

RESEARCH ARTICLE

Analysing human mobility patterns of hiking activities through complex network theory

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Abstract

The exploitation of high volume of geolocalized data from social sport tracking applications of outdoor activities can be useful for natural resource planning and to understand the human mobility patterns during leisure activities. This geolocalized data represents the selection of hike activities according to subjective and objective factors such as personal goals, personal abilities, trail conditions or weather conditions. In our approach, human mobility patterns are analysed from trajectories which are generated by hikers. We propose the generation of the trail network identifying special points in the overlap of trajectories. Trail crossings and trailheads define our network and shape topological features. We analyse the trail network of Balearic Islands, as a case of study, using complex weighted network theory. The analysis is divided into the four seasons of the year to observe the impact of weather conditions on the network topology. The number of visited places does not decrease despite the large difference in the number of samples of the two seasons with larger and lower activity. It is in summer season where it is produced the most significant variation in the frequency and localization of activities from inland regions to coastal areas. Finally, we compare our model with other related studies where the network possesses a different purpose. One finding of our approach is the detection of regions with relevant importance where landscape interventions can be applied in function of the communities.

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Introduction

The increment of outdoor activities in recent years has had an economical and an environmental impact for a wide number of parties: landscape owners, environmental organizations, public administrations, and tourism entities among others. The extended use of GPS devices in outdoor activities together with the proliferation of social sport trackers sites enables people to share and comment their tracks and training measurements. This type of data sources provides large volume of information that can be analysed. For example, the occupation of outdoor areas or the characterization of human mobility patterns can be inferred from the records of social sport trackers [1, 2] In addition, understanding the factors that influence the practice of a certain sport has a wide range of applications: for example in preserving and planning natural areas [3–6], determining the most frequented attractions [3, 7–10], predicting

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agglomerations [11, 12], discovering travel patterns [8, 13–15], or measuring the overlapping of activities [4].

The problem of modelling human behaviour in urban and natural environments has been widely studied. In urban environments, human mobility data have been extracted from internet and mobile phone connections [1, 16–18], geolocalized tweets [19–21], and GPS-tagged photos [13, 22, 23] among other sources. In natural environments, generally natural parks, visitors or hikers mobility data come from GPS devices instead of mobile phone connections due to insufficient precision or the lack of coverage. To obtain trajectories from visitors, in several cases, authors provide them preconfigured GPS devices to facilitate the applicability of statical techniques within small confined areas [3, 4, 24]. In the analysis of the movement, several techniques are used such as point density [5, 25, 26], counting the frequency of visits on a determined area [6, 27], identifying suspension patterns (areas with a reduction in the speed), and flow distribution among areas [3]. In these studies, the goal is to obtain a rank of areas or trail segments according to some characteristic (e.g. trail degradation, frequency, etc.).

We provide an approach for the use of geolocalized activity to build a network that allows the identification of places of relevance and the relationship among them. Other studies addresses the problem of finding points of interest by considering small specific and confined regions without exploring interferences with other environments and external factors. The environment choices can dictate the flow of the movement and the pressure on it forming a network of paths. In hiking activities, the structure of paths can be associated to roads through which hikers perform their activities reflecting the conditions of them: access, services, and other factors such as personal goals or weather conditions. The transformation of the activity into a network allows to the analysis and identification of places of relevance where interventions can be conducted. We perform a complex network analysis of 15376 hiking routes performed during 2009–2016 in the Balearic Islands. Our dataset, coming from a sport tracker application, is highlighted by the variability of cases, by the topography of each island, and by the fact that the uploaded data are not conditioned by the study. We conduct various topological analysis taking into account external factors such as the seasonal weather, the difficulty of the route, or trailhead facilities.

Complex network theory enables the extraction of non singular topological features [28]. In the literature, there are several cases of applicability to transport system [29–35]. For example, in [34] the transport network of Singapore subway has been analysed where the nodes are transport stops and stations, the edges represent the transport lines connection between the nodes, and the weights of the edges are the number of passengers between the nodes. Another case of study is the human impact in natural environments [36], where different types of ecological characteristics to describe the interaction between human activities and the ecosystem are combined. In our approach, the nodes of the network are head and cross trails, and the edges represent the hiking activity that join these elements. Thus, the modelling of the network provides the location of points of relevance and the relationship between them, as well as the flow of the movement and indicators about the pressure of certain regions.

From our approach, we derived the following research issues:

- How to design and develop a method to convert GPS traces into a complex network representation without loss of geospositional data?
- Are the complex network outcomings useful to provide more contextual data in the location of points of relevance?

Therefore, the contribution of this paper is two-fold: on the one hand, to generate an information retrieval method to obtain points of relevance and the relationship between them. On the other hand, to apply complex networks theory to a real-world geospatial scenario.

Trail network model

A network is made up of vertices or nodes which are connected by edges. In the modelling process, we need to provide semantics in each graph element since the topological features must be associated with real indicators of the modelled environment. In our model, nodes are trail crossing locations, forks or intersections, and trailhead places. Trail crossings locations are critical points since they can involve accessibility to different areas, change of direction, encounter with other users, or a link to other transportation system. Furthermore, the identification of these points are crucial because they are places to perform interventions, influencing, for example, the distribution of visitors [37]. Trailhead places require some effort in terms of transport, time or supplementary services to reach them. The edges represent in our model the hiking activity connecting the nodes.

Definition: trajectory

A trajectory (τ) is a finite, time-ordered sequence of coordinates $\langle c_1, c_2, \dots, c_n \rangle$.

Definition: trajectory vector

A trajectory vector ($\bar{\tau}$) is the sequence of vectors between consecutive coordinates:

$$\bar{\tau} = \langle v_0, v_1, \dots, v_{n-1} \rangle, \text{ where } v_i = \overline{c_i c_{i+1}}.$$

Definition: intersection

An intersection operation (\perp) between two trajectories gives a set of ordered coordinates: $\tau_1 \perp \tau_2 = \bar{\tau}_1 \perp \bar{\tau}_2 = C$ and $\forall c_i \in C: c_i \in \{\tau_1 \cup \tau_2\}$. **C1:** The union of consecutive points defines a common segment. **C2:** A loop is an intersection operation in the same trajectory: $\tau_1 \perp \tau_1$

We combine all the trajectories to generate the network. From the perspective of a trajectory, we can extract start, end, and loop points. With the combination of several trajectories, we can detect intersections among them. This process is represented in Fig 1 that contains three GPS trajectories (hiker's records where the sequence of coordinates goes from left to right) with positions biased under unknown recording conditions and the generated graph (G). The three trajectories should be overlapped but this will difficult the interpretation process. Trajectory 1 (τ_1) is a circular route, and possesses a loop, which represents a intersection of two segments, a start and end points. Both points are considered as identical. The considerations on whether two points are identical in space depend on the GPS accuracy and we explain it later. Trajectory 2 (τ_2) contains a loop at the same point that τ_1 -loop but the segment is at another location. The start and end points do not match, so it is not a circular trajectory. Trajectory 3 (τ_3) is a non circular route, where the start and end points coincide with τ_2 points. The result is a directed graph: (G), where nodes n_1 and n_3 are produced by the start and end points of all routes. The n_2 -node is determined by the origins of each loop (τ_1 and τ_2) and by two intersections: $\tau_1 \perp \tau_3$ and $\tau_2 \perp \tau_3$. The weight of each node is the number of traces that match in that place. Following the example, the weight of n_1 is $W_{n_1} = 3$, $W_{n_2} = 3$ and $W_{n_3} = 2$.

Edges are defined by the sequence of nodes. The n_2 -node possesses two different loops, each loop represents an alternative route. The weight of each edge is the number of routes between the nodes.

The graph depends on the number of samples. For example: (I) if we only consider τ_3 , there is no n_2 -node. (II) If we do not consider that the τ_2 does not have a loop and there is no τ_1 , the intersection between τ_2 and τ_3 will define n_2 -node.

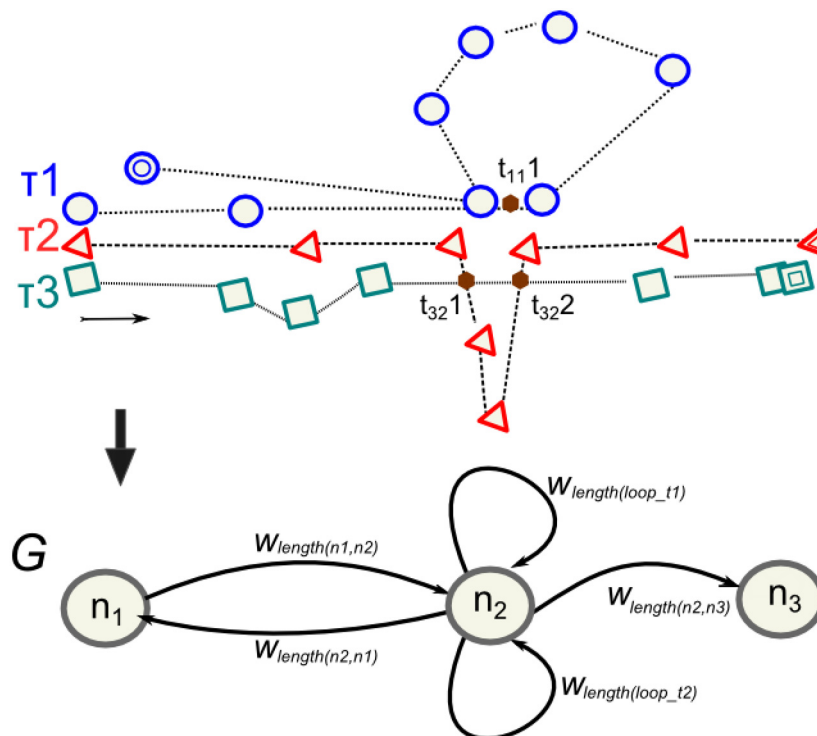


Fig 1. Sketch of the network generation from GPS traces. Upper panel shows the track points of three GPS traces where coordinates are represented by geometric symbols (circles, triangles, and squares) and the crossing points are in brown colour. Lower panel is the directed network generated with different edge weights (w).

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Algorithm

The time complexity of a brute-force algorithm that computes the intersection between two pairs of coordinates using the whole dataset is $O(n!)$, where n is the sum of coordinates of all trajectories. To reduce the number of cases due to GPS accuracy and several device configurations, we decide to split the process of computing intersections in two parts. These intersection are candidate nodes in the modelling of the network because it is necessary to consider all of them to valid the final nodes. We present a pseudo-code of the algorithm in alg. 1. The algorithm has two main loops. In the first part (lines 1–10), we individually analyse each trajectory to obtain: trajectory bounds, start and end points and a new smoothed trajectory (τ'). If start and end points are approximately equals ($threshold_{length}$), both points are considered equals (line 5). We filter the trajectory using Ramer-Douglas-Peucker algorithm [38] obtaining a simplified trajectory τ' (line 6). After that, we compute the loop points (line 8). In this case, the route contains an overlap with itself. For instance, a route that goes back the same way. First and last point of each segment are estimated trail crossings, omitting nearby places ($threshold_{sq}$). In Fig 2(left), we show an example of a route with a common segment. In this case, we detect two nodes (in yellow colour) applying the first part of the algorithm. Left yellow point is both the beginning and the end of the trajectory, and at the same time, it is the start point of the common segment. Right yellow node is an intersection and is the other end of that segment. In the second part of the algorithm (lines 11–19), we only compute the intersections of smoothed trajectories that have an overlap of bounds. As before, we proceed in the same way with the sequences choosing start and end points. Fig 2(right) shows an example of this second

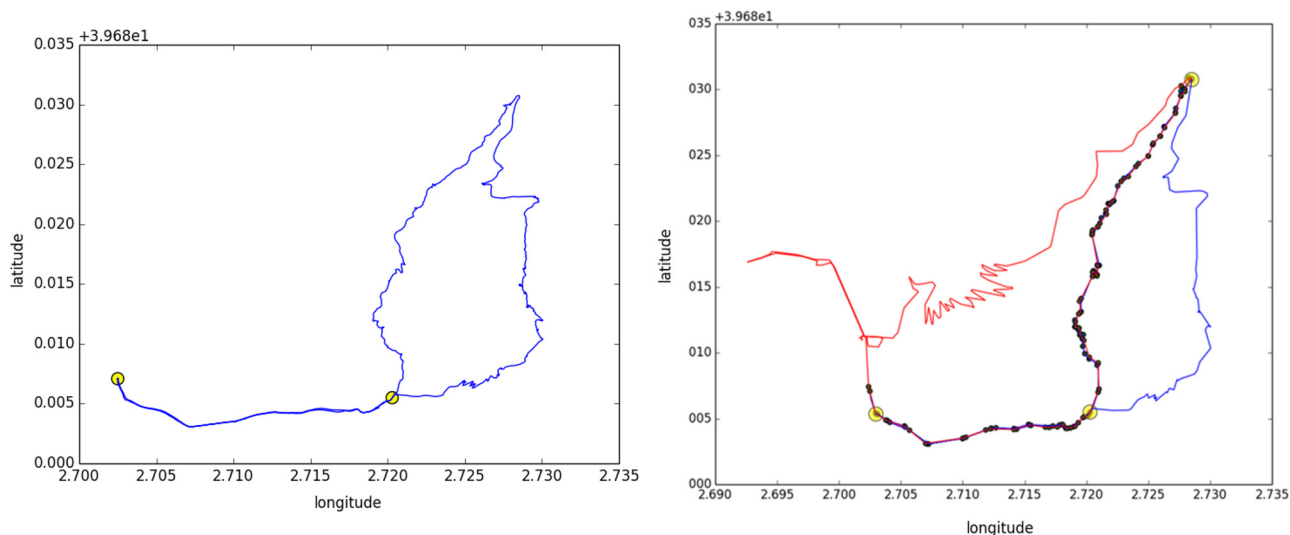


Fig 2. Example of the detection of candidate nodes. (Left) The first part of the algorithm detects the start, end, and intersection points indicated by yellow circles of the trajectory. (Right) The second part of the algorithm, detects the intersection points between two trajectories. Black points define the common segments and yellow points are the candidate nodes.

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part of the algorithm. In the overlapping of both trajectories, there are some common points which are in black colour. The union of these points defines various segments using a threshold of separation ($threshold_{sq}$). In this case, selected nodes are the endpoints of the sequences (in yellow colour).

Algorithm 1 Computing Candidate Nodes

Data: trajectorydataset T , $Threshold_{length}$, $Threshold_{sq}$

Result: intersectionpoints IS , IB ; start/endpoints sC , eC

```

1: for each  $\tau_i \in T$  do
2:    $B_i \leftarrow \text{get Bounds}(\tau_i)$ 
3:    $sC(\tau_i.id, i) \leftarrow \text{get First Coordinate}(\tau_i)$ 
4:    $eC(\tau_i.id, i) \leftarrow \text{get Last Coordinate}(\tau_i)$ 
5:   If  $\text{distance}(sC_i, eC_i) \leq Threshold_{length}$ :  $sC(\tau_i.id, i) \leftarrow eC(\tau_i.id, i)$ 
6:    $\tau'_i \leftarrow \text{do a Smooth Filter}(\tau_i)$ 
7:    $T' \leftarrow \text{insert}(\{B_i, \tau'_i\})$ 
8:    $ipoints_i \leftarrow (\tau'_i \perp \tau'_i)$ 
9:    $IS(\tau_i.id, i) \leftarrow \text{compute Start/Endpoints of each sequence}(ipoints_i, Threshold_{sq})$ 
10: end for
11: repeat
12:    $\{B_i, \tau'_i\} \leftarrow pop(T')$ 
13:   for  $\{B_j, \tau'_j\} \in T'$  do
14:     if  $B_i \cap B_j \neq \emptyset$  then
15:        $ipoints_{ij} \leftarrow (\tau'_i \perp \tau'_j)$ 
16:     end if
17:      $IB(\tau'_i.id, i, j) \leftarrow \text{compute Start/Endpoints of each sequence}(ipoints_{ij}, Threshold_{sq})$ 
18:   end for
19: until  $T'.size == 0$ 

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The intersection process (lines 8 & 15) uses a k -d tree algorithm to facilitate the nearest point matches [39]. The idea is to detect the longest common subsequence between two trajectories [40]. In this way, intersection points are obtained from real coordinates, they are not obtained from an interpolation process or an average computation. The algorithm requires a

threshold to compute the closeness and returns a ordered sequence of coordinates. In the second call (line 15), the algorithm avoid nearest points of the same route since they are obtained in the first loop. We make publicly available this part of the algorithm [41].

Depending on the distribution of coordinates among trajectories and on the selection of thresholds, there may be a random distribution of points around a real trail crossing. Thus, we need to group nearby points when all intersection points of the whole set of trajectories is calculated in previous algorithm. We compute centroid points applying a mean shift clustering algorithm [42]. The centroids are the nodes of the network, and their weights are the number of GPS traces that goes there. Returning to the example of Fig 1, if we assume that selected thresholds are exceeded due to distance issues then the intersection process ($\tau_2 \perp \tau_3$) provides two intersection points: $\tau_{32}1$ and $\tau_{32}2$. At the same time, τ_1 has a intersection point ($\tau_{11}1$) for its loop which is physically collocated between both. Thus, we have three possible points to represent an unique trail crossing: $\tau_{32}1$, $\tau_{11}1$ and $\tau_{32}2$. In Fig 3 we show an example of the dispersion of candidate nodes. After the application of mean shift algorithm, we obtain the centroids of the cloud of candidate nodes. These centroids are the nodes of the generated network.

The edges are the sequences of candidate nodes of each route. Before the clustering process, we have a sorted sequence of nodes of each route: start point, n-intersections (loops and intersections among trajectories) and end point. The range of nodes of each trajectory is (1..n). We transform this sorted sequence in edges by mapping the points in the correspondent final centroids. We discard edges with the same source and target node since they represent nearby intersections, and sequence length values equal to one. The weight of each edge is the length between nodes considering the original trajectory.

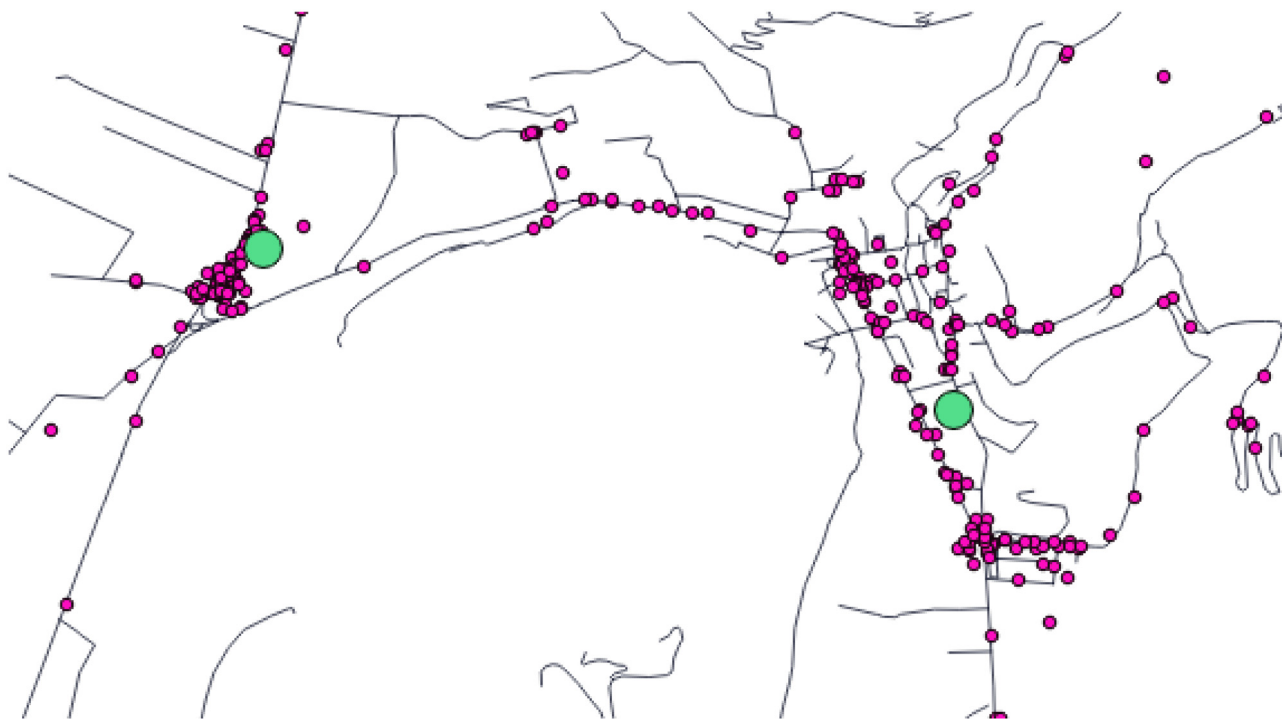


Fig 3. Illustration of the obtained centroids. The start, end, and fork points in Bunyola (Majorca) are represented in purple. After the mean shift algorithm, two centroids are obtained (green points). Black lines correspond to roads.

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Case study: Hikes in Balearic Islands

Our dataset consists on GPS traces from a sport social tracker application that is used as a collection of routes [43]. The application only stores the same route once per user. The recorded data represents the real human movement in any localization (urban, interurban and natural areas), and reflects external and personal factors in every individual and collective records. Outdoor activities are conditioned by external factors such as weather conditions, daylight hours, holidays, specific planning trails, social events, etc. These meaningful data are registered by different devices and configurations which affect the distribution of points and their accuracy. For each GPS trace, we have the following metadata: start and end timestamps, the degree of difficulty of the route assign by the user, and a GPX file with the coordinates of the track points. We make publicly available the anonymized set of GPS traces [44]. In total there are 15376 records (21.2 millions of coordinates) performed by 2965 users over 8 years (from 2009 to 2016) on the Balearic Islands (Spain). This archipelago is interesting for the study by the following reasons: (I) they are relatively small confined pieces of land where the spatial dimensions are closed to the human movement scales, (II) the three main islands possess very different geographical characteristics, (III) the weather conditions allow for the practice of sport activity during all the year, and (IV) a future applicability of findings in well-known tourist region in Europe. A more detailed description of the GPS traces can be found in the Data Description section in [S1 File](#).

Basic statistics

We introduce the following statistical measures about weather conditions and topography of our scenario in order to clarify the results of the network analysis.

Weather conditions. Outdoor activities are influenced by weather conditions. Balearic Islands have a Mediterranean climate: warm winters, and hot and humid summers. The average temperature in August is 25.9°C with an average maximum temperature of 29.5°C. In contrast, in January the average temperature is 11.7°C with an average minimum of 8.3°C. We obtained the temperature log from [45]. This range of temperature has a direct consequence in the number of activities as [Fig 4](#)(left) shows. In summer, the number of activities is significantly lower than in other seasons, due to high temperatures. This is clearly seen in [Fig 4](#) (right) in which the number of activities decreases when temperatures increase.

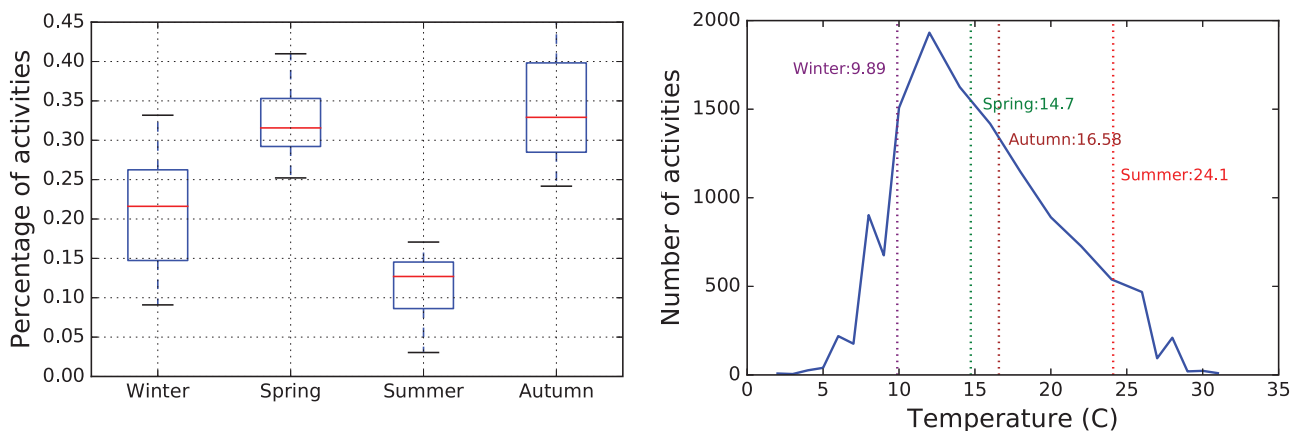


Fig 4. Analysis of hiking activities. Seasonal frequency of hikes for the four seasons (left). The number of hiking activities as a function of the average temperature of the day (right). Vertical dotted lines represent the averaged seasonal temperature.

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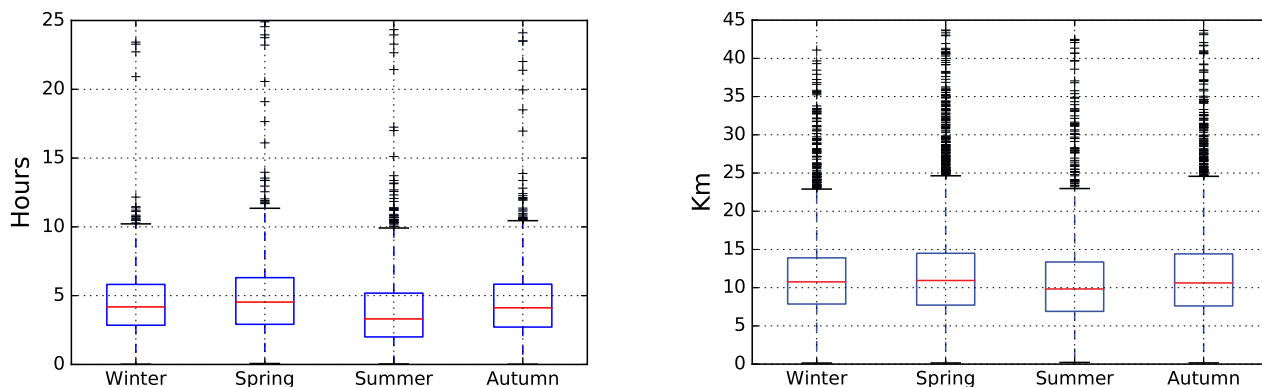


Fig 5. Seasonal analysis of hiking duration and length. Box plot figures: duration (left) and length (right).

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The number of daylight hours also influences in the behaviour of the hikers. In summer the number of daylight hours is approximately 14 hours, however, in winter it is around 10 hours. Fig 5 (left) shows the distribution of the duration of activities for each season. We can observe that the temperature has a greater influence than daylight hours in order to determine the duration of activities. Furthermore, there are many routes with a mean duration below 5 hours; and in spring, there are a small group of striking routes lasting more than a day, which correspond to long-distance footpaths. The length of the hikes is represented in Fig 5 (right).

Topography. The topography of each island influences also in the hiker activity. We consider the four main islands: Majorca, Minorca, and Ibiza & Formentera. Majorca has a lower-intermediate mountain range called *Serra de Tramuntana* with several peaks over 1000 meters where Puig Major is the highest peak (1445 m), the most important trail is GR221 (*Grande Randonnée*) with a length of 135 km. Minorca has a well-known trail called *Camí de Cavalls* or GR223 which is a circular trail with a length of 185 km around the perimeter of the island. Finally, Ibiza trails are scattered among the small villages. We include Formentera island in the same analysis than Ibiza. From now on, we only mention the three groups, or the three islands. Fig 6 shows the cumulative distributions of the duration and length of the hiking activity in each island. The distributions of the length are very alike indicating similar hiking length in the three islands. However, the distributions of durations exhibit substantial differences,

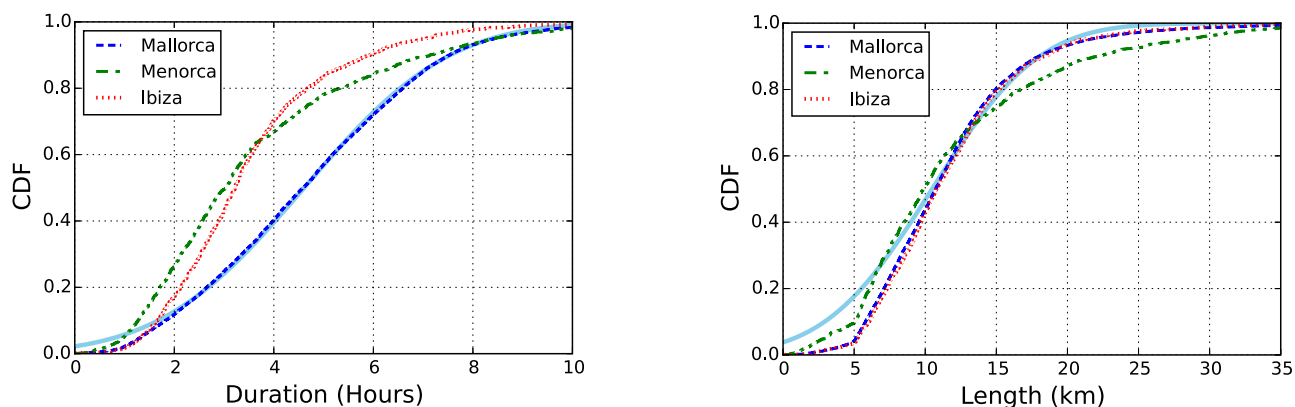


Fig 6. Hiking duration and length. Cumulative distribution function of the hiking duration (left) and hiking length (right) in each island. In both panels, solid line represents a fit to a cumulative Gaussian distribution: $f(x) = 1/2[1 + \text{erf}((x - \mu)/\sigma\sqrt{2})]$ with mean $\mu = 4.6$ (10.87) and standard deviation $\sigma = 2.3$ (4.57) for the duration (length) distribution in Majorca.

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significantly in Majorca showing a wider distribution. Although the hiking length is similar in the three islands, in Majorca the hikes tend to have a longer duration. The distribution of duration (length) follows a Gaussian distribution with mean $\mu = 4.6$ (10.87) and standard deviation $\sigma = 2.3$ (4.56) for Majorca.

Analysis of the hike network

Trail network

To analyse the Balearic Islands trail network, we configure the previous algorithm with the following parameters: $threshold_{sq} = 3$, $threshold_{length} = 10$ meters, k -d tree query distance = 55 meters and a mean shift bandwidth of 0.0043 (approx. 480 m). These values are defined through empirical analyses on different regions of the islands. The value with more sensitivity in the features of the network is the bandwidth of the mean shift algorithm. Setting this value is a trade off among the size of the region, the physical characteristics of the area and the level of resolution of trail crossings. We set to have a resolution of a half a kilometre. In any case, the topological features remain proportional up to a value above two kilometres. The k -d tree query distance allows the differentiation of nearby paths. Paths less than 55 meters are considered similar. Finally, we choose a sequence of three sampling $threshold_{sq}$ in the overlapping of the paths. This value is close to 60 meters, enough to differentiate nearby paths.

We observe that the number of candidate nodes is high with a huge volume of traces. There is an effect of sequencing intersection points due to the dispersion of coordinates. The problem of finding the intersection of trajectories has become a problem of finding the real trail crossing. The number of intersections of a route is so high that this number exceeds the number of coordinates of a route. The average ratio of intersection points is approximately twice the number of coordinates on the route. For instance, the trajectory shown in Fig 2 (left) has 1054 coordinates for a length of 12.3 km, the number of intersections points with the rest of routes (approx. 1.4k in this area) is 3428 points. In order to reduce the number of possible candidates, we introduce an extra step to the previous algorithm, by applying the mean shift algorithm to the node candidate of each traces. Then, the same algorithm is applied on all candidate nodes of all traces. Now, the position of the nodes gives us an approximation for the real intersection.

Overview

We characterize the network resulting from the algorithm previously described by computing the standard properties summarized in Table 1. These values are obtained using NetworkX library [46]. Furthermore, with the aim to study the seasonal variation, we consider three different segmentation of the data analysing the following seasonal networks: spring (SP), summer (SU), and the aggregation of the four seasons (4S). These networks have different number of isolated subgraphs, which value varies seasonally on each island. The number of subgraphs is an indicator of the distribution and use of places. The main subgraph of Majorca is localized in the Serra de Tramuntana area, where there are sections of the GR221. In Majorca and Ibiza, we observe greater variability of subgraphs in each season.

The number of activities decreases in summer in all areas, but this trend is lower in coastal areas. In any case, Minorca is the only example that maintains approximately the same localizations of nodes in each season. In addition, Minorca presents special circumstances: some of the coast lines and beaches are only accessible by going bordering private lands.

The extracted networks for Majorca, Minorca, and Ibiza & Formentera aggregated for the four seasons are shown in Fig 7, respectively. In Majorca island, the nodes are concentrated in the mountain area. In Minorca, the nodes are around the perimeter. In Ibiza & Formentera, the localization is more uniform. The locations of nodes change according to the season,

Table 1. Summary of topological features of the three networks.

Property	Majorca			Minorca			Ibiza & Formentera		
Island	Majorca			Minorca			Ibiza & Formentera		
Area	3640 km ²			702 km ²			654 km ²		
Season	4S	SP	SU	4S	SP	SU	4S	SP	SU
Number of traces	11984	3964	1209	1492	427	390	2243	702	277
Number of nodes (n)	884	784	767	203	161	218	293	246	210
Number of edges (e_m)	10864	3119	1225	1616	314	475	1944	454	146
Degree (k)	14.943	7.3083	4.4067	11.3899	4.9507	6.0041	8.0469	4.2651	3.2426
Degree range	(1,22)	(1,22)	(1,22)	(1,24)	(1,7)	(1,24)	(1,28)	(1,24)	(1,7)
Avg. shortest path	5	5	8	3	6	4	4	4	4
Diameter	16	18	25	9	11	11	10	18	11
Avg. clustering (C)	0.342443	0.313013	0.199265	0.321705	0.137489	0.207485	0.3152	0.189795	0.198618
Avg. weighted clustering (C_i^w)	0.011435	0.008306	0.005601	0.030659	0.011814	0.015959	0.0221	0.011479	0.016277
Assortativity (r)	0.138867	0.121049	0.022	0.027258	-0.051515	-0.0127	0.0044	-0.142534	0.273333
Avg. edge weight (km)	5.47	4.023	6.43	7.03	6.44	5.12	4.02	4.16	6.44
Edge weight range (km)	(0.39,86.6)	(0.39,65.3)	(0.39,65.2)	(0.3,42.2)	(0.37,18.9)	(0.4,37.3)	(0.6,34.38)	(0.4,37.2)	(0.37,18.4)
N. of subgraphs ($n > 3$)	5	5	3	1	1	1	1	1	4
N. of isolated nodes	73	156	223	15	26	30	15	41	127
N. of unique edges (e)	2567	1314	764	595	202	307	706	291	96

Results of the three islands considering all seasons (4S), and both most extreme seasons in terms of frequency of activities: spring (SP) and summer (SU).

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except the nodes with more weight which remain relatively in the same area. We experience that the high temperatures in summer make coastal areas more attractive. We include the spring and summer figures of the networks of each island in the section of Hiking activity networks in [S1 File](#). In addition, networks can be found in the Supporting Information ([S2 File](#)).

Basic network properties: Nodes and edges

As we mentioned, nodes represent relevant areas where intervention tasks could be executed. The node weights are the number of activities that have been performed in that area. From [Table 1](#), we observe that the number of nodes is slightly similar during spring and summer within each island. The difference of nodes between seasons does not depend on the number of samples. Thus, we can infer that the number of visited areas does not change many among seasons despite of the reduction in the activity frequency and the change of the localizations.

The locations of nodes with bigger weights remain the same among seasons while the locations of nodes with lower weight change from inland to coastal areas in summer. It is remarkable the absence of nodes in the inland area of Majorca during the summer. Moreover, we highlight the importance of GR trails since most weighted nodes are localized there. In Ibiza, the non-existence of guided hikes may lead to greater dispersion of trailheads and forks.

The edges are an indicator of the connectivity of segments of multiple trails that a node possesses although the number of edges depends on the intersections of a route. If a trajectory does not intersect with another or does not have loops, the resulting graph will only have the start and end nodes. Thus, a set of connected nodes represents the utilization and existence of a network of paths linking all these locations. In [Table 1](#), the *number of edges* (e_m) represents the edges in the whole network and the *number of unique edges* (e) is the value using a directed graph. We know that the average number of loop hikes is around 59.9%, then, we can estimate the average number of intersections of one trajectory with another. This indicator is the ratio

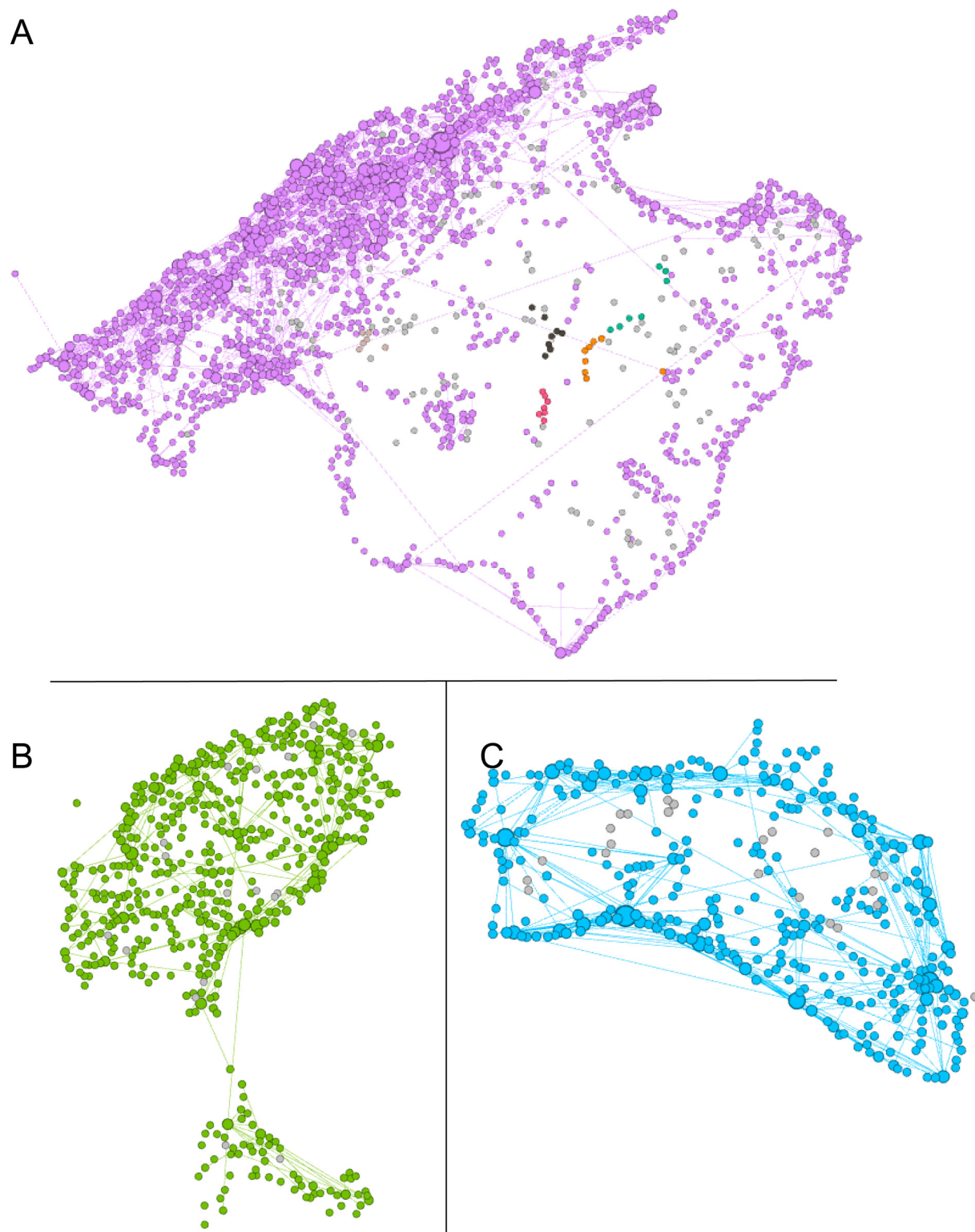


Fig 7. Hiking activity networks in the Balearic Islands obtained from algorithm 1. Majorca (A), Ibiza & Formentera (B), and Minorca (C) networks correspond to the aggregation of the four seasons. Black nodes represents small subgraphs (number of nodes < 4). In addition, the size of the nodes is proportional to the number of different hikes in that area.

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between the number of unique edges e and nodes (n): $e/(n * 59.9\% + n * 40.1\% * 2)$. This value is 2.073 in Majorca, 2.09 in Minorca, and 0.71 in Ibiza & Formentera.

The existence of disconnected nodes generates isolated subgraphs. The number of isolated subgraphs increases in summer season due to the lower number of activities and a reduction in long distance routes. Long routes lead to a greater probability of intersection with others. This indicates that the temperature influences the attractiveness of the location and the utilization of places.

Degree and connections

The degree of a node is an indicator of the connectivity among different areas. The average degree is different in each island and it decreases from spring to summer in Majorca and Ibiza. In contrast, in Minorca, the average degree increases during the same period. In general, the connectivity decreases in summer except in Minorca where the presence of nodes is still intensified in the coastal areas.

Fig 8 shows the degree distribution for each of the three islands for the 4 season aggregated network. Majorca shows a larger degree values while Minorca and Ibiza present similar values.

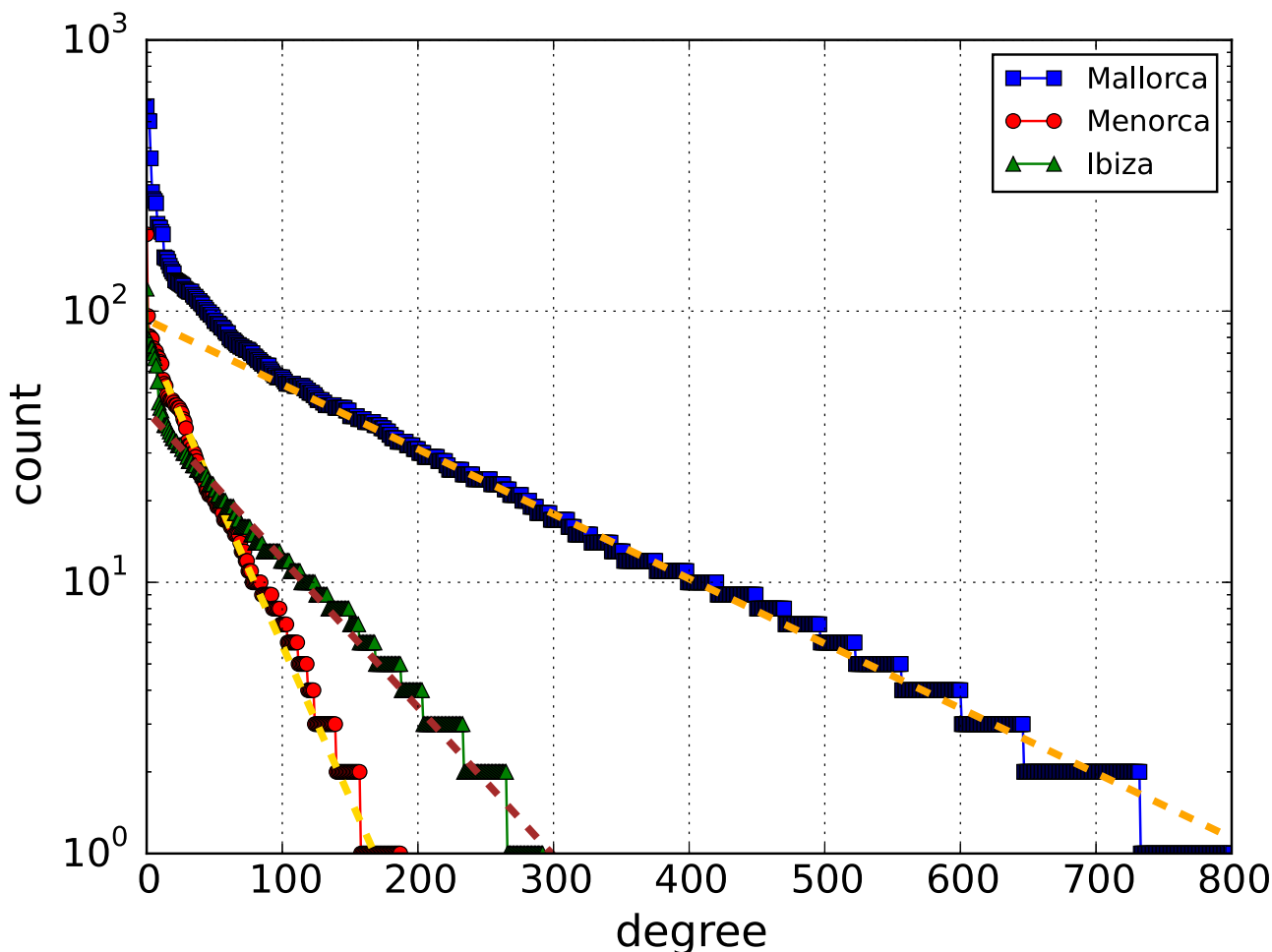


Fig 8. Node degree distribution. The degree distribution for the three islands for the aggregated 4S. Dashed lines represent fits to $f(x) \sim \exp(-bx)$ with $b = (0.005, 0.026, 0.012)$ for Majorca, Minorca, and Ibiza & Formentera respectively.

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This indicator shows the same evolution in other seasons among the three islands. The degree distribution of the three islands follows an exponential distribution. Similar behaviour has been observed in different transport networks, for example, in the Singapore's bus network [34].

The weight of an edge represents the straight distance between two nodes. Thus, the real segment of a trail that joins two nodes can possess bigger length than the weight of the edge. The weight value grows in the summer season in Majorca and Ibiza. The lower the density of trajectories, the smaller number of intersections, and consequently, the shorter the lengths between them. The range of weights is an indicator of the minimum and maximum lengths of the trails in each island. In the case of Majorca, the maximum distance corresponds to the GR trail length.

On the other hand, we compare the possible relationship between two indicators conceptually close: the weight and degree of a node. We use Pearson correlation coefficient to compare both. In spring, the correlation values are the following: 0.9374 in Majorca, 0.4157 in Ibiza, and 0.9612 in Minorca. In summer, the values are: 0.8281 in Majorca, 0.1221 in Ibiza, and 0.9612 in Minorca. This implies that both features are an indicator of the number of alternative hikes of a given place: the larger the degree of choices, the greater the number of alternative recorded trails. We are able to detect places with a high number of alternatives using topological features. We observe that the position of the main nodes in terms of degree, weight, and their locations matches with well-known places e.g: water reservoirs (Cuber and Gorg Blau), mountains towns (Escorca, Esporles), to mention some of them.

The average shortest path is also affected by the attractiveness of coastal areas in summer. In Majorca, the average shortest path is 5 in spring, and it increases to 8 in summer. In Ibiza is identical in both seasons. However, in Minorca the value decreases in summer since there are more activities around the coastal areas and then, the nodes are better linked. The diameter is defined by the maximum shortest paths between two nodes. In terms of hiking, it is representative of the longest route that hikers can make and it depends on the localization of the nodes. Majorca has a larger diameter than the rest of the islands. In Minorca, the diameter remains equal between both seasons since the locations of nodes remain around the perimeter of the island. In Ibiza the diameter decreases from spring to summer due to the increase in the number of isolated subgraphs.

Community analysis

We perform a community analysis to the 4S network of Majorca island using the Louvain method [47] implemented in Gephi [48]. Fig 9 shows colored the largest communities found. The communities segment the island by in areas revealing the distribution of hiking activities. The community analysis also reveals the area of influence of the main points of relevance. For Minorca and Ibiza & Formentera a big dominant community is found in each island.

Clustering and correlations

Clustering coefficient (C) is a measure of cohesiveness around a node. It takes values from $[0,1]$ where 0 and 1 indicate that none or all neighbouring nodes are linked [49]. The highest clustering values correspond to nodes with the highest number of hikers. In Table 1, the average clustering coefficient has a range from 0.13 to 0.31. We contextualize this value comparing it with other network models. For example, Singapore rail system possesses a value of $C_{Sing.} = 0.934$ [34]. Poland transport systems has a range of $0.68 < C_{Poland} < 0.85$ [50]. Our case of study is slightly above to the Portland network $C_{PL} = 0.0584$ [51]. It is desirable that a transport network is designed to minimize the number of exchanges and maximize the use.

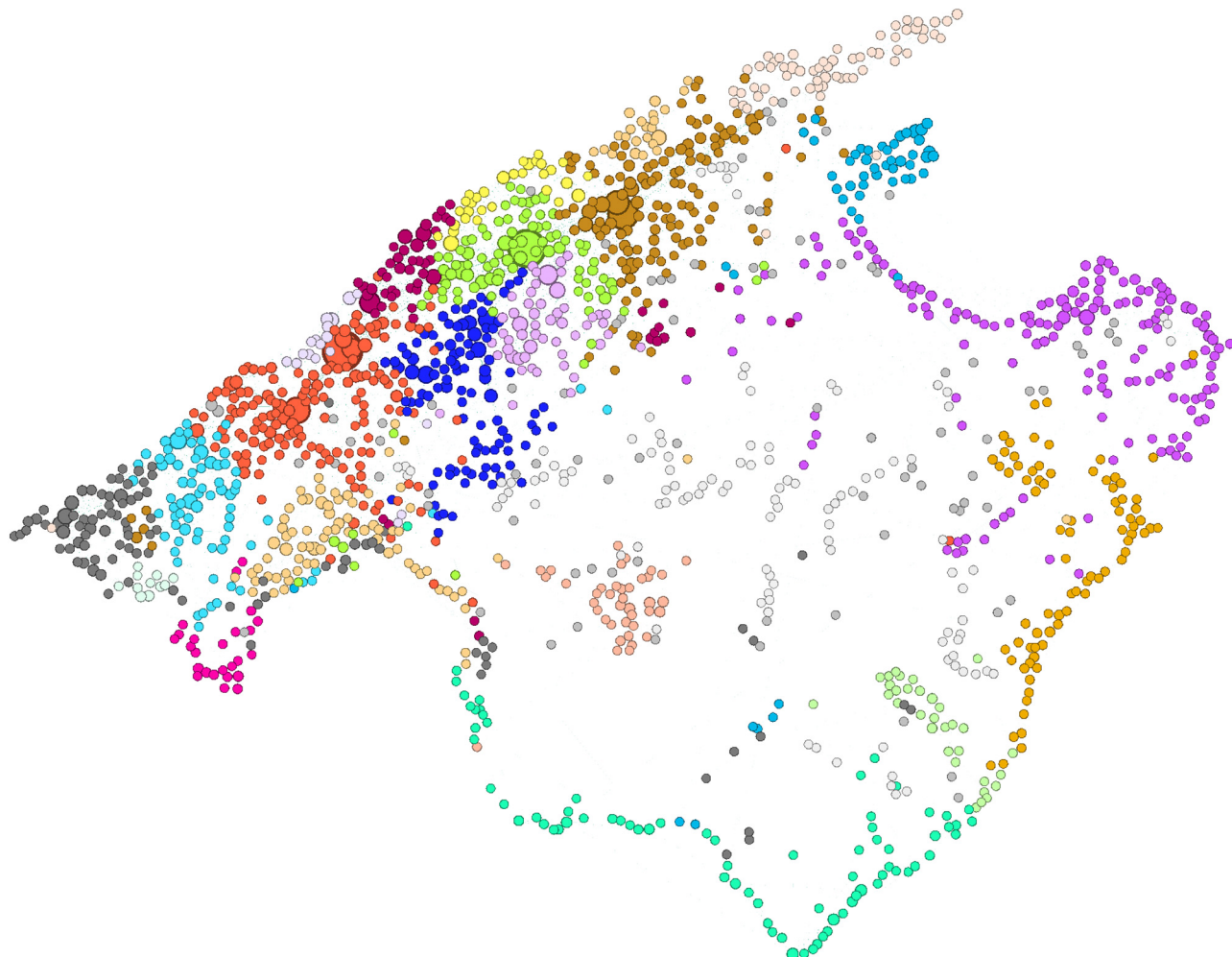


Fig 9. Community analysis of Majorca island. Different colors indicates the largest communities. Communities with size smaller than 20 nodes are colored with light gray.

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The network of trails were built to connect areas or to achieve natural resources (i.e. cultivated fields, hunting trails, etc.). In our study, we observe that the clustering cohesiveness is formed by edges with low weights.

Another topological property of the network is the type of correlation among nodes. A network is assortative whether high-degree nodes have a trend to connect to other high-degree nodes [52]. Otherwise, a network is disassortative whether the low-degree nodes tend to connect to high-degree nodes. Assortativity takes values in the interval $[-1,1]$ where -1 indicates a disassortative network and 1 indicates an assortative one. The assortativity of the studied networks depends on the season especially in the two small islands. In Majorca, the assortativity tends to 0 in summer.

Discussion

The novelty of this study is the applicability of complex network theory to trail networks. The exploration of trail networks through hiker activities offers a real vision in the understanding the use of natural resources. In our case, the agglomeration of intersections of trajectories and

trailheads define the network. This theory is already applied in transportation systems such as Singapore RTS and BUS [34], Boston subway [31], Chinese railway [53], world-wide airports network [54] and Beijing traffic road network [35]. In most of the cases, the interpretation of the network is defined by the two basic matching rules: the “transport stop places” are nodes and the connections or movements of passengers among the nodes are edges. The weight of each edge can have different values: the number of passengers, the distance, the duration of the trip, etc.

A typical trajectory obtained from GPS devices is a sequence of longitude, latitude, and timestamps. Modern devices include more information: velocity, heart rate, elevation, slope, etc. Unfortunately, the quality relies on the precision of the coordinate acquisition from satellite signals. The error and the size of the sequence are relevant to match them to physical areas and, for instance, to decision making regarding a change of direction between other analysis. In the case of mobile phone connections, the sequence of the trajectory is set by the carrier’s antennas. A GPS trajectory can possess more intermediate points but they are subject to external constraints (e.g. natural or urban canyons, atmospheric conditions, time to acquire fix, etc.) or to user forgetfulness (e.g. battery charge, keeping in bag, auto travel before acquiring fix, etc.) [55]. Filtering and other statistical methods can be applied to mitigate the error. Each trajectory can be processed to reduce noise avoiding outlier coordinates or interpolating points. However, the position and velocity are typically biased and have unknown distributions. If the goal of the study is to discover specific areas, the homogenization of points may not be effective. Other group of techniques called map-matching establishes relationships among the coordinates with real information coming from maps. In this way, it is determined which road segments have been used in each trajectory. It is not an easy task since it depends on the velocity of the vehicle, the frequency of samples, the precision of the position and the density of roads [56, 57]. We address our approach to the identification of trail crossings without map information. Collaborative resources such as Open Street Map provides trail networks but our goal is only to depend on the network that is traced by hikers. For a future work, we want to compare our model with the network generated from this spatial sources.

Conclusions and future work

In this article, we present a novel approach to exploit records of sports activities through the generation of a hiking activity network and the application of complex network theory for identifying points of relevance. The obtained points of relevance, together with the extracted topological features, reflect the utilization of trail segments and trailheads where environmental management plans can be carried out. In addition, our method relates places among them in contrast with other approaches where the regions or points of interest are obtained as isolated elements. In the modelling of a network, it is important to consider the semantics of its elements, therefore we decided to model nodes as trail crossings. The use of trail crossings is a powerful concept to describe passageways and redirect the exploitation of natural spaces. In the first part of this article, we propose an algorithm to detect trail crossings from GPS trajectories which generates the network. As the generated network depends on the activity of the users, this study is also the first step of a global analysis of human outdoor activities considering geographical and topological aspects.

We detect that weather conditions affect outdoor activities and we reflect this fact in the construction of different networks according to the season of the year. Thus, we generate three networks considering the aggregation of trajectories in the four seasons, summer and spring seasons, which are the most extreme in terms of frequency of activities, analysing for each network the main topological features. From the localizations of nodes, we observe for the three

islands that the number of visited areas remains similar during the year but there is a reduction in the number of frequencies and a relocation from inland regions to coastal areas in summer season. Regardless the season, the segments of the long trails (*Grande Randonnée*) have a high density of nodes and do not lose importance in topological terms. For summer in the case of Minorca island, the nodes tend to cluster together along the perimeter of the island where the GR is located. The community analysis performed in Majorca island allows the identification of the area of influence of each point of relevance. From the degree feature, we detect that the attractiveness of a place depends on the number of connections, that is, the number of alternative routes. To sum up, the interpretation of each feature provides indicators on the utilization of regions and can be used in forecasting models.

One limitation of this study is to ascertain with high precision the discovery of trail crossings among all the samples. Our resolution is a local approach considering sequence of pairs of coordinates with the same route and pair of routes. As future work, a global approach should be considered the whole dataset; from this perspective it can rule out slight variations of the course and inaccurate samples of GPS devices. This study can be extended in two directions. The first one is to analyse the flow of outdoor activities and their distribution throughout the year. The second one, given that this study provides measures on a precise area, is to analyse conflicts among other type of activities, the discovering of new paths, or identification of the access to restricted areas.

Supporting information

S1 File. Detailed information of raw data, and hiking activity networks.
(PDF)

S2 File. Four seasons, spring, and summer networks in GEXF format.
(ZIP)

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Formal analysis: IL TP.

Funding acquisition: CJ.

Investigation: IL TP.

Methodology: IL TP.

Project administration: IL.

Software: IL TP.

Supervision: CG VE CJ.

Validation: TP.

Visualization: IL TP.

Writing – original draft: IL.

Writing – review & editing: IL TP CG VE CJ.

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