Identifying the main physical and socio-economic drivers of illegal landfills on the island of Gran Canaria, Spain.

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Abstract

The proliferation of illegal landfills (IL) has negative impacts on the environment and the economy, especially in both ecologically sensitive and touristic areas. This work focuses on the characterisation of illegal landfills located on the island of Gran Canaria. 287 IL were obtained through fieldwork and the visual interpretation of digital orthoimages at a spatial resolution 0.5 m from 2012 and 2015. This information was included in a geospatial database together with a set of 177 potential explanatory features of different types: waste type, surveillance and control, socioeconomics, accessibility, distance to elements of interest, visibility and terrain features. Multivariate analyses such as exploratory analysis (EA), factor analysis (FA) and discriminant analysis (DA) were applied to assess the degree of association between the explanatory features and IL occurrence. FA explained a cumulative variance of 81.83% considering 6 factors (Kaiser-Meyer-Olkin test: 0.71). DA showed a canonical correlation of 0.78, and lead to discrimination between affected and unaffected areas by using the distance of feature types to elements of interest, such as: industrial areas, large commercial areas and coastline. Additionally, FA identified the above features as the main drivers of IL occurrence.

Keywords: Illegal landfill, factor analysis, discriminant analysis.

1. Introduction

The European Parliament directive on waste (Directive 2008/98/CE, 2008) defines a landfill as a waste disposal site for the deposit of the waste onto or into land. Despite the above directive not providing a definition for an illegal landfill (IL), the directive on environmental liability with regard to the prevention and remedying of environmental damage (Directive 2004/35/CE, 2004) establishes that unmanaged waste must be managed, including its collection, transport, recovery and disposal. Furthermore, it requires measures to prevent and evaluate environmental damage to plan for its remedy. On the other hand, the autonomous regions of Spain (NUTS 2) consider illegal landfills as those areas that are affected by deposits of waste, without any type of management or control, which exceed 2,000 m^2 for more than two years. Thus, this paper focuses exclusively on IL with these features.

The problem of the emergence of illegal landfills has been addressed principally in mainland territories such as: Italy (Silvestri & Omri, 2008), France (Biotto et al., 2009), Slovenia (Matos & Kranjc, 2012), Greece (Alexakis et Sarris, 2013), and Spain (Jordá-Borrell et al. 2014), neglecting island areas. Gran Canaria, with its 840,000 inhabitants, is the second-most populous island of the outermost region of the Canary Islands. Furthermore, it is next to the island of Tenerife, which has the highest economic and touristic weight of the archipelago, having received 4,223,679 visitors in 2016 (http://estadisticas.tourspain.es), thereby establishing itself as one of the most important tourism destinations in Spain and on an international level.

This research focuses on the characterisation of factors that have an influence on locating IL on the island of Gran Canaria, and in the prediction of potential areas on the island. It will therefore be possible to improve the enforcement of prevention and recovery policies for damage by environmental agents.

2. Methodology

2.1 Fieldwork

The process of locating IL was carried out in three stages: i) Identification of potential IL through photointerpretation of orthoimages at a spatial resolution of 0.5 m from 2012 and 2015; ii) Field inspection of 387 potential sites; and iii) Sorting IL from deposits that have existed for less than 3 years, thereby obtaining 286 IL sites. Information referring to the waste type, degree of accessibility, fencing, access control and the presence of deterrent measures was incorporated for each IL site.

The sample is supplemented by the inclusion of unaffected sites where no IL were present, following the methodology described by Carranza et al. (2008). To this end, a random sampling that met the following conditions was applied: i) distance of greater than 1088 m from IL sites, ii) equal number of unaffected and affected areas. Affected and unaffected areas were coded with a value of 1 or 0, respectively, which resulted in a total of 572 cases.

2.2.Feature extraction

Similar to other works (Tasaki et al., 2006; Silvestri & Omri, 2008; Biotto et al., 2009, Alexakis & Sarris, 2013), this study began with a series of different types of spatial features: socioeconomic features such as per-capita income, population, indicators of tourism activity, industry and economic activity; management features such as waste type, degree of access, accessibility, security and control; and finally terrain features, such as elevation and concavity. Based on this initial set of features, a subset of derived features was obtained through the application of different GIS analysis procedures. Criteria that were taken into account include: the Euclidean distance (ED) between the IL site and the features of interest (Tasaki et al., 2006; Biotto et al., 2009; Jordá-Borrell et al., 2014), and densities within three search radio (250 m, 500 m, and 1500 m) (Table 1). The densities were obtained by applying the kernel functions and other search functions based on the distance to a particular radius. Finally, in order to extract the features related to land use, both the density calculation and distance to a specific land use were considered.

Each feature was standardised, rasterised and resampled at a spatial resolution of 10 m. The values for all previously mentioned features were extracted for the affected and unaffected IL sites.

2.3. Exploratory and multivariate analysis

An exploratory analysis of the data was performed and IL sample outliers were filtered. The multivariate analysis techniques, factor analysis (FA) and discriminant analysis (DA) were applied in a SPSS 24.0 software environment. The FA was applied with the objective of determining the relationship between the different features (Cuadras, 2014), and the DA to predict the potentiality of IL occurrence.

Principal component analysis (PCA) was selected as the FA method. The PCA was only applied to values of 1. Features were grouped into factors considering eigenvalues greater than 1. The multivariate normality of the features and their interrelation were tested using the Kaiser-Meyer-Olkin test for sampling adequacy (KMO: 0.711) and Bartlett's sphericity test, respectively. The ratio chosen for the PCA of 10 cases per feature was respected. The factors were rotated using

Table 1. Selected features

Short name	Long name	Unit of measurement	Short name	Long name	Unit of measurement
C_TYPE	Cadastral plot type		**E_PZ35**	ED to pit (35-metre kernel)	m
D_ARCC	Impervious cover transition density (1990–2012)	km^2	**E_RAVI**	ED to cliffs	m
D_BUIL	Density of buildings	buildings / km^2	**E_REEQ**	ED to leisure equipment	
D_CC00	Cover transition density between (2000–2006)	km^2	**E_ROAD**	ED to roads	m
D_GRHO	Density of greenhouses	greenhouses / km^2	**E_SPOI**	ED to sports infrastructure	m
D_ROAD	Road density		**E_TELI**	ED to telecommunications infrastructure	
E_COAS	ED to coastline	m	**E_URAR**	ED to urban areas	m
E_COME	ED to commercial areas	m	**E_WAYS**	ED to paths	m
E_ENEQ	ED to energy infrastructure		**F_MDTG**	Elevation	m
E_GRZO	ED to green zones	m	**H_DPPA**	Population density	population / km^2
E_HIGH	ED to motorways	m	**H_IBIR**	Rustic property tax	€ / m^2
E_IELE	ED to features of interest	m	**H_RPCD**	Per-capita income	€ / person
E_INAR	ED to industrial areas	m	**I_COMA**	Wholesale trade index	%
E_MURC	ED to municipal recycling centres	m	**I_ECAC**	Economic activity index	%
E_PRAR	ED to protected areas	m	**I_INDU**	Industrial index	%

the quartimax method. It was ensured that a minimum of 2 features were present per factor, and that each feature had correlations equal to or greater than 0.40.

In the DA, just as many 0s were used as 1s, and the features that condition the appearance of 1s instead of 0s were identified. The number of independent features required to achieve a greater discrimination between affected and unaffected areas was determined using the forward selection inclusion method. The standardised coefficients, along with the centroids of the discriminant function (0s: 1.49; 1s: -1.49) were used to determine the sign and magnitude of the relationships between the features and IL occurrence. The canonical discriminant analysis was constructed as a linear combination of the independent features selected to distinguish both groups:

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

Where D is the Z-score, c is a constant, b is the canonical discriminant function coefficient and x is the feature.

The suitability of the DA was evaluated based on the eigenvalue (2.198) and the canonical correlation (0.829). On the other hand, both the significance (0.00) and the Wilks' lambda distribution (0.313) were analysed.

The discriminant function was applied to each of the selected features in a GIS environment in order to obtain the mapping for the potentiality of IL occurrence.

3. Results and discussion

3.1. Descriptive statistics

52% of IL cases located on the island of Gran Canaria are deposits of construction and demolition waste (CDW), followed by 60 sites (20%) containing waste derived from mining or extraction activities (MEA), primarily from the ploughing of terrain. 38 sites (13%) were mainly linked to plastics and 28 (9%) contained urban waste.

The EA showed that 100% of IL are located less than 1000 m from farming areas. 75% of IL are located less than 500 m from cover with a high densities of transitions in use between 2000 and 2006, less than 420 m from a regional motorway or less than 700 m from a cliff. 50% of IL occur at a radius of 500 m from between 59 and 250 buildings, and between 15 and 40 greenhouses; or they are located less than 1475 m from the coastline.

3.2. Factor analysis

The PCA explained 81.83% of overall variance (Table 2). Of the 6 factors obtained, the first 3 accumulated 52.82% of the data variance. Thus, the first, second and third factors explained 19.84%, 16.54% and 16.44% of the variance, respectively. The fourth and subsequent factors explained the variance to a lesser extent: 12.22% (fourth), 10.03% (fifth), 6.75% (sixth).

The first two factors grouped together features related to the distance to elements of interest. The first factor showed an inverse relationship between the distance to green areas and the distance to large commercial spaces, areas of subsidence and motorways. This could be

Table 2. Principal component analysis model

Factors (1st level of rank)	Initial eigenvalues	Weight %	Features (2nd level of rank)	Weight (correlation)	Rotation sums of squared loadings
				% Variance	**% Accumulated**
F1 Distance to element of interest	4.56	19.84	E_COME	-0.94	19.84
			E_GRZO	0.88	
			E_PZ35	-0.81	
			E_HIGH	-0.69	
F2 Distance to industrial areas	3.80	16.54	E_ENEQ	-0.94	36.39
			E_INAR	-0.93	
			E_REEQ	-0.74	
			E_TELI	-0.66	
			E_MURC	-0.61	
F3 Socio-economic	3.78	16.44	I_ECAC	0.96	52.82
			I_COMA	0.91	
			I_INDU	0.88	
			H_RPCD	-0.64	
			H_IBIR	-0.59	
F4 Distance to coastline	2.81	12.22	F_MDTG	-0.93	65.05
			E_COAS	-0.90	
F5 Density of cover change	2.31	10.03	D_CC00	0.85	75.08
			D_ARCC	0.79	
			H_DPPA	0.63	
F6 Road accessibility	1.55	6.75	E_ROAD	-0.78	81.83
			D_ROAD	0.76	

related to IL occurrence at a distance from the first feature and with proximity to the last three features. Similarly, the second factor comprises the features of distance to: industrial areas, telecommunications infrastructure, electrical stations, recreational equipment, and distance to clean points, and these features could maintain an inverse relationship with IL occurrence.

The third factor grouped together features of a socio-economic nature. IL could be interpreted has having a higher occurrence in populations centres where there are higher levels of economic activity, and wholesale and industrial business. Contrariwise, less per-capita income and value-added tax on goods and rural properties could inversely condition IL occurrence.

The fourth factor grouped together the features of elevation and proximity to coastlines. The areas of lowest elevation and with the least amount of distance to coastline could have a direct relationship with IL occurrence. The fifth factor comprises the features of density in terms of: population, transitions to artificial cover and changes in cover in the period between 2000 and 2006.

Finally, the sixth factor grouped together the features of distance to secondary motorways and roadway density. Unlike other works (Biotto et al., 2009; Matos & Kranjc, 2012), this factor does not have as much relevance when compared with the foregoing factors.

Table 3. Discriminant Analysis model

	Canonical discriminant function coefficient	Standardised canonical discriminant function coefficient
D_GRHO	-0.041	-0.408
C_TYPE	-0.008	-0.292
E_GRZO	-0.014	-0.285
D_ARCC	-0.022	-0.281
E_PRAR	-0.019	-0.141
E_RAVI	0.067	0.183
E_IELE	-0.033	0.190
E_URAR	0.020	0.205
E_SPOI	0.018	0.221
E_ROAD	0.040	0.253
D_BUIL	0.041	0.287
E_INAR	0.013	0.338
E_COAS	0.029	0.538
Constant	*1.274*	

3.3. Discriminant analysis

100% of data variance was explained by 13 features selected from the 30 starting features. Figure 1 shows the mapping of IL occurrence potentiality obtained after applying the discriminant function. According to the standardised coefficient, the features that contributed most significantly were: distance to coastline, density of greenhouses, distance to industrial areas and the cadastral plot type (Table 3).

Thus, the greater the distance to the coastline, the greater the discriminant function score, and consequently, the greater the tendency for a map area to be predicted as having a high potential for IL occurrence. The feature D_GRHO had a negative coefficient. If we focus on the group centroids, it would mean that for cases with equal scores in the remaining features, the areas where lesser D_GRHO value were obtained would have a higher score in the discriminant function, and would be predicted as 0s.

IL were closer to roadways, coastlines, urban centres and industrial areas, and were further from green areas. On the other hand, the DA tended to predict areas with higher densities of surrounding buildings and transitions between cover and artificial surfaces as IL occurrence. It should be noted that socio-economic features such as per-capita income were not decisive in the DA, and may be due to the level of municipal aggregation of income statistics.

4. Conclusions:

Both the FA and DA show how the location of illegal landfills on the island territory of Gran Canaria is not random. The PCA was a first approach in identifying factors and features that are best to include in the DA. This work applies methodologies used in mining studies through the inclusion of cases of unaffected areas (0s) to the IL case study. Therefore, the DA can be applied to map the potentiality of IL occurrence.

The first three PCA factors, which correspond to the features of distance to elements of interest and socio-economic features, explained 52.82% of data variance. The remaining factors, which were of less explanatory significance, corresponded to the distance from the coastline, the density of cover transition and distance from roadways.

The DA reduced the feature space from 31 to 13, amongst which the influence of the coastline, transitions between land use, density of greenhouses, proximity to urban centres, roadways and industrial areas are emphasised. The socio-economic features used may not be adequate due to their level of aggregation and low spatial variability, demonstrating the need to incorporate additional information.

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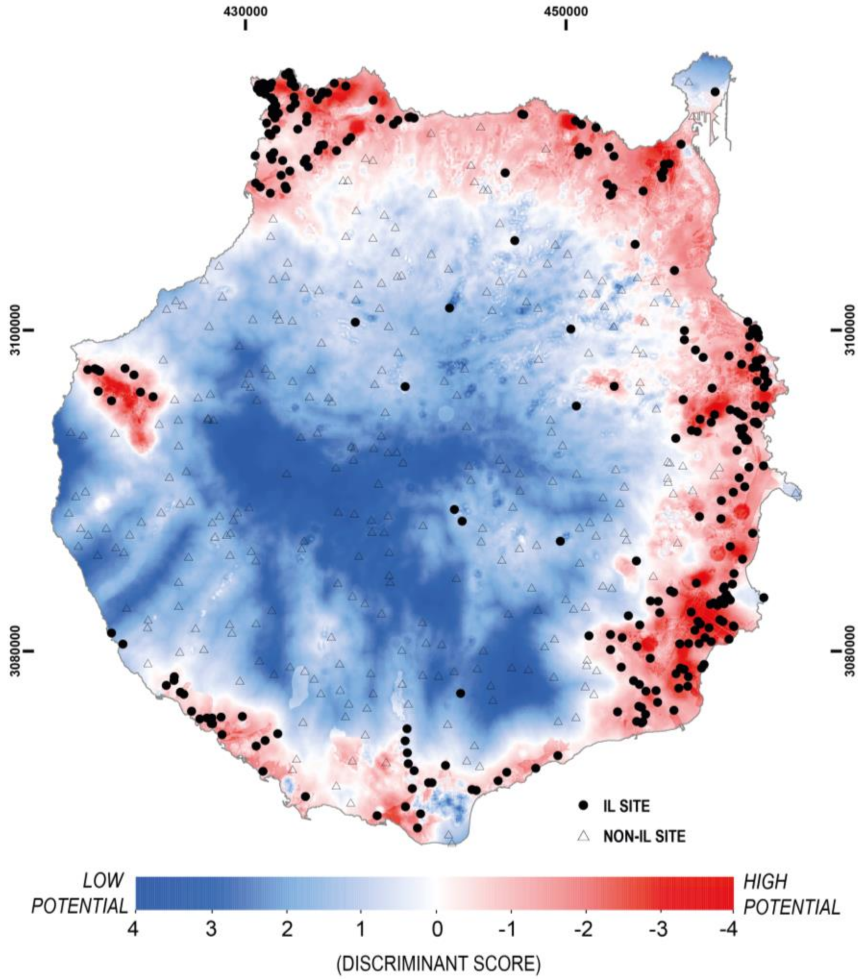

Figure 1. Potential for illegal landfill occurrence

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