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Characterization and mapping of illegal landfill potential occurrence in the Canary Islands

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ABSTRACT

The proliferation of illegal landfills (IL) has a negative impact, especially for ecologically sensitive areas or those attractive for tourists. This research focuses on the drivers of the IL spatial distribution in archipelagic environments for mapping the IL potential occurrence. 286 and 153 illegal landfills localizations were identified through fieldwork in the islands of Gran Canaria (GC) and La Palma (LP), respectively. The characterization of IL was carried out from a set of features (177) such as: waste type, control and surveillance, socioeconomic, accessibility, distance to elements of interest, visibility and physiographic. Feature selection was performed using the Discriminant Analysis technique (DA). The DA model selected 10 and 9 features for GC and LP, respectively. The GC IL potential occurrence was mainly related to the greenhouse density, type of cadastral plot and distance to the coast. For the case of LP, the following features were selected: population density, distance to natural protected areas, distance to urban areas, slope and Normalised Difference Vegetation Index (NDVI). Different potential illegal landfill occurrence maps were obtained: (i) likelihood of occurrence of IL; and (ii) areas potentially affected by IL, based on the application of ROC (Receiver Operating Characteristics) curves and success rate. ROC was equal to 0.973 and 0.979 in LP and GC, respectively. Success rate was equal to 81.58% considering an affected area of 21.95% in LP, whereas success rate was equal to 87.32% in GC considering 20.10% affected area.

1. Introduction

The proliferation of illegal landfills (IL) is a major environmental problem for many countries. According to the report by the European Union Action to Fight Environmental Crime (EFFACE), the total amount of IL in the European Union (EU) is of 12,628, adding 2,871,186 t of waste (Watkins, 2015). Most European countries are affected by the presence of IL within their territory, with the exception of Denmark, Lithuania and Luxembourg, the most affected countries being Slovakia (3542 t), Croatia (1982 t) and Romania (1410 t) (Fig. 1A). Following EFFACE (Watkins, 2015), the whole of the EU have relatively low occupation densities of IL per km^2, such as Malta as the most alarming case, possibly due to its status of island. However, the amount of illegally dumped waste is high for nearly all the countries linked to the EU (Fig. 1B). Poland with 371,119 t, Germany with 345,154 t and Italy with 332,903 t are the countries with the highest amount of tons of illegal waste within their territory (Watkins, 2015). Nevertheless, relatively speaking, less populated eastern countries stand out, such as Bulgaria (12,273 t per 1 M inhabitants), Romania (11,664 t per 1 M inhabitants) and Lithuania (10,511 t per 1 M inhabitants). Spain and Italy stand out as well, as they exceed more populated countries such as France and the United Kingdom (Watkins, 2015). There are many reports, which alert on the IL costs. The UK Environment Agency estimated in 100–150 million pounds a year the localization and cleaning cost of IL in the United Kingdom (Ichinose and Yamamoto, 2014). The Department of Environment and Heritage Protection of the Local Government of Queensland (Australia), with a population of 4,546,200 inhabitants (Australian Bureau of Statistics, 2014), collected 9300 tons of waste between 2011 and 2012, with an approximate management cost of 6.2 million dollars ($670 per t) (Glanville and Chang, 2015b). The occurrence of IL is also a problem for the local communities of the United States (EPA, 1998). For instance, according to the Pennsylvania Department of Transportation, the cost of annual tax on waste clean-up of IL is of about 10.1 million dollars ($835 per t) (PPRC, 2016).

The proliferation of IL generates impacts such as the deterioration of local landscapes (Ichinose and Yamamoto, 2011), air pollution (Bridges et al., 2000) and aquifer pollution (Monteiro Santos et al., 2006) or the increase of risk for human health. Moreover, IL have an influence on the economies of the affected areas, reducing the returns of the touristic operations and incurring in high

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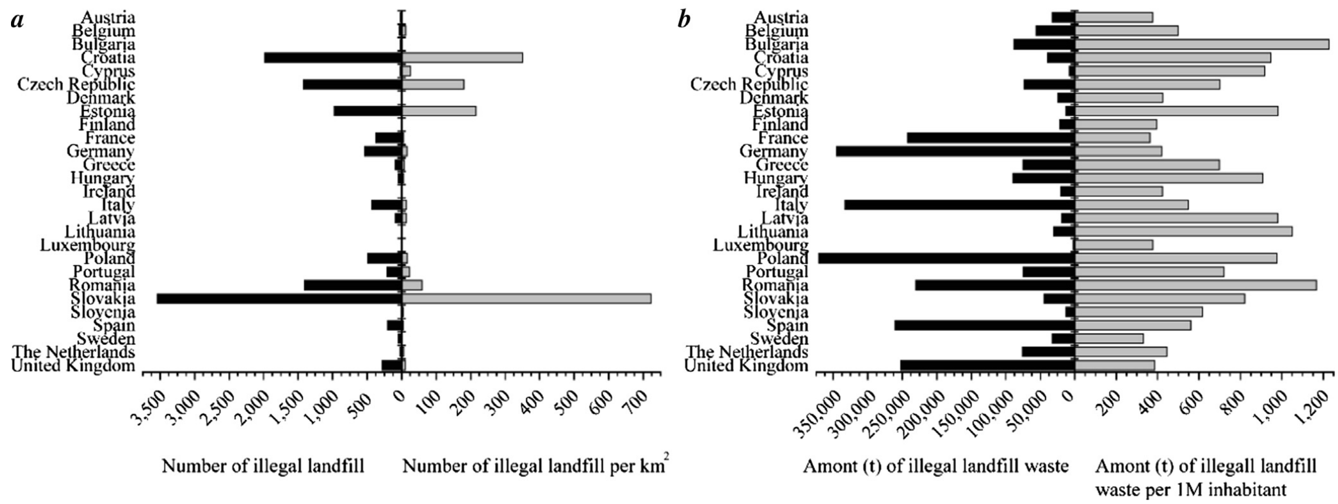

Fig. 1. Illegal landfills in the European Union. (a) Number of illegal landfills (b) Amount of illegal waste. Created from EFFACE (2015).

reparation costs which may consume up to 30% of some budgets of local administrations (Abd-EL Monse, 2015; Calò and Parise, 2009; Chu et al., 2013; Ichinose and Yamamoto, 2011; Jones, 2008; Matos et al., 2012; Matsumoto and Takeuchi, 2011; Mohee et al., 2015; Notarnicola et al., 2004). Some countries have started to revise their regulations on IL in response to this situation and are introducing more restrictive laws and penalties for waste crime. The Directive on Environmental Responsibility with Relation to the Prevention and Reparation of Environmental Damages (EC, 2004) establishes that waste must be managed, thus being collected, transported, recovered and eliminated. Moreover, this directive requires that measures be taken which prevent and evaluate environmental damages, which contribute to plan their repair. The EU in its Directive related to Waste (EC, 2008) defines a landfill as a site to eliminate waste which is intended for waste store in surface or underground. The Directive on the Landfill of Waste (EC, 1999) establishes the standards and requirements for landfill exploitation. However, neither directive define the term "illegal landfill" directly. Accordingly, the regions of Spain (NUTS 2) have agreed to define as IL those surfaces affected by disposal sites, without any type of management or control, which for a time over two years present an extension over 2000 m^2.

The increase in waste generation is usually related to economic and demographic growth, high industrialization and improvements in the standards of living (Kothari et al., 2014). Kim et al. (2008) found that the increase of 1% on the price of waste deposit meant an increase of 3% in the number of IL localised. Various authors have supported that a better understanding of the specific components which have an influence on the IL patterns in a region improves the effectiveness of waste management and reduces the impacts derived from the growth of IL (Glanville and Chang, 2015a; Matos et al., 2012). Therefore, the predictive modelling and the mapping of those areas of IL potential occurrence can be essential in the prevention and diagnosis of the situation of IL (Tasaki et al., 2007; Biotto et al., 2009; Jordá-Borrell et al., 2014). These initiatives are limited by the lack of IL inventories or official statistics (Jordá-Borrell et al., 2014), which has provoked that IL have been hardly studied. Some countries have created their own databases to solve this information need: the National Registry of Illegal Landfills in Slovenia (Ekologi brez meja, 2011); the BASOL database created in 1994 by the Ministry of Ecology and Sustainable Development (French Agency for the Ecology and sustainable Development); or the IL identification programs of Italy, the Veneto region (Biotto et al., 2009) and the Region of High Altamura (Uricchio et al., 2010). There are also examples of collaborative mapping in the identification of IL in New Spirit (East St. Louis, IL, USA) (EPA, 1998) or citizens' initiatives like the Trashout software application (Trashout nf., 2018).

The studies on landfills focus both on the multi-criteria analysis for the localization of new sites of legal landfills (Abd-EL Monse, 2015; Alexakis and Sarris, 2013; El Maguiri et al., 2016; Gbanie et al., 2013; Premalatha et al., 2014) and the characterization and modelling of IL. Both approaches integrate Geographical Information Systems (GIS) and the application of multivariate statistical techniques. The occurrence of IL has been approached from the identification of affected areas (i.e. remote sensing) (Doak et al., 2007; Jones, 2008; Kim et al., 2008; Mohee et al., 2015; Salleh and Tsudagawa, 2002; Silvestri and Omri, 2008; Uricchio et al., 2010); the identification of the drivers (Biotto et al., 2009; Jordá-Borrell et al., 2014; Keser et al., 2012; Matos et al., 2012; Matsumoto and Takeuchi, 2011; Tasaki et al., 2007) or the prediction of IL potential areas (Biotto et al., 2009; Chu et al., 2013; Glanville and Chang, 2015b; Lucendo-Monedero et al., 2015; Tasaki et al., 2007). This work has a double approach: the application of multivariate analysis techniques to the mapping of IL potential occurrence and the characterization of the physical and socioeconomic features which control the occurrence of IL on island environments. There are two unpublished study cases: the case of the island of La Palma (LP) and the case of the island of Gran Canaria (GC). Different factors affect the waste management in both islands: (i) high population densities; (ii) mass tourism; (iii) significant urban growth; (iv) intense farming activity; (v) limited number of treatment infrastructures; and, (vi) the lack of citizen awareness. As far as the authors are concerned, it is the first time that in a single study of IL the following are integrated: methods such as discriminant analysis (DA), the consideration of areas non affected by landfills or of negative occurrence in the construction and validation of the models and mapping of potential areas (Carranza et al., 2008), as well as the evaluation of the mapping accuracy from the ROC (Receiver Operating Characteristic) analysis and the success rates as a method to distinguish between potential areas of positive and negative occurrence. Finally, this research goes into detail about the drivers of the IL spatial distribution in archipelagic environments with the aim of improving the development of prevention and damage repair policies.

2. Study area

This paper focuses on LP and GC, both islands of the Canary archipelago (Fig. 2). The Canary Islands make up one of the 17

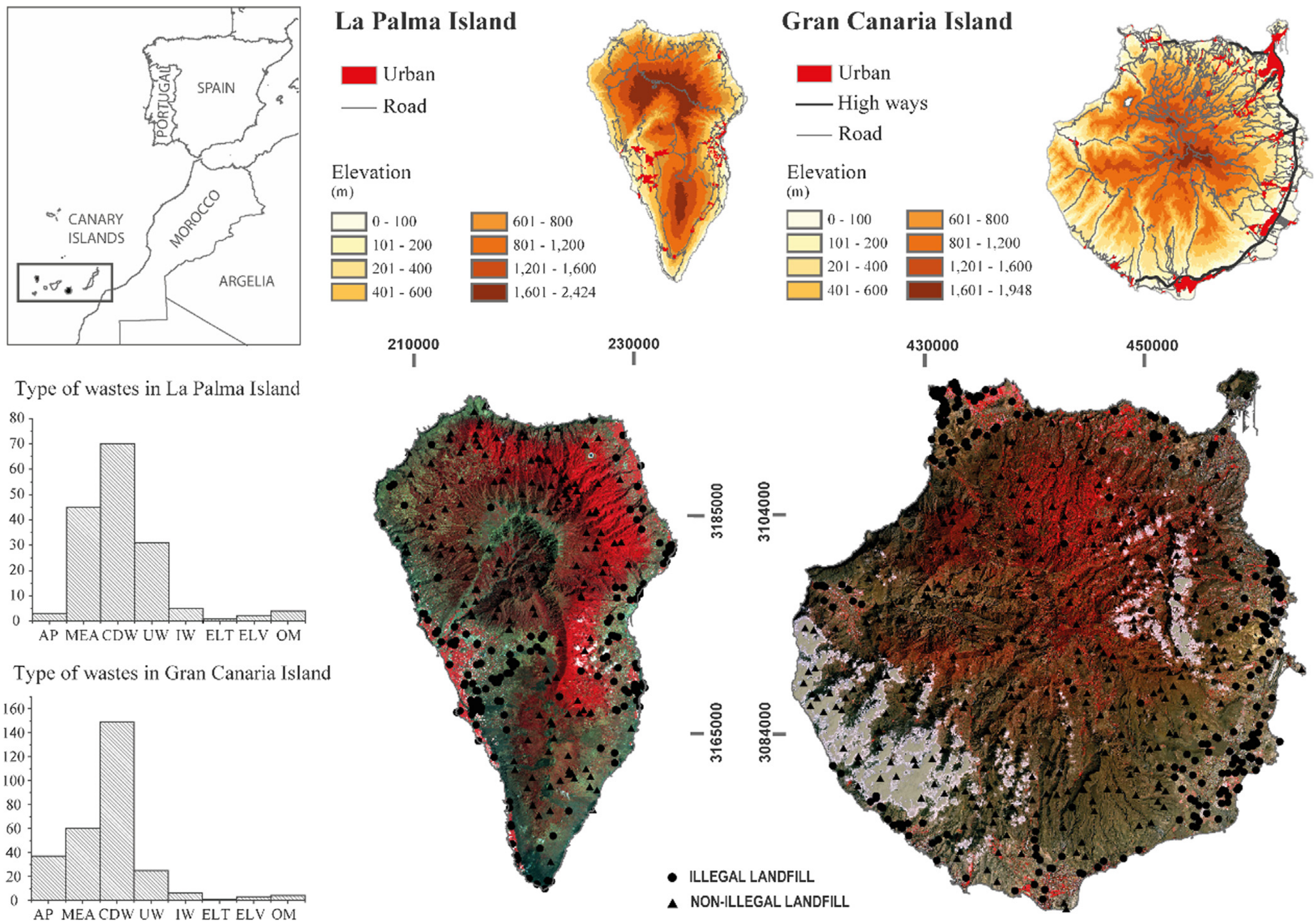

Fig. 2. Study area. Agricultural plastic (AP), mining and extraction activity (MEA), construction and demolition waste (CDW), urban waste (UW), industrial waste (IW), end-of-life vehicles (ELV), end-of-life tyres (ELT), organic matter (OM).

Spanish autonomous regions, and these are considered as an outermost region of the European Union. LP and GC are the third and fifth islands in terms of extension, with 708.3 km^2 and 1560 km^2, respectively. The maximum elevation of LP and GC is of 2426 m and 1949 m, respectively. After Tenerife (891,111 inhabitants), GC was the second most populated island in 2016 (845,195 inhabitants), and LP (84,486 inhabitants) being the fifth one (INE, 2016). The average air temperature values per year in LP and GC depend on the terrain and vary from 20 °C to 21 °C in those areas at sea level to values lower than 10 °C and 12 °C in the most elevated zones of LP and GC (AEMET, 2012). Rainfall distribution between windward high areas (1400 mm) and the downwind coast (100 mm) is very unequal. The geomorphology of the Canary Islands is related to volcanic activity. LP, with a high aspect ratio, runs north-south and comprises two volcanic areas separated by a valley: the extinct volcanic ridge of the north shield, with an ample network of deep ravines, and the meridional volcanic ridge, the latter being the most active volcanic region on the Canary Islands. GC has a circular shape, with a diameter of approximately 45 km, and has a radial network of deep ravines and canyons, and a mountainous inland area (Troll and Carracedo, 2016).

The vascular flora comprises 1995 species, 511 of which are endemic (GOBCAN, 2014). Different plant communities can be distinguished on the grounds of their altitudinal distribution and physiognomy: coastal scrub, thermophilic forests, green bush or laurisilva, pine forest and summit scrub. The Canary archipelago has 146 natural protected areas which represent 40% of the archipelago's surface, 4 of them among the 15 national parks of Spain (GOBCAN, 2014; MAPAMA, 2015). Both LP and GC have been categorised as Biosphere Reserves by UNESCO. This extent the whole of the island of LP and includes the Caldera de Taburiente National Park and 40% of the island of GC, with 33 different categories of protected areas.

The population density of the Canary archipelago is fairly high in comparison with the rest of Spain, 284.46 inhabitants/km^2 and 91, 95 inhabitants/km^2, respectively. In GC the population density is even higher (543.45 inhabitants/km^2) and in LP is noticeably lower (122.16 inhabitants/km^2). The population in GC is concentrated in the coastal areas, where, in turn, the capital city is localised, while the inland part is depopulated. In LP, the population in the north and northwest is much lower as they are geographically isolated. Most of the population lives in the west, where the economic centre and greater amount of touristic resorts of the island are. However, it is in the capital city, which is in the east, where the administrative headquarters and the most important historical-touristic centre of the island are.

The Canary Islands are the eight region in Spain in terms of their GDP. However, it is one of the regions with the highest unemployment rate (25%; INE, 2016) and it is two places above the bottom in terms of their income per capita (19,900 €; INE, 2016). The economic activity of LP and GC has tourism as a major driver of economic development (Cruz et al., 2011), which has boosted the building sector. The commercial activity is equally important in GC, particularly around the port, and it is much lower in LP. There is a small industrial sector in GC, focused on agri-food production, light manufacturing and cement (Hernández Torres, 2003). The touristic activity in GC is mainly beach tourism (Cruz et al., 2011), being concentrated in the south of the island, receiving 4,223,679 visitors in 2016 (http://estadisticas.tourspain.es). In contrast, LP offers a touristic activity focused on rural tourism, hiking, adventure sports and health (Hernández Rodríguez, 2006), with a lower number of visitors (167,838 visitors) (http://estadisticas.tourspain.es). Agriculture is still important in some rural districts of GC, although to a lesser extent than years ago. The most important crops are banana irrigated intensive and tomato from greenhouses for export. In LP, there is a high specialization in banana crops, but, unlike GC, the intensity and cultivation under plastic (greenhouses) is dramatically lower (Morales Matos and Macias Hernández, 2003).

The Canary Islands is a reduced and fragmented territory where space is scarce, which is a fact that limits land availability for the creation of authorised landfills and other management infrastructures (GOBCAN, 2008, 2015). The distance, with respect to the main treatment and valorisation centres of the collected materials increases the costs and makes it difficult to manage that waste which cannot be treated on the islands. Nevertheless, the Canary Islands has 9 environmental complexes, 9 transfer plants and waste facilities on each of the islands. There is one environmental complex and 4 waste facilities in LP, while there are 2 environmental complexes, 2 transfer plants and 8 waste facilities in GC. Despite the availability of these infrastructures for waste treatment and management, these are not enough to satisfy the demand of waste deposit.

Fig. 2 shows 43.13% of the IL cases located on LP are building and demolition landfills against 52% of IL of this type located on GC, followed by 43 locations (LP:28.10%) and 60 locations (GC:20.97%) with waste derived from mining or extractive activities, soil break-up mainly. Twenty-seven (LP: 17.68%) and twenty-eight (GC: 9.79%) locations are mainly linked to urban waste. In GC, the prevalence of IL with plastic from agriculture is higher, with 38 locations (13.28%) against only 2 locations in LP. IL of other types are comparatively few for both islands: industrial (LP: 2.61%; GC: 2.09%); organic matter (LP: 1.96%; GC: 1.40%); end-of-life tyres (GC: 0.35%); end-of-life vehicles (LP: 0.65%; GC: 1.05%).

3. Materials and methods

3.1. Field work

The location of IL was made in three stages: (i) identification of potential IL through the photointerpretation of orthophotographies with spatial resolution of 0.5 m of the years 2012 and 2015; (ii) On-site inspection of 215 (LP) and 387 (GC) potential locations; (iii) filtering of illegal IL with deposits of less than 2 years of age, finally obtaining 153 (LP) and 286 (GC) locations of IL. To each IL location information related to waste type, degree of accessibility, fencing, access control and existence of deterrents was added (Quesada-Ruiz et al., 2018).

In order to apply the DA and with the aim of distinguishing areas of positive and negative occurrence of IL, the sampling was supplemented by the inclusion of locations non affected sites following the methodology described by (Carranza et al., 2008). To that end, a stratified random sampling was applied fulfilling the following conditions: (i) dissimilarity in the multivariate information with the locations of IL (ii) distances over 1594 m (LP) and 1088 m (GC) to locations of IL on the basis of the analysis of closer distances between the IL, (iii) equal number of areas of negative and positive occurrence (e.g., Breslow and Cain, 1988; Schill et al., 1993). The areas of positive and negative occurrence were codified as 1 s and 0 s, respectively, resulting a total of 302 (LP) and 572 (GC) cases. A training subset and test subset were generated with 75% and 25% of the cases, respectively.

3.2. Feature extraction

As in other works (Biotto et al., 2009; Alexakis and Sarris, 2013; Tasaki et al., 2004, 2007; Doak et al., 2007) the starting point has been a series of specialised features of different types: socioeconomic features like income per capita, population, economic indicators, industrial and of touristic activity indicators; management indicators, as waste type, degree of access, accessibility, security and control; finally, land features, such as elevation and slope. From this initial set of features a subset of derived features was extracted by means of the application of different GIS analysis procedures (Demesouka et al., 2014; Kontos et al., 2005; Şener et al., 2010; Şener and Karag, 2011; Uyan, 2014; Akbari and Rajabi, 2017). Hence, new features were obtained (Table 1) from: the interpolation of the socioeconomic information disaggregated by population centres from the rest of the territory, the application of Euclidean distance (ED) criteria between the location of the IL and the features of interest (Tasaki et al., 2007; Biotto et al., 2009; Jordá-Borrell et al., 2014), the calculation of the densities of the elements of interest through the application of kernel functions (Silverman, 1986) and other searching functions based on distances considering different radiuses (250 m, 500 m, 1500 m) and the extraction of features related with land occupation considering both the calculation of densities and the distance to a given land use. Finally, the normalised difference vegetation index (NDVI) was obtained from a SPOT-5 image of 31st August 2014 (Silvestri and Omri, 2008). Each feature was standardised, rasterised and resampled at a spatial resolution of 10 m. The values of all the above mentioned features were extracted for the locations of positive and negative IL occurrence.

3.3. Multivariate analysis

To predict IL potential occurrence, both 0s and 1s were used in the DA, and the features which determine the appearance of 1s against 0s were identified. The independent features which are necessary to reach the best discrimination among areas of positive

Table 1
Feature subset used for the mapping of IL potential occurrence in Gran Canaria or La Palma.

Short name	Long name	Unit of measure	Short name	Long name	Unit of measure
C_TYPE	Cadastral plot type		E_PRAR	ED to natural protected areas	m
D_ARCC	Impervious cover transition density (1990–2012)	km^{-2}	E_RAVI	ED to cliffs	m
D_BUIL	Buildings density	km^{-2}	E_ROAD	ED to roads	m
D_GRHO	Greenhouse density	km^{-2}	E_SPOI	ED to sport infrastructures	m
D_ROAD	Road density	km^{-2}	E_URAR	ED to urban areas	m
E_AGAR	ED to agricultural areas	m	P_NDVI	NDVI index	Unitless
E_COAS	ED to coast	m	P _SLPE	Slope	%
E_GRZO	ED to green zones	m	H_DPPA	Population density	km^{-2}
E_INAR	ED to industrial areas	m			

occurrence and negative occurrence were determined by using the forward step-wise regression method. This model with fewer variables was compared to the model which uses all the features through the analysis of ROC curves (see Section 4.2). The standardised coefficients together with the centroids of the LP discriminant function (0s:1.634; 1s:−1.634) and that of GC (0s: 1.387; 1s:−1.387) were used to determine the magnitude and the sign of the relations between the features and the occurrence of IL. The canonical discriminant function for each island was built as a linear combination of the independent features chosen to distinguish between both sets (Huberty, 1994):

$$D = c + b_1 * x_1 + b_2 * x_2 + \ldots b_n * x_n$$

where *D* is the discriminant score, *c* is a constant, *b* is the coefficient of the canonical discriminant function and x is the independent feature.

The suitability of DA was evaluated on the basis of the eigenvalue, the canonical correlation and the Wilks Lambda statistic, obtaining values of 2.694 and 1.932; of 0.854 and 0.812; and of 0.271 and 0.341 for LP and GC, respectively. The models obtained for both islands were statistically significant at a confidence level of 99%. The discriminant function for each island was applied from the set of selected features in a GIS environment to obtain the mapping of the IL potential occurrence of each island.

3.4. Assessment of the accuracy of the applied model

A ROC analysis was carried out from the test subset to evaluate the performance of the global and forward step-wise DA models. The ROC curves consider the ratio of true positives (TPR) and the ratio of false positives (FPR). Generally, the FPR is represented on the x axis against the TPR, which is represented on the y axis. The results are apparent in a pair (TPR, FPR) also known as "sensitivity (TPR)" and "specificity (1-FPR)". The Area Under the Curve (AUC) was used to determine the accuracy of the DA models. A value of AUC of 1 is considered perfect and a value of AUC equal to 0.5 is considered as a random guessing (Bradley, 1997).

In order to transform the mapping of IL potential occurrence (continuous feature) into a categorical map of affected and non-affected areas a method based on the success rate was applied. It is important not to overestimate the potential areas of IL potential occurrence, as the costs of activation and application of prevention measures before possible landfilling may be very high. The success rate is defined as the percentage of the test subsample of IL outlined correctly within the IL potential occurrence areas (ratio of true positives; TPR), considering different thresholds of affected area (Agterberg and Bonham-Carter, 2005). The thresholds of percentages of potential occurrence areas were classified from the discriminant scores and their value, with respect to the centroids. According to the success rate, different binary maps of IL potential occurrence were proposed, with the aim of quantifying the accuracy of the identification of IL minimizing the affected area.

4. Results

4.1. Discriminant analysis

The DA model of LP explained 100% of the variance of the data from the 9 selected features of the initial 22 (Table 2). The features, which according to the standardised coefficients had a more important contribution, were: distance to population centres, density of communication routes, distance to green[1] zones and distance to agricultural areas (Fig. 3). Therefore, the greater the density of communication routes, the smaller the score in the discriminant function, and, consequently, a greater tendency towards the fact that an area of the map be predicted as having a high IL potential occurrence according to the value of the canonical discriminant score. The feature E_GRZO showed a negative coefficient. With relation to the centroids of the set, for cases with equal scores in the rest of features, the areas which obtained a smaller value in the E_GRZO feature would have a greater score in the discriminant function and would be predicted as 0s. In contrast, the E_AGAR feature showed a positive coefficient. Therefore, the areas with a smaller value in the E_AGAR feature and equal score in the rest of features, would have a smaller score in the discriminant function and would be predicted as 1s.

Table 2
Discriminant Analysis model. La Palma.

	Canonical discriminant function coefficient	Standardised canonical discriminant function coefficient
D_ROAD	−0.030	−0.555
E_GRZO	−0.027	−0.472
D_ARCC	−0.015	−0.294
E_AGAR	0.015	0.207
P_SLPE	0.015	0.214
P_NDVI	0.016	0.280
H_DPPA	0.049	0.282
E_URAR	0.033	0.474
E_PRAR	0.029	0.574
Constant	*−1.641*	

The IL of LP presented a smaller distance to agricultural and urban areas. The E_PRAR feature was introduced in the DA model. However, there is no cause-effect relationship with the occurrence of IL. Its inclusion could be due to the multiple areas and the fact of almost the whole island being a natural protected area. Nevertheless, the same does not happen with the E_GRZO feature, which could be seen as a feature which, once its value is diminished, inhibits the occurrence of IL. Hence, the DA tended to predict the areas with less vegetation (P_NDVI) and slope as IL occurrence. On the other hand, the locations that combine high land cover transition densities, high communication route densities and low values of population density could take place at a higher IL potential occurrence.

The DA model of GC (Table 3) showed that 100% of the data variance was explained by 10 features selected from the 25 initial features. The features that according to the standardised coefficients had the most important contribution were: distance to the coast, greenhouse density, distance to industrial areas, building density and transition to artificial surfaces between the years 1990 and 2012. Therefore, the smaller the distance to the coast, the smaller the score in the discriminant function, and, consequently, a greater tendency to predict a high IL potential occurrence. The D_GRHO feature showed a negative coefficient. Additionally, if centroids were considered the areas which obtained a smaller value in the D_GRHO feature would have a greater score in the discriminant function and therefore, would be predicted as 0s (see Section 3.3). The IL showed a smaller distance to roads, urban and industrial areas, and a greater distance to natural protected areas. On the other hand, the DA tended to predict as the greater IL potential occurrence, urban cadastral surfaces, areas close to sport facilities, and the areas with the highest building densities and land cover transitions to artificial surfaces between the years 1990 and 2012 (Fig. 7A). It is worth mentioning that socioeconomic features such as income per capita did not turn out to be decisive in the DA of both islands, and might be due to the level of municipal aggregation of the statistics on incomes.

As a result of the application of the canonical discriminant functions for each DA model, the IL potential occurrence maps were

[1] For interpretation of color in Fig. 3, the reader is referred to the web version of this article.

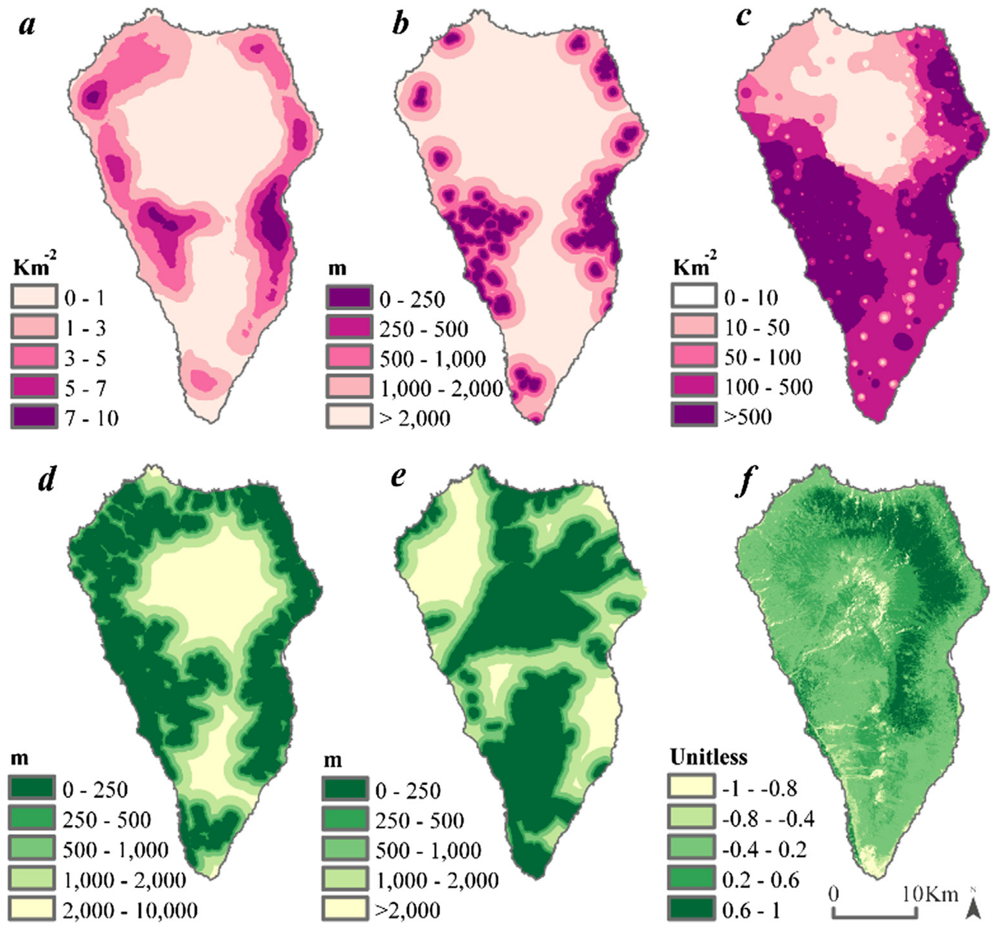

Fig. 3. Main features selected by the Discriminant Analysis method for the mapping of IL potential occurrence in La Palma. (a) Density of road network. (b) Urban areas. (c) Population density (d) Distance to agricultural areas (e) Distance to protected areas (f) Normalized Difference Vegetation Index (NDVI).

Table 3
Discriminant Analysis model. Gran Canaria.

	Canonical discriminant function coefficient	Standardised canonical discriminant function coefficient
D_GRHO	−0.042	−0.416
C_TYPE	−0.01	−0.368
D_ARCC	−0.017	−0.197
E_PRAR	−0.025	−0.195
E_URAR	0.020	0.205
E_SPOI	0.017	0.200
E_ROAD	0.089	0.267
D_BUIL	0.034	0.231
E_INAR	0.006	0.157
E_COAS	0.027	0.487
Constant	−1.019	

obtained (Fig. 4). Fig. 5A shows the IL potential occurrence map in LP. The areas with a higher IL potential occurrence were located in nearly the whole coastline, in the east sector and in the central area of the west sector of the island, these areas corresponding to the areas with the highest population density (Fig. 3C). On the other hand, the zones corresponding to natural protected areas (Fig. 3E) showed a low or very low IL potential occurrence. Fig. 5B shows the IL potential occurrence in GC. As with LP, the areas with a greater IL potential occurrence are located on the coastline. However, there is a greater potential on those zones close to the east communication axe and on the zones with greater agricultural activity under plastic of the southeast, west and north-east (Fig. 4E).

4.2. Accuracy of the IL potential model

Fig. 6 shows the result of the ROC analysis considering the TPR and FPR for the DA models (global and step-wise). In both cases, the reduction of the feature space through the application of a step-forward algorithm had a performance similar to the global model. In the case of GC (Fig. 6A) the AUC values for the step-forward DA model was of 0.973 and for the global model, 0.979. In the case of LP (Fig. 6B) the AUC values for the step-forward DA model was of 0.967 and for the global model, 0.966. For both islands, the step-forward model was chosen as it reduces the number of features, improving its interpretability while keeping its accuracy (Figs. 6 and 7).

The success rate was computed to evaluate the suitability in the selection of the threshold values in obtaining a binary map of positive and negative occurrences. Fig. 7A and B show the success rate of the estimation of areas of IL potential occurrence with relation to the test sample. If 21.95% of the affected area in LP was to be considered, a success rate of 81.58% would be obtained, while if 20.10% was to be considered, the success rate would be of 87.32% in GC. Figs. 8 and 9 show the maps of affected areas considering different success rates. The areas with greater IL potential are mainly located in the east, west and south sectors of LP, coinciding with the areas of greater urban and agricultural development. On the other hand, the high IL potential in GC occurs in the coastal belt

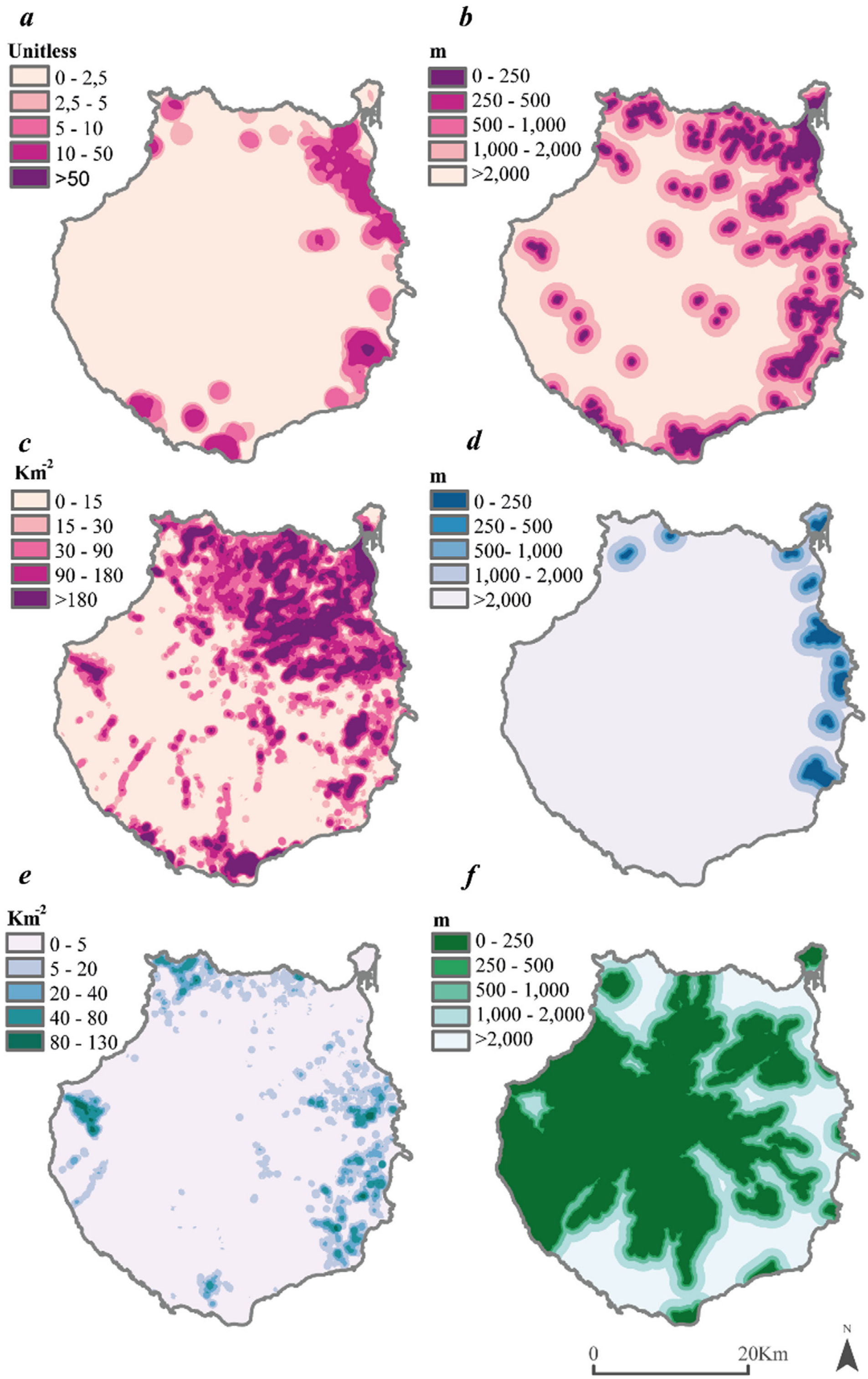

Fig. 4. Main features selected by the Discriminant Analysis method for the mapping of IL potential occurrence in Gran Canaria. (a) Density of cover transition to impervious. (b) Urban areas. (c) Density of buildings. (d) Distance to industrial areas (e) Density of greenhouses (f) Distance to protected areas.

and close to population centres. However, there was a higher potential in the northwest, east and southeast of the island.

5. Discussion

The IL have been researched in continental territories mainly such as: Germany and Austria (Allgaier and Stegmann, 2006), Australia (Glanville and Chang, 2015b), Slovenia (Matos et al., 2012), peninsular Spain (Jordá-Borrell et al., 2014; Lucendo-Monedero et al., 2015), Greece (Alexakis and Sarris, 2013), Italy (Biotto et al., 2009; Silvestri and Omri, 2008)), Ireland (Doak et al., 2007), Romania (Alexakis and Sarris, 2013), Serbia (Zelenović et al., 2012), Vietnam (Duc Luong et al., 2013), but ignoring the islands. Most of those studies are focused on the location or the analysis of their occurrence (Biotto et al., 2009; Glanville and

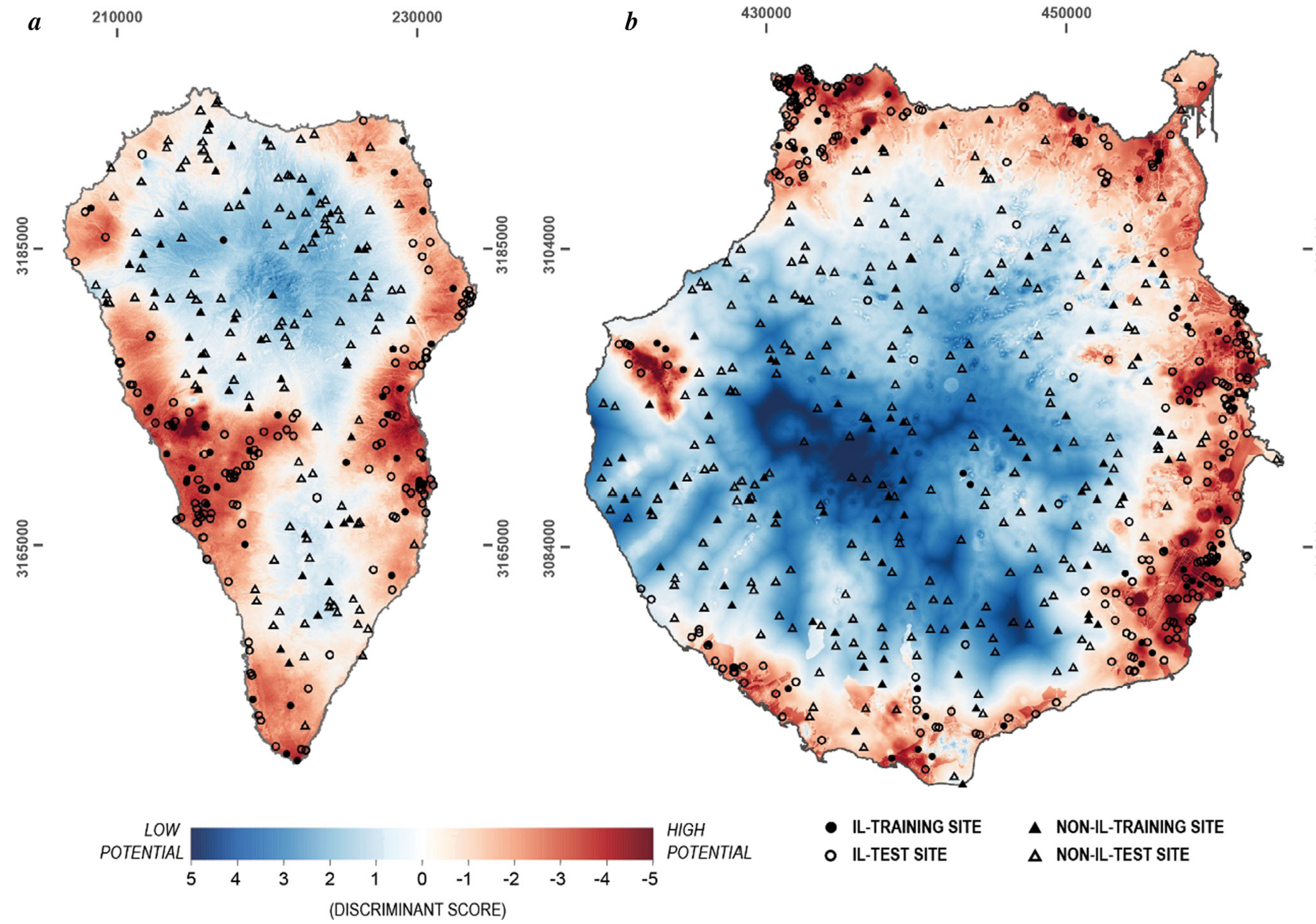

Fig. 5. Map of illegal landfill potential occurrence in a) La Palma and b) Gran Canaria.

Chang, 2015a; Jordá-Borrell et al., 2014; Lucendo-Monedero et al., 2015; Silvestri and Omri, 2008). However, the works focusing on islands are scarce, among which the characterization of IL in Great Britain (Liu et al., 2018), the study of the impact of population habits in the proliferation of IL in Japan (Matsumoto and Takeuchi, 2011) and the analysis of the occurrence of IL in Taiwan (Chu et al., 2013) stand out, being very different territories to the Canary Islands in terms of extension and socioeconomic features. There are numerous socioeconomic and environmental features in the Canary Islands, such as high population density, relative isolation, surface unavailability and scarcity of human and financial resources, that have had a negative impact on waste management (UNEP,1998). These features together with their high ecological and touristic values, make it necessary to adopt initiatives which allow to reduce those impacts. Hence, the analysis and characterization of the IL is essential to identify those human activities related to waste generation, especially those involved in the deposit of illegal long-lived waste. The mapping of the IL potential occurrence has been tackled from two different perspectives: the stochastic model of data through a multicriteria analysis (Biotto et al., 2009; Chu et al., 2013; Matos et al., 2012), and the application of multivariate statistical methods to generate mechanistic models from data-based learning, such as binary logistic regression and PCA (Jordá-Borrell et al., 2014; Lucendo-Monedero et al., 2015; Quesada-Ruiz et al., 2018). The latter allow to identify the features related to their appearance. Tasaki et al. (2007) and Jordá-Borrell et al. (2014) used PCA to select the features related to the appearance of IL from the location of the existent IL. Unlike previous works, we propose to use DA to identify causal relationships between the explanatory features and the occurrence of the illegal landfills for the first time, given most techniques which have been applied so far only allow to identify associations between features.

All previous studies identified population and distance to elements of interest as the distance to industrial zones as determining factors. In other works, authors emphasised the relationship between the proliferation of IL and the absence of waste treatment facilities, (Jones, 2008; Kim et al., 2008; Matos et al., 2012; Matsumoto and Takeuchi, 2011; Mohee et al., 2015; Tasaki et al., 2007; Uricchio et al., 2010) or low accessibility to them (Matos et al., 2012; Matsumoto and Takeuchi, 2011; Renou et al., 2008; Salleh and Tsudagawa, 2002; Tasaki et al., 2007; Uricchio et al., 2010); and the cost of legal waste deposits (Ichinose and Yamamoto, 2011; Liu et al., 2018; Tasaki et al., 2007). This research suggested the existence of a relationship between waste generation from building and demolition due to the urban sprawl and housing bubble of the first decade of the 21st century, given spatial relationships are observed between spaces with high cover transitions and the occurrence of IL. As far as the authors are concerned, there is no other instance, at least in Europe, in which house building has reached the levels it has reached in Spain (Díaz Parra and Romano, 2016; Cruz, 2014; Fernández-Tabales and Cruz, 2013). In the case of the Canary Islands, this problem worsens due to the joint development of the house market and the touristic market (Garcia-Cruz, 2016). Similarly, our study identified distance to urban areas as a relevant feature for the identification of IL potential occurrence areas in LP and GC. However, the features related to communication routes, both distance and density, had more importance in studies focused on Slovenia (Matos et al.,

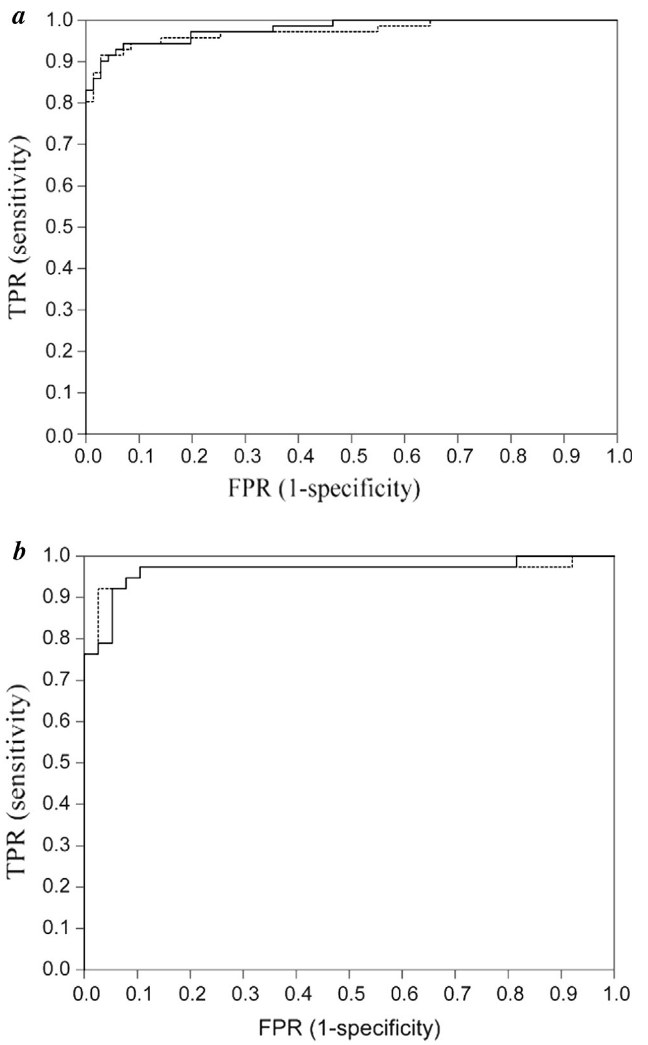

Fig. 6. ROC curves. (a) Gran Canaria (b) La Palma. Dotted line: Global method. Continuous line: Forward Method.

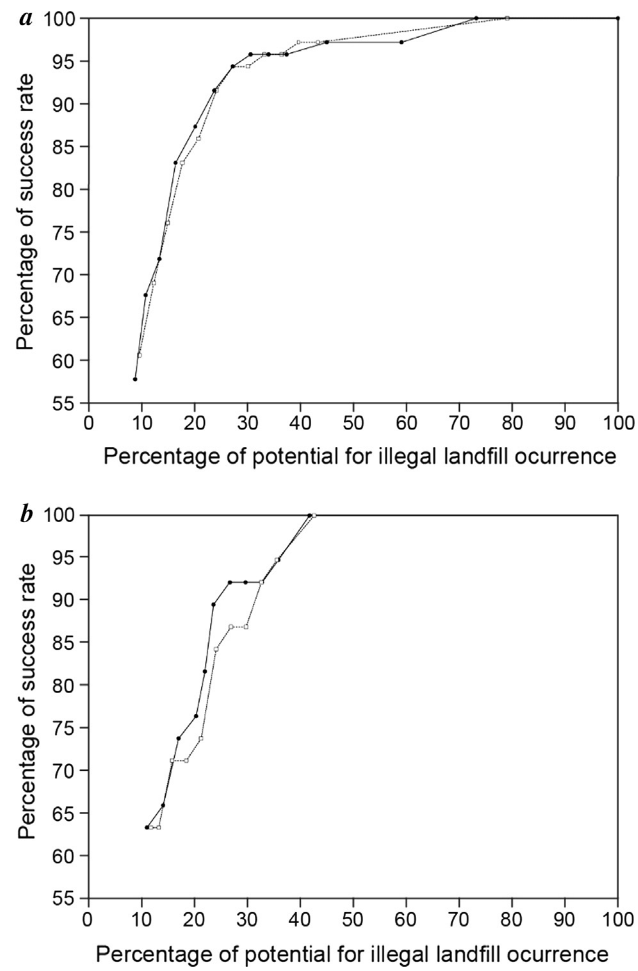

Fig. 7. Success rate. (a) Gran Canaria (b) La Palma. Dotted line: Global method. Continuous line: Forward Method.

2012) and the northeast of Italy (Biotto et al., 2009), probably due to a higher accessibility of the Canary Islands. Socioeconomic features such as rustic property tax, income per capita, wholesale trade index, economic activity index or industrial index, were not as relevant as other studies: Tasaki et al. (2007) and Matsumoto and Takeuchi (2011) where the unemployment rate in Japan was used; Jordá-Borrell et al. (2014) who used the income per capita in Andalusia (Spain SE); and Gorsevski et al., (2012) and Al-Khatib et al. (2007) who associated the municipal income rate with the higher occurrence of IL in Turkey. These differences might be due to the geographic scale and to the disaggregation of official socioeconomic information into local administrative units (NUTS3). Unlike the studies by Tasaki et al. (2007), Matsumoto and Takeuchi (2011), Jordá-Borrell et al. (2014), Gorsevski et al. (2012) and Biotto et al. (2009), land orography and the distance to the coast were determining features, as they allowed to remove the inaccessible areas from both islands. The NDVI allowed to remove inaccessible forest areas from the island of LP. On the other hand, the analysis of the GC case showed the need to consider the features of the agricultural holdings and their potential to generate certain waste types as plastics in greenhouses. The feature "distance to agricultural zones" was of greater relevance due to the smaller presence of this type of agricultural holdings in LP. Furthermore, the influence of the features related to population are of greater importance in LP, due to the smaller demographic and building pressure, the lower accessibility and the greater presence of forest areas and natural protected areas. In contrast, the occurrence of IL on the island of GC is more influenced by the transition among covers and the distance to industrial areas due to the process of urban sprawl and the greater economic activity of GC's coastal belt.

IL potential occurrence has been measured on the basis of the score obtained by fulfilling different criteria (multicriteria analysis; Biotto et al., 2009; Matos et al., 2012) and the likelihood of landfill occurrence on the basis of linear relationships established by multivariate regression (logistic regression; Lucendo-Monedero et al., 2015). The former does not consider the negative occurrences (no landfills) in the modelling, being possible for the affected areas to be overestimated. The latter considers both positive and negative occurrences, obtaining continuous potential values between 0 and 1. However, it is frequent to assign an arbitrary potential threshold value of 0.5 to differentiate between areas which are potentially affected and not affected. There are alternatives to the arbitrary choice of the potential threshold such as the ROC curves analysis where the balance between false positives (overestimation) and false negatives (underestimation) is sought (Chu et al., 2013; Rodriguez-Galiano et al., 2014; Tasaki et al., 2007). Additionally, in this work the use of the success rate was proposed as a complementary method to ROC to differentiate affected areas maximizing the accuracy of positive occurrences while minimizing the

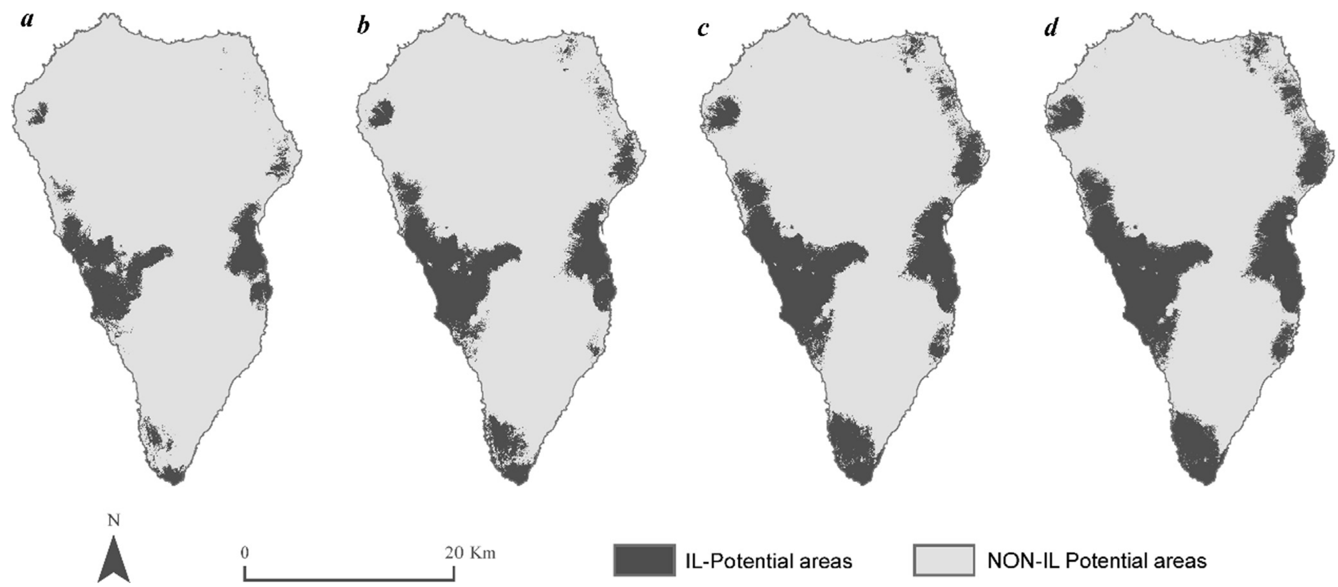

Fig. 8. Illegal landfill potential occurrence maps considering different affected areas' thresholds in La Palma. (a) 10.99%. (b) 16.98% (c) 21.95%. (d) 23.58%.

affected area. This might be an alternative to applying arbitrary thresholds such as those used by Biotto et al. (2009) and Lucendo-Monedero et al. (2015). This method has been successfully applied to mineral prospective studies (Carranza et al., 2008; Rodriguez-Galiano et al., 2015), where, as it is the case of our study, it is not only important not to underestimate the affected area, but also not to overestimate it to reduce the scouting costs, or surveillance costs in our case.

The main limitations in the development of our methodology relies in the lack of official statistics. An extensive and time consuming fieldwork was necessary. Additionally, the shortage of suitable 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; limits the capabilities to understand and model the IL occurrence. Hence, the IL modelling studies need the generation of a comprehensive database with the aim of including a large amount of features which are able to explain most of data variance. This effort to include as many features as possible involves an increase in its complexity. On the other hand, the inclusion of a high quantity of similar features (i.e. distance or density features) increases redundancy or correlation among features, and may negatively affect the accuracy of models due to the Hughes effect (Bellman, 2003; Rodriguez-Galiano et al., 2012, 2018). The DA method used in this study has allowed eliminating redundant features by applying a forward algorithm. Hence, models with 10 features of 25 in GC and 9 features of 22 in LP, presented the highest accuracy and simplicity. However, all the above mentioned models (multicriteria analysis, PCA, logistic regression and DA) are linear methods and, therefore, unable to recognize more complex relationships among features. Accordingly, new methods based on machine learning such as Classification and Regression Trees, Random Forest and Support Vector Machines (Rodriguez-Galiano and Chica-Rivas, 2014) open new lines of research in the modelling of landfills as they can be used as wrappers for feature selection, and they are non-parametric and non-linear methods (Rodriguez-Galiano et al., 2018).

6. Conclusions

DA allowed to select the features and the analysis of IL potential occurrence in LP and GC. The DA model for LP reduced the feature space from 22 to 9, among which NDVI, slope, density of communication routes, the changes in land use and proximity to urban areas stand out. The reduction of feature space for the GC case was of 25 to 10, among which the influence of the coastline, the transitions in land use to artificial covers, greenhouse density, and proximity to urban areas and distance to industrial zones stand out. The socioeconomic features used could not be adequate due to their level of aggregation and their low spatial variability in both islands, with an evident need to incorporate additional information. The areas with the highest IL potential are located in the east and west sectors of LP and in the northwest, east and southeast of GC, coinciding with the most developed zones, both agricultural and urban, and the coastal belt and the zone of influence of urban areas respectively. Additionally, this research suggests the existence of a relationship between waste generation from building and demolition due to the urban sprawl and housing bubble of the first decade of the 21st century. The ROC method allowed to validate the maps products which discriminated between potential and non-potential areas of IL occurrence. In the case of LP the AUC values for the step-forward DA model was of 0.967 and for the global model, 0.966. In the case of GC the AUC values for the step-forward DA model was of 0.973 and for the global model, 0.979. In both cases, the step-forward DA models were selected. The success rate, a new method for IL mapping, made it possible to reach a balance between the accuracy in true positive occurrences and the percentage of affected area. 81.58% and 87.32% of IL were correctly identified considering a 21.95% and 20.10% of the affected area in LP and GC, respectively.

The lack of official statistics limited the IL modelling and the generation of a comprehensive database for this target. The waste volume in landfills should be considered, given the presence or absence of landfills presents limitations as IL of different magnitude are considered at the same level. Other aspects such as the punitive and deterrence measures and monitoring policies play on the part of local governments, community participation in the prevention of IL, the degree of public awareness and their possibilities to access waste treatment infrastructures, in waste generation should be seen to complement the study of IL occurrence. Likewise, the risk of IL for the touristic activity and natural heritage should be assessed. In addition, more sophisticated feature selection techniques such as machine learning or even the simulation of future scenarios could be explored in future works.

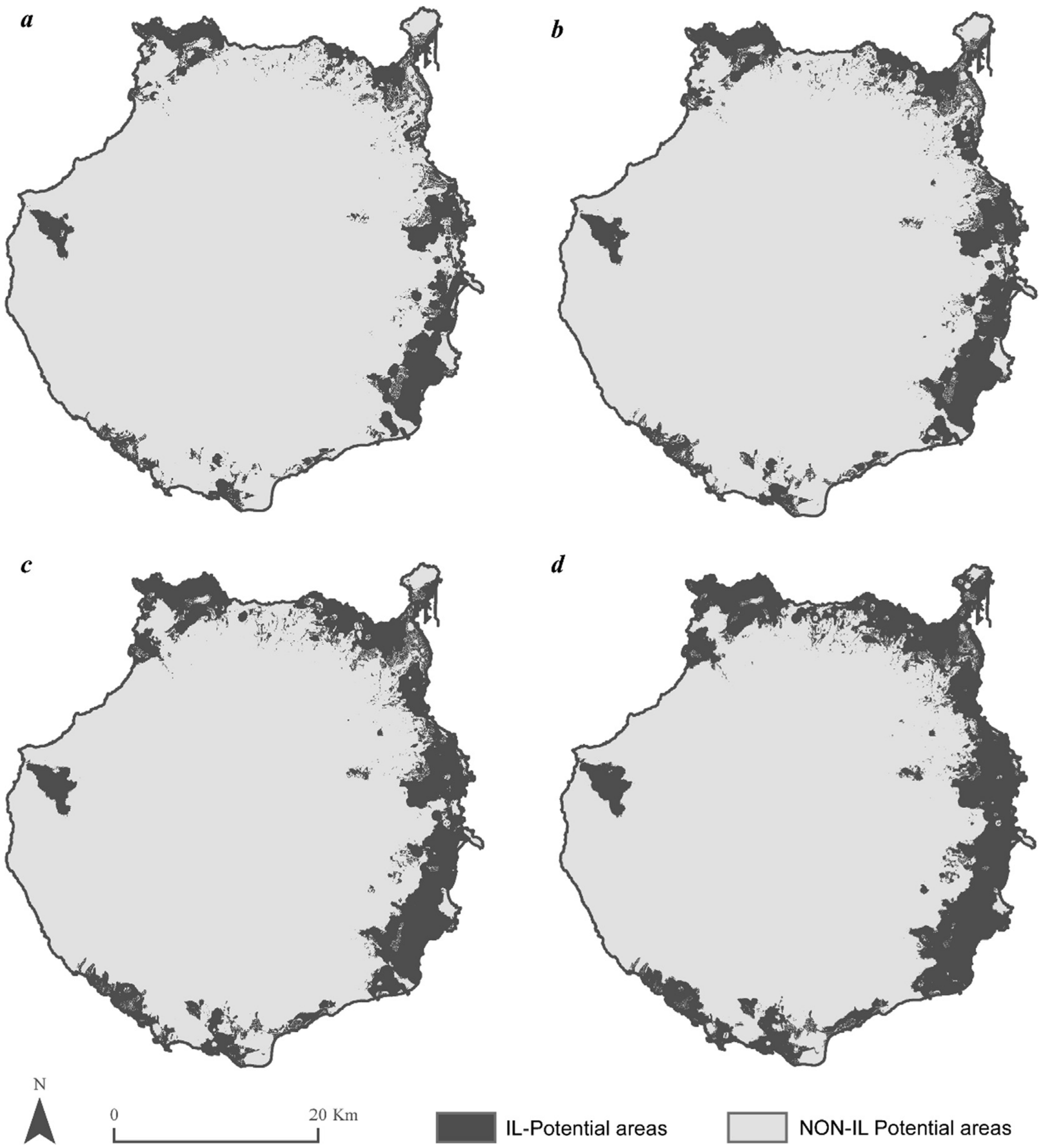

Fig. 9. Illegal landfill potential occurrence maps considering different affected areas' thresholds in Gran Canaria. (a) 10.73%. (b) 13.33% (c) 10.38%. (d) 87.32%.

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