zone A and 10.1% in Zone B (see Supplementary material: Tables 5s and 6s). Fig. 3s in Supplementary material shows the gains or losses of land affected by ILs for each period. The gains were mainly located along the coast of both zones, mainly in abandoned agricultural spaces and unfinished urban development projects. Also, the new ILs of the 2006 and 2012 periods were located in spaces close to old landfills; those spaces may have acted as a factor of attraction. Contrary to this, the losses do not present a specific pattern; they may occur due to land clearing or new uses such as residential housing.

As far as the authors know, there is no other example, at least in Europe, in which home construction has reached the levels of Spain

(Fernández-Tabales and Cruz, 2013; Cruz, 2014; Quesada-Ruiz et al., 2019). This problem is aggravated by joint development of the housing market and the tourist market in the case of the Canary archipelago (García-Cruz, 2016; Quesada-Ruiz et al., 2019). It was thus observed that the growth rate of ILs close to urban environments was higher during the period of more urban expansion before the 2008 economic crisis (Quesada et al., 2013) and *Law 8/2007 on Land* (Gobierno de España, 2007). Furthermore, the concentration of population around consolidated built-up areas due to the population shift from marginal metropolitan areas to the periphery may have driven the urban expansion process and therefore the generation of waste (Salvati et al., 2016). In addition, urban expansion and the decline of agrarian activity along the coast may have enhanced environmental deterioration, as it was the case for other regions of Europe such as the island of Sardinia (Bajocco et al., 2012), the Roman coast (Salvati et al., 2014), Greece (Hadjimichalis, 2014; Alexandri and Janoschka, 2017) and Catalonia (Parcerisas et al., 2012), where the distance to the coast has been identified as an important factor of land use change. Both processes may have favoured the appearance of new peripheral urban uses with presence in low-density residential areas, roads and new infrastructures (Parcerisas et al., 2012). Indeed, municipal administrations may have encouraged the urban expansion process, aiding urban developers with tax benefits and the provision of goods and services. Municipal budgets may also have become dependent on income stemming from licences for construction activity during this phase (Hortas-Rico, 2014). The supply and distribution of services, infrastructures and amenities to citizens, mainly buildings for residential use, may thus have changed as demand was exceeded. That may have brought many construction projects to a halt, with a consequent accumulation and generation of waste. At the same time environmental impacts not foreseen by municipal administrations occurred, which may have their root in the urban expansion.

3.2. Validation results

The simulations' preciseness was very high with respect to the Kappa indices (see Supplementary material: Table 7s). All the simulations indicated nearly perfect agreement for $K_{standard}$, K_{no} and $K_{location}$, with values very close to 1. The high values of the K_{no} Index would thus show that our simulation correctly specifies the quantity of pixels for each class of simulated maps with the reference maps of each zone. The $K_{location}$ index also shows high agreement regarding localisation of the classes. The Kappa indices used may nevertheless not be appropriate for validating alone the simulation models due to the dominant presence of one category (Watson and Petrie, 2010), in our case IL absence. In addition, these problems specific to the validation of simulation models have been extensively dealt with and are widely debated in the scientific community (Pontius et al., 2004; Wang and Mountrakis, 2011; Mas et al., 2012; Sinha and Kumar, 2013). The QD and AD analysis proposed by Pontius and Millones (2011) may accordingly be a good alternative. However, the existence of a majority category does produce high agreement between the covers of the simulated maps and the reference maps for the indices, as occurs with the Kappa indices. The use of indicators alternative to Kappa and others associated to landscape metrics may therefore help assess the validity of our models. In this regard, the use of a variant of the Kappa indices, such as fuzzy Kappa indices solely applied to one category (IL presence) might show different results (see Supplementary material: Table 8s). However, the preciseness fell sharply until obtaining models with fair or good precision. Among those models, the CAM simulation models had a higher degree of success compared to the MOLA models. The simulations of Model 1 (kfuzzy: 0.61) and Model 2 (kfuzzy: 0.64) were the ones with best results for Zone A and Zone B, respectively (see Supplementary material: Table 8s). The results nevertheless continue to be close to 1 for the k_{no} statistic in all the simulated maps, showing their good ability to quantify the total affected surface in the future scenario of 2012 (see Supplementary material: Table 8s). We could therefore state that all the models are able to quantify the surface affected by ILs in a future scenario. Despite this, the simulations of Model 3 and Model 4 exaggerate both the gains of surfaces affected by new ILs and the loss of IL-affected surfaces (see Table 3). With a view to planning, one should not overestimate IL presence in order to make the most of efforts to track and monitor areas potentially affected by ILs. On the other hand, the models had a very low capacity to correctly situate the new areas affected by ILs, as reflected in results of the $k_{location}$ statistic. This may generally be due to a certain randomisation of the phenomenon, the need to include new characteristics that better describe the ILs' behaviour, or to an excessive spatial scale of detail (10 m in the case of this study).

The indicators associated to landscape metrics, AI and PCI, showed the simulation models' ability to reproduce the IL proliferation distribution patterns similarly to the reference map. Those metrics may thus be an alternative for validating the IL simulation models, as they are applicable to a single landscape category, in our case the presence of ILs. Table 2 summarises the PCI and AI values exclusively to the 'IL presence' category; there are slight differences between the simulation models and the reference maps for each study zone. High cohesion and spatial aggregation of the ILs was accordingly shown. Moreover, the analysis of the PCI and AI indices for all study periods showed that the ILs present a connectivity and aggregation among themselves which gradually increases in each of the periods (see Supplementary material: Table 9). The IL occurrence zones may thus by themselves be a focus of attraction for new ILs. In this sense, the Model 1 simulations showed more agreement for the indices in both zones. The simulations made for the year 2012 (see Supplementary material: Figs. 4s and 5s) and the simulations in the future scenario of 2018 (Fig. 3; and Fig. 6s in Supplementary material) show the mapping results of the different simulation models for each zone. The choice of the CAM models based on LR for both zones was deemed adequate. Both CAM models showed the greatest agreement in the Kappa statistics, Kfuzzy, and high agreement with the landscape metrics. They were also the models that least overestimated the gains and losses.

In both Zone A and Zone B the impact of the physiographic terrain features (e.g. slope and height), the closeness to built-up areas, and agricultural areas as well as the distance to communication routes were considered in the analyses of potential for IL occurrence for all periods. Although significant differences were seen in the quantification granted to the associated variables in the land uses for each period (e.g. distances to urban areas and distances to agricultural areas), as reflected in the LR equations (see Supplementary material: Tables 10s and 11s). The Model 1 simulation predicted increases of 52.3 ha in Zone A and 81.5 ha in Zone B affected by ILs for the year 2018 (Table 3). Fig. 4 and Fig. 7s in Supplementary material show the maps of gains and losses for the 2018 period. The good gain prediction ability of the simulation models based on MOLA (Table 3) was observed, though not for losses; it could not consider or overestimate them. The selected simulation models could thus allow better delimitation of the possible spaces affected by ILs, facilitating monitoring and oversight of the territory.

Table 2
Landscape configuration validation results.

Zone	Map	PCI	AI
A	Reference	86.386	79.544
	Model 1	87.248	81.279
	Model 2	89.427	86.517
	Model 3	88.823	78.576
	Model 4	90.232	83.982
B	Reference	85.365	77.290
	Model 1	90.804	83.576
	Model 2	90.831	87.219
	Model 3	93.568	84.261
	Model 4	91.861	85.564

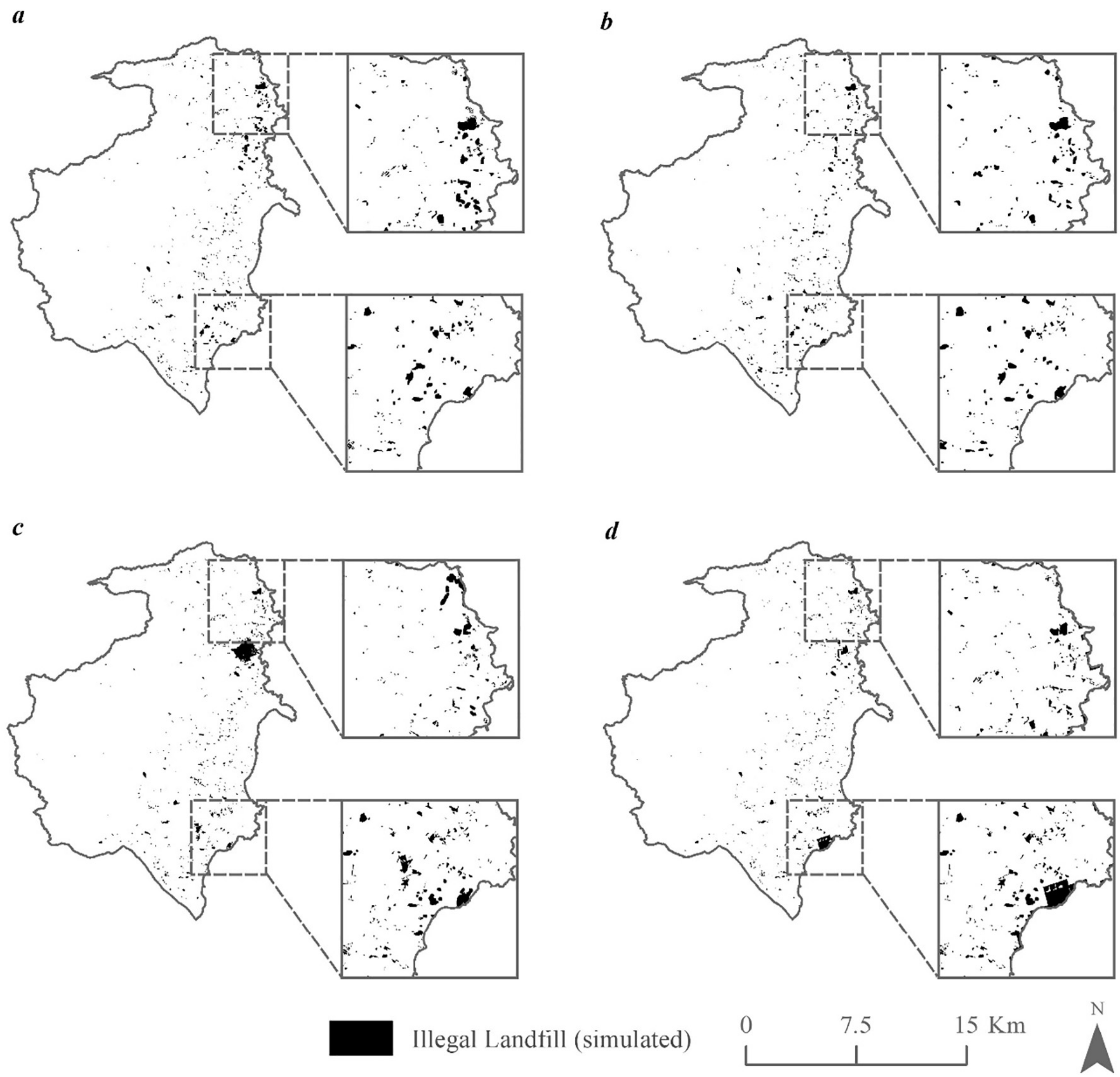

Fig. 3. 2018 illegal landfill simulation model for eastern Gran Canaria. a) Logistic regression CA_Markov model; b) multicriteria evaluation CA_Markov model; c) logistic regression MOLA; d) neural network MOLA.

3.3. Illegal landfill simulation models and land cover changes

The transition rules obtained using the suitability analyses and their respective set of transition potential maps reflect the influence of the characteristics most associated to the evolution of IL occurrence through time. All the simulation models also showed very similar results in the delimitation of areas with higher IL potential for the respective study periods. The influence of the coastal margin and the proximity to urban areas were notable drivers in the time evolution of the ILs, similar to studies focusing on spatial characterisation (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019). The areas with the highest potential for IL occurrence were also located on coastal margins. This exposure of coastal areas to landfilling may entail implications for touristic image and environmental quality. Furthermore, the coastal areas situated close to agricultural areas, industrial areas, urban settlements, and communication routes were particularly affected (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019). The simulation models hence showed the influence of the changes in the land-use types with respect to the delimitation of the potential areas of both zones. The abandonment of consolidated agricultural areas, especially those associated with intensive greenhouse agriculture in both zones, could be related to the relative increase of the potential for occurrence in agricultural and less urbanised environments. Specific strategies would therefore be required, complementary to the monitoring of IL occurrence, to prevent the occurrence of new ILs in those spaces. It may also be necessary to address unused agricultural plots relatively accessible to built-up areas and main communication routes, as they may be attractive sites for landfilling. Simulation Models 1 and 3 of Zone B demonstrate this question, as there is a relative increase of IL occurrence potential for those spaces, probably due to the substantial decline in agricultural activity during the period between 2006 and 2012 (Martín-Fernández and Martín-Martín, 2016). It was nevertheless seen how proximity to areas

Table 3
Gains and losses between 2012 illegal landfill sampling and 2018 illegal landfill simulation.

Zone	Model	Gains	Losses	Differential
A	1	55.280	2.960	52.320
	2	59.770	7.450	52.320
	3	88.710	0.000	88.710
	4	88.630	0.000	88.630
B	1	109.470	27.930	81.540
	2	109.470	27.930	81.540
	3	191.580	170.800	20.780
	4	174.430	0.000	174.430

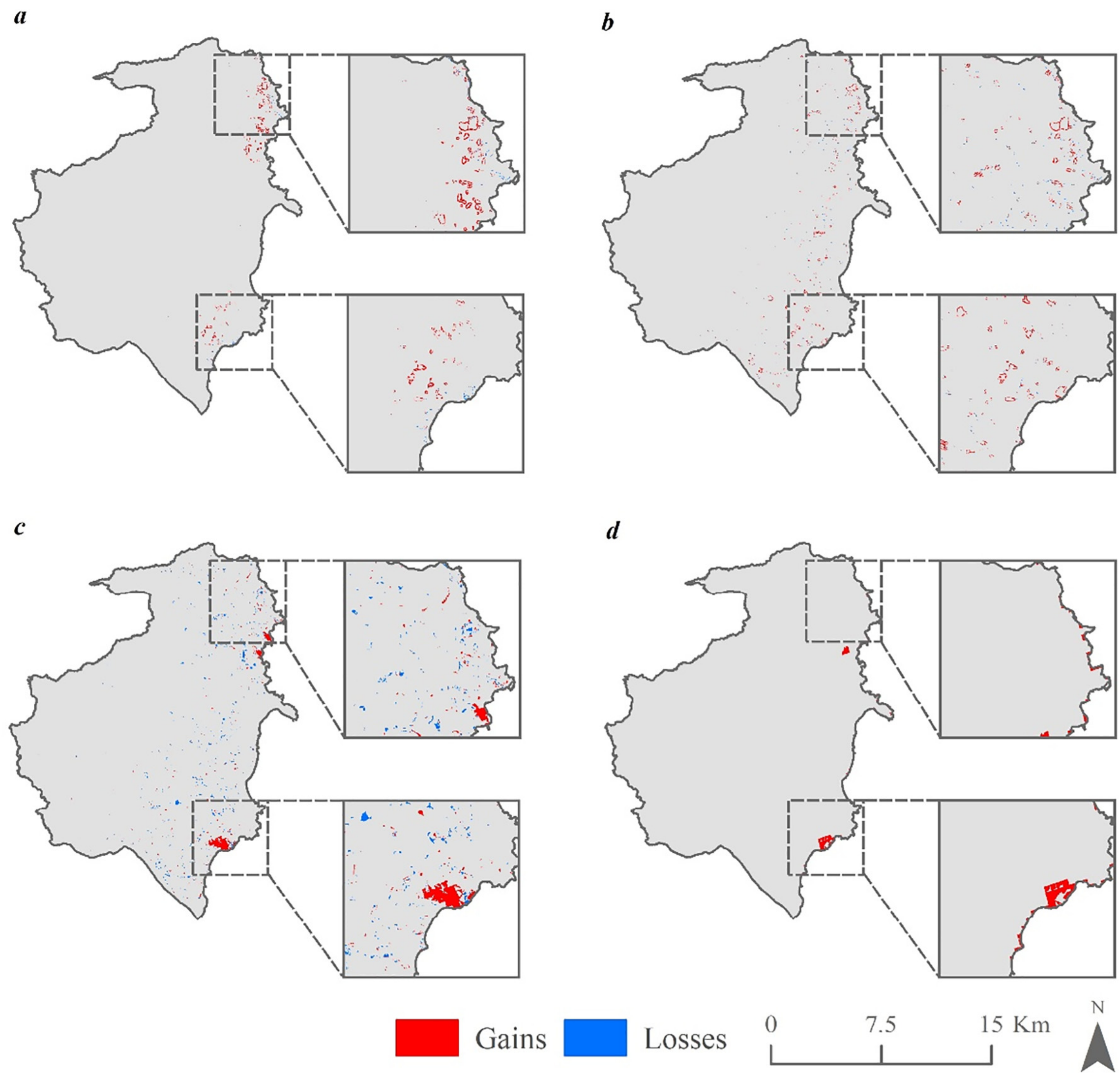

Fig. 4. Gains and losses 2018. Illegal landfills – simulated model for eastern Gran Canaria. a) Logistic regression CA_Markov model; b) multicriteria evaluation CA_Markov model; c) logistic regression Land Change Model; d) neural network Land Change Model.

with denser construction of artificial surfaces may be highly important for IL proliferation, especially those associated with residential uses, this has been corroborated in previous empirical studies (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019). The presence of new urban developments or unfinished urban spaces might thus foment the potential area of IL occurrence. This influence was reflected in the derived transition maps of the year 2006 (Fig. 5; and Fig. 8s in Supplementary material), one of the most important during the real estate boom. The transition from agricultural land and the appearance of new industrial areas may also have encouraged urban expansion and the areas of potential IL occurrence.

Analysis by zones enables observation that in Zone A, Model 1 (see Supplementary material: Fig. 8sA) indicated coastal spaces and zones close to urban areas as places with higher IL potential. Model 2 (see Supplementary material: Fig. 8sB) reduced the relative occurrence of coastal areas in favour of the interior zones. The transition potential maps obtained in Model 3 (see Supplementary material: Fig. 8sC) and Model 4 (see Supplementary material: Fig. 8sD) highlighted a greater influence of the terrain's relief characteristics, showing a higher probability of occurrence in interior ravines and less steep areas. In Zone B the transition potential maps obtained in Model 1 (Fig. 5A) and Model 2 (Fig. 5B), along with the transition potential maps obtained in MOLA, Model 3 (Fig. 5C) and Model 4 (Fig. 5D), indicated higher IL occurrence in areas close to industrial areas and agricultural zones. Models 2 and 4 nevertheless showed higher occurrence potential along the entire coastal margin in Zone B for all periods. The differences in the models' results may have their origin in the application of the statistical techniques used to generate the transition potential maps. In this regard, Models 1 and 3 based on LR allowed control of the characteristics entered by the user, as the respective involvement throughout the process could be known. The same does not happen with Model 4 based on NN, because the selection of drivers is based on a black-box model, preventing knowledge of the characteristics involved in the process. Conversely, Model 2 is a model that skews the suitability analyses, weighting characteristics per expert criterion. On the other hand, the CAM and MOLA models present very small differences, as MOLA uses the same algorithm as CAM. The use of transition probability matrixes for CAM as opposed to the transition area matrixes used in MOLA may nevertheless have marked the difference between the models. The former may thus be more appropriate for studying the problem of IL proliferation, as it considers changes of neighbouring cells. Hence, not only were land-use changes considered for each of the cells but also the influence of their neighbours. The transition area matrix considered instead the change of values from one period to another for a pixel. Validation of the models nevertheless demonstrated similar results.

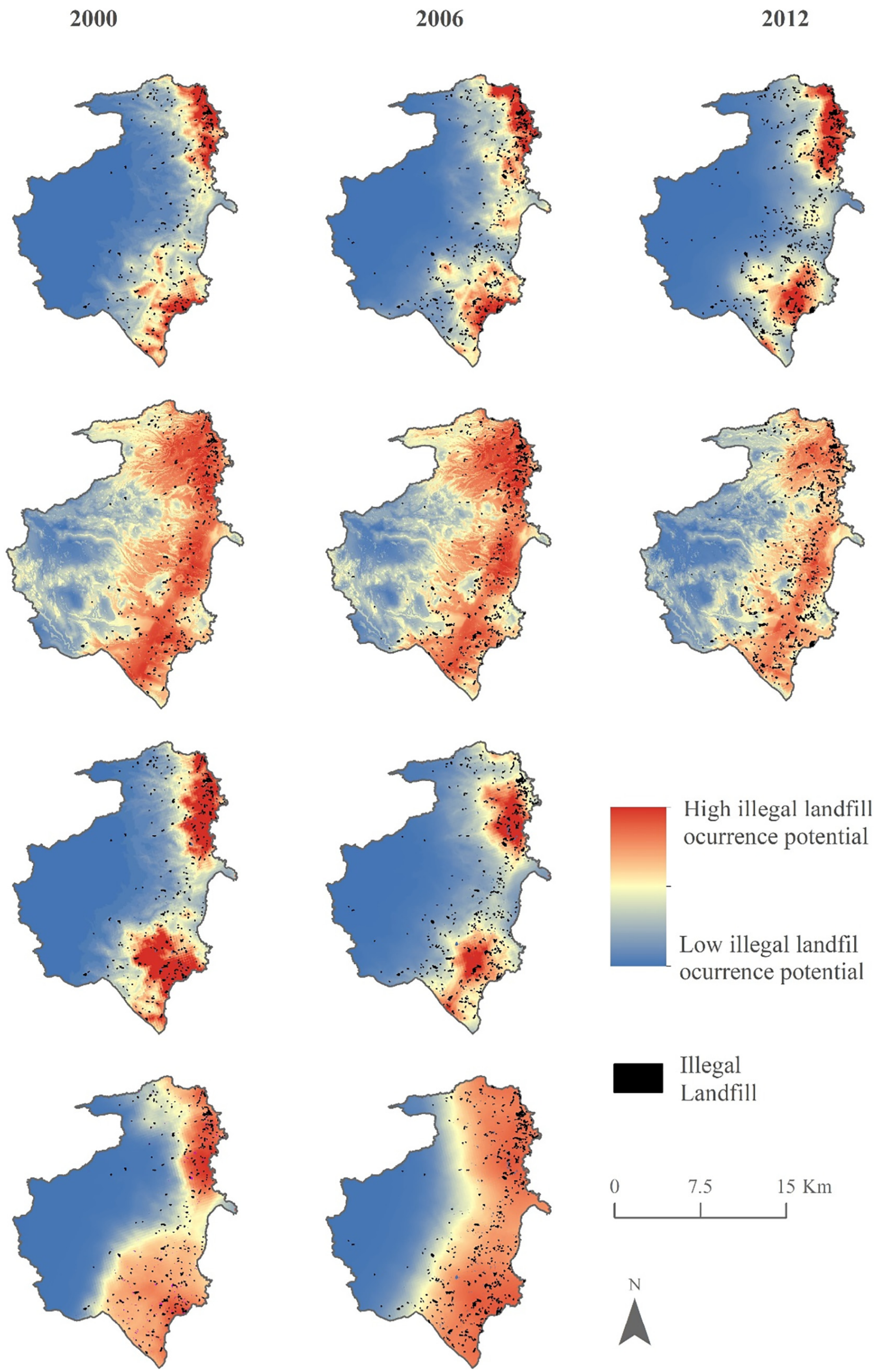

Fig. 5. Suitability analysis of illegal landfill occurrence in eastern Gran Canaria. a) Logistic regression CA_Markov model; b) multicriteria evaluation CA_Markov model; c) logistic regression MOLA; d) neural network MOLA.

3.4. Applications of the simulation models

This paper shows the application of CA in the analysis of IL occurrence, with ILs considered to be a dynamic and complex system. This may supply added value to policies for environmental repair and protection as well as territorial planning (land use and management), by delimiting possible future areas of IL occurrence. In this regard, future waste management plans should examine and control the relationship between spaces for urban expansion and increased waste, especially waste from construction and demolition (Quesada-Ruiz et al., 2018). In addition, agricultural abandonment stemming from urban expansion and the transition to a service economy may be demonstrated as a phenomenon very closely associated to the increase of waste, mostly plastic and with higher incidence in irrigated greenhouse farming areas (Quesada-Ruiz et al., 2018; Quesada-Ruiz et al., 2019). The delimitation of possible new areas for IL occurrence may thus enable assessment of the possible costs of recovery of those spaces potentially affected by IL occurrence and help plan environmental education policies with the aim of improving the waste collection process in those spaces. The efficient introduction of dissuasive measures (e.g. video surveillance and signage) could also be improved. On the other hand, the study of IL occurrence over time may help us conduct complementary studies that evaluate the incidence of ILs in soil composition, contamination of underground water, or emission of atmospheric pollutants.

The main limitations of this study lie in the lack of equivalent official statistics for all the periods, since the simulation approaches rely on the use of spatiotemporal dynamic characteristics. Likewise, the shortage of socioeconomic features such as information about the behaviours and the degree of awareness on recycling and respect for the environment or the relation of dumpers to the landlord of a site on illegal landfills, for all the periods, limits the capabilities to understand and model IL occurrence. Consequently, the IL simulation models require the creation of a comprehensive database with the aim of including a large amount of features for all the periods which are not always available. An additional limitation concerning data input is the extensive and time consuming orthophotointerpretation that was required in this study. Furthermore, the analyses of potential for IL occurrence show limitations resulting from the use of methods that only recognise non-linear relationships between the characteristics and the occurrence of ILs. The use of artificial intelligence algorithms and machine learning may be able to improve the models' prediction capacity (Rodriguez-Galiano and Chica-Rivas, 2014; Rodriguez-Galiano et al., 2018), especially with chronological series (Bishop, 1995; Lai and Wong, 2001; Li and Yeh, 2002). Improving the suitability analysis based on selection of the group of most representative characteristics might consequently improve the transition rules and hence the simulation models. Finally, the main limitations in the development of the proposed simulation models are due to a lack of inclusion of outside elements such as the price of waste treatment facilities (Liu et al., 2017), the degree of citizen awareness (Smrekar, 2011) or the influence of legislative changes (Matsumoto and Takeuchi, 2011).

4. Conclusions

This paper approached the temporal study of the problem of IL occurrence for the periods of 2000, 2006 and 2012 in two representative zones of GC, one situated in the northwest (Zone A) and the other situated in the east (Zone B). The interannual growth rate of surfaces affected by ILs obtained for the period between 2000 and 2006 was 4.5% and 9.5% in Zone A and Zone B, respectively. For the period between 2006 and 2012 the growth rate was 6.6% and 6.7%. These changes represent an increase in absolute terms in the year 2006 of 20.5 ha and 97.8 ha, and in 2012 of 97.8 ha and 111.6 ha. Analysis of the relationship between the ILs and land uses showed that the ILs of both zones were located during all periods mainly in agro-livestock zones and areas of sparse vegetation far from built-up areas and were accessible, with neither control nor monitoring. Growth of ILs during the period between 2000 and 2006 was higher in urban areas, construction sites and industrial zones, and may be closely related to the urban expansion process linked to the real estate boom. However, the IL growth rates of urban environments declined during the period after the 2008 economic crisis and the appearance of new urban planning regulations.

The use of dynamic characteristics such as those associated to land uses and static characteristics such as elevation and slope helped model the ILs' growth. Consideration of the ILs within CA enabled the generation of simple rules for carrying out the simulations, allowing complex and non-linear interactions to be modelled in a long timescale (18 years). CA also enabled surface growth of ILs to be estimated in both areas thanks to the Markov matrixes. The modelling of IL proliferation was divided into three phases: calibration, validation and simulation of the future 2018 scenario. Synchronic data series were used, along with Markov chains and transition rules, in all phases. In the calibration phase the suitability analysis was done and the transition rules and transition potential maps were obtained. The calibration was done based on the suitability analyses produced in CAM and MOLA. Four models were generated: i) CAM with logistic regression; ii) CAM with multicriteria evaluation; iii) MOLA with logistic regression; and iv) MOLA with neural networks. The precision of the output simulations was evaluated using the Kappa indices, fuzzy Kappa, Quantity Disagreement, Allocation Disagreement and landscape metrics such as Path Cohesion Index and Aggregation Index. The results obtained from the Kappa indices were very high for all the simulations, with almost a perfect agreement (values close to 1) for $K_{standard}$, K_{no} and $K_{location}$. However, the Kappa indices should not be used alone when validating the outputs of dynamic models. For this reason, landscape metrics such as QD and AD may be a good complementary validation approach. The existence of a majority category nevertheless produces high agreement between the covers of the simulated maps and the reference maps for the two indices, as occurs with the Kappa indices. Also, application of fuzzy Kappa solely to the category for 'presence of ILs' obtained less solid results, showing the difficulties faced by all the models when simulating the surface affected by ILs. That forced us to use alternative indicators associated to landscape metrics, AI and PCI. They showed the simulation models' ability to reproduce the distribution patterns of IL proliferation similarly to the reference map. These metrics might thus be an alternative for validating the IL simulation models, as they are applicable to a single landscape category, in our case the presence of ILs. The choice of best simulation model depended on consideration of all the previously examined statistics and on the result obtained for gains and losses of the simulated future scenarios. The Model 1s of both zones obtained the best validation results overall and correctly quantified the gains and losses of surfaces affected by ILs, which the Model 3s and Model 4s did not. The simulation of the Model 1s predicted an increase of 52.3 ha and 81.5 ha respectively affected by ILs in Zone A and Zone B for the year 2018.

In both Zone A and Zone B the physiographic terrain characteristics (e.g. slope and elevation), the proximity to built-up areas and agricultural areas, as well as the distance to communication routes were considered in the analyses of potential IL occurrence for all periods. Although important differences are seen in the quantification granted to the variables associated to the land uses for each period (e.g. distances to urban areas and distances to agricultural areas). In this regard, it was seen how the areas with more urban expansion and agricultural abandonment were affected by a higher increase in IL incidence. The selected simulation models were thus able to allow a better delimitation of possible spaces affected by ILs. In addition, the simulation models could enable the evaluation of the possible costs of recovery, planning of environmental education policies or improvement of the efficient introduction of dissuasive measures (e.g. video surveillance and signage). Furthermore, temporal study of IL occurrence might help us when conducting complementary studies that evaluate IL incidence in the composition of soils, contamination of underground water, or emission of atmospheric pollutants. The main limitations of this study implementation rest on the data requirements and the need for matching (or identical or standard) official statistics for all the periods, especially for the socioeconomic features. The IL simulation models require the creation of a comprehensive database and an extensive and time consuming orthophotointerpretation phase. In future work, and with a view to improving adjustment of the IL simulation models, the analyses of potential for IL occurrence based on the use of different algorithms from artificial intelligence and machine learning could improve the models' prediction ability, especially with the chronological series, considering non-linear relationships between the characteristics and IL occurrence for each study year. Other techniques framed within the study of complex systems such as agent-based models (ABMs) may improve the IL occurrence simulation process, considering multiple scenarios in space and time and including outside elements such as the price of waste treatment facilities, extent of citizen awareness or influence of legislative changes.

Acknowledgements

LQR is the holder of a FPU grant awarded by the Spanish Ministry of Science, Innovation and Universities (reference FPU14/04975). The second author (LP) is thankful to the Natural Sciences and Engineering Research Council (NSERC) of Canada for their support under the Discovery Grant Program. This work was supported by project RTI2018-096561-A-100 (Spanish Ministry of Science, Innovation and Universities).

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.scitotenv.2019.06.079.

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