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COMBINING HIGH-RESOLUTION TESSELLATIONS AND DETAILED TRANSPORT NETWORKS FOR ACCESSIBILITY ANALYSIS IN LARGE AREAS: INDICATORS OF HUMAN PRESSURE ON COASTAL AREAS

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ABSTRACT

Human pressure on coastal areas poses a serious threat to their conservation. This pressure can be measured using accessibility indicators. However, a detailed accessibility analysis, with highly spatially disaggregated information and complex transport networks, requires millions of optimal routes to be obtained. To reduce processing times, this paper uses the centroid of a regular tessellation representing trip origins (square tiles with population and average income) and a layer of points associated with the coastline to represent destinations. Route calculations between all origins and all destinations are performed once, and then, depending on the objective of the study (accessibility to ports, beaches, lighthouses, or other points of interest), optimal route selections to the corresponding destination type can be made. The study results show the different degrees of human pressure on Andalusian beaches using different accessibility indicators.

Keywords: Accessibility indicators; human pressures on beaches; high-resolution tessellations; TomTom Speed Profiles data, network analysis.

COMBINANDO TESELACIONES DE ALTA RESOLUCIÓN Y REDES DE TRANSPORTE DETALLADAS PARA EL ANÁLISIS DE ACCESIBILIDAD EN ÁREAS EXTENSAS: INDICADORES DE PRESIÓN HUMANA EN ÁREAS COSTERAS

RESUMEN

La presión humana sobre las áreas costeras supone una seria amenaza para su conservación. Esta presión puede ser medida mediante indicadores de accesibilidad. Sin embargo, un análisis detallado

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de la accesibilidad, con información muy desagregada espacialmente y redes de transporte complejas, requiere la obtención de millones de rutas óptimas. Para reducir los tiempos de proceso, en este artículo se utiliza como orígenes de los viajes los centroides de una teselación regular (teselas con población y renta medias) y una capa de puntos asociados a la línea de costa para representar los destinos. Los cálculos de rutas entre todos los orígenes y todos los destinos se realizan una sola vez y después, en función del objetivo del estudio (accesibilidad a puertos, playas, faros u otros puntos de interés), se pueden hacer las selecciones de las rutas óptimas al correspondiente tipo de destino. Los resultados del estudio muestran el distinto grado de presión humana sobre las playas de Andalucía utilizando diferentes indicadores de accesibilidad.

Palabras clave: Indicadores de accesibilidad; presión humana sobre las playas; teselaciones de alta resolución; datos de TomTom Speed Profiles, análisis de redes.

1. Introduction

Accessibility studies play a long-standing role in geography and other related sciences. The concept of accessibility emerged in the 1950s. Hansen (1959) defined accessibility as the potential of opportunities for interaction. Unlike the concept of mobility, which refers to something real (movement of people or goods across space), accessibility refers to the interaction potential of the places where individuals and businesses are located (ease of reaching a destination or a set of destinations from a given point) (Gutiérrez and García-Palomares 2020). Accessibility is a key criterion in public policy decision-making (Omer 2006) from both an economic perspective (market access potential) and a social (equality in access to opportunities) and environmental (human pressure on spaces of high environmental value) point of view. Accessibility is usually seen as a positive factor, but it may also have negative implications. High-value natural spaces may be in danger if they are very accessible to the population (Gutiérrez and García-Palomares 2020).

Accessibility analyses must incorporate at least two components (Gutiérrez 2001; Condeço-Melhorado *et al.* 2013). The first component is the impedance or cost to reach the desired destinations, measured in distance units, travel times or transport cost. Travel distance is often used to model pedestrian accessibility, and travel time is usually used for longer trips by car or public transport. The second component is the number or importance of the opportunities intended to be reached. For studies on active accessibility, which measures access to supply, this component can be understood as the attractiveness of the destinations; it can be expressed in terms of population, number of jobs, or retail space, among others, depending on the focus of the analysis. In contrast, for studies on passive accessibility, which measures access to demand, this component shows the importance of origins, expressing how much demand (for example, population) benefits from the level of accessibility calculated for each destination point. In the case of accessibility under competition, this must be calculated in both directions.

From the very start, accessibility studies have faced the problem of obtaining results with high spatial resolution. This problem is because of the lack of sufficiently spatially disaggregated transport and land use data and the low performance of the computers available, given that as the number of origins and destinations increases, along with the extension and complexity of the networks, calculation times increase exponentially. This meant that researchers were forced to use simplified networks for a long time, with origins and destinations representing spatial units such as census tracts and transport areas (in urban studies) or municipalities and provinces (in regional studies). While the use of spatially aggregated data based on administrative units allows for simplified calculations, it is nonetheless closely related to ecological fallacy and the Modifiable Areal Unit Problem (MAUP) (Openshaw 1984, Nakaya 2000, Taylor *et al.* 2003), in that changing the spatial resolution of the data (scale) and modifying the boundaries between spatial units can lead to very different results. Langford *et al.* (2008), in a study on accessibility to services, demonstrated that two different forms of spatial disaggregation of the population at origin produced significantly different results. One strategy for limiting the effects of MAUP is to use regular tessellations (Zhang and Kukadia 2005).

In recent years, the availability of high spatial resolution networks and computers with greater processing power has allowed accessibility studies to be conducted at increasingly greater spatial resolution. Thus, for example, Omer (2006) and Yu *et al.* (2020) analysed accessibility using house-level data and detailed networks containing all the streets in the city. However, these works were still limited by using the researchers' estimated traffic speeds and not rigorously considering the variation of speeds throughout the day due to congestion.

Recent studies have used new data sources with comprehensive networks and actual or theoretical dynamic speeds to overcome this limitation. Thus, for example, Moya-Gómez and García-Palomares (2017) used data from TomTom Historical Speed Profiles to calculate accessibility in cities with data measured at different times of the day, whereas García-Albertos *et al.* (2019) used travel times between transport zones obtained through the Google Maps API. In the field of accessibility to services, data from TomTom Historical Speed Profiles have been used in different ways. For example, they were used by Moyano *et al.* (2018) to calculate access times to high-speed railway stations, by Tomasiello and Giannotti (2022) to detect inequalities in access to leisure, and by Pérez-Fernández (2022) to calculate accessibility to hospitals. When calculating accessibility by public transport, one option is to consider timetables using GTFS files. With these data, several studies have been conducted on temporal variability in public transport accessibility, considering different times of day (for example, Boisjoly & El-Geneidy 2016, Farber *et al.* 2014, Pritchard *et al.* 2019; Stępniak *et al.* 2019). GTFS files have proven useful for dynamic accessibility studies, considering that they contain scheduled times, not actual travel times, which can differ considerably from the former (Wessell and Farber 2019). The above studies, with a high number of origin-destination relationships, complex transport networks and accurate calculations of travel times, have generally been conducted in urban settings. When large areas with extensive networks and multiple origins and destinations are analysed, the calculation times are much longer.

The contribution of this paper is to provide a solution to the detailed calculation of accessibility over large areas, taking accessibility (human pressure) to the beaches of Andalusia as an example. This solution is based on a high-resolution tessellation to represent the origins, a layer of destination points representing the position of the beaches along the coast, data from mobile devices and a detailed transport network containing all streets and roads in the study area. The transport network offers empirically measured speed data sourced from mobile devices. The high-resolution tessellation stores population, which is disaggregated into important categories for the accessibility analysis, such as age, gender and income level. In turn, the coastline is represented by a set of points with a spacing of 250 m, with attributes for the type of coastline (beaches have been selected in this case). This solution allows for a single calculation of the travel times from the populated tiles to the points representing the coastline. The accessibility from every populated tile to every beach is then calculated by selecting the points representing beaches. In the same way, accessibility calculations can be completed for other coastal points of interest, such as headlands, lighthouses or ports, by making the corresponding selections.

In this paper, we have used the calculation of accessibility to beaches as an example since it is a subject of great interest due to human pressure on beaches having intensified in recent decades, putting these natural spaces at risk. These pressures act at many temporal and spatial levels, translating into ecological impacts that are seen across several dimensions in time and space, the result being that today, almost every beach on every coastline is threatened by human activity (Defeo *et al.* 2009). Many studies have examined the anthropogenic impact on beaches from different perspectives, such as geomorphological vulnerability (Vallés *et al.* 2011, Peña-Alonso *et al.* 2017), fauna (Martínez *et al.* 2020, de Souza *et al.* 2017, Cardozo, 2016) and vegetation (Farris *et al.* 2013, Kelly, 2014, Seer *et al.* 2016), concluding that environmental impacts are higher on beaches with greater ease of access and human pressure. However, these papers do not calculate accessibility; they simply study beaches that are considered very or not very accessible. Accessibility to beaches has been also addressed in studies on environmental justice on an urban scale and using straightforward metrics, such as distance to the nearest beach (Kim *et al.* 2018, Montgomery *et al.* 2015, Kim *et al.* 2019, Kim *et al.* 2023). However, to the best of our knowledge, no paper has undertaken a systematic study of human pressure on beaches based on accessibility indicators on a regional or national scale, probably due to the difficulties involved in calculating millions of optimal routes.

The structure of the paper is as follows. After this introductory section, the second section describes the data and methods, the third section shows the main results, and the fourth section is devoted to the discussion and conclusions.

2. Materials, data and methods

2.1. Area of study.

The study area is Andalusia, the southernmost region of mainland Spain, with a total population of 8.5 million inhabitants in 2022 and a surface area of 87,268 km², roughly equivalent to the size of Portugal. The 361 beaches in Andalusia have very different features as they share two maritime façades with distinct biophysical and socio-economic properties: the Atlantic and Mediterranean façades (Prieto and Ojeda, in press). The beaches in the province of Huelva and a part of the province of Cádiz are long, while those in the area of the Strait of Gibraltar, the coast of the province of Granada and the east of Almeria are generally shorter, separated by headlands and cliff areas.

2.2. Spatial reference, data sources and data pre-processing.

For this study, we have taken as a spatial reference for the trip origins the centroids of a regular tessellation of 51,338 square tiles of 250x250 m², which is also used by the Institute of Statistics and Cartography of Andalusia (IECA). This tessellation provides a high spatial resolution cartography, with tiles of equal shape and size, that should mitigate the MAUP problem[1]. Data on the characteristics of the population (IECA, 2020) and its average income (Ojeda *et al.* 2021), extracted from the Household Income Distribution Atlas (Spanish Statistical Office - INE, 2019), have been stored for this tessellation. In the case of average income, given that the original INE source provides this information by census tracts, dasymetric techniques (downscaling) have been used to disaggregate the census tract data and assign them to the tiles. This dasymetric technique involves two steps: (i) Firstly, the census tracts containing income information are intersected with the IECA tessellation containing resident population information (there can only be income where there is population). (ii) Secondly, values from the census track are assigned to tiles. If a tile (with resident population) is wholly included in a census track, the average income of this census tract is assigned directly to the tile. Otherwise, in those tiles that intersect several census tracts, the average income for these tracts are averaged, taking as a weighting factor the resident population of each intersected area. This resident population was estimated from the number of properties in the land registry buildings (ATOM format) multiplied by the average household size. In this way, each tile finally contains the socio-economic data of interest to us: resident population from the IECA and average income from the INE.

Next, the spatial reference for the destinations was a layer of points (3,446) representing the Andalusian coastline (equidistance 250 m). For this article, the points representing the 361 beaches were selected (2,423 points). As beaches are basically linear elements, each beach is represented by a set of aligned points that can rise to 100 points in the case of very long beaches; this is the case of Matalascañas beach, approximately 25 km long, represented by a total of 99 points.

[1] https://www.juntadeandalucia.es/institutodeestadisticaycartografia/VisorGrid/visor.htm

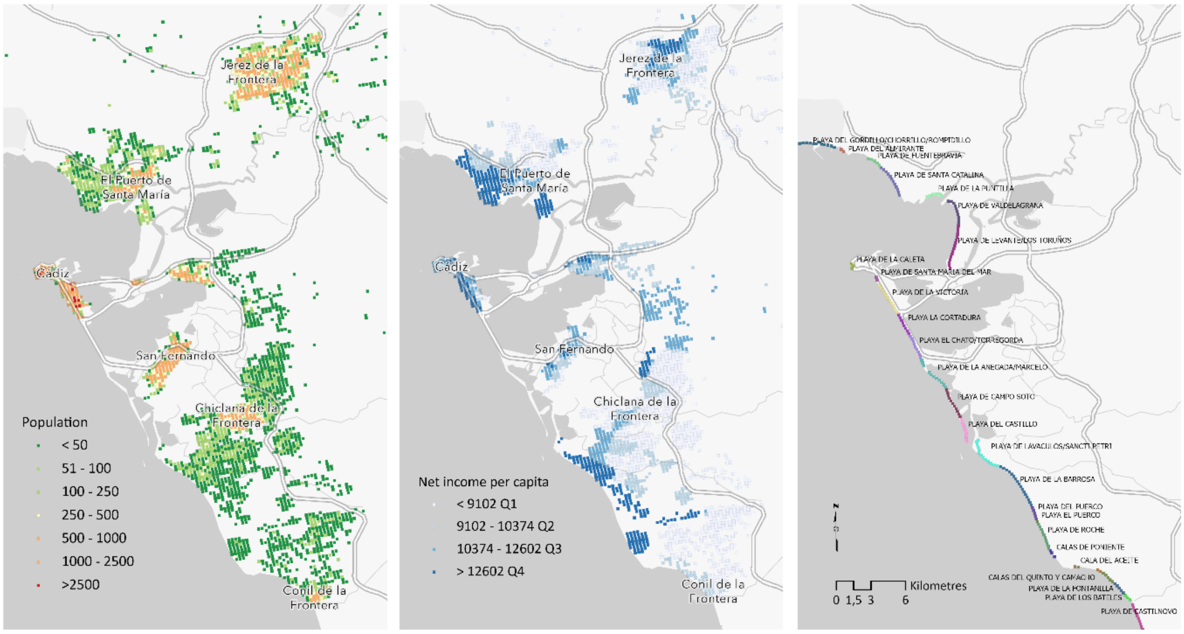


Figure 1. Population distribution, income level and location of beaches in the Bay of Cádiz area in the 250x250 m tessellation and the layer of points

Car travel times between tile centroids and beach points were calculated using the 'Network Analysis' extension of ArcGIS Pro and TomTom Historical Speed Profiles data. This product contains a very detailed transport network, including all streets and roads in Andalusia. Each section of the network stores data on average traffic speed every 5 minutes measured over 24 months, except in the sections corresponding to local roads, where only daily average speeds are reported. This paper has used average traffic speed for the central hours of the day, from 11 am to 4 pm, on weekdays, but future research aimed at analysing changes in accessibility caused by congestion could calculate travel times at different times of the day.

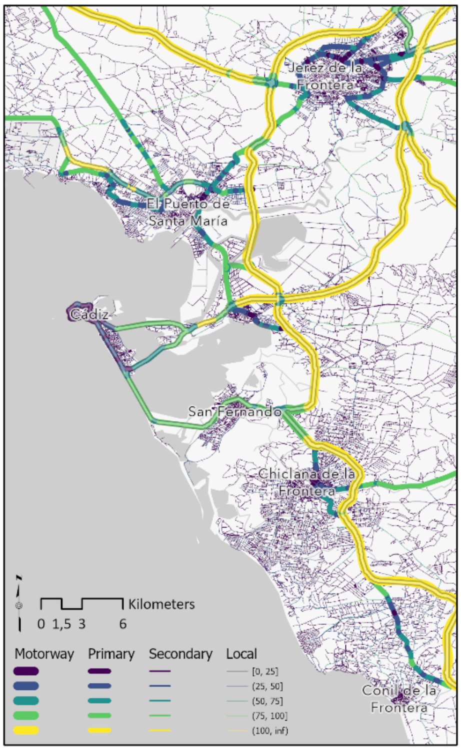


Figure 2. Details of the TomTom Speed Profiles network in the Bay of Cádiz.

Given that in Andalusia, there are a total of 51,338 populated tiles and 3,446 points representing the coastline, travel times were initially calculated for almost 177 million origin-destination relationships. Subsequently, those relationships with an origin in any populated tile and a destination in the 2,423 points representing the beaches were selected for accessibility calculations. Next, a new selection was made to consider only the shortest access time to each beach from each of the tiles. In this way, the calculation of travel times is performed only once, and then destinations are selected according to the study's objective.

2.3. Indicators of human pressure on beaches

Human pressure on beaches has been quantified using different accessibility indicators. Accessibility reflects either the ease of a traveller to reach places in the study area where they can carry out a particular activity, referred to in the literature as active accessibility, or the ease with which an activity can be reached by potential users in the study area, referred to in the literature as passive accessibility (Cascetta *et al.* 2016). This study adopts the logic of passive accessibility, *i.e.* focusing on demand access. Following this logic, attractive spaces, easily accessible from highly populated areas, will be under greater human pressure. This is the case for beaches, since the more accessible they are to a large population, the greater the potential human pressure they will be under. The accessibility indicators used in this study are as follows:

2.3.1 Cumulative Potential Demand

This indicator considers the amount of cumulative potential demand for one or more points of interest given a distance or travel time threshold (Handy & Niemeier 1997, Paez *et al.* 2012, Kelobonye *et al.* 2020, Kapatsila *et al.* 2023). This indicator is used in this study because the population closest to a beach will visit it more frequently, putting more pressure on it. In a passive formulation, this indicator is calculated as shown in Equation 1:

$$A_j = \sum_{i=1}^{m} P_i\, f\left(T_{ij}\right), where\ f\left(T_{ij}\right) = \begin{cases} 1, if\ T_{ij} \leq T \\ 0, otherwise \end{cases} \qquad (1)$$

Where: A_j is the potential demand for beach j, P_i is the population number in tile, T_{ij} is the travel time between tile i and beach j, $f(T_{ij})$ is the accumulative function, and T is the travel time threshold. Our analysis considered travel time (T) thresholds of 15, 30, 45, 60, 90 and 120 minutes. Cumulative opportunity indicators are advantageous over gravity indicators because their results are easier to explain. However, they lack a sound theoretical foundation, as they depend heavily on the definition of artificial boundaries and not really the distance decay effect (Morris *et al.* 1979). Perhaps the biggest weakness of the cumulative opportunities measure is its low accuracy, which stems from, among other factors, its disregard for competition effects (Kelobonye *et al.* 2020).

In order to socially characterise potential users accessing the beaches, the Andalusian population was divided into four per capita income levels (quartiles), according to the average net income of the tile in which they reside. The population of each income level in each travel time interval was then calculated, and a map was produced showing the percentage of the population in the highest income level at each beach.

2.3.2 Potential Accessibility

This indicator overcomes one of the limitations of the previous indicator by considering the distance decay effect. In fact, it belongs to the family of gravity indicators (Equation 2) and has been widely used in accessibility studies (for example, Gutiérrez 2001, Condeço-Melhorado *et al.* 2013, Weng *et al.* 2020). According to this model, the level of opportunity decreases with the impedance between areas and increases with the weight of the destination (or origin) area. The formula adopted for this case, following the passive accessibility approach, is as follows:

$$Pot_j = \sum_{i=1}^{m} P_i \, f(T_{ij}), where\ f(T_{ij}) = \begin{cases} \frac{1}{T_{ij}}, if\ T_{ij} \leq T \\ 0, otherwise \end{cases} \tag{2}$$

Where: Pot_j is the potential accessibility of beach j, P_i is the population of origin tile i, T_{ij} is the travel time of the shortest route through the network between populated tile i and beach j, and a is a gravity parameter assumed to be equal to 2. This model can also have a travel time threshold (T) to limit the number of relationships to be calculated. This study uses a maximum travel time threshold of 120 minutes. The justification for selecting this travel time threshold is based on the evidence that it is improbable that there will be trips to the beach (with a round trip on the same day) exceeding four hours in total.

Compared to the cumulative potential demand indicator, this second indicator gives more weight to the relationships with the tiles closest to the beach and with a larger population size. However, it does not consider the attractiveness of the beaches or the competition effect. Another disadvantage is that it is measured in less intuitive units than the other types of indicators, although the interpretation is straightforward: the higher the value, the greater the human pressure on that beach.

2.3.3. Huff model: indicators of potential demand and human pressure considering competition

To consider the effect of competition and the attractiveness of the beaches, we have considered their length. For the calculation, we adopted the approach in the Huff model (Huff, 1963, Huff, 1964), a probabilistic gravity model initially proposed to estimate the area of influence of shopping centres. Nevertheless, the applicability of that model to a wide range of problems and its relative ease of use justify its longevity (Moura *et al.* 2017). Unlike the previous ones, this model requires some intermediate values to be calculated before calculating accessibility under competition.

Applying this model to the study topic, the probability that the population of tile i will visit beach j is directly proportional to the length of the beach and inversely proportional to the distance between the tile and the beach, also considering the competition effect represented by the attractiveness of alternative destinations (beaches), according to equation 3:

$$Prob_{ij} = \begin{cases} \dfrac{\frac{S_j^b}{T_{ij}^a}}{\sum_{j=1}^{k} \frac{S_k^b}{T_{ik}^a}}, if T_{ij} \leq T, T_{ik} \leq T \\ 0, \qquad otherwise \end{cases} \tag{3}$$

Where: $Prob_{ij}$ is the probability of the population of tile i accessing beach j, S_j is the length of beach j (expressed in metres); T_{ij} is the access travel time from tile i to the nearest point of beach j, and a and b are parameters to be estimated or empirically determined. Note that the sub-index k is used to denote all competing beaches. In the absence of data for the calibration of parameters a and b, as in most similar studies, it is assumed that parameter "a" has a value of 2 and parameter "b" has a value of 1, consistent with the estimate made for the previous indicator. This model can also have a travel time threshold (T) to limit the number of relations to be calculated. This study uses a maximum travel time threshold of 120 minutes.

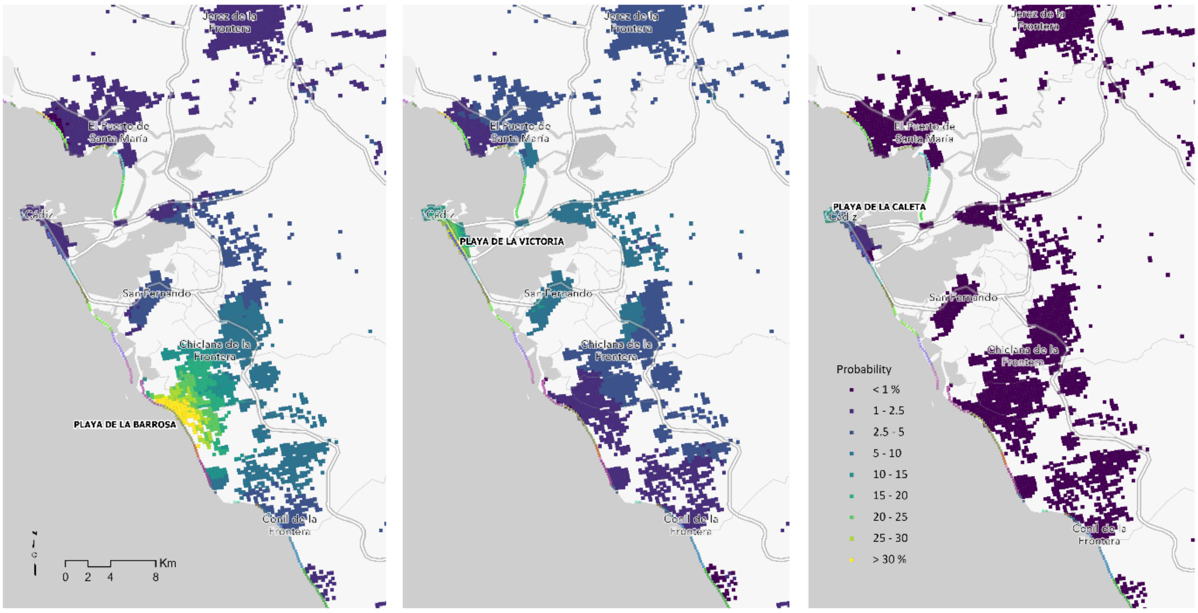


Figure 3. Example of the probability of visiting the beaches of La Barrosa (left), La Victoria (centre) and La Caleta (right), in the province of Cádiz.

The value obtained in this indicator is simply a probability, without considering the different population sizes of the origin tiles, which we need to estimate human pressure on the beaches. Therefore, in a second step, the probability obtained for each origin/destination pair is multiplied by the population size in origin tessellation i and the values obtained are added up for each beach j according to equation 4:

$$Pdc_j = \sum_{i=1}^{n} P_i \cdot Prob_{ij} \tag{4}$$

Where: Pdc_j is the potential demand on beach j under competition, and the other terms are already known.

Finally, the indicator of potential demand under competition for each of the beaches Pdc_j is divided by the number of points that each beach contains, thus obtaining a value of human pressure on each beach (Equation 5):

$$Hpc_j = \frac{Pdc_j}{s_j} \tag{5}$$

Where: s_j is the number of points of beach j, and the other terms are already known. In this way, to calculate the human pressure on the beaches, the capacity of the beaches is considered, so that on longer beaches the potential demand is spread over a larger number of tiles, resulting in lower human pressure.

3. Results

3.1 Cumulative Potential Demand

The cumulative potential demand indicator shows the closer proximity of the Andalusian population to its beaches (Table 1). Of the population in this region, 36.5 % can reach a beach by car in less than 15 minutes, 63.3 % can reach it in less than an hour, and only 2.8 % live more than two hours away.

The values for this first indicator vary greatly depending on each beach (Figure 4a). The beaches with the largest number of people living less than half an hour away are those in the most urbanised coastal areas, particularly the Costa del Sol, the Bay of Cádiz and the Bay of Almeria. In contrast, the beaches of eastern Almeria, the coast of Granada, the area of the Strait of Gibraltar, and the west of the province of Huelva are sparsely populated and suffer less human pressure. Seventy beaches (19.4 % of the total) have more than half a million inhabitants within 30 minutes, and for 14 beaches (3.9 %), this figure is more than one million inhabitants (Figure 5).

If we compare the number of people according to the time interval to access the nearest beach and per capita income levels (Table 2), we can see that, in general, and as expected, the wealthier population groups have better access to the beaches. Thus, among the population with access to the nearest beach in less than a quarter of an hour, 28.8 % belong to the highest income quartile and only 22.3 % to the lowest income quartile. This result indicates the population's location in the coastal cities, with the wealthiest owning the properties closest to the beaches. In contrast, among the population located more than two hours from the nearest beach, 32.3 % belong to the lowest income level and only 5.4 % to the highest income level.

The beaches can be characterised according to the population's income level with the easiest access to them. If we look at the percentage of the high-income population with access to each beach (Figure 4b), a clear duality is observed between urban and rural areas, in such a way that the most urban beaches (Costa del Sol, Bays of Cádiz and Almeria, Huelva area) have the highest percentage of high-income population within half an hour (above even 40 %), as opposed to beaches with less pressure, far from the big cities, where this percentage is much lower (below even 5 %).

Table 1. Population according to access time to the nearest beach.

Travel time to the nearest beach	Population	%	Cumulative	%
< 15	3,096,757	36.5	3,096,757	36.5
15 – 30	663,366	7.8	3,760,123	44.3
30 – 45	751,610	8.9	4,511,733	53.2
45 – 60	859,519	10.1	5,371,252	63.3
60 – 90	1,908,456	22.5	7,279,708	85.8
90 – 120	960,936	11.3	8,240,644	97.1
> 120	242,618	2.8	8,483,263	100.0
Total	8,483,263	100.0	8,483,263	100.0

Table 2. Population according to income level (quartile) and access times to the nearest beach.

Income level	**Low**	**Medium-low**	**Medium-high**	**High**	**Total**
< 15	689,897	649,817	866,533	890,510	3,096,757
15 – 30	220,917	222,145	147,909	72,396	663,366
30 – 45	160,902	195,435	198,845	196,428	751,610
45 – 60	230,697	219,249	222,452	187,121	859,519
60 – 90	496,510	495,544	403,532	512,869	1,908,456
90 – 120	241,779	245,470	226,275	247,411	960,936
> 120	78,469	95,812	55,211	13,128	242,618
Total	2,119,171	2,123,472	2,120,757	2,119,863	8,483,262
Income level	**Low**	**Medium-low**	**Medium-high**	**High**	**Total**
< 15	22.3%	21.0%	28.0%	28.8%	100.0%
15 – 30	33.3%	33.5%	22.3%	10.9%	100.0%
30 – 45	21.4%	26.0%	26.5%	26.1%	100.0%
45 – 60	26.8%	25.5%	25.9%	21.8%	100.0%
60 – 90	26.0%	26.0%	21.1%	26.9%	100.0%
90 – 120	25.2%	25.5%	23.5%	25.7%	100.0%
> 120	32.3%	39.5%	22.8%	5.4%	100.0%
Total	25.0%	25.0%	25.0%	25.0%	100.0%

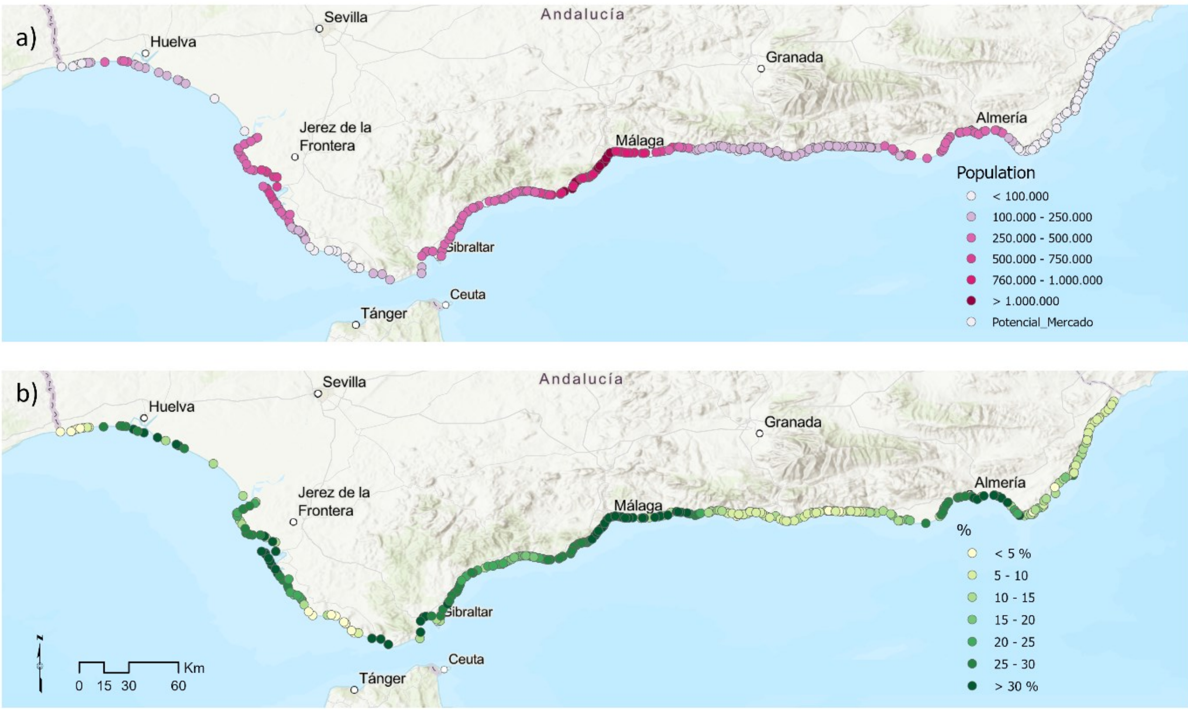
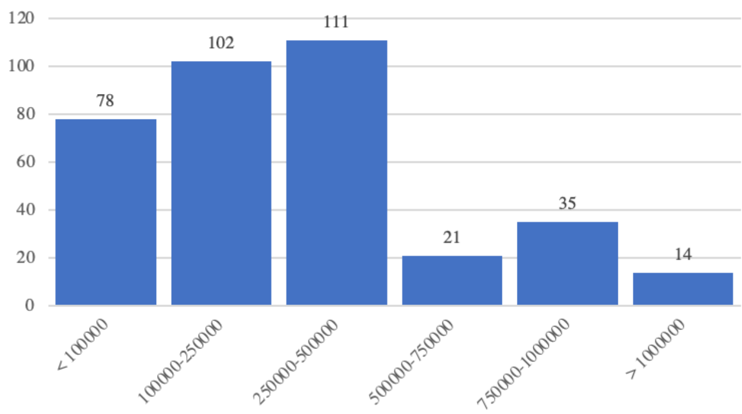


Figure 4: Cumulative potential demand: Total population within 30 minutes of the beach (a) and percentage with high income level - Q4 (b).



Minimum: 0

Maximum: 1,104,996

Mean: 330,287

Median: 255,636

Standard Deviation: 284,944

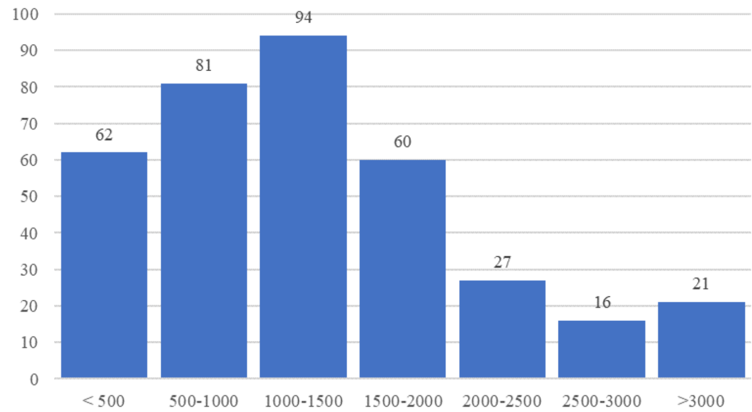
CV: 0.86

Figure 5: Distribution of the number of beaches according to the cumulative potential demand in 30 minutes and descriptive statistics.

3.2 Potential Accessibility

The potential accessibility indicator offers more nuanced results than the previous indicator, as it considers the distance decay effect up to 120 minutes. Particularly noteworthy is the very high value for the beaches in the metropolitan area of Malaga, while the rest of the Costa del Sol and the areas of Cádiz and Almeria now obtain intermediate values. The lowest values correspond particularly to the beaches of eastern Almeria, which are very inaccessible for the rest of Andalusia, and to a lesser extent to some beaches on the coast of Huelva and the area of the Strait of Gibraltar. Again, the values are very different, resulting in a few beaches (around Malaga) having high potential values (Figure 6 and 7).

Figure 6. Potential accessibility
Source: Own research



Minimum: 0.71

Maximum: 4,882

Mean: 1,344

Median: 1,150

Standard Deviation: 886.22

CV: 0.65

Figure 7: Distribution of the number of beaches according to the potential accessibility indicator and descriptive statistics.

3.3. Huff model: indicators of potential demand and human pressure considering competition

In keeping with the potential accessibility model, the indicators based on the Huff model have been calculated considering all the populated tiles within 120 minutes of a beach and an exponent of 2, although it is additionally estimated in this case that the capacity of each beach is proportional to the number of destination points that define it. Therefore, larger beaches will have a higher attraction capacity (greater potential demand under competition), but their potential demand will be spread across larger tiles (less human pressure).

The potential demand under the competition indicator (Figure 8a and 9) results in much greater local differences than the potential accessibility indicator, as it considers the different lengths of the beaches. Thus, for example, on the coast of Huelva and in the metropolitan areas of Cádiz and Malaga, beaches with very high potential demand values are interspersed with others with very low values. These local differences are mitigated in the human pressure indicator, as the higher potential demand is diluted across the greater number of beach points), as can be seen in many of the beaches in the areas mentioned above (Figure 8b and 10).

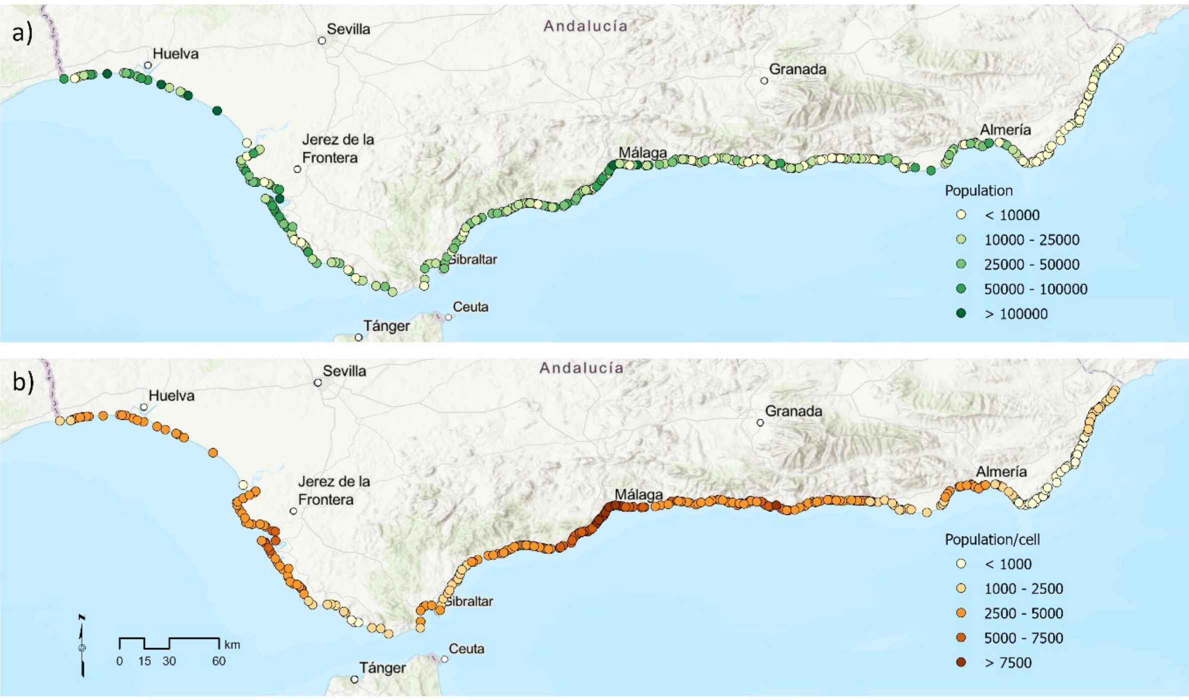
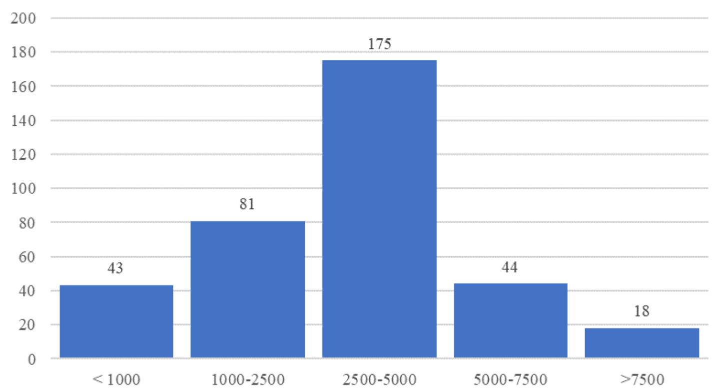


Figure 8. Huff model: a) potential demand and b) human pressure, both considering competition
Source: Own research



Minimum: 1.2

Maximum: 10,061.9

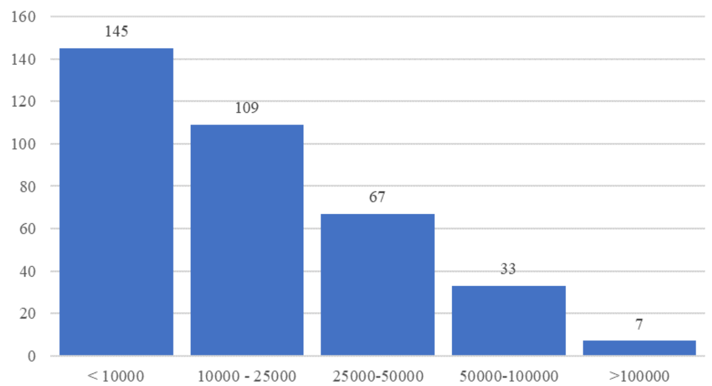
Mean: 3,329.2

Median: 2,958.7

Standard Deviation: 2,036.9

CV: 0.61

Figure 9: Distribution of the number of beaches according to the potential demand under competition indicator and descriptive statistics.
Source: Own research



Minimum: 37

Maximum: 300,602

Mean: 22,465.1

Median: 14,265

Standard Deviation: 30,331.9

CV: 1.35

Figure 10: Distribution of the number of beaches according to the human pressure under competition indicator and descriptive statistics.
Source: Own research

4. Discussion and Conclusions

Accessibility studies face the problem of knowing the actual speeds on the road network and the efficiency of accessibility calculations. The first difficulty has been successfully overcome due to the availability of road networks with measured speed data taken from mobile devices, such as the TomTom Speed Profile product used in this study. The latter remains a critical issue as, especially in the case of the analysis of detailed networks covering large areas, the number of origin-destination relationships to be considered when calculating travel times is enormous, often including millions of relationships and requiring many hours of calculations.

This problem has been overcome by dividing the space into, first, a high-resolution tessellation and the storage of the demand variables (population and average income) in this, and second, the supply variables in a layer of points dividing up the coastline. This solution means that it is only necessary to calculate travel times for each relationship once, and then perform specific accessibility studies by simply selecting the destinations (points) with the required characteristics. In our example, 177 million optimal routes were calculated, providing travel times for all origin-destination relationships between populated tiles (origins) and points representing the coastline (destinations). Subsequently, the valid routes were filtered to calculate accessibility to the beaches, with their corresponding travel times (124 million optimal routes). A similar strategy can be used in other projects, such as accessibility to services, where it is not necessary to calculate the travel time matrix for each type of service.

The approach of dividing up the space into tessellations and using their centroid for travel time calculations is an interesting methodological contribution as it reduces the number of origin-destination matrix calculations. On the other hand, given that the origins are the centroids of the square tiles, and these have a size of 250 m, the maximum estimated error we make when assigning the accessibility time for any variable incorporated into the origin tessellations is +/-10.5 seconds, that is, the time for travel 175 metres, which is the maximum distance between the centroid and the corner of the tile, at an average speed of 60 km/hour. This error is very low and perfectly acceptable for the purposes of this paper, in which the accessibility time thresholds are expressed in minutes.

The paper has covered a second research gap: calculating the human pressure on beaches using accessibility indicators over large areas, an unexplored topic. Papers on the anthropogenic impact on beaches recognise the importance of accessibility on this impact, but do not measure it as such. Measurements of accessibility to beaches are only found in environmental justice studies, albeit with straightforward metrics and on an urban scale. This paper demonstrates that accessibility indicators can be calculated over large areas, such as regions or nations, providing useful general information for managers and planners.

The Andalusian beaches with the greatest human pressure have been identified using indicators of varying complexity, providing complementary information by adding the distance decay effect and competition between beaches. It has been found that, as expected, the beaches under the highest pressure are those located near metropolitan coastal areas, particularly Malaga (due to its central position on the Andalusian coast for high travel time thresholds), while other beaches suffer much less human pressure. It has also been verified that higher-income groups have better accessibility to beaches, which is consistent with the results obtained in previous studies, which showed that the most socially vulnerable groups are in an unfavourable situation regarding access to these public spaces.

A limitation of this paper is that, for clarity in the presentation of results, these have been shown at the beach level, but the results can also be obtained at the level of the points into which each beach is subdivided. A second limitation is that considering the length of the beaches as a proxy for their attractiveness is a simplification. In future research we will try to build a more complex beach attractiveness indicator using the available sources.

In this paper we have used accessibility to beaches as an example. However, future studies of accessibility to ports, lighthouses, or other points of interest could also be carried out simply by selecting the points containing these types of elements and the travel times for the relationships with these points as destinations.

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