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Dasymetry Dash Flood (DDF). A method for population mapping and flood exposure assessment in touristic cities

Alfredo Pérez-Morales [a,*], Salvador Gil-Guirado [a], Víctor Martínez-García [b]

[a] Departamento de Geografía, Facultad de Letras, Universidad de Murcia, C. Santo Cristo, 30001, Murcia, Spain
[b] Departamento de Economía de la Empresa, Escuela Técnica Superior de Ingeniería Agronómica, Universidad Politécnica de Cartagena, Paseo Alfonso XIII, 48, 30203, Cartagena, Spain

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ABSTRACT

Population disaggregation methods are a land management tool that is necessary to robustly assess the exposure of populations to natural hazards. The aim of these methods is to translate population values from large spatial units to smaller spatial units. Due to their improvement, the accuracy in quantifying the population exposed to natural hazards has increased significantly in recent years. However, in the case of floods, where the actual exposure to the hazard depends on the height of the buildings, there is a methodological deficiency with regard to reaching the necessary level of detail. This is a methodological challenge that is exacerbated in urban areas specialising in tourism, where there are a large number of dwellings dedicated to the housing of tourists. In this paper we propose a 3D cartographic dasymetry (DDF) method that, based on cadastral information and the population and housing census, manages to solve these problems of flood hazard exposure assessment reasonably well. For validation, the results are compared with three widely used 2D methods. Our work shows that the proposed method offers better outputs for use in high-precision work; but also, when such detail is not necessary, more basic methods achieve results with only marginal differences.

1. Introduction

Floods are the most frequent natural hazard on the planet (CRED, 2015; UNISDR, 2017) and the one that causes the greatest economic losses (Marchi et al., 2010; UNISDR & CRED, 2015). In Europe, the intensity and frequency of floods recorded in recent years (Gaume et al., 2009; Llasat et al., 2005; Marchi et al., 2010) have led to an increase in the number of related disasters (Barredo, 2007, 2009; CEA, 2007; European Environment Agency (EEA), 2010).

Two main types of measures are usually adopted to address this problem: structural and non-structural. The former are aimed at mitigating the intensity and propagation of floods by means of infrastructures (dams, modification of channels, diversion channels, etc.). On the other hand, non-structural measures are considered as preventive measures and are based on correct land-use planning. The objective of non-structural measures is to minimise the damage caused by floods by reducing exposure to the hazard (Berga, 1990; Klijn et al., 2015).

The scientific community seems to have given the importance it deserves to preventive measures in recent decades (Olcina, 2009; Van Alphen et al., 2009). However, it is still necessary to devote more time to the implementation of this type of action, to reduce the risk to the population (Blaikie & Muldavin, 2014; Hirabayashi et al., 2013; Jongman et al., 2012; Lugeri et al., 2006). In this sense, adequate risk mapping that spatially identifies flood-prone areas and the socio-demographic characterisation of the exposed population are the most useful tools for mitigation of the impact of floods (Pérez-Morales, 2012).

The methodologies used to assess exposure have evolved significantly in recent years. These methodologies can be classified according to the scale of the work to which they are applied. The methods used to assess large regions, despite the possible masking of information that their implementation entails, are currently at a very acceptable level of development, thanks to the improved availability of information at a global level and statistical or machine learning techniques (Smith et al., 2019). High-spatial-resolution or small-scale analysis has reached a high level of precision due to huge advances in spatial hazard delimitation and the increased availability of socio-demographic information (Smith et al., 2019; Spielman et al., 2020). Unfortunately, with notable exceptions (Andrienko et al., 2021; Kogure & Takasaki, 2019), high-resolution work is subject to the limits of statistical confidentiality

* Corresponding author.
E-mail addresses: alfredop@um.es (A. Pérez-Morales), salvador.gil1@um.es (S. Gil-Guirado), victor.martinez@upct.es (V. Martínez-García).

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and therefore provides data that are disaggregated into broad spatial units (census tracts, districts, postcodes, etc.). These units are often too large and irregular to capture the real heterogeneity of the exposed and non-exposed populations. For this reason, it is necessary to apply downscaling techniques in a similar way as for climatic variables (Wilby et al., 2004).

Spatial disaggregation methods are generally used to overcome the above limitation. According to (Goerlich & Cantarino, 2013), these methods consist of “transferring data from an area of origin to various destination areas, when these constitute a partition of the first”. In other words, the information from the spatial units delimited by the public administration (census track, postcode area, etc.) is disaggregated into others of higher resolution and spatial precision.

These population disaggregation methods can be classified initially into three main groups (Wu et al., 2005; Bakillah et al., 2014; Maantay & Maroko, 2017, p. 670). Firstly, there are statistical modelling methods, which attempt to estimate the number of inhabitants by means of explanatory statistical models that have the population as the dependent

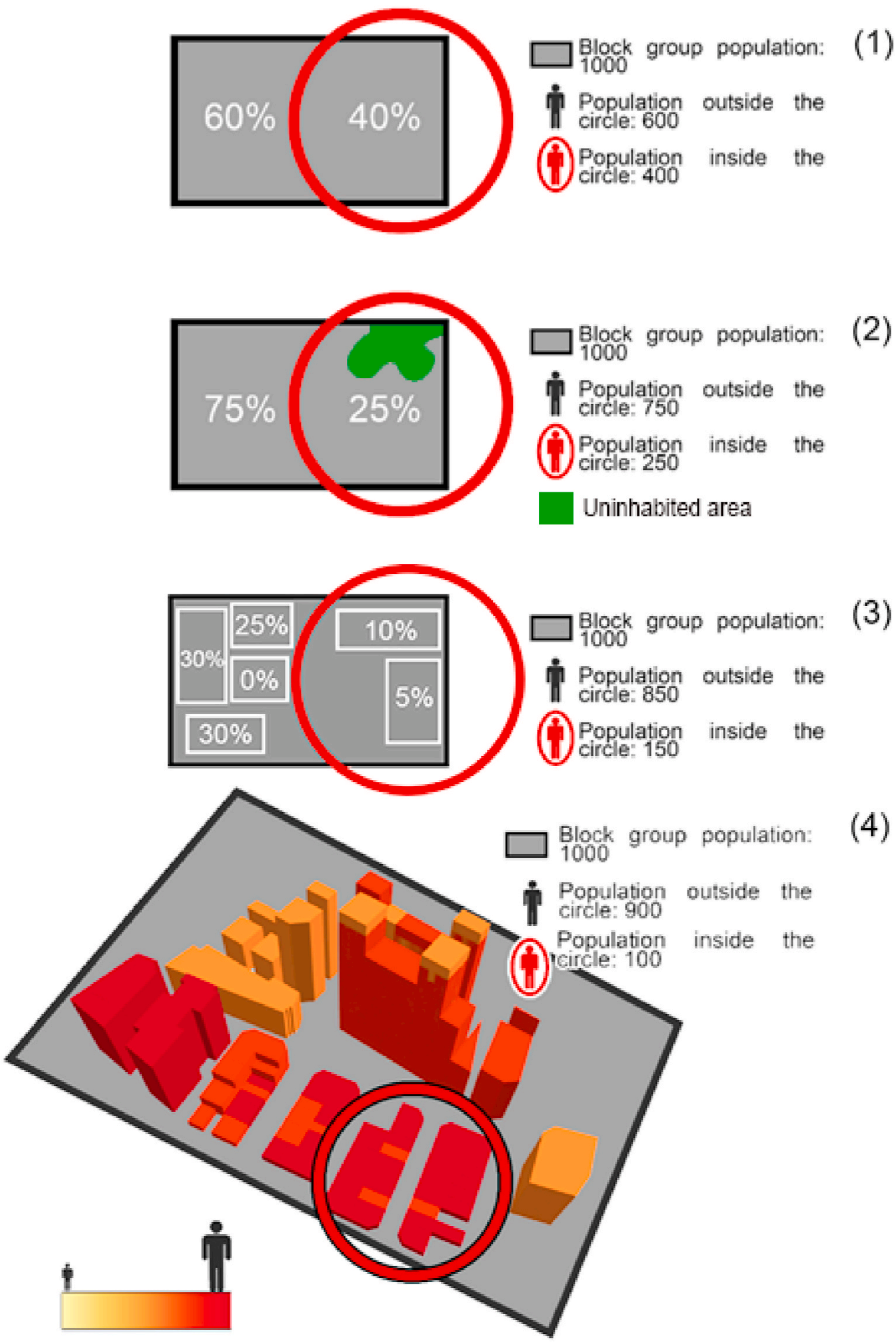

Fig. 1. Comparison of dasymetric methods: Areal Interpolation (1), Binary (2), CEDS (3) and Dasymetry Dash Flood (4). Methods 1, 2 and 3 were obtained from (Maantay et al., 2007). The red circle represents the exposed area.

variable and other socioeconomic and physical variables as independent variables (Bielecka, 2005; De Cos Guerra, 2004; García González & Cebrián Abellán, 2006; Ye et al., 2019; Shang et al., 2021). The second group is constituted by the methods known as *Areal interpolation* (Fig. 1-1) (Mora-García & Marti-Ciriquian, 2015; Preciado, 2015; Zoraghein & Leyk, 2019). These consist of apportioning the population in each tract according to the amount of the tract that is within the affected surface area (e.g. buffer, continuous surface, …) (Maantay et al., 2007; Maantay & Maroko, 2017, p. 670). One major deficiency of this approach is that it is based on the erroneous assumption that the population is distributed evenly and equally throughout the unit of aggregation. The third group is Dasymetric mapping, whose main characteristic is that it uses additional or auxiliary information for disaggregation. The most primitive interpretation of the term dasymetry corresponds to a cartographic technique used to represent, continuously but irregularly, variables distributed in space, in a continuous or dotted manner, by means of a set of areas with discrete values (Dent et al., 1999; Robinson, 1961). An example of an early application of dasymetry to population distribution is that of (Wright, 1936), who considered areas of different population densities and used knowledge of the city to disaggregate the population by means of choropleth maps.

Among the dasymetric methods, one of the most basic is the Binary Method (Eicher & Brewer, 2001), also known as filtered areal weighting (Fig. 1-2). With Binary, the disaggregation process consists of transferring the information from the source unit proportionally to the area of each target unit. This is done by distinguishing between inhabited and non-inhabited units, usually by means of land use/land cover (LULC) such as Corine Land Cover (CLC).

In recent decades, population disaggregation using dasymetric techniques has reached a high level of development, supported by sources of data diverse in origin and detail. The *Cadastral Expert Dasymetric System* method (CEDS) of Maantay et al. (2007) stands out for its simplicity of execution and successful results (Fig. 1-3). This method uses census tracts as an aggregate starting unit and cadastral parcels with information on buildings as target units. In other words, the method uses the buildings where the population lives. The distribution of the population by building is determined taking into account the number of dwellings or the total residential area. With the above, this method overcomes the disaggregation limitations of those methods that only use footprints or remote sensing products as auxiliary data due to unavailability (Yao et al., 2017).

Although the dasymetric techniques described so far present an acceptable accuracy for the estimation of the population with a high level of detail (Pavía & Cantarino, 2017b), when they are applied to specific tasks in the assessment of the exposure to certain natural hazards, their limitations and shortcomings become evident. The main problem usually arises when the exposure to the hazard is of a differential type and is limited to low-rise portions of buildings, as in the case of floods (Maantay & Maroko, 2009; Zhu et al., 2020) or atmospheric pollution (Maroko et al., 2019). Recently, to overcome these limitations and achieve greater accuracy, the use of CEDS has been improved by incorporating the third dimension or building height (Lwin & Murayama, 2009; Maroko et al., 2019), mainly through the LIDAR-based approach (Chen et al., 2021; Ural et al., 2011).

Despite these recent advances, there is still ample room for improvement, which could be covered with more detailed data on buildings and population typology. Regarding the former, volunteered geographic information (VGI) and countries' official cadastral information have substantially added to this advance. VGI has recently been widely used in those situations where official data is not readily available (Yao et al., 2017; Chen et al., 2021). In this regard, Bakillah et al. (2014) proved its great usefulness in population disaggregation tasks. As for official cadastral data, a so detailed level of accuracy is being achieved that it allows for outstanding exposure assessment work to be developed (Maroko et al., 2019).

Nevertheless, population-wise, there are promising solutions such as GPW, GRUMP or the recent WorldPop. Thanks to these open access databases, it is becoming increasingly possible to assess population spatial heterogeneity in high resolution. However, despite the major progress made with mobile location-based services, population mobility entails certain challenges (Yao et al., 2017). Hence, population censuses remain as the most conservative and rich in demographic features sources to be used in population disaggregation tasks. In this regard, the lastest censuses of some advanced countries include new variables that facilitate distribution and differentiation by population type: gender, age, ethnicity (Maantay et al., 2007; Maantay & Maroko, 2017, p. 670). Despite these improvements, studies about the type of dwelling (main, secondary or vacant) or about the type of population that is disaggregated in said dwellings are still difficult to find (resident or seasonal population) (Zandbergen, 2011). Having this data available is crucial when preventing over- and underestimation issues regarding hazard exposure, given that the exposed population data may vary greatly depending on timing (Camarasa-Belmonte et al., 2011; Yao et al., 2017). Such obstacles are even more striking in areas where the population varies seasonally, as are touristic cities.

In the case of Spain, the limitations mentioned above have been partially overcome thanks to the valuable data collected in the latest census on population (year 2011) and cadastral housing characteristics. This has enabled the proposal of a new methodological approach for 3D population disaggregation based in CEDS: Dasymetry Dash Flood (DDF) (Fig. 1-4). The main reason to use this new high-precision method is that it allows for the evaluation of the population exposure to flood hazards in urban areas with a large floating population (mainly tourists). In a novel way, the proposed technique achieves two notable advances. Firstly, it overcomes the homogeneous distribution of the population within the buildings in case of flooding. For this purpose, the resident and seasonal populations are assigned to the dwellings intended for primary and secondary use, respectively. In addition, dwellings registered as vacant are excluded from the population distribution. Secondly, only those occupied dwellings that intersect in height (z) with the height of the sheet of water estimated for different return periods (10, 100 and 500 years) are considered as dwellings exposed to the risk of flooding.

The new methodological procedure was applied to the coastal municipalities of the Region of Murcia (Southeast Spain). This study area has been especially affected by floods in recent decades (Gil-Guirado et al., 2019; García-Ayllon & Radke, 2021), mainly due to the increase in exposure motivated by two factors: the boom in "sun and beach" tourism and the "real estate boom" prior to the 2008 crisis (Pérez-Morales et al., 2018).

The overall structure of this paper takes the form of five chapters. The following section is concerned with the data used for the case study and the methodological approach. Then, the experiments, the results and the reliability assessment of the method are presented in section 3. The discussion of said results is included in section 4 and conclusions are comprised in the final section.

2. Materials and methods

2.1. Data sources

The methodological procedure usually used in disaggregation and exposure studies combines three types of databases: one representing the hazard or physical factor and two referring to the exposure or human factor (Table 1).

Regarding the physical factor, the information used in this work comprised the flood zones and the height in centimetres of the sheet of water, obtained from hydrological modelling of the Sistema Nacional de Cartografía de Zonas Inundables (MTERD, 2020). Return periods (T) of 10, 100 and 500 years, in raster and vector format, were used for this work.

The human factor was characterised by two databases that were related by means of DDF. The first of these was the Spanish Cadastre

Table 1
Data sources and variables definitions.

Factor	Variable	Categories	Spatial aggregation	Spatial disaggregation	Definition	Source
Human	Main use of each floor of the building	Residential	Building	Building floor	Buildings and buildings' floors which main use is residential: dwellings.	Cadastre (Ministeriode Hacienda, 2021)
		Commercial	Building	Building floor	Buildings and buildings' floors which main use is commercial: shops, pharmacies, coffeehouses, etc. Given its non-residential use, it is excluded from population disaggregation.	
		Industrial	Building	Building floor	Buildings or buildings' floors which main use is industrial: workshops, factories, etc. Given its non-residential use, it is excluded from population disaggregation.	
	Building floor	Floor number	Building	Building floor	Number of floors per building.	
	Building area	Floor area	Building	Building floor	Surface area of each building.	
	Population	Resident population	Census track	Building floor	People who established their habitual residence within the study area at the time the census was conducted.	National Population and Housing Census (INE, 2013)
		Seasonal population	Municipality	Building floor	Set of people who spend certain periods of time during the year (such as holidays or weekends) within the study area, as well as those who live, work or study there.	
	Dwellings	Main dwellings	Census track	Building floor	Dwellings in use all or most of the year as habitual residences of one or more individuals. These dwellings were assumed to accommodate the resident population.	
		Secondary dwellings	Census track	Building floor	Dwellings used only part of the year, on a seasonal, periodic or sporadic basis, which are not habitual residences. These were assumed to accommodate the seasonal population.	
		Vacant dwellings	Census track	Building floor	Uninhabited dwellings which are neither habitual residences nor used seasonally, periodically or sporadically by anyone. Thus, they were excluded from population disaggregation.	
Physical	Floodable area	Height of the sheet of water in each T	Raster with 2 m × 2 m resolution	–	Floodable area raster for return periods of 10, 100 and 500 years used to assess buildings exposure.	SNCZI (MTERD, 2020)

(Ministerio de Hacienda, 2021). This constitutes the inventory of the country's immovable goods (Martín-Varés, 2007). Its basic spatial aggregation unit is the building (Preciado, 2015) and the spatial information is provided in vector format. Following the methodology proposed by (García, 2013), the number of floors per building and then the use of said floors (residential, commercial and industrial) were added to the information vectors.

The data on the type of population and dwellings disaggregated in each floor of these buildings were obtained from the 2011 population and housing census (INE, 2013). In both cases, the information was aggregated at the census track level except for the seasonal population variable, where the starting aggregation unit was the municipality. This is because the Spanish National Statistics Institute (INE) does not provide seasonal population data for the census tracts, being the municipalities the most detailed disaggregation unit.

Finally, domestic water consumption is used to verify DDF reliability in touristic cities, to ascertain the occupation rate of secondary dwellings on a monthly basis. Data was extracted from the Spanish official water suppliers of each municipality (Villar-Navascués & Pérez-Morales, 2018).

2.2. Methodology

The proposed methodology followed a sequential stepwise procedure that is summarised in Fig. 2. First (Fig. 2, step 1), non-residential uses (industrial and commercial) were filtered out from the cadastre database and the information for each dwelling was added to the vector information layer of the buildings by means of the cadastral reference field. Second, the main, secondary and vacant dwellings of each census section were randomly distributed among the cadastre buildings located within those same sections (Fig. 2, step 2). As the cadastre and the census are sources that differ in the frequency of their updating (census every 10 years, cadastre every 4 months) the number of dwellings in their different categories may not coincide. To correct this and to avoid estimation errors, the proportion of dwellings in each category of the census was taken as a reference and was applied to the absolute number of dwellings in the cadastre in each building so that the proportion was the same.

Once the number of dwellings per category in each building was known, the resident population of the section was distributed among the main dwellings using a random distribution (Fig. 2, step 3). In similar works (Maantay et al., 2007), this placement was carried out in two ways. The simplest one is to obtain the average number of inhabitants per main dwelling and generalise this value per dwelling to all buildings in the study area. Other more complex options use the residential area in m^2, when working with 2D (Mora & Marti, 2015), or the volume in m^3, when mapping in 3D (Lwin & Murayama, 2009; Maroko et al., 2019). Although the latter distribution might seem more accurate, it entails important biases, especially in large dwellings, where inflated population figures are obtained when the type or model of building (dwellings in single-family buildings vs. dwellings in multi-family buildings) is not considered. To overcome this, in the present work, a process of assigning population density weights by categories modulated according to the average surface area of the dwellings (data available at the census section level) was carried out. These categories have been estimated from a calculation of deciles of surface area, as the relationship between dwelling size and number of inhabitants is positive, but non-linear. The use of deciles allows for the complexity of this relationship to be reflected in a simple way while maintaining it. The estimation of these decile-based categories followed the formula:

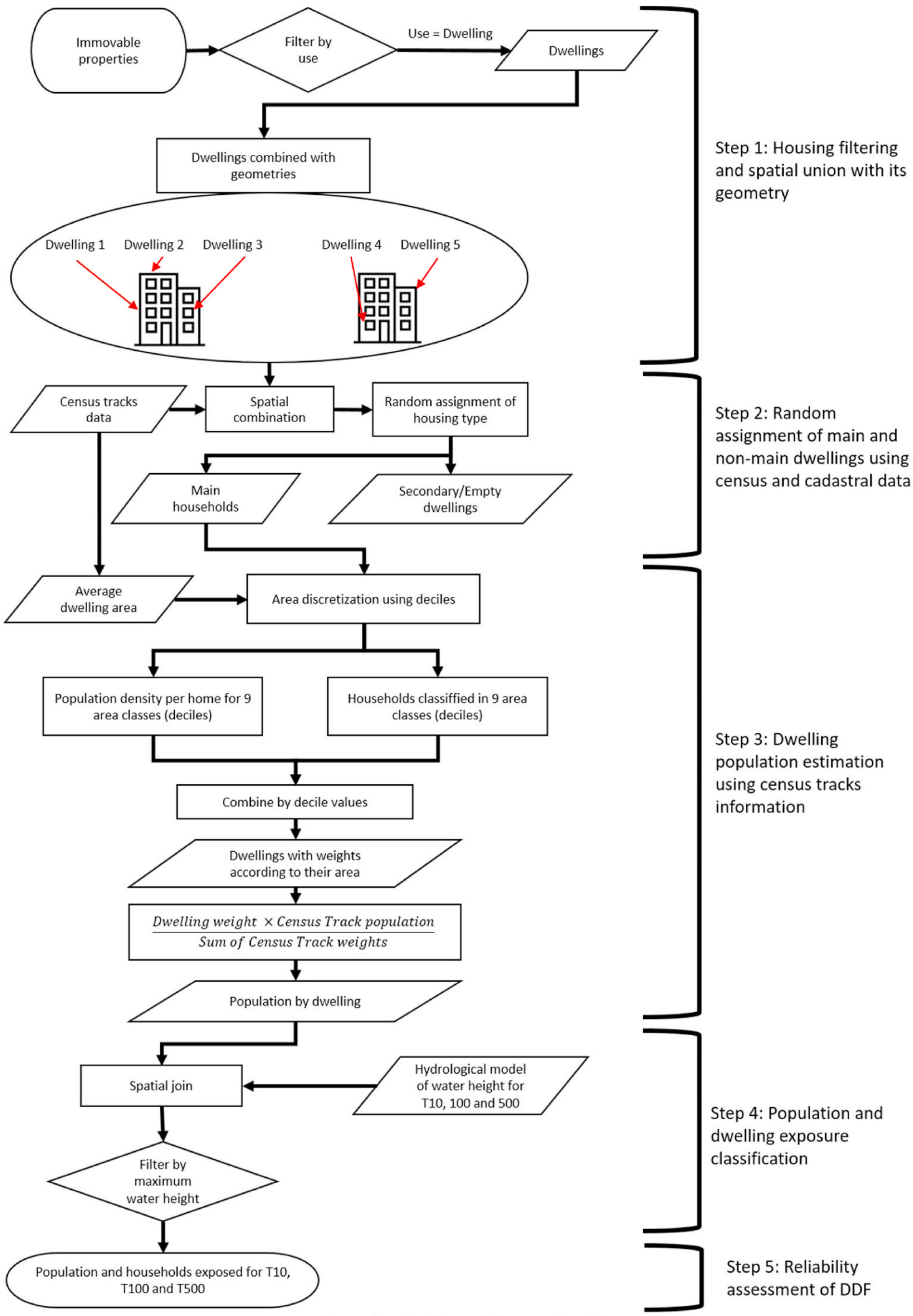

Fig. 2. Outline of the methodology.

$$Dk_c = L_i + \left(\frac{\frac{k \times N_c}{10} - F_{i-1}}{f_i} \right)$$

where Dk_c is the decile or class boundary k of the average floor area of the main dwellings in the census tract c, L_i the lower limit of the selected interval, N the total number of census tracts, f_i the absolute frequency of the interval i and F_{i-1} the cumulative absolute frequency of the class above the selected interval i. In this way, the census tracts were classified in nine classes according to the average housing area at the census track level (k).

Subsequently, for each of these census tract classes k_c, the average density of inhabitants per main dwelling of these census tract classes was calculated, according to the following expression:

$$\bar{s}_{k_c} = \frac{1}{N_{k_c}} \times \sum_{i=1}^{N_{k_c}} s_{k_{c_i}}$$

where N_{c_k} is the total number of census tracts c in the class k and $s_{k_{c_i}}$ the mean population density per main dwelling associated with the i census tract c in class k. Thus, for the 9 ordinal categories of average housing area at each census track level (k_c), an associated mean population density value was obtained ($\bar{s}_k$). The dwellings in the study area were also classified in 9 ordinal surface area classes by deciles, as in the previous procedure:

$$Dk_v = L_i + \left(\frac{\frac{k \times N_v}{10} - F_{i-1}}{f_i} \right)$$

where Dk_v is the decile or class boundary k of the average floor area of the dwellings in the study area v, L_i the lower limit of the selected interval, N_v the total number of dwellings, f_i the absolute frequency of the interval i and F_{i-1} the cumulative absolute frequency of the class previous to. i.

This procedure makes it possible to associate dwellings with population density values ($\bar{s}$), since k_v and k_c are ordinal categorical variables with the same levels. By means of these variables, the $\bar{s}_{k_c}$ values are related to k_v, considering $k_c \subseteq k_v$, which implies that $\bar{s}_{k_v} := \bar{s}_{k_c}$, and that $\bar{s}$ corresponds to the population density associated with dwellings v of category k.

Finally, this value of population density associated with the dwellings was used as a weighting in the following formula:

$$h_v = \frac{H_c \times \bar{s}_{k_v}}{\sum \bar{s}_{k_{v_c}}}$$

where h_v is the population assigned to each dwelling v, H_c the total population of the section c, $\bar{s}_{k_v}$ the population density associated with the dwelling v in category k and $\bar{s}_{k_{v_c}}$ the total of the s values associated with the dwellings v inside a section c.

After the aforementioned calculations, the breakdown of the population resident in the main dwellings of each census section was obtained. In turn, for the breakdown of the seasonal population, a procedure almost identical to the previous one was followed, in which the population linked to the secondary dwellings was redistributed, with the exception that the starting aggregation unit was the municipality. Both breakdowns are summarised in Fig. 3.

In the fourth step of the procedure (Fig. 2, step 4), the assessment of the exposure of the buildings, dwellings and population was carried out using the occupancy models described above. To identify the exposed buildings, the procedure of (Pérez-Morales et al., 2015) was followed. In relation to the dwellings, the height of the sheet of water affecting each plot was considered, as well as the use of the building by floor, excluding uses other than dwellings. In other words, only dwellings located on ground or underground floors where the height of the sheet of water of the floodable surface is equal to or greater than 20 cm were taken into account. This height threshold was considered since, according to (Baro et al., 2012), from this height onwards, substantial economic losses and

Table 2
Comparison of the disaggregation capacity by variables of the different methods used in this work. Marked in green when the comparison was possible and in red when it was not.

Method	Population		Buildings	Dwellings
	Resident population	Seasonal population		
Areal	☑	☒	☒	☒
Binary	☑	☒	☒	☒
CEDS	☑	☒	☑	☒
DDF	☑	☑	☑	☑

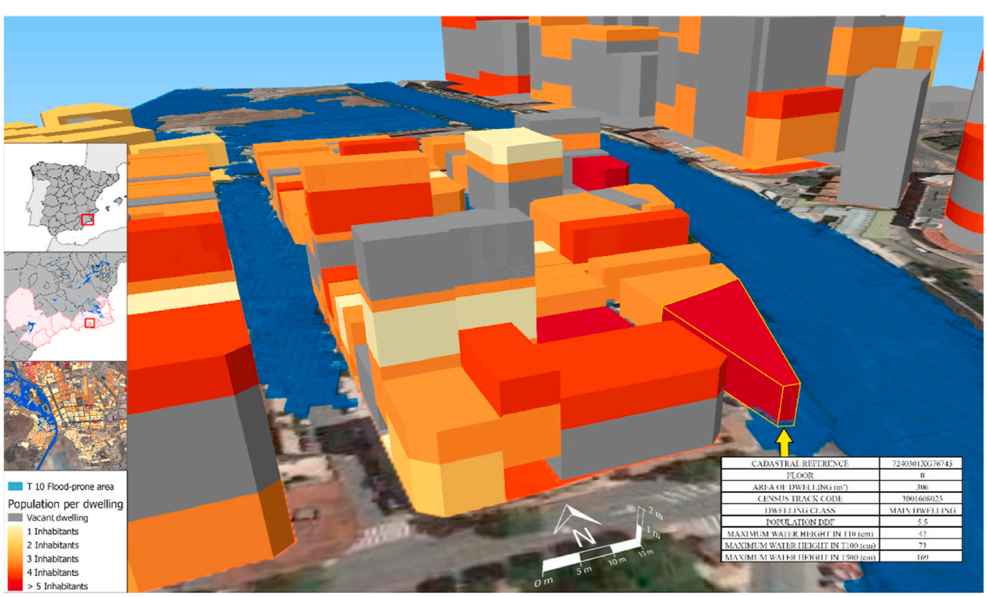

Fig. 3. 3D representation of the structure of the spatial information obtained after the dasymetric disaggregation process.

damage begin to occur inside dwellings. For the population, the DDF method was used to assess the resident population living in primary dwellings and the associated population in secondary dwellings.

Finally, with the aim of demonstrating the proposed method validity and reliability (Fig. 2, step 5), two test were carried out. In the first one, the results were analysed and compared with those of Areal, Binary and CEDS when there was a coincidence in the level of disaggregation among the methodologies, which is shown in Table 2.

In the second, to prove DDF reliability in touristic cities, an analysis of the relevance and variation of seasonal population within the study area was required. To do so, exposed resident population was compared to the total population (resident and seasonal combined) that is exposed to hazards throughout the year. Resident population was assumed to remain consistent every month while seasonal population varies. To simulate such variation, the database of domestic water consumption per municipality was used to get the occupation coefficient of the secondary dwellings.

This occupation coefficient is the result of the normalisation

$$n_i = \frac{X_i}{\max X}$$

where x corresponds to the domestic water consumption accrued in the study area in m^3, i is a certain month and n the occupation coefficient.

Accordingly, to estimate the seasonal population in secondary dwellings that is exposed for every RP, month and census tract, the following formula is used:

$$SPE_{jci} = \frac{(n_{ci} \quad y_{jc})}{TP_c}$$

where SPE is the proportion of exposed population in the census tract c; i is a certain month; j the return period; n is the occupation coefficient; y is the seasonal population, and TP the total population.

Finally, means are contrasted to check if there are important differences between the proportion of the exposed resident population and the proportion of total exposed population in every return period, monthly and per census tract.

Table 3
The population, dwellings and buildings in the study area.

Population		Dwellings		Buildings
Resident population	465,640	Main dwellings	163,825	102,739
Seasonal population	237,172	Second dwellings	88,949	
Total population (Resident + Seasonal)	702,812	Vacant dwellings	52,098	
		Total dwellings (Main + Second + Vacant)	304,872	

2.3. Study area and descriptive statistics

The study area is comprised of the 8 coastal municipalities of the Region of Murcia (Águilas, Los Alcázares, Cartagena, Lorca, Mazarrón, San Pedro del Pinatar, San Javier and La Unión). Between them they cover a surface area of 2886 km^2 (Fig. 4). The hydrographic network is typical of the dry Mediterranean climate and is represented by more than 50 basins drained by coastal ephemeral and ephemeral wadis (Olcina-Cantos, 1999; Calvo, 2001).

These municipalities, together with those in the neighbouring province of Alicante, experienced one of the most pronounced urban growth rates in the whole of the European Union during the first decade of the 21st century (Pérez-Morales et al., 2018). The practically unlimited and generalised increase in the housing stock throughout the Spanish Levante region was accelerated by speculation in residential tourism (Gaja, 2008). This led to a 400.6% increase in the number of secondary and vacant dwellings in the study area during the decade, and the proportion of the total number of dwellings that they represented (35.7%) was well above the Spanish average (15.2%) (INE, 2013). Consequently, urban morphology was characterised by expanded cities where urban agglomeration focused on coastal zones, and peri-urban areas experiment the most intense variation of seasonal population. Table 3 compiles population, dwellings and buildings typology according to INE (2013) and cadastre data.

The environmental effects of this urban development have been very negative in terms of the flood risk since, in addition to having

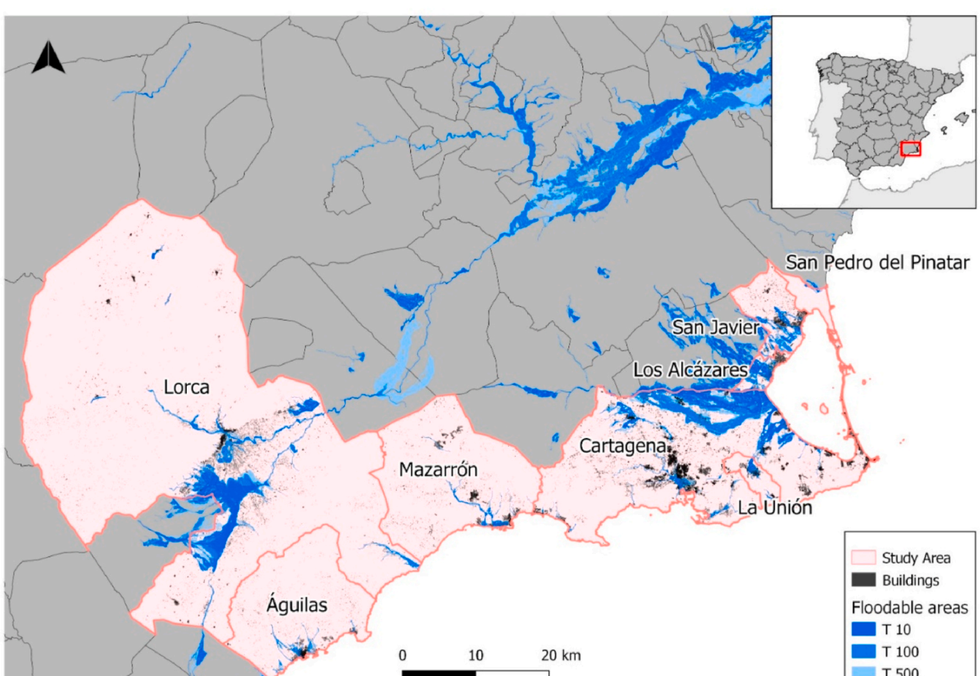

Fig. 4. Study area and flood zones for each return period.

Table 4
Number of buildings exposed to a flood hazard, for the year 2011, for the DDF and CEDS methods.

Return Period	Buildings	%
T10	8863	8.62
T100	17,676	17.20
T500	22,772	22.16
NON-EXPOSED	79,967	77.84
TOTAL	102,739	100

accelerated exposure to flood beds (López-Martínez & Pérez-Morales, 2017; Pérez-Morales et al., 2015), the artificialisation of the soil with the consequent sealing (Romero-Díaz et al., 2017) has contributed to an increase in surface runoff and, consequently, an increase in the frequency of flooding (Gil-Guirado et al., 2019). In fact, the precipitation threshold above which problems occur on the Mediterranean coast is decreasing (Gil-Guirado et al., 2014).

3. Results

3.1. Comparing DDF results with other methods

This section presents the results of the exposure assessment using DDF and their comparison with the results obtained using other methodologies (Areal, Binary, CEDS), considering, firstly, exposed buildings; secondly, the exposed population; and thirdly, exposed primary dwellings, secondary dwellings and ground floor vacant dwellings.

With respect to the buildings, only DDF and CEDS achieved this level of disaggregation. Thus, when using the Cadastre as auxiliary information in both methods, the results are identical. The values show that for T500 there are 22,772 buildings exposed to flooding, which represent 22.2% of the total number of buildings. Hence, 77.8% of the buildings are not exposed (Table 4).

For the exposed resident population, depending on the method, the differences can exceed 18 percentage points (Table 5). However, these variations are consistent with those reported by Maantay and Maroko (2017, p. 670). That is, the number of people exposed to flooding gradually increases as the area of the flood zone increases, for all four

Table 5
The population exposed, by assessment method and return period, and the percentage with respect to the total population (N = 465,610).

Methodology	T10	%	T100	%	T500	%
DDF	17,342.92	3.72	39,797.54	8.55	61,094.35	13.12
AREAL	17,316.82	3.72	48,457.75	10.41	77,332.76	16.61
BINARY	13,214.77	2.83	42,456.92	9.12	71,976.3	15.46
CEDS	29,904.94	6.42	94,360.71	20.27	145,956.6	31.35
	(%MAX-%MIN)	3.59		11.71		18.22

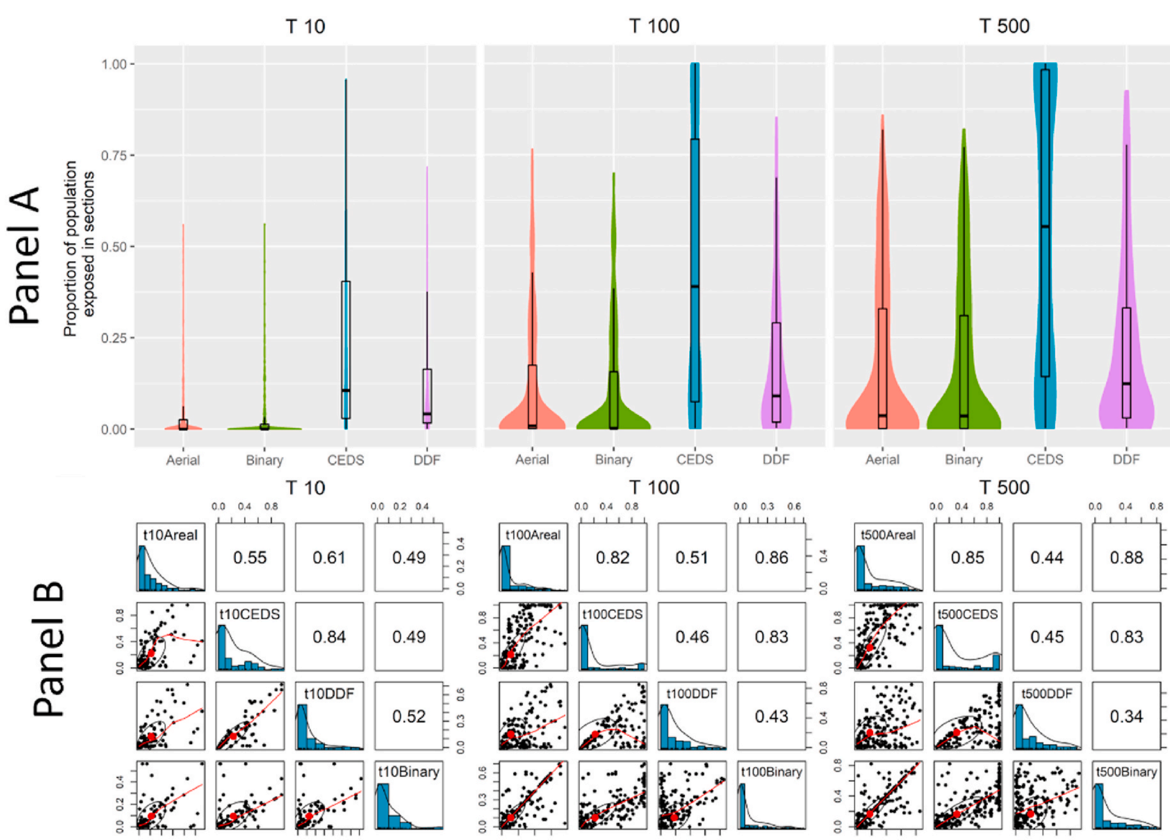

Fig. 5. Graphical comparison of the exposed population by census tract calculated using Areal, Binary, CEDS and DDF. Panel A shows, in box and violin plots, the proportion of the exposed population by census tract, return period and applied method. Panel B shows, for each return period, matrices with bivariate scatter plots displaying the percentage of the population exposed according to the contrast of methods, histograms of the percentage of the population exposed according to each method and R^2 results for the crossing of each method with the rest.

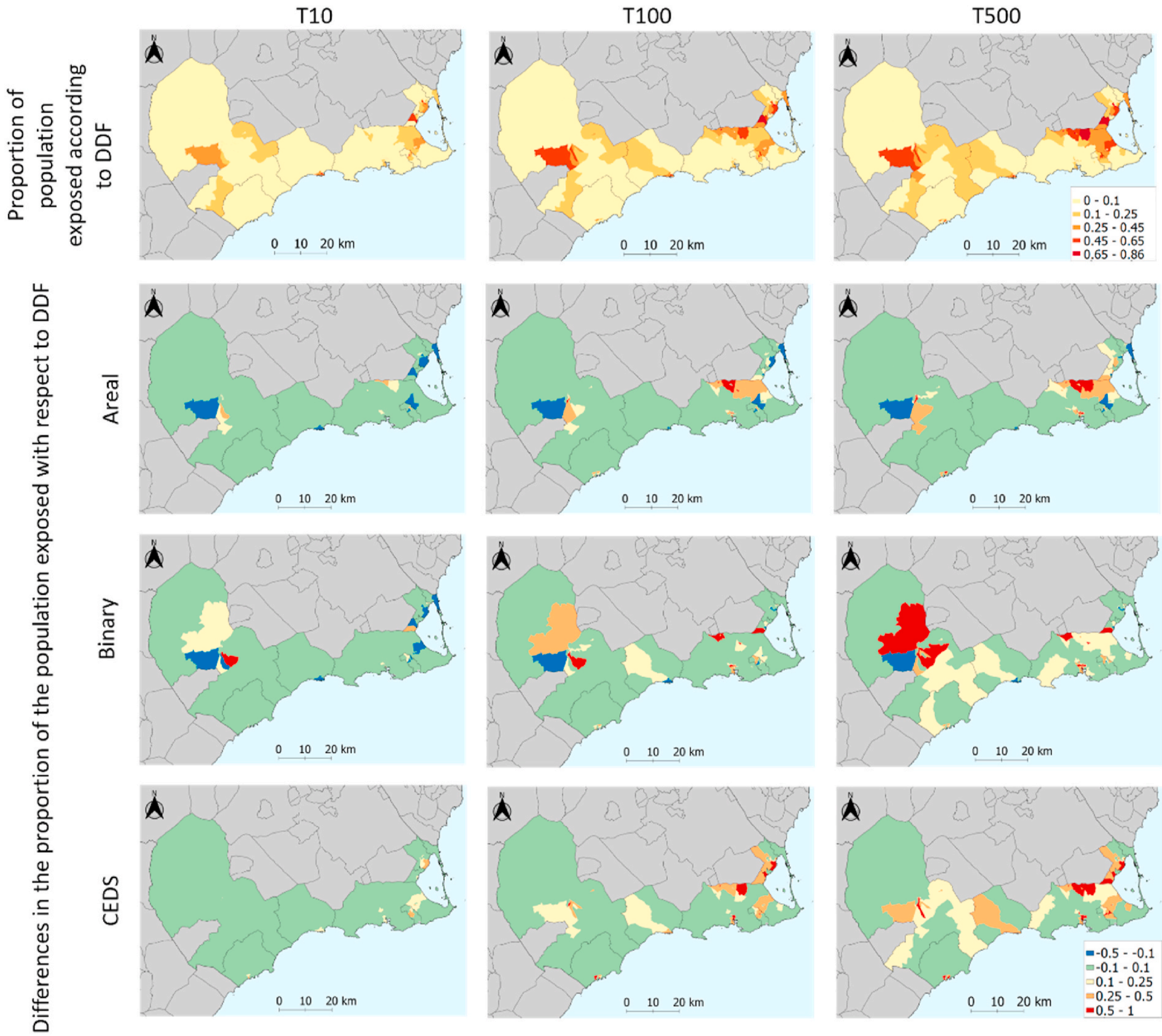

Fig. 6. Map of the exposed population by census tract according to DDF and the differences found with respect to Areal, Binary and CEDS in percentage terms.

methods, as do the differences between the methods used.

The discrepancies noted above are more evident, visually, in Fig. 6. Broadly speaking, Areal and Binary are increasingly very similar in their assessments for each return period due to the similarity of their calculation procedures (Fig. 5, Panel A). However, it is worth remembering that, although the differences are marginal, significantly lower values are observed for all return periods in Binary compared to Areal, due to the fact that Binary uses the auxiliary information of the inhabited space provided by Corine Land Cover (CLC) within each section to improve its accuracy.

As for CEDS, its resemblance to DDF is high at T10, as shown by the scatter plot and the r^2 value of 0.84 (Fig. 5, Panel B). However, the fit worsens dramatically at T100 and T500, as shown by the frequency distribution of CEDS when polarised at T100 and T500. This should be interpreted as CEDS overestimating the population in non-floodable census tracts and underestimating non-floodable census tracts as the exposed area increases. This decline in the similarity between CEDS and DDF can be explained in spatial terms (Fig. 6). As can be seen in the corresponding mapping of the differences (DDF vs CEDS), as less densely populated exposed census tracts with a larger surface area are included, such as those in the peri-urban area of the affected populations (T100 and T500), CEDS tends to overestimate to a greater extent than the other methods. Consequently, its use is not recommended for this type of peri-urban area, as pointed out by Pavía and Cantarino (2016) and, when no other option is available, it is opportune to correct it with other statistical methods (Cockx & Canters, 2015). In comparison with DDF, both Areal and Binary generally underestimate the population of exposed sections at T10 and overestimate it at T100 and T500. These results are logical because, as the flood zone increases and exposure reaches the peri-urban area, the differences are accentuated in those sections where the population is dispersed. Therefore, in order to avoid this type of error, it is not advisable to use Binary or Areal in works of precision

Table 6
Wilcoxon test of hypotheses for the comparison of the proportion of the population exposed to a flood hazard, by census tract, calculated by DDF with that of the other methods. P-value <0.01 = **; <0.001 = ***; ns = not significant.

	T10			T100			T500		
	Areal	Binary	CEDS	Areal	Binary	CEDS	Areal	Binary	CEDS
DDF	***	ns	ns	**	ns	**	***	ns	***

Table 7
Variation in the population exposed to flooding, for the resident population and for the resident and seasonal populations combined, according to DDF (Total population = 702,812).

	T10	% (total population = 100)	T100	% (total population = 100)	T500	% (total population = 100)
(a) Resident population exposed	17342.9	2.4	39797.54	5.6	61094.3	8.6
(b) Resident population + seasonal population exposed	31890.7	4.5	66316.61	9.4	92422.2	13.1
(b) - (a)	14547.8		26519.07		31327.9	

where the sections are large and the population is scattered.

As a final check on the exposed population data, the hypothesis test shown in Table 6 was carried out to find the possible statistically significant differences between DDF and the other methods. This shows the improvement in the overall results of DDF compared to the other methods. In this sense, the statistical similarity between Binary and DDF for all return periods is striking. Thus, both methods could be used for the same purpose if the accuracy requirements are lax, as the differences can be considered marginal (Pavía & Cantarino, 2017a). In relation to CEDS, as long as the census tracts in the study area are densely populated, the differences from DDF are negligible, as can be seen for T10.

As another interesting result in relation to the exposed population, DDF makes it possible to find out, due to the information available in the census on the non-resident or seasonal population, the maximum population exposed to the flood hazard and, with this, fill a gap that most methods tend to have. In the case study, the seasonal population is 237,172 inhabitants, representing 50.9% of the 465,640 residents at times of peak occupancy such as during summer holiday periods. Consequently, according to Table 7, if we consider (a) as the minimum exposed population and (b) as the maximum, there is a percentage increase that would vary between 1.02%, for T10, and 2.31%, for T500. Furthermore, if the population disaggregation process is carried out considering this seasonal population, the similarity between DDF and Binary disappears, with significant differences between them in the T100 and T500. Given the high number of second homes in the study area, this information may be of great importance in the avoidance of large errors of omission.

In relation to dwellings, only DDF reaches this level of detail necessary to carry out the disaggregation due to the cadastral information and its relationship with that of the INE population and housing censuses (INE, 2013). According to the data in Table 8, between 3.89 and 12.91% of the main ground floor dwellings would be exposed to flooding where there is a sheet of water greater than 20 cm. However, although the above data are striking, it is also noteworthy that the fraction of secondary and vacant dwellings exposed is greater than that of the main dwellings, in all the return periods.

Table 8
Ratio of exposed primary, secondary and vacant dwellings to total dwellings (N = 308,503), according to DDF.

	Total exposed main dwellings	% Main dwellings exposed (100 = total main dwellings)	% Main dwellings exposed (100 = total dwellings)
T10	6512	3.89	2.11
T100	14,652	8.75	4.75
T500	21,622	12.91	7.01
	Total exposed secondary dwellings	**% Secondary dwellings exposed (100 = total secondary dwellings)**	**% Secondary dwellings exposed (100 = total dwellings)**
T10	6400	7.20	2.07
T100	11,218	12.61	3.64
T500	12,844	14.44	4.16
	Total exposed vacant dwellings	**% Exposed vacant dwellings (100 = total vacant dwellings)**	**% Exposed vacant dwellings (100 = total dwellings)**
T10	2909	5.58	0.94
T100	4971	9.54	1.61
T500	6422	12.33	2.08

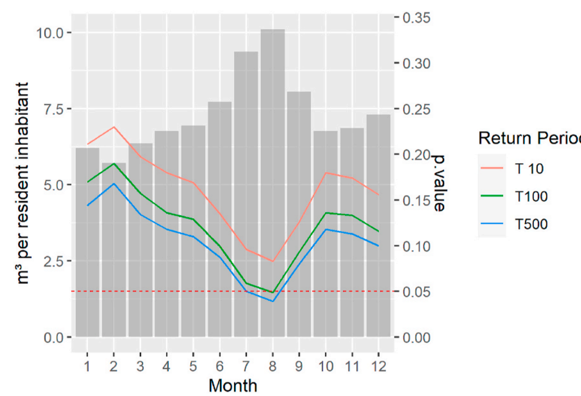

Fig. 7. Lines show p-value variation when contrasting resident population and total population (resident + seasonal). Bars show the variation of the seasonal population based on domestic water consumption.

3.2. DDF reliability assessment

To assess DDF reliability in touristic cities, it is necessary to check whether or not the inclusion of seasonal population is truly representative in the exposure results when compared to total population. In order to achieve that, the proportion of resident population and the proportion of total population exposed in each return period per month and census tract are contrasted. P-value monthly results are summarised in Fig. 7, where significant differences can be appreciated when considering exposed seasonal population during high season months (July and August) for T100 and T500, while no differences are observed during low season months.

Thus, during highest touristic activity periods, it is confirmed that secondary dwellings and seasonal population that temporarily live there must be considered when using DDF to avoid underestimating the actual population exposed to hazards.

4. Discussion

Due to the improved availability of demographic information, disaggregation methods have been increasing in number, accuracy and consideration as useful tools to be applied for such important purposes as the assessment of exposure to natural hazards (Maantay et al., 2007; Mennis, 2009; Pavía & Cantarino, 2017a). However, the results may differ significantly between the different existing methodologies depending on the degree of accuracy and the hazard considered. Maroko et al. (2019) pointed out that, when the exposure only affects certain parts of the building, methodologies that estimate the population by surface area or in 2D tend to exaggerate the exposed population compared to those that estimate the population by volume or in 3D.

These problems particularly arise for flood hazards, the effects of which are generally confined to the lower parts of buildings. To solve this problem of differential assessment according to the height, DDF represents a valuable tool for several reasons. Firstly, it overcomes the problem of overestimation of exposure arising from the assumption of a homogeneous distribution within a building by distinguishing between floors and only considering those that are commonly affected by flooding; i.e., the lower floors. Secondly, it differentiates between three types of dwellings (primary, secondary and vacant), which also allows the filtering out of those that are not occupied and that with other methods are considered as occupied. Thirdly, DDF provides a more realistic approximation of the real exposure than other methods due to the information on the population that tends to occupy its secondary dwellings temporarily (mainly weekends and holiday periods). This way, limitations mentioned in literature are partially overcome (Zandbergen, 2011; Cockx & Canters, 2015).

However, results obtained using other techniques such as Binary, Areal or CEDS should not be underestimated. Depending on the scale of the work, the way the population is distributed and the urban compactness (Mubareka et al., 2011), the results can vary drastically. Consequently, as indicated by (Maantay & Maroko, 2017, p. 670), it can be argued that each method provides better results depending on the scale of the work and the objective. With our case study data, if the objective were the assessment of the overall exposure of the study area, the Binary and DDF results could be treated in an analogous way, as the statistical differences are marginal. Given the calculation characteristics of these two methods and the information limitations that exist in less developed countries, the use of Binary is recommended on small scales, for general results and when no auxiliary information from the cadastre is available. A similar consideration should be made with respect to CEDS. When applied to densely populated areas, it is almost as accurate as DDF, but shows shortcomings when the population density is lower if it is not applied with a 3D volume technique (Pavía & Cantarino, 2017a) or a dasymetric mapping with a spatial non-stationary approach (Cockx & Canters, 2015).

Despite the great advantages achieved with DDF, the application of methods such as DDF for exposure assessment still has much room for improvement. Firstly, because census data only take into account the residential location of the population, who may not be at home as many hours as assumed since they are in school or at work, thereby overestimating the population that might be impacted (Maantay & Maroko, 2009). A number of recent studies have explored the daily spatial mobility of individuals to demonstrate the heterogeneity of the activity of many people (Yao et al., 2017), and such information has been studied in relation to flooding (Camarasa et al., 2011).

Secondly, although the results provide a fairly accurate simulated scenario of the above situation, they should be treated with reservations because of a number of limitations. In this respect, secondary dwellings or the resident population in each main dwelling could also tend to follow a certain spatial clustering that does not conform to a random distribution. That is, urban socio-economic or spatial dynamics may be spatially concentrated while the census tract does not show this. In touristic cities, it is common to find completely vacant buildings while at the same time there are others where all the dwellings have a similar density of inhabitants.

Finally, with regard to the DDF results for the study area, the exposure of the population to flood hazards is generalised but, depending on the typology of the dwellings, notable spatial differences can be observed. For the main dwellings and the resident population in them, there is an increase in exposure where the urban development model incorporates low compactness values (García, 2016). In other words, in compact urban areas (municipal capitals such as Lorca and Cartagena), as there is a predominance of multi-storey buildings, the exposure values are proportionally lower than in those municipalities with urban sprawl growth aimed at meeting the needs of residential tourism (the case of Los Alcázares, San Pedro del Pinatar, San Javier and Águilas) (López-Martínez and Pérez-Morales, 2017).

The exposed fraction of the secondary and vacant dwellings exceeds, in proportional terms, that of the main dwellings in the flood zones, for all the return periods. This is explained by the fact that in the study area the non-flood-prone areas were the first to be occupied due to their safe condition. These are where the oldest dwellings are located, where the majority of the permanent population resides (Pérez-Morales et al., 2021). Subsequent urban growth occurred at the expense of flood beds. This lack of planning is explained by the demand for developable land during the real estate bubble prior to the 2008 economic crisis (López-Martínez et al., 2020).

5. Conclusions

Given that economic losses triggered by floods have been rising in the last decades —and that climate change is expected to worsen the situation—, the need for detailed studies to assess exposure by using mapping fine-scale population distributions has increased. Nevertheless, in order to improve this assessment and as shown in Dasymetric mapping literature, detailed information on the type, size, floor and vacancy of residential units and the type of individuals living in them must be included. To tackle this issue, we proposed a framework for population estimation (DDF) at the dwelling level by integrating the three-dimensional morphological information derived from cadastral data and the human activity information extracted from population and dwelling censuses. With this three-dimensional data we could accurately identify those dwellings that are actually exposed to flood hazards, since the only ones affected are usually ground floors. Meanwhile, information on the type of dwellings (main, secondary or vacant) and type of individuals (residents or seasonal) allows for the distinction between permanently inhabited dwellings (by resident population) and temporarily inhabited dwellings (by seasonal population) to be made. To assess our framework reliability in touristic cities, a domestic water consumption database was used and, to validate the proposed methodology, results were compared to three other widely used methods.

When there is no need for a population differentiation, our findings show that both binary and DDF methods can be applied with similar results. Nonetheless, if the exposure assessment is applied to touristic cities, where seasonal population increases substantially during high season months, we strongly suggest using DDF to avoid underestimation problems when feasible.

CRediT authorship contribution statement

Alfredo Pérez-Morales: Conceptualization, Methodology, Investigation, Writing – review & editing, Writing – original draft, Supervision, Project administration. **Salvador Gil-Guirado:** Writing – original draft, Methodology, Writing – review & editing, Conceptualization. **Víctor Martínez-García:** Software, Formal analysis, Data curation, Visualization.

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Appendix A. Supplementary data

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