Integrated geo-referenced data and statistical analysis for dividing livestock farms into geographical zones in the Valencian Community (Spain)

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1. Introduction

The livestock sector of the Valencian Community (Eastern Spain) has recently experienced a profound change. Generally, this sector has tended towards intensified farming with an increase in the number and size of pig and poultry facilities, characterized by farms with a high level of technology and skilled labour. Farms are independent of the land as a production factor. Thus, there has been a separation between livestock and agriculture.

The absence of previous environmental requirements in this region has produced a high concentration of facilities in some areas, and urban sprawl has resulted in many farms being located in problematic areas close to villages or towns, residential areas and protected areas. Conflicts arising from land use and environmental issues have caused problems in the region for many years (Recatalá *et al.*, 2000). The most recent European Union environmental legislation (Nitrate Directive 91/676/CEE and IPPC Directive 2008/1/EC) and social pressure on food security, environmental pollution and animal welfare protection (Tamminga, 2003) have emphasised these challenges. Therefore, a system was adapted to overcome these conflicts and to establish measures according to the conditions of the territory and the characteristics of the farms. In this context, the Department of Agriculture of Regional Administration developed a strategic plan to establish actions and policies covering different components of the livestock sector.

Consequently, it is necessary to obtain information on the typology, classification, characterization and spatial analysis of farms, which enables the development of a decision support system that allocated priority activities to each territorial space in the region. Riveiro *et al.* (2009) discusses some models and systems developed as support for agricultural planning.

The models developed for Classifying Variable farms use qualitative and quantitative analysis, but these models do not use the geographic component to make a spatial planning of livestock. This study has taken into account the geographical location of the farms, and a combinatorial method of statistical analysis and Geographical Information Systems (GIS), have delimited livestock zones.

Methods for delimiting management zones vary widely in the information and techniques used for creating zone boundaries (Kitchen *et al.*, 2005). Using GIS for suitable delimitation is important to account for the geographical data characteristics and spatial data points. For our purpose, clustering methods were categorised into two groups: statistical and spatial. Statistical clustering methods include partitioning or disjoint algorithms, agglomerative hierarchical algorithms and fuzzy clustering algorithms. Disjoint and hierarchical algorithms have been widely used, either together or separately, for different classifications or separations of groups. In agricultural problems, for example, these types of algorithms have been used for typification, characterising farming systems (Floyd *et al.*, 2003; Köbrich *et al.*, 2003; Ottaviani *et al.*, 2003; Iraizoz *et al.*, 2007), delineating landscapes and/or characterisation zones (Jaynes *et al.*, 2003; Van Eetvelve & Antrop, 2009; Castillo-Rodríguez *et al.*, 2010; Soto &Pintó, 2010), classifying fields according to yield patterns and establishing management zones for precision agriculture (Ortega & Santibañez, 2007). In purpose precision agriculture, fuzzy clustering methods for geographical attributes in different fields have been most widely employed, particularly for delineating management zones (Lark, 1998; Jaynes *et al.*, 2003; Ping & Dobermann, 2003; Kitchen *et al.*, 2005; Yan *et al.*, 2007; Morari *et al.*, 2009; Xin-Zhong *et al.*, 2009). Fridgen *et al.* (2004) developed software for the fuzzy-based delineation of management zones.

In spatial data analysis methods, researchers use techniques to describe spatial distributions, either grouped or dispersed, in terms of global and local spatial association patterns (Saizen *et al.*, 2010). Due to the geographical nature of the data, many of the authors mentioned above (Kitchen *et al.*, 2005; Yan *et al.*, 2007; Morari *et al.*, 2009; Xin-Zhong *et al.*, 2009) have employed these techniques for studies of management zones in precision agriculture when using various spatial analysis tools. Lark (1998) used fuzzy analysis with GIS to create coherent spatial regions.

In addition, the spatial planning of territories involves dividing a geographical area into different units. The partitioning of a geographical group occurs in units of smaller areas to create a new spatial structure that reflects livestock criteria.

Integrating geographical information systems allows access to the data and immediate display of the results, allowing verification of the suitability of the solution (Kalcsics *et al.*, 2005). There are several methods to solve design problems of the territory, but they have limitations. The primary limitations of these models include integrity, compactness and contiguity, with the latter being the most important (Shirabe, 2005). Alternative methods that use spatial information, such as Voronoi diagrams (Moreno *et al.*, 2012), have been applied in various fields of study, such as economics, urban geography, market analysis and resolution optimum location services (Okabe & Suzuki, 1997; Okabe *et al.*, 2000).

In recent years there has been the development of tools in ArcGIS spatial statistics, designed to describe patterns of spatial data (Scott & Janikas, 2005).

The main purpose of this study is to group livestock farms into geographical zones with similar livestock characteristics using multivariate statistical analysis. The results will be presented by using a GIS to generate a new spatial structure that allows livestock spatial planning. In addition, spatial dependency patterns within the livestock sector in each group will be identified and characterised.

2. Material and methods

2.1. Study area

The study area, illustrated in Figure 1, is the entire territory of the Valencian Community, a region located in eastern Spain that belongs to the West Mediterranean area of Europe, with an area of 23250 km^2. More than 4 million inhabitants live in this area, and agriculture is one of the main economic activities. Approximately 44% of the land area is used for agricultural purposes, whereas approximately 52% of the Valencian Community is forest area. There is a large variety of different soil types, ranging from arenosols (AR) to chernozems (CH), passing through fluvisols (FL), calcisols (CL), leptosols (LP), luvisols (LV) and regosols (RG), defined reference soil groups of the World Reference Base for Soil Resources 2014, with varying degrees of degradation (De Paz *et al.*, 2006).

The climate is mainly arid to semi-arid (51% of the territory) with dry, hot summers and rainy autumns. However, in the north, the climate is frequently sub-humid to dry sub-humid with rainy autumns and warm summers influenced by the Mediterranean Sea.

The regional environments differ substantially in terms of topography, landscape and territory use between the inland, intermediate and coastal zones. The inland zone is characterised by pasture, forest, scrub, thicket, towns, extensive wood production, land abandonment and terraces. The intermediate zone includes towns, intensive wood production, dry land uses, urbanisation, and irrigation crops. There are conflicts in land use in the coastal zone next to the Mediterranean Sea, where substantial industry and tourism occurs (Recatalá *et al.*, 2000).

Valencian agriculture is characterised by its diversity. In general, two groups can be distinguished: one group that is based on irrigation near the coastal zone and one group in the intermediate and inland zones where more extreme weather occurs, with low levels of water and less fertile soils. The first group is intensively managed with a specialisation in the production of citrus, fruits and vegetables. The second group specialises in Mediterranean dry crops based on olives, almonds and grapes.

The livestock structure is characterised by two distinct subsectors: extensive and intensive (or landless livestock production systems). The most important livestock sector is the intensive farming of poultry and pigs followed by bovines and rabbits, whose geographical distribution is more uniform throughout the region but is concentrated mainly in the Castellon and Valencia provinces. Extensive livestock farming is comprised of bovine, sheep and goats and occurs particularly in inland areas.

2.2. Step 1 and 2. Data input and GPS and GIS procedures

Data processing was performed using the following sources:

1) A database with all of the farms in the Valencian Community, i.e., 4984 farms with basic information on the numbers and types of animals and their locations.
2) The base cartography of the Valencian Community on a scale of 1:10000 in a shapefile format from the Valencian Cartographic Institute.

This information was processed as shown in Figure 2, which represents the various steps in the process. The following section describes the entire procedure.

In Step 1 (Figure 2), 4984 holdings were registered with a GPS to obtain their coordinates. The process of defining the geographical position of an object, georeferencing or geocoding, simply consists of attributing latitude and longitude values (and possibly altitude) to any sample. For livestock, the coordinates correspond to farm location and can be recorded with a GPS. The use of a GPS delivers the required level of accuracy, particularly if a standard procedure is followed, thereby avoiding any bias associated with employing different operators. These protocols permit the recording of sampling sites within a unified and standardised geodetic reference system (Joost *et al.*, 2010).

Once the UTM (Universal Transverse Mercartor) coordinates were added to the database, a point layer was generated using the ArcMap module in ArcGIS (ESRI, Redlans, CA, USA). The point layer was exported to a file in DBF format for statistical analysis (Step 2 in Figure 2).

2.3. Step 3. Clustering methodology

A cluster analysis was performed in two stages. First, a hierarchical technique was used to determine the cluster range. Second, the observations were then clustered by a disjoint non-hierarchical method, which was used repeatedly to divide the observations in the range of the hierarchical cluster results.

The CLUSTER procedure (using the average method) in SAS was used for the hierarchical analysis. The variables used were the UTM coordinates of each farm. The final analysis included a tree diagram (dendrogram), the Cubic Clustering Criterion (CCC) (Sarle, 1983) and the pseudo T^2 statistic. These outputs were used to determine the range of possible clusters.

The FASTCLUS procedure (maxclusters options) was used to perform a disjoint non-hierarchical cluster analysis based on the distances computed from the quantitative variables (UTM coordinates). The observations were divided into clusters so that every observation belonged to only one cluster. The FASTCLUS procedure uses euclidean distances; therefore, the cluster centres were based on least-squares estimations. When the sample size is greater than 100, the k-means cluster analysis should be employed, in which the precondition is the number of clusters (Ottawiani *et al.*, 2003; Huang *et al.*, 2009).

2.4. Step 4. The GIS methodology for geographical aggregation

The information obtained from the statistical analysis and the results associated with each of the initial records were imported into the database of the GIS using the "Join Data" operation.

To obtain a region in each of the previously generated categories, the «Minimum Bounding Geometry» tool in the ArcToolBox™ by ArcGIS® (ESRI, 2011) was used. Using this tool, the regions can be generated from the point layer, with multiple polygons based on the field values in the table of attributes to calculate the minimum area that contains every group of points with an identical category.

When all the regions were obtained, a spatial union of all the attributes of the points contained in every region in the table of attributes of the polygon layer was performed with the tool "Join Data". This spatial union was based on the spatial location of the points with reference to the polygons (zones), resulting in the total number of livestock units (LUs) being obtained by species and region.

Thiessen polygons methodology was used to divide the territory according to the groups obtained by the statistical procedures (Figure 2). Using this methodology, we concluded that the sides of the polygons were equidistant from the starting regions, as shown in Figure 3.

The cluster analysis included new inputs in the database, as the number of the cluster for each farm was entered (see Figure 2). This database was divided into 19 databases, one for each cluster, for the analysis of spatial data. Each new database included the identification, coordinates, farm number and livestock species.

Spatial data analysis techniques and the search for spatial patterns are discussed in Perry *et al.* (2002).

2.5. Step 5. Characterisation procedures

2.5.1. Descriptive statistical analysis

The descriptive techniques of a multivariate analysis were used to characterise the clusters. Quantitative variables were analysed using FREQ and MEANS procedures, and qualitative variables were analysed using the CORRESP procedure in SAS.

2.5.2. The spatial analysis of Moran’s I and variogram

Spatial autocorrelation is a measure of spatial dependence between values of random variables over geographic locations.

The index of spatial dependence most often used and cited is Moran’s I (Zhang & Lin, 2007).

Moran’s I measures spatial autocorrelation using the following equation:

$$I = \frac{N}{\sum_i \sum_j Wij} \frac{\sum_i \sum_j W_{ij}\left(X_i - \bar{x}\right)\left(Xj - \bar{x}\right)}{\sum_{i=1}^{N}\left(X_i - \bar{x}\right)^2} i \neq j \qquad [1]$$

where N is the number of farms, Xi is the number of LUs on farm i, Xj is the number of LUs on farm j, $\bar{x}$ is the mean number of LUs in each cluster by livestock species and Wij is a matrix of spatial weights. Moran’s I values ranged from -1 to 1, where -1 signified a negative spatial autocorrelation and 1 signified a positive spatial autocorrelation. The software package used to obtain this index was GeoDa 0.9.5, developed by Anselin (2004). This software generated inferences based on the permutational approach (999 permutations); however, similar results were obtained by following the standard procedures under spatial randomness (Anselin, 1995).

Moreover, the techniques of variogram (or semivariogram) were used to measure the spatial variability of a regionalized variable, and provide the input parameters for the spatial interpolation of kriging (Webster & Oliver, 2001). The semivariogram can be expressed as:

$$\gamma(h) = \frac{1}{2N(h)} \sum [z\,(x_i) - z(x_i + h)]^2$$

where γ (h) is the semivariance at a given distance h; z (x_i) is the value of the variable z at location of x_i , h is the lag distance, and N (h) is the number of pairs of sample points separated by h. The variable x_i is the number of LUs on farm. A log-transformation was applied to this variable before analysis. The software package used to obtain the semivariance was ArGis 10.1 (geostatistical analyst extension).

A variogram plot can be acquired by calculating variogram at different lags. Then, the variogram plot is fitted with a theoretical model, such as spherical, exponential, or Gaussian models. The fitting model used was spherical.

With the increase of distance, if the variogram stabilizes, it reaches a sill ($C + C_0$). The distance at which the variogram reaches the sill is called the range (a). Beyond this distance, data are considered to be independent. Discontinuities at the variogram origin could be present; such an unstructured component of variation at $h = 0$ is known as nugget effect (C_0), which may be due to sampling errors and short-scale variability (Pilar *et al.*, 2006).

A variogram plot is obtained by calculating values of the variogram at different lag distances. These values are usually fitted with a theoretical model, such as spherical, exponential or Gaussisan models. The fitted model provides information about the spatial structure as well as the input parameters for kriging.

Kriging, a spatial interpolation technique, only visually identifies hotspots but does not generate statistics, which are required to establish farm spatial clusters or spatial outliers. Therefore, we considered that spatial clusters of farms would be surrounded by others farms within short distances. By contrast, farm spatial outliers were farms surrounded by other farms located further away. These outliers can be identified using Moran's I index (Zang *et al.*, 2009).

All information obtained by precedent threats was processed and visualised using the GIS procedure to draw thematic maps based on the statistical analysis (Step 6 in Figure 2).

3. Results

3.1. The hierarchical cluster analysis results

The database, which contained 4984 farms based on their spatial location, was statistically analysed. The dendrogram (Figure 4a) output from the hierarchical analysis did not show the optimal number of groups because of the large number of farms but suggested that the number of clusters varied between 6 and 20 (the number of clusters from which the distance between clusters was calculated was small, as shown in Figure 4b). In addition to the graphical representation (Figure 4c) of Hottelling's pseudo T^2 statistic, approximately 16 clusters were suggested because the preceding values tended to be much lower, and the CCC graphical representation (Figure 4d) suggested values between 6 and 17 clusters.

In summary, the optimal number of clusters would be between 6 and 20, and it would be necessary to perform a non-hierarchical cluster analysis to test the different numbers of clusters.

3.2. The optimal number of clusters using the disjoint cluster analysis

The outputs from the non-hierarchical cluster analysis are the CCC index, the Pseudo-F values and the associated R^2 values. The results of 14 analyses are presented in Figure 5, and these plots show that the optimum number of clusters is 19.

These results were plotted geographically on the map of the Valencian Community, and the space was divided into 19 livestock areas using Thiessen's polygons (Figure 6).

3.3. Results of the characterisation procedure

3.3.1. Results of the descriptive statistical analysis

Each of the clusters differed from the rest by the number of farms and LUs of each species. The characteristics of each cluster (Table 1) identified that in the northern Valencian Community, there was an area with a greater number of farms (clusters 3, 1 and 18). Clusters 18 and 3 had the highest number of LUs, and cluster 8 had the least number of farms but many LUs. The clusters with the fewest number of farms were 2 and 16, and the ones with the lowest number of LUs were 19, 2 and 4.

The numbers of farms and LUs in each cluster were characterised by livestock species (Table 2). Therefore, clusters 18, 8 and 3 were the groups with the most LUs, and these clusters predominately contained poultry and pigs with different weights.

In cluster 18, poultry represented 50.9% of the LUs, and pigs represented 44.6% (18.3% of the total poultry, and 11.3% of the total number of pigs, respectively). In cluster 8, poultry represented 57.1% of the LUs, and pigs represented 38.4% (19.7% of the total poultry and therefore the cluster with the highest percentage of poultry and 9.3% of the total number of pigs, respectively). In Cluster 3, pigs represented 73.3% of the LUs, and poultry represented 16.6% (16.7% of the total number of pigs, and therefore the cluster with the highest percentage of pigs, and 5.4% of the total poultry, respectively). Cluster 3 also had the highest number of farms with 59.7%, of which 33.8% had pigs, and 29.5% had sheep and goats. Cluster 1 had the second highest number of farms with 583, of which 34.5% had sheep and goats, 29.7% had cattle, and 28% had pigs.

Fewer LUs occurred in clusters 19 (6665), 2 (8052) and 4 (9910). In these three clusters, sheep and goats (36.1% in cluster 19, 43.1% in cluster 2 and 41.3% in cluster 4) had the highest percentage of LUs. In addition, cluster 2 had fewer farms (86 farms, of which 77.9% had sheep and goats), followed by cluster 16 (118 farms, of which 57.6% had sheep and goats) and Cluster 5 (132 farms, of which 37.9% had sheep and goats).

Poultry were concentrated in clusters 8 and 18, although there were a large number of holdings in cluster 14. Cattle were concentrated in clusters 12 and 11, although the clusters with the largest number of farms were 1 and 3. Horses were concentrated in clusters 12 and 10, rabbits in clusters 7 and 18 and pigs in clusters 3 and 6. Although sheep and goats were distributed throughout the Valencian Community, they were concentrated in cluster 10, which contained a greater number of LUs and farms.

3.3.2. Results of the spatial analysis of Moran’s I and variogram

The spatial dependence patterns of livestock species are presented in Table 3 with the corresponding Moran's I indices obtained for each cluster for all farms and livestock species, and figure 7 shows examples of the obtained variograms in some clusters.

Table 3: Number of farms and Moran's I indices and significance levels obtained for the 19 clusters.

Throughout the Valencian Community, low rates of Moran’s I index and the results of variograms imply the absence of spatial autocorrelation, i.e., livestock farms are randomly distributed according to the size of farms and therefore do not follow any spatial pattern. For example, the spatial distribution of farms in each cluster consisted of large farms surrounded by large farms, small farms surrounded by small farms, large farms surrounded by small farms or small farms surrounded by large farms.

4. Discussion

The livestock sector in the Valencian Community has produced a high concentration of farms in some areas, which has led to conflict over land use and the environment (Recatalá *et al.*, 2000). This study adapted the multi-resources inventory of Arvanitis (2000) to create a database containing farm coordinates, livestock species and number of LUs of each farm to determine whether the distribution of farms was directly influenced by the specific characteristics of the surrounding environment. This database contained all of the Valencian farms, a total of 4984 farms. All farms in the region with more than 1 LU were sampled to characterise the livestock sector, resulting in a sample size much greater than in the study conducted by Riveiro *et al.* (2013).

Subsequently, these areas were grouped according to spatial characteristics. The grouping of farms with homogeneous characteristics that separate them from other farms has been observed in several studies in Spain and other countries, but these studies objectives were to characterise livestock territory or livestock species as paths regarding socio-economic, structural, management factors, among others. For example, recent studies have investigated the regions of Castilla-Leon (Riveiro *et al.*, 2013), Galicia (Riveiro *et al.*, 2008), Navarra (Iraizoz *et al.*, 2007) and Extremadura (Gaspar *et al.*, 2007). Outside of Spain, Kostov and

McErlean (2006) studied Northern Ireland, while Köbrich *et al.* (2003) compared Chile and Pakistan, and Landais (1998) studied France.

The study by Riveiro *et al.* (2008) considered the municipality variable of farms, which was determined by administrative boundaries and limits.

These studies did not account for the geographical and spatial location of the livestock farm itself; therefore, the aims were different from this study.

The combination of statistical methods for grouping the farms into a smaller number of units and the implementation of the results using a GIS to generate new spatial structures solves design problems and allows spatial planning from Voronoi diagrams or Thiessen polygons. These techniques are typically used separately to solve these types of problems using traditional methods, such as heuristics or mathematical models (Kalcsics *et al.*, 2005) or specific applications of GIS to resolve spatial partitioning problems in various areas (Moreno *et al.*, 2012).

The clustering methods were categorised into two groups: statistical and spatial. Statistical clustering methods or disjointed partitioning and hierarchical agglomeration algorithms have been widely used together or separately to fulfil different objectives of group classification or separation, such as in the livestock clustering studies noted above (Köbrich *et al.*, 2003; Usai *et al.*, 2006; Riveiro *et al.*, 2013). Clustering has also been used in agricultural problems for agricultural system classification and characterisation (Floyd *et al.*, 2003; Köbrich *et al.*, 2003; Ottaviani *et al.*, 2003; Iraizoz *et al.*, 2007). In addition, clustering has been used for landscape delimitation and/or areas of characterisation (Jaynes *et al.*, 2003; Van Eetvelve & Antrop, 2009; Castillo-Rodriguez *et al.*, 2010; Soto & Pintó, 2010) to classify fields as performance patterns or to establish management zones for precision agriculture (Ortega & Santibañez, 2007). Similar to this study, these studies analysed whether the variables exhibited spatial patterns. However, these classification schemes did not account for coordinates as classification variables in the above-mentioned studies.

After grouping the farms, each group was characterised by livestock and spatial characteristics. Moran's I index, which was used to determine spatial autocorrelations, has been used in environmental studies, including groundwater changes in China (Liu *et al.*, 2013), socioeconomic and demographic studies in China (Zhang & Lin, 2009), and geomarketing and tourism (Chasco & Fernandez, 2008; Sánchez, 2008). Later, the Variograms were computed from the same variables (the units of livestock species) to management zone delineation, like the method proposed by Oliver and Webster (2001), use a variograms to identify the neighboring of each data point. The Variograms are used like an additional support to consider kriging as the interpolation method. This study is used to determine the autocorrelation spatial. Variograms have been used to study spatial characteristics in farms, but using another variables like, as for instance, environmental characteristics of soil (Lesch, 2005), water (Fu *et al.*, 2010), and also infection diseases (Van Boeckela *et al.*, 2012). For livestock farms in the Valencian Community, the absence of spatial correlations indicated that the farms were randomly distributed according to size.

This study showed that the distribution of livestock farms in each area was grouped, emphasising the intensification in certain areas and the need for regional planning for livestock.

5. Conclusions

Territorial planning requires information from previous studies to intervene and correct current developments to adapt to new European environmental regulations. An initial step is to study the farm territories located in the Valencian Community (4984) and the territory zones grouped by livestock (livestock geographic zones). This would allow for the identification of ideal locations for livestock-specific public or private services, such as those offered by regional agricultural offices, feed companies and slaughterhouses.

In addition, livestock characterisation is the basis for developing studies in areas of high production and increased environmental conflict to determine solutions for sustainable livestock.

This paper presented an analysis based on GIS and statistical methods for dividing livestock farms into zones as well as the characterisation of these areas. We obtained nineteen livestock geographical areas with unique characteristics, such as livestock species composition. These areas did not follow spatial patterns, i.e., clustering patterns were not large farms surrounded by large farms, small farms surrounded by small farms, large farms surrounded by small farms or small farms surrounded by large farms.

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