Chapter 7: Capturing affordances for health and well-being at the city scale

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Introduction

One of the central theories applied throughout this book and in the research within the BlueHealth project has been that of affordances. Environmental affordances are perceived properties of a place which might influence behaviour (Ward Thompson, 2013). For example, a physical element such as a ledge may be a functional signifier for designed or spontaneous activities (sitting, skateboarding), highlighting the importance of understanding the physical environment (Heft, 2010). Affordance as a concept and its role in designing different physical environments has been amply demonstrated, for example, in studies of children's activity in different play settings (Kytä, 2004). Understanding people's behaviour in outdoor public spaces can provide convincing evidence for urban planning and design aiming to promote more activity. In the case of blue space, for example, wider views of water bodies with spacious and natural characteristics, the presence of bank vegetation, moist atmosphere, rich and diverse wildlife and non-visual sensory stimulation may afford positive perceptions and create fascination (Völker and Kistemann, 2011, 2015).

We focus on urban blue spaces and therefore potentially want to find out what role all blue spaces within a particular city play in providing affordances for obtaining the benefits for health and well-being. Thus it is beneficial if we have the means of collecting information about this from the users themselves. We now have access to detailed and fine-grained geographic information about different land covers or land uses in many larger urban areas through the Urban Atlas vector dataset provided by the European Union's Copernicus Land Monitoring Service (www.eea.europa.eu/data-and-maps/data/copernicus-land-monitoring-service-urban-atlas#tab-data) or, if the city is not included, through Corine Land Cover, also provided through Copernicus (<https://land.copernicus.eu/pan-european/corine-land-cover>), although this is much coarser grained and raster based. Alternatively, we can also pick up detailed information from high-resolution aerial photographs. These datasets can tell us a lot about what kind of blue spaces are present and what the land cover types and water-land interface are. However, while we can observe what goes on at specific sites (see Chapter 6), we need a way of identifying the key affordances as a city-wide pattern, and for this, we need to capture people-based as opposed to territorially based data related to blue spaces.

We can refer to the kind of geographic information system (GIS) described previously as "hard GIS", as it deals with objective facts about spaces. If we can capture more subjective values which are also spatially related, by asking residents to tell us about, for example, their favourite blue space or the one which they go to in order to de-stress or to carry out a particular activity at or on the water, then we have the means to capture the affordances associated by different people with specific places. This can help a great deal in urban blue space planning. This "SoftGIS", or, as it is also known, public participation GIS (PPGIS), can be applied top down or bottom up and, depending on the system used, can capture highly detailed information from a large number of residents, which has real value for planners as well as researchers (Kahila-Tani et al., 2016; Schmidt-Thomé et al., 2014; Brown and Weber, 2013).

In the BlueHealth Project, we applied a PPGIS approach to study and collect people-based data related to blue spaces. In this chapter, since we did not develop a tool specifically for the project (unlike the BlueHealth Environmental Assessment Tool [BEAT], BlueHealth Behavioural Assessment Tool [BBAT] or decision support tool [DST]) but used a proprietary tool, we do not spend time on tool development but much more on what can be obtained from applying such approaches and what kind of analyses and outputs are useful for planning purposes. First, we introduce some of concepts behind the PPGIS method and then describe how it can be applied, using the BlueHealth case study of Plymouth to illustrate some of the outputs.

Public participation geographic information systems: concepts

PPGIS refers to methods that use geospatial technology to engage the public in producing spatially related knowledge for land-use planning, decision-making and scientific purposes (Schmidt-Thomé et al., 2014). PPGIS methods offer convenient tools for studying and investigating human behaviour in a context-sensitive way. Localisation of human experiences and behavioural patterns by PPGIS methods attaches them to specific physical contexts, providing geographic coordinates to human behaviour and experiences. PPGIS approaches enable a collection of large datasets with user-friendly online survey applications (Figure 7.1) (Brown and Kyttä, 2014; Fagerholm et al., 2021). Combination of collected PPGIS data with conventional register-based GIS data allows for simultaneous GIS-based analysis of human behaviour in relation to the physical environment.

PPGIS approaches have become one of the most efficient knowledge-based methods gathering new and, in many cases, previously non-existing spatially referenced information from residents for planning, public participation and scientific purposes (Brown and Kyttä, 2014, 2018; Kahila-Tani et al., 2019). One of the earliest examples of an advanced online PPGIS approach is the so-called SoftGIS methodology developed in Aalto University, Finland, since

Figure 7.1

The overall concept of PPGIS

(Source: Fagerholm et al. 2021)

2005. The development work of SoftGIS methods was later outsourced from Aalto University, and the tool that is based on SoftGIS methodology is nowadays called Maptionnaire. The development of PPGIS tools has accelerated during the last decade, and there are many examples of differing PPGIS tools available (Brown and Kyttä, 2018).

Regardless of the tool used, PPGIS surveys produce two types of data, spatial and non-spatial. In the often self-administered, online PPGIS surveys, individual respondents map various spatial attributes (points, lines or polygons) and answer questions that can be related to both that specific location, such as a park, street or coastline, and information on their sociodemographic background, personal values, attitudes and preferences, personal behaviour intentions and motivations, well-being and health, to name only a few possibilities (Fagerholm et al., 2021). Mapped spatial attributes produce spatial data, and the more traditional survey types of attributes non-spatial data. Spatially explicit data can then be compared with the underlying objective characteristics of the places respondents have marked for further analysis, and both statistical and qualitative, spatial and aspatial analyses can be performed (see the following).

The application of PPGIS in the BlueHealth project

Using PPGIS approaches in BlueHealth Project – specifically, we used the Maptionnaire tool – we were able to study what kind of place-based positive and negative experiences residents have related to blue spaces. The overall aim was, like everything else in the BlueHealth project, to understand the affordances of residents of the cities studied. It was also important to relate many of the questions asked of respondents to the other surveys undertaken at different scales. Thus, as will be explained in more detail in the following, a number of the questions related to health and well-being were taken directly from both the BlueHealth International Survey (BIS) and the BlueHealth Community Level Survey (BCLS) (see Chapters 4 and 8 for details on the relationship of the various surveys), potentially allowing for a comparison of results emerging from surveys at different spatial scales.

Underlying the application was the research objective, which naturally related to the overall aims of the project. We wanted know which the favourite blue spaces in each city were and why; we also wanted to be able to determine how the health benefits of such spaces were experienced by the residents, and we were also interested in relating these preferences and opinions to the physical characteristics of the spaces so identified.

Setting up the survey

The Maptionnaire system is very straightforward to use. It is first necessary to apply for a license from the company, and, once obtained, users can log in to their account and set up their surveys using a wide range of different tools for setting up the questionnaire. Maptionnaire uses OpenStreetMap (© OpenStreetMap contributors) as a base, which allows the user to specify the geographical location for the survey. Some satellite images are also available. It is possible for users to zoom in and out of the map in order to focus on specific places in more detail, for example, for accurately identifying a particular area. The first setup includes choice of language, background images for use in the survey and the style of the appearance, to mention some features. This is important from a usability perspective (Gottwald et al., 2016). An easy-to-use, attractive and welcoming interface can help in persuading respondents to take part.

The questionnaire setup takes place by adding a series of pages – such as a welcome page where the basic information and explanation of the project is presented. There may be a further information page, perhaps explaining anonymity, data protection, consent procedures and other ethical information before the respondent is able to proceed further. Following this, it is useful to identify the general location of the respondent's residence – usually a spot within 300 m of their home, so that while the general district is identifiable (for relating this to, for example, socio-economic characteristics), the specific address remains completely anonymous. For this, the respondent merely needs

to drop a pin to a location. Then it is possible to ask questions which require the respondent to place a point or draw a line or polygon marking a specific location or route or area, for example, and to answer questions about that place – which can be open text questions or include choices, using different tools (rating scales, slider scales, tick boxes, etc.), all very easily added to the question. Non-spatial questions may also be asked, including ones related to preferences, health and well-being and demographic information (gender, age, educational levels, household income, etc.).

The BlueHealth Maptionnaire structure and content

In the surveys for the four BlueHealth case study cities, we wanted to understand what makes a place important for the respondent, asking them to describe why some places are more important to them than others, and then, based on the results of these questions, we wanted explore what sort of topics emerged that could be mapped or measured by looking at the site itself. We wanted to have a combination of place-based insights and also general attitudes/blue space usage habits in each city region (and, of course, this allowed us to compare different geographical regions). We were also interested in the general factors related to the frequency of visitation, the personal importance of blue spaces, perceived health benefits connected with the visitation of blue spaces, region- and user-specific aspects and, finally, what general notions of these topics are over the four European countries.

In the BlueHealth Project, we looked for the blue spaces that users visit in relation to the distance from their home compared with other perceived attributes of the site, such as safety, naturalness and role played by visitation frequency, plus their perceived positive health benefits and habits (such as relaxing after work, resting, sports, physical activity or socialising with friends and family). We were also interested in how important the role of water was in the overall visitation experience.

In order to make the survey interesting and to give it a recognisable title, we named it “My blue Plymouth” (or Tartu, Tallinn or Barcelona). We illustrate this for Plymouth because the survey was in English. The questionnaire structure used in BlueHealth was in several parts, as follows (each illustrated by shots of the appearance of the interface). The survey was pilot tested to ensure that people understood the questions and could answer them easily.

The entry page featured the title, the visual identity of the BlueHealth project, some basic information about what the survey aimed to do, some details about who should fill it in and that it was anonymous. Figure 7.2 shows the appearance of the title page, which has the map in the background.

Figure 7.2
The welcome page of the “My blue Plymouth” Maptionnaire survey
 (Source: © OpenStreetMap CC-BY-SA)

Following this, the next page asked for personal information so that demographic factors could be taken into account in the subsequent analysis. These factors were exactly the same as in the BIS and BCLS and are fairly standard questions. In this survey, the questions were compulsory, but in others, for reasons of sensitivity, they might not be or might include “prefer not to say” as an option. In this survey, no ethnic data were collected, but they could be included in other versions if deemed particularly relevant. Gender may also need to include additional options such as “other” or “prefer not so say” under certain circumstances. Next, the respondents were asked to note a place close to their home and to give some information about garden access before saving it.

The next set of related questions focused on general use of blue spaces: with a short definition of blue spaces, then recent visit frequency, association with childhood and means of getting to the blue space. Then the respondent was asked to mark the first of up to five blue spaces they liked to visit – the first being the most favourite (Figure 7.3a and b). Each of these locations was then associated with a set of questions about it and about activities and feelings

Figure 7.3a and b
The system for identifying points on the map – the most favourite one
 (Source: © OpenStreetMap CC-BY-SA)

associated with it. It is possible to zoom in closely to be as accurate as possible and also to use the OpenStreetMap imagery instead of a map base.

On identification of the location, a series of questions then appeared, in several sections. These were divided into activities on land or water, the importance of water in the visit, the feelings generated by the visit (using a slider with a range from strongly agree to strongly disagree) and the time spent on the visit (taken from the same list as in the BlueHealth Community Level Survey).

This sequence was then repeated for each of the next four locations. This was followed by a series of questions about health, also using the slider and the range of different answers. Finally, some more personal information questions were asked, including dog ownership, household size, relationship status, employment status and income level (not in absolute terms because of difficulties of comparison but of how comfortable the respondent was financially). Finally, there was a finishing page with thanks and contact details if any respondent wanted to obtain more information.

The data entered to the survey are automatically saved – including those respondents who fail to complete the entire survey – into the servers of the Maptionnaire company, Mapita Ltd., where it is securely held and only accessible by password.

Respondent recruitment and sampling strategy

As an online survey instrument, the Maptionnaire survey is always going to be limited in its ability to reach every segment of a given population, since there is not 100% penetration of the internet or 100% of the population as users. It is also not possible to ensure a representative sample by age, gender or any other demographic trait, as in any other surveys. Given that proviso, and since data are generated about the demographic characteristics, some idea of the bias in the sample can be obtained, and the results can be considered with these limitations in mind.

As a web-based survey, it is important to have a strategy of ensuring it is widely publicised through different media and communication methods. If it is possible to obtain help from the local council or municipality in promoting the survey (especially when the research is undertaken with the cooperation and involvement of such bodies), together with links to relevant organisations such as schools, clubs and societies, local residents' associations and so on, hopefully wide coverage can be obtained.

The sample size obtained in each BlueHealth survey was between 250 and 300 individuals, with up to five sites being recorded per respondent; this meant around 1000 or more specific locations being identified and commented on. These are not large numbers as a proportion of the population but nevertheless give a good picture overall. Figure 7.4 is a map of Plymouth showing the home locations of all respondents. While there is wide distribution, there are also significant areas with few or no respondents, meaning that the results are not completely representative, at least in geographical terms. This is a common challenge in web-based as well as in more traditional social scientific surveys.

Analysis of results

There are various analysis methods that can be applied to PPGIS data. Fagerholm and colleagues (2021) examined the analysis possibilities of PPGIS data and created a PPGIS data analysis framework with three phases. The three analytical phases, *explore*, *explain* and *predict/model*, proceed from basic to more advanced methods and connect to varying types of knowledge claims as an output of PPGIS data analysis (Fagerholm et al., 2021).

Explore analytics aim, as the name suggests, at exploring spatial patterns and focus mostly on visual representations of spatial PPGIS data. According to Fagerholm and colleagues (2021), one of the main analytical steps included in the *explore* phase is the external and internal validation of collected PPGIS data. Descriptive and visual analysis are listed as the most common explorative PPGIS analysis methods.

Figure 7.4

All respondents' home locations recorded in the Maptionnaire survey in Plymouth

(Source: © OpenStreetMap CC-BY-SA)

The next analytical phase, *explain* analysis, focuses on explaining the spatial patterns of the spatial and non-spatial PPGIS data, and the majority of PPGIS data analysis methods fall into this phase (Fagerholm et al., 2021). There are numerous different possibilities that can be applied for explanatory analysis, such as visual and overlay analysis, proximity analysis, analysis of spatial associations and cluster analysis, to name a few (Fagerholm et al., 2021).

The third analysis phase, *predict/model*, represents advanced PPGIS analytics in its aim to generalise and predict mapped attributes across other places and contexts or produce a representation of a system to make inferences (Fagerholm et al., 2021).

It is worth noting that the analysis framework by Fagerholm and colleagues (2021) presents the three different phases proceeding almost in a linear order, but they also highlight that data analysis is an iterative process where one moves back and forth between the phases. Moreover, not all phases are necessary; it is often the case that the data analysis is focused solely on one of the phases.

The Maptionnaire system itself includes some basic and quite useful analysis tools, especially for exploring the spatial patterns. For example, it is possible to explore the points, lines or polygons on a web browser and to examine the content of the responses, including any text recorded by respondents. Generally, however, the data need to be downloaded as a CSV file, which can then be examined, cleaned and exported into a GIS such as ArcGIS or QGIS or into a statistical package, allowing for various kinds of data analysis to be performed.

Analysing the BlueHealth Maptionnaire data

In this section, we present some examples of the techniques possible for analysing the Plymouth data: first using a range of map approaches and then using the data in a non-spatial way.

Exploring the maps for spatial patterns

Once downloaded, the data are opened in a GIS program, where several simple-to-use exploring possibilities are available. One approach is to use a heat map to show the relative densities and therefore popularities of the different locations. A spatial hot-spot analysis is a more statistically sophisticated approach with a similar aim. These can be used to show the focus of different aspects beyond simple popularity when determined against different variables, such as those in the health and well-being questions. Using the demographic variables can also point to places more popular with men than women, older versus younger and so on. The map base beneath these patterns can simply be the same OpenStreetMap. It is useful to start with a simple look at the data to see what patterns jump out and then to delve into them in more and more detail. Figure 7.5a and b shows the identified favourite places (a) and other visited places (b).

Figure 7.5a and b

The simplest maps showing the distribution of favourite and other spaces already contain some visually clear patterns which deserve further exploration

(Source: © OpenStreetMap CC-BY-SA)

Figure 7.6

Visit durations for part of the sampled area: favourite places (darker red means shorter visits) and other places (darker green shows longer visits). Lower intensity colours mean a visit duration somewhere between these extremes

(Source: © OpenStreetMap CC-BY-SA)

Taking these maps, it is possible to examine some patterns in more detail by first coming into some clear density clusters and then, for example, looking at variables within them. Visit duration is one aspect. Figure 7.6 shows the locations of favourite visits by visit duration (darker red means shorter visits) and the other locations (darker green shows longer visits). Lower intensity colours mean a visit duration somewhere between these extremes. Some interesting patterns emerge in terms of where these visits take place: for example, the shortest visits are the most frequent ones and to places close to the city centre in the famous Plymouth Hoe area, while longer ones are the less frequent ones and are to places further afield.

Zooming in further, it is easy to select for other variables such as gender or age of visitors (Figure 7.7a and b), although nothing really stands out in this example. What is also apparent when this detail is revealed is the fact that many points are recorded in the water. When checking for activities associated with these points, it becomes clear that not all are actually water based. This means that the points are not necessarily recorded as accurate spots, probably due to the zoom level used by respondents when identifying the points. Therefore, some statistical tools for spatial analysis can be applied to overcome this issue and to provide a clearer picture.

Figure 7.7a and b

a) Breakdown of all visited locations between men (blue dots) and women (pink dots) and b) by age group (darker signifies older people, lighter younger)

(Source: © OpenStreetMap CC-BY-SA)

The GIS analysis tools allow for some cluster analyses so that points at varying distances from one another can be identified through statistical distancing parameters to belong to clusters. These can then be analysed as statistical meta-units instead of taking each point separately. Other methods include placing a grid of a suitable interval over the map and assigning points to the grid squares according to the number of points along a range, showing as a

Figure 7.8a and b
a) **Cluster analysis of the favourite places** and b) **of the other locations**
(Source: © OpenStreetMap CC-BY-SA)

Figure 7.9
Cluster analysis of all visited locations
 (Source: © OpenStreetMap CC-BY-SA)

result a pattern of density of selected values. Here we demonstrate a hot-spot analysis using a hexagon mesh, with a cut-off for clusters at two recorded points. The diameter of the hexagon grid can be changed to create tighter or looser clusters. Figure 7.8a and b shows two clusters for favourite locations (orange) and other locations (blue). The patterns are much more visible when visualised and analysed like this.

If both sets of locations are pooled and clustered, then, due to the increased total number of points, an even clearer pattern emerges (Figure 7.9), with several distinct visiting zones.

Next, an interesting aspect for us was the most-visited places – what kind of places are they, and what do they have to offer? One approach can be to overlay the hexagons from the clusters over land cover data in GIS, such as from the Urban Atlas, so that the values expressed by survey respondents can be related to land use types, although this is not very revealing in this example due to the resolution of the map data.

Overlaying the same data on a map (an aerial photograph would also be very useful) allows much more of the detailed features of the specific sites to be scrutinised. Figure 7.10 clearly shows what makes the cluster attractive as both favourite and other visited places: the proximity to the Hoe, beaches, open-air swimming pools and the sea itself. Figure 7.11 shows two different locations – the Admiralty Road area and the beaches of Mt Edgecombe Country Park, and Figure 7.12 shows the Barbican area, the most popular city centre place for food, drink, marinas and so on.

Of course, these can then be followed up and checked in the field. A BEAT assessment could also be carried out to capture the physical qualities of the place, too (see Chapter 5).

Figure 7.10
Overlaying the cluster hexagons for all visited spots on the map reveals the exact characteristics of the place which attract visitors
(Source: © OpenStreetMap CC-BY-SA)

Figure 7.11
The clusters along the Admiralty Road area and the beaches of Mt Edgecombe Country Park, showing the type of popular blue spaces found here
(Source: © OpenStreetMap CC-BY-SA)

Figure 7.12
The clusters lying over the Barbican area in the city centre
 (Source: © OpenStreetMap CC-BY-SA)

Explaining the patterns using non-spatial analysis techniques

The collected data contain a lot of variables so that a number of descriptive and inferential statistics can also be found. Associations between the activities, demographics and health and well-being variables can be used to see the main benefits obtained from the blue spaces identified by the respondents. Additional data on the blue space types could be included in the database so that relationships between the well-being outcomes and blue space types could also be identified. As an example, we took the main focal cluster at the Hoe and formulated a question: what characterises the people who use this place? We associated the home locations with the points belonging to the cluster (Figure 7.13), and we interrogated the data for age, employment type, how the respondents reach the site and their frequency of visits to all blue spaces (not just the Hoe – the question did not ask that specifically). We found that visitors are in the young to middle age range, mainly working, and live in a variety of areas but, we infer, commute in (by car in many cases) and then visit in their lunchtimes (on foot), for example. This inference is borne out to some degree by the comments offered by respondents, who stated that it was a great place to go on their lunch breaks. Thus, we can use the statistics to identify one of the main user groups and to see what kinds of health benefits they might receive, such as restoring themselves after a morning or afternoon of day's work. Figure 7.14a–d shows some of the descriptive statistics from this example analysis. When we look at visit outcomes, we can also see some interesting results suggestive of the benefits to health and well-being that such visits to the Hoe provided (Figure 7.15).

Figure 7.13
The home locations of the respondents belonging to the Hoe cluster – showing a wide distribution around the city
 (Source: © OpenStreetMap CC-BY-SA)

Figure 7.14a–d
a) Age group; b) employment status; c) frequency of visits and d) mode of transport to blue spaces of the respondents who marked points in the Hoe cluster
 (Source: Peeter Vassiljev and Anna Wilczyńska)

Figure 7.15

Visit outcomes of respondents in the Hoe cluster, showing high levels of agreement for all positive outcomes and a high level of disagreement with the negative outcome, suggesting important benefits to mental health and well-being gained from visiting the Hoe – especially at lunchtime, enabling workers to restore themselves

(Source: Peeter Vassiljev and Anna Wilczyńska)

Conclusions

PPGIS, using interfaces such as that provided by Maptionnaire, enables very user-friendly surveys which capture whatever spatially explicit information in, for example, uses, preferences, perceptions or affordances is desired by researchers or planners. There are some practical challenges, such as reaching all segments of the target population, since it requires internet access and familiarity – something which is becoming less of a problem as time goes on but still persists in places. Other challenges include the accuracy of placing points on the map – respondents need to zoom in to identify a specific spot and to place a marker exactly where it is needed. Failure to do so reduces some of the value associated with the aim of spatial explicitness.

It is worth noting that while PPGIS is a highly useful spatial method for both research and practice, to date it has mostly been focused on mobilising knowledge; it has been weaker at contributing for synthesising and translating PPGIS insights across knowledge systems into action more generally (Fagerholm et al., 2021). In particular, there are recognised challenges of communicating and integrating the vast knowledge base gained through these methods into decision-making and planning practices without a broader coupling of the development of advanced analytical methods with knowledge co-creation and deliberative valuation processes (Fagerholm et al., 2021; Raymond et al., 2014). Moreover, the challenge of bringing PPGIS methods that are, arguably, highly useful, for instance, for participatory planning practices, into action lies perhaps not so much in the usability of the method itself but more in the pragmatic and normative motivations for more inclusive planning processes (Kahila-Tani, Kyttä, and Geertman, 2019). However, significant results have been shown for the use of PPGIS methods at various spatial scales and in different phases of planning; PPGIS methods can provide an operational

bridge between various sciences and practices, and they offer considerable opportunities for addressing societal challenges and the effective arrangements of public participation (Fagerholm et al., 2021; Kahila-Tani, Kyttä, and Geertman, 2019).

Finally, as we move away from mere public participation into citizen science, then such tools enable large amounts of data to be collected for use in other tasks which are not necessarily directly planning related (although they may have implications for planning) – such as information on how people perceive particular spaces or which are the most beneficial for health and well-being.

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