BlueHealth
Linking environment, climate & health

# BLUEHEALTH BEHAVIOUR ASSESSMENT TOOL

## A guidebook for analysing data from participant site observations

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# Contents

# INTRODUCTION

One of the challenges facing planners and designers of outdoor public spaces is to know exactly for whom the space is being provided and how successful a space is once it has been developed. If a completely new space is being created, for example at a former dockside to which no one had access except for the dock workers, then designers must try to predict how and when a place might be used. Once implemented, however, it is possible, through the application of different tools, to measure the success of the project and the design. If, on the other hand, an existing public space is to be the focus of an improvement or regeneration project, it is extremely useful to be able to find out how people already use the site and then use this information alongside the assessment of the site itself, using, for example, the BlueHealth Environmental Assessment Tool (BEAT), to design the layout and programming of the site. Then, as in the previous example an assessment of the success of the project can be gained.

Of course, when a larger-sized site is the subject of a project, it may be subdivided into different zones (eg. functional, ecological or aesthetic) where there are different affordances for physical or social activity – places within the site which may also be known as “behaviour settings” (Barker, 1968). In addition, where a location has very pronounced seasonal differences a site may be used very differently in eg. summer or winter. Just walking around a site to observe casually what is going on will provide a general picture of its use but something rather more systematic and reliable can provide valuable evidence for use in planning, design and management. When we add a desire to capture the health and well-being benefits provided by a public space, we must use another tool for this purpose. It needs to be a tool that helps to identify the range and amount of physical or social activities of different types being undertaken by different groups of users and maybe able to convert some of this into calories expended by them. This could provide really valuable information. The generic name for this kind of data collection and analysis is “behaviour observation” and it has developed significantly over recent years to become a tool which not only relates well to theory but which has been developed methodologically and technically for both research and practical application in planning, design and management of public open spaces.

The BlueHealth Behaviour Assessment Tool has different the aim of being able to link what people do, who does it, where they do it and when they do it both before and after the introduction of the social or spatial intervention. This approach can help to uncover spatial, temporal and weather-related associations between all kinds of passive and active behaviour, social groups and the physical locations or behaviour settings.

Environment–behaviour research using behaviour mapping for understanding the interaction between people and place was initially developed by Ittelson et al. (1970) to record behaviour in a design setting. Bechtel et al. (1987) noted the value of observational methods and behavioural mapping to identify kinds and frequencies of behaviour and to demonstrate their association with particular sites. Cooper Marcus et al (1998) stated: “with a very limited investment of time the investigator can achieve considerable insight into the actual use of designed places – a vast improvement over the conjecture and guesswork generated by studying a site plan from the remove of the studio or office” (Cooper Marcus and Francis, 1998:

346). They emphasise its systematic approach, being based on function rather than aesthetics. Work on mapping use of public spaces was advanced by Goličnik and Ward Thompson (2010) in a study of squares and parks in Ljubljana and Edinburgh and also by Unt and Bell (2014) in their use of mapping of a single space in Tallinn at two time periods, before and after a so-called "urban acupuncture" spatial intervention – which was also the inspiration for the BlueHealth intervention case studies. There has also been extensive work by Cosco et al (2010) on mapping the use of children's play areas, related to specific "behaviour settings" (Barker 1968). One of the drawbacks of these methods is the fact that they are paper-based, points have to be recorded using colours and symbols and analysis has been somewhat limited, especially statistical analysis. One of the strengths is the ability to show spatial patterns.

Some earlier behaviour mapping methods, e.g. Project for Public Space (2005) involves dividing the mapped site into zones and using a matrix to record use by people across each zone. This results in large amounts of data but, because the precise location of individuals is not recorded on the map, it is not good at determining how behaviour relates to the layout of the space. The value of the Cooper Marcus et al., Goličnik and Ward Thompson, Unt and Bell or Cosco et al. techniques is that they take a more detailed approach to behaviour mapping, using techniques that allow detailed recording of each individual's location on a site map. They all stress the importance of time, weather, activity, social interaction, etc. in relation to the mapping of individuals' use of a site.

# THE DEVELOPMENT, APPLICATION AND UTILITY OF THE BBAT

## General Approach

The BBAT takes the basic theory and approach as described earlier and moves on from the paper-based mapping to the application of a geographic information system (GIS)-based recording application on a tablet computer used on site (see Figure 1) where all the data is automatically linked to a database. This system is not only more accurate but it is quicker, enables more points to be collected without the map becoming crowded and allows for primary and secondary activities to be noted simultaneously. The specific GIS program used in the system described in this chapter is Quantum GIS (QGIS) (The QGIS Community at https://www.qgis.org/en/site/) which is a free, open source software. When supplied with some additional scripting (freely available via the BlueHealth Tools website at https://bluehealth.tools/2020/09/13/bbat/) it can easily be set up for use and tailored for activities which might be specific to the site in question. The BBAT protocol document which is also available gives detailed information on setting up and applying the tool in the field in QGIS. The guidebook focuses more on the ways that the data captured can be analysed and presented

*Figure 1: A photo showing how the GIS digital interface is operated on a tablet computer on site. Here the drop down menu for recording the attributes of someone using the site is open over the map base (Source: Peeter Vassiljev).*

# Application

The demonstration of the application will use a site of Pelgurand beach at Kopli in Põhja-Tallinn, Estonia, where an experimental intervention was constructed, although we focus only on the pre-intervention state for illustration purposes. The application of the methodology includes several steps (see also Figure 2) which are presented in detail in the BBAT data acquisition protocol. These are as follows:

1. Background data collection
2. Preparation of site maps divided into specific areas or behaviour settings
3. Planning the observation points or routes
4. Identifying the range of likely activities to be recorded and designing the specific coding system for each
5. Selecting the time periods for sampling
6. On-site data collection
7. Preparation of a spatially explicit database
8. Analysis of results both statistically and visually
9. Repetition of steps 6-8 for post intervention surveys (two phases).

In this guidebook we start at step 8, while steps 1-7 are dealt with in more detail in the Data Acquisition Protocol document.


*Figure 2: Schematic workflow for BBAT application.*

## Analysis of results using maps and statistics

Once the database is complete the layer can be examined and interpreted e.g. according to type of activities, estimated age of people observed, weather and water conditions, etc. in GIS but the database file containing all the attribute data associated with the point shapefile can also be separately imported and analysed in a spreadsheet or a statistics program. Descriptive statistical analysis, e.g. the production of time series graphs, histograms and bar charts to illustrate activities and behaviour for different segments of the population at different times of day or days of the week can be used to reveal temporal, weather and activity variations. Comparison of the mapped data allows analysis of the different spatial attributes of site use according to different layers of data. Once steps 6-8 have been repeated, a comparison of pre- and post-intervention surveys can be undertaken. In this section we will use pre-intervention data from observations made at the experimental intervention site at Pelgurand in Tallinn, Estonia in order to demonstrate different ways of looking at the data in order to answer certain research questions. We used the high definition aerial photograph available from the Web Map portal of the Estonian Land Board as the base, as it clearly shows the different landscape features and allows us to make visual associations of uses with specific locations or elements.

### Isolating parts of the data by different attributes

Firstly, it is quite useful just to open the GIS and load all the data points in order to see what stands out spatially, if anything and to obtain the first overall impression – so-called "eyeballing the data". This may produce a very crowded picture depending on the degree of zoom into or out of the site so it may be best to separate the data between, eg male and female users. This can be achieved by filtering data by attribute value and/or setting categorised, graduated or rule based display styles in layer properties. Figure 3a and b shows this thematic separation between male and female users for the entire observation period in 2017. The size of the points in combination with the zoom level in the GIS means a lot of data points will overlap but in general it can be seen that there are some indicative patterns present, such as a very dense area along the beach to the south, clusters along paths and so on.


*Figure 3a and b: a) shows all the points for the observation period of 2017 for male users and b) for female users (Orthophoto: Estonian Land Board 2020).*

If we zoom into the northern, less well-used area then the points separate and we can see the distributions more clearly, as shown in Figure 4a and b.


*Figure 4a and b: observation points of a) men and b) women. The patterns become somewhat clearer – concentrations along the water edge, beach, access paths and so on (Orthophoto: Estonian Land Board 2020).*

This is still rather crude – we do not know what age groups these points represent, nor what activities are being undertaken, nor the pattern over the days and so on – much more potentially useful analyses and very easy to differentiate. Figure 5a-c shows the same area with female users differentiated by age group as an example. This starts to reveal more refined patterns.


*Figure 5a-c: These images show a separation of observation points between different age groups of female users a) younger children (palest colour) and teenagers (darker colour; b) adults and c) the older users (Orthophoto: Estonian Land Board 2020).*

Of course, we also want to see what activities are being undertaken on the site – land and water-based – where and by whom. We can then visually split the data further and identify the most and least popular locations. Figure 6a and b shows active and passive behaviours for a different section of the study area. The points are colour coded according to activities but the gender or age differentiations are not shown. It can be seen that passive use is much more popular and spread over larger territory, with sitting/crouching, lying and standing on the beach and immediate area behind it most preferred, although the grassy places next to and between the trees are also well-used. The active uses congregate on the paths (walking, cycling, jogging) and also along the waterline on the beach.

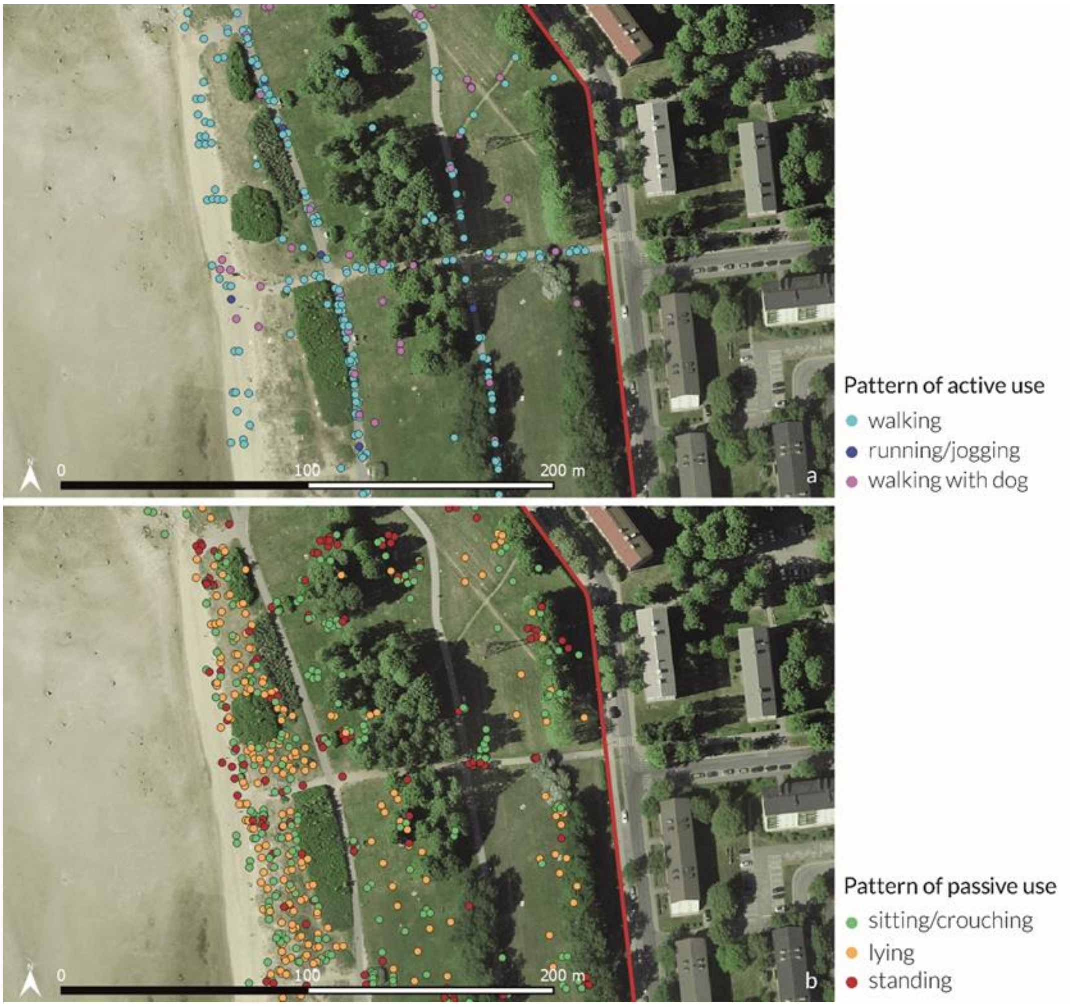


*Figure 6a and b: a) shows the pattern of active use in one section of the study area (see legend) and b) the pattern of passive use (see legend) (Orthophoto: Estonian Land Board 2020).*

Next we are interested in activities taking place in the water (a separate activity group in BBAT). Figure 7 shows this for the whole site – there are not so many records for this due to colder weather that year – colour coded by activity type and differentiated by gender using the symbols. When there are fewer records this affects the degree to which useful information can be extracted this way.


*Figure 7: all water-based activities split between gender (triangles for males and circles for females) and activity types (see legend) (Orthophoto: Estonian Land Board 2020).*

Another important variable to explore is time of day. Figure 8 shows three maps of all activities involving sunbathing according to the time of day – a) in the early to mid-morning, b) in the middle of the day and c) in the late afternoon/early evening. The pattern is fairly obvious for this type of use – according to the heat and angle of the sun. Yet another observation in the location pattern can be made – contrary to a cliché that sunbathing occurs mainly on the beach, a lot of sunbathing took place away from the beach on the grass in the park. That is especially prominent in the middle of the day but as the sun sinks to the west, these areas are cast in shadow so most people use the beach and grassy dunes immediately behind it.

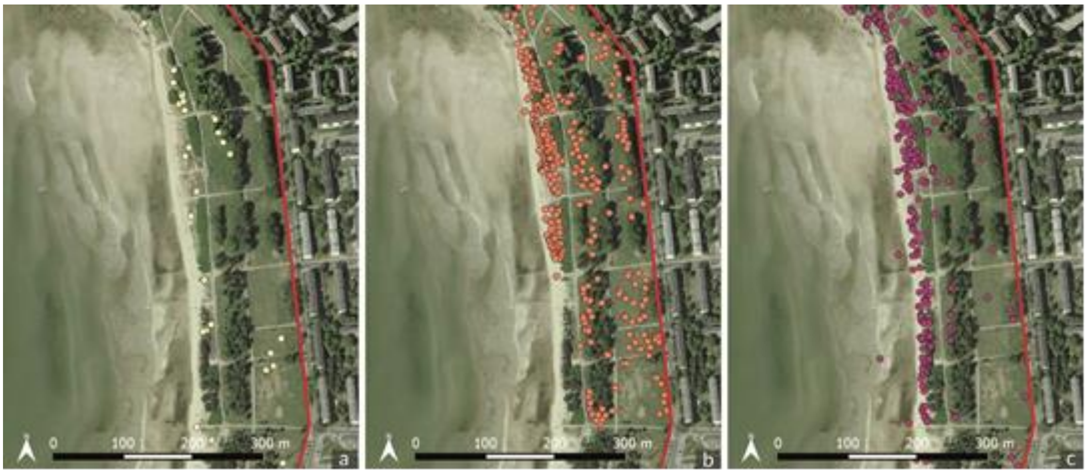

*Figure 8a-c: Pattern of sunbathing (all records) a) early/mid-morning; b) midday/early afternoon; c) later afternoon/early evening (Orthophoto: Estonian Land Board 2020).*

Another variable is that of the weather, especially air temperature. The next set of maps show the level of use (all records) during cooler and warmer periods (Figure 9a and b). In the cooler times (14°C and below) the paths are busiest – for active behaviour – while in the warmth (20°C and above) it is the beach and grassy areas for passive behaviour.


*Figure 9a and b: a) shows the usage of the area during the colder periods of the 2017 summer and b) during the warmer periods (Orthophoto: Estonian Land Board 2020).*

We can also explore the social aspects of site use by differentiating between the users as individuals, in pairs/couples and in groups (and of course by gender and age or activity type if needed). Filtering out data by different variables or combination of variables and viewing the distribution patterns of the filtered data offers many possibilities, but it also requires considerable time spent in trials as every site is different and combinations are multiple. It is also worth remembering that besides looking for differences in the data it is just as valuable to look at similarities between different groups.

## Combining observation data with specific parts of the landscape

It is possible to generate similar maps for many combinations of the variables collected. However, these require to be interpreted in a rather subjective way – for instance when relating the users/uses to specific parts of the landscape. The next section shows the possibilities when the site has been divided into behaviour settings (Barker, 1968). For this it is necessary to define the different types of setting based on the physical elements and potential affordances offered by them and then to create a new GIS layer of polygons. Following this the observation points falling within each behaviour setting can be isolated and analysed to detect the patterns of use and users. This is of value when understanding the actualised affordances offered by each setting and for improving the potential of a site. Figure 10 is a close up of one section of the behaviour setting map which shows how sunbathing or non-sunbathing can be clearly seen as directly associated with the settings of the beach (more non-sunbathers than sunbathers) and the vegetated sand dunes immediately behind the beach (majority of sunbathers). This difference is also brought out by the percentages of these two sets of activity for each behaviour setting (for the entire site) as shown in Figure 11.


*Figure 10: The differentiation between two behaviour settings (beach and vegetated dunes) where a clear relationship between sunbathing (orange) and non-sunbathing (blue) stands out (Orthophoto: Estonian Land Board 2020).*

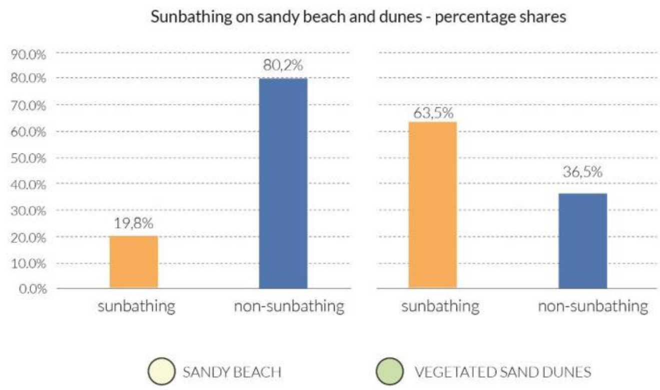


*Figure 11: percentage shares of sunbathers/non-sunbathers for two behaviour settings at the study site – beach and vegetated sand dunes.*

On looking at other behaviour settings – mown grass, worn grass and tree clumps – we can also see patterns for passive behaviour with observation points being clearly associated with west-facing edges of tree clumps (to catch the sun), often clustered in groups with a certain separation between them. This reveals how people use open spaces prefer to find an edge and a location reasonably distant from other people, for example (Figure 12).

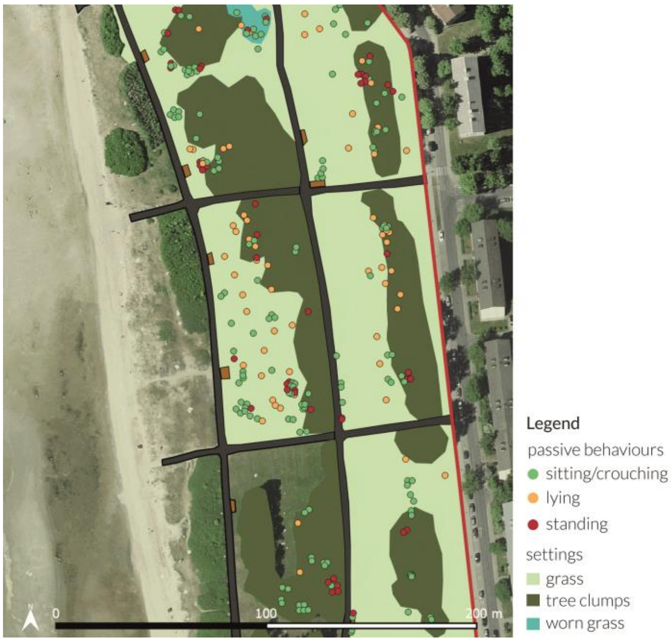


*Figure 12: Distribution of passive behaviours (see legend) on the settings of grass, tree clumps and worn grass for a selected section of the study site (Orthophoto: Estonian Land Board 2020).*

A further interesting example is of bench users. Benches were identified as a specific behaviour setting. The differences in the distribution are not so apparent on a map while the differences presented as percentages of observations for all benches on the entire area (Figure 13) with more occupation by female users, especially older, become apparent.

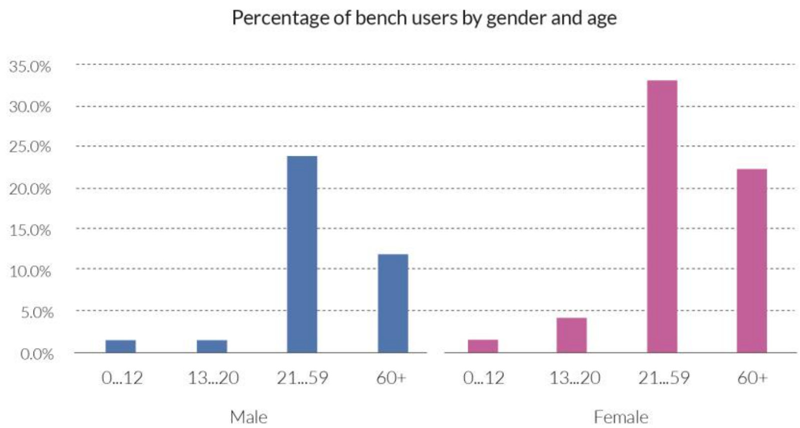


*Figure 13: Percentages of observations of bench users by age and gender*

## Geostatistical analysis

The maps so far show points presented over the map base, aerial photo or the behaviour settings. It is also possible to examine the data points using geo-statistical approaches such as central tendency measures, some other form of cluster analysis or spatial regression.

A very straightforward way of characterising the distribution within a point cloud is to generate a standard deviation ellipse out from the mean centre of the cloud encompassing locations of roughly two thirds of the points. This can be done for different e.g. social groups in the data to compare distributions in relation to each other and to the boundaries of the site. Figure 14 shows an example of ellipses calculated for older visitors to the rocky beach park, the mean centres of which, for both genders, are located in roughly the same place - to the east of the centre of the area itself - indicating that both groups make more use of the eastern part of the beach that is next to the sandy beach park which has better amenities. We can also see that men are more dispersed over the area compared with women, as indicated by the considerably larger radius values of the ellipse. In the case of the sandy beach park the radii of the ellipses are very similar for both genders, but the mean centres vary significantly. For women, the standard deviation ellipse fits within the boundaries of the park and is close to its centre, while the location of the ellipse for men is considerably shifted towards the south. The reason for such a shift might be something particular in the landscape that affects this user group and will be investigated further in the following section.


*Figure 14 a-c: a) Standard deviation ellipses for men and women aged 60+ on two comparison areas: the rocky beach park (b) and the sandy beach park (c). Centroids for ellipses are also shown along with the radius values of the ellipses in metres. (Orthophoto: Estonian Land Board 2020, photos Peeter Vassiljev)*

A slightly more sophisticated statistical technique to consider is the hot spot analysis (not to be confused with heat maps) based on the Getis-Ord Gi* statistic which uses counts of points within a square or a hexagonal grid of a pre-determined mesh size to determine local regions of higher or lower values. In this way it is possible to reveal neighbourhoods where the congregation of users (or a subgroup of users) is beyond a random chance with 99%, 95% or 90% statistical confidence. Figure 15a and b shows two examples – for older women using the southern part of the site contrasted with older men. These are overlaid on the behaviour settings map and can be seen to relate to combined areas of beach and grass in the case of the older women and to two specific spots in the case of the older men. These two specific hot spots are around a cafe and a set of chess tables (Figure 16) and are also responsible for the differences in the standard deviation ellipses described earlier (see Figure 14a). The same hot spot analysis layer can also be overlaid on the aerial photograph (see Figure 17a and b) to reveal finer landscape detail.

*Figure 15a and b: a) shows the hot spot analysis of older women and b) for older men overlaid on the behaviour setting map of the southernmost tip of the area (Orthophoto: Estonian Land Board 2020).*


*Figure 16a and b: a) shows the hot spot analysis of older women and b) for older men overlaid on the aerial image (Orthophoto: Estonian Land Board 2020) of the same area as Figure 6.26.*

*Figure 17: A set of chess tables and regular picnic tables that attract a large portion of older male users of the park into a specific, well defined hot spot. (Source: Peeter Vassiljev.)*

## Non-spatial analysis

The maps, as demonstrated so far, are very revealing of how people use the different parts of the site but so far we have presented limited quantitative information on the numbers or proportions of users in relation to different attributes. The next set of analyses demonstrate how the data can be analysed non-spatially, taking different sets of attributes associated with the data points to identify trends and patterns associated with the mapped results. Descriptive statistics can be used to explore aspects such as the proportion of gender and age groups compared to the local general population (see Figure 18), the relative popularity of different primary activities in general (see Figure 19) and by gender (see Figure 20 a and b).

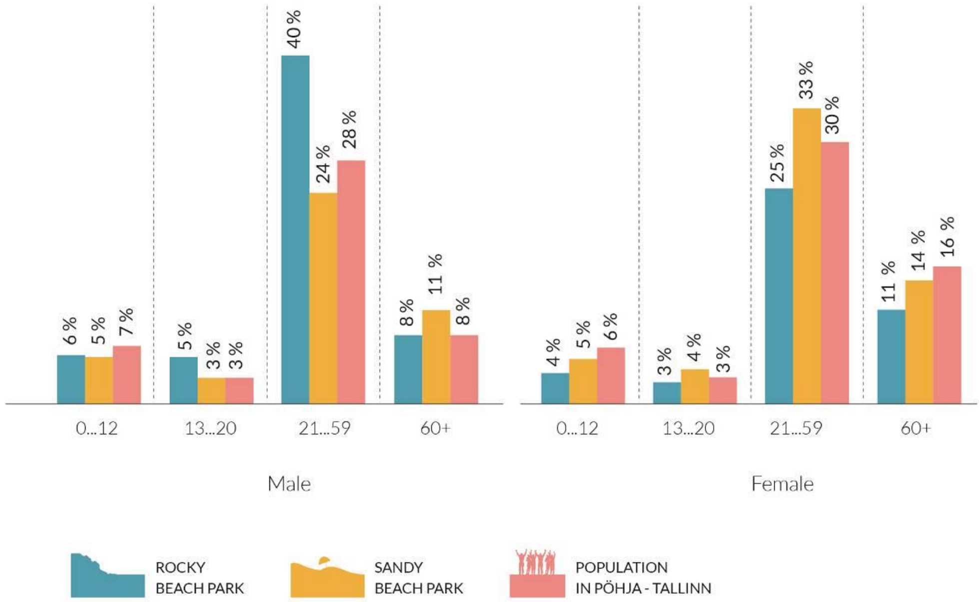


*Figure 18: Proportions of gender and age groups within observed visitors to the two parts of the study area, and comparison with the proportion of these groups in the general population living in the area of Põhja-Tallinn (Statistics Estonia. 2020).*

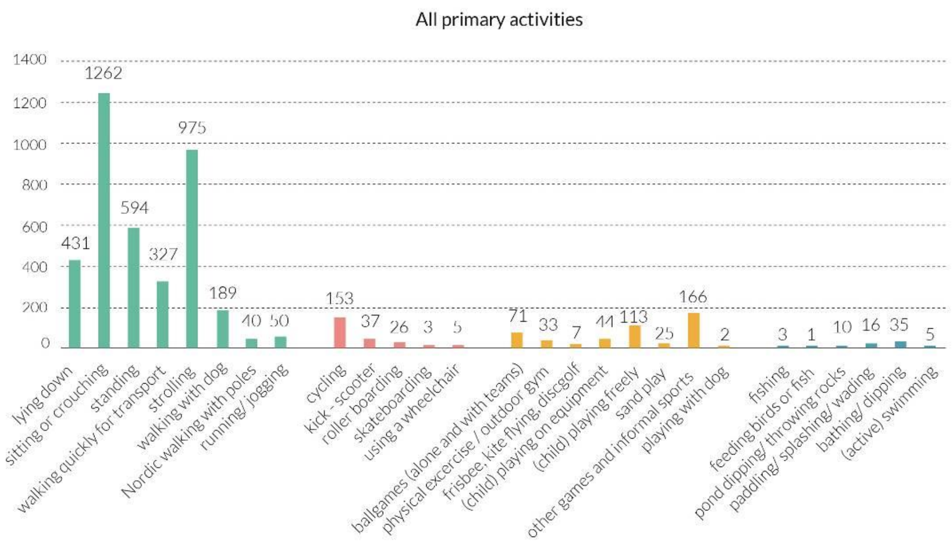


*Figure 19: Number of users engaged in different primary activities during all observations in 2017*

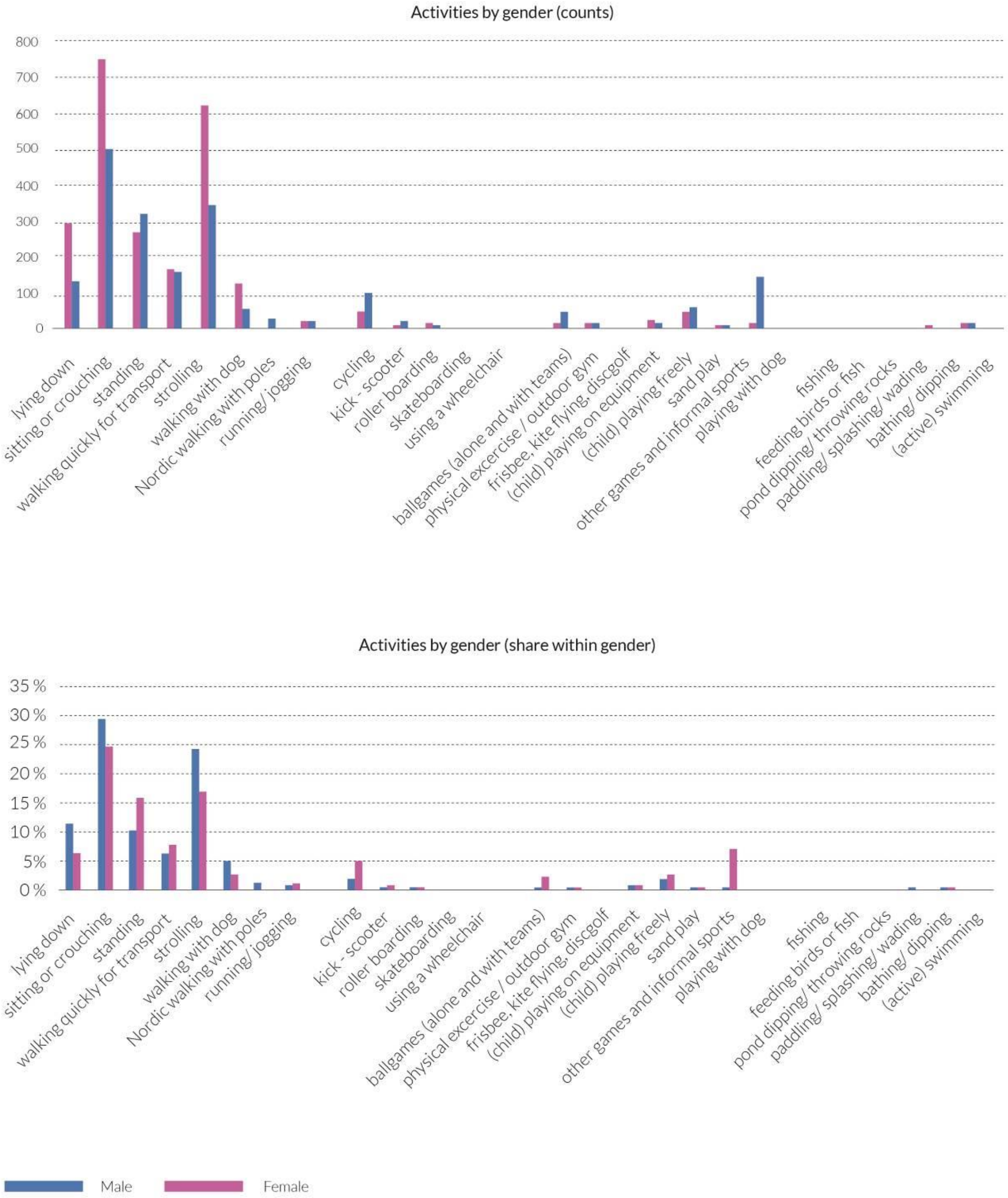


*Figure 20a and b: a) numbers of observations of primary activities by gender and b) percentage share within the gender group.*

Clearly, there are important findings here which are not apparent from the maps alone. There are also many different attributes which can be explored in this way, depending on what information is needed from the analysis. Another possibility of analysis of the attribute data is to explore changes over time. Figure 21 shows a time series graph revealing that visitor numbers tend to follow air temperature fluctuations to some degree. In the second half of the warm season the number of female visitors appears to become more sensitive to temperature fluctuations, increasing dramatically with warmer periods and returning to the same level as male visitors during cooler spells.

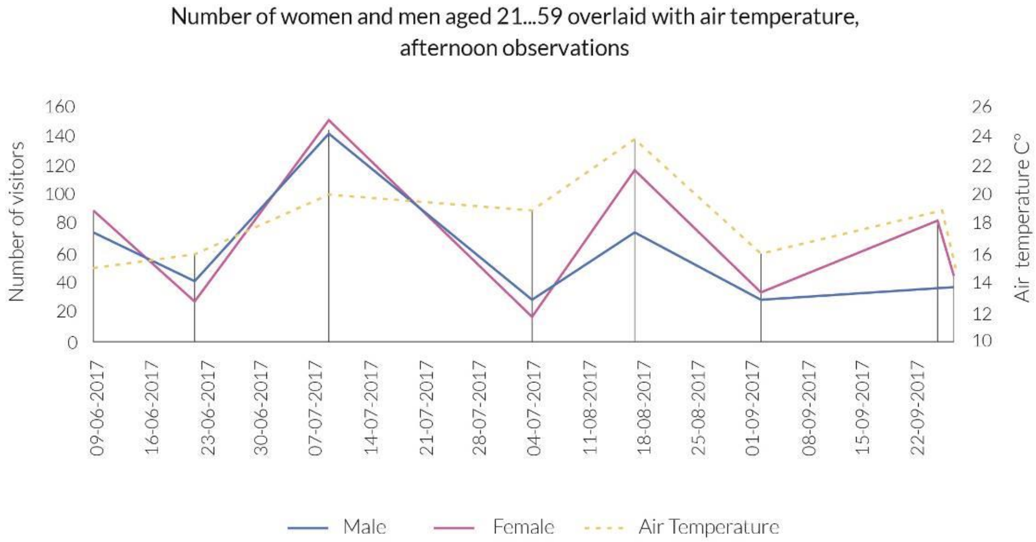


*Figure 21: The number of observed women and men overlaid with air temperature during the afternoon observations.*

It is also possible to run some inferential or predictive statistics using correlations or regressions. Table 1 shows an example of a regression looking at the influence of a range of independent variables such as time of visit or weather conditions "predicting" use of the site by people of different ages. Overall, it can be noted that the regression model performs very well except for age group 60+ where the R squared value (an indicator of how much variation in visitor numbers the model can explain) is very low. Looking at the particular components in this model, it is possible to observe that air temperature is positively affecting the observed visitor numbers (also confirming the observation presented on the time series graph at Figure 6.21) and the effect is strongest with activities that imply spending a longer time on site – something that seems intuitively logical. However, contrary to what might be expected, the rain does not affect the number of observed visitors. Instead, the level of cloud cover is affecting the visitor numbers negatively, suggesting a far more sensitive response to even a hint of unfavourable weather. From the temporal perspective, weekends by themselves do not seem to affect the number of observed users, but weekends during summer vacations do seem to cause a reduction in the number of visits. Lastly, among various age groups the number of teenagers is affected by the fewest number of factors – air temperature and time of day.

*Table 1: Multiple linear regressions of observed visitor counts in various groups with a number of environmental and temporal factors. Green indicates statistically significant results and the value of Beta indicates the direction and magnitude of the influence on visitor numbers.*

| Dependent variables -> | All users | | Age group 0…12 | | Age group 13…20 | | Age group 21…59 | | Age group 60+ | | All stationary activities | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Adjusted R square -> | 0.476 | | 0.383 | | 0.378 | | 0.565 | | 0.181 | | 0.430 | |
| F -> | 9.388 | | 6.722 | | 6.614 | | 12.968 | | 3.039 | | 7.955 | |
| p -> | 0.000 | | 0.000 | | 0.000 | | 0.000 | | 0.004 | | 0.000 | |
| Independent variables | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p | Beta | p |
| Influence of vacation on visitor numbers | 0.031 | 0.786 | 0.092 | 0.452 | 0.134 | 0.278 | -0.012 | 0.906 | 0.003 | 0.981 | 0.058 | 0.623 |
| Influence of years on visitor numbers | 0.089 | 0.274 | 0.208 | 0.021 | 0.173 | 0.054 | -0.012 | 0.872 | 0.225 | 0.030 | 0.099 | 0.247 |
| Influence of weekend on visitor numbers | 0.154 | 0.158 | 0.151 | 0.202 | -0.047 | 0.691 | 0.182 | 0.069 | 0.165 | 0.225 | 0.132 | 0.246 |
| Influence of weekends during vacation period on visitor numbers | -0.248 | 0.043 | -0.287 | 0.031 | -0.196 | 0.139 | -0.237 | 0.035 | -0.156 | 0.304 | -0.232 | 0.069 |
| Influence of time of day on visitor numbers | 0.205 | 0.022 | 0.074 | 0.438 | 0.365 | 0.000 | 0.267 | 0.001 | -0.173 | 0.119 | 0.127 | 0.170 |
| Influence of air temperature on visitor numbers | 0.469 | 0.000 | 0.476 | 0.000 | 0.256 | 0.036 | 0.496 | 0.000 | 0.303 | 0.031 | 0.518 | 0.000 |
| Influence of cloudiness on visitor numbers | -0.273 | 0.003 | -0.208 | 0.036 | -0.143 | 0.146 | -0.290 | 0.001 | -0.269 | 0.019 | -0.219 | 0.022 |
| Influence of rainy weather on visitor numbers | -0.103 | 0.257 | -0.073 | 0.464 | -0.147 | 0.140 | -0.097 | 0.246 | -0.070 | 0.541 | -0.068 | 0.478 |
| Influence of windiness on visitor numbers | -0.084 | 0.307 | -0.029 | 0.741 | -0.110 | 0.219 | -0.112 | 0.135 | 0.040 | 0.698 | -0.065 | 0.444 |

**Observations in years 2017, 2018, 2019**

statistically significant result

statistically non-significant result

With the ability to model the level of use by different groups in various weather, environmental and temporal conditions it is possible to identify factors that influence different user groups. This sort of information provides valuable insights into behaviour predictors but also gives hints of possible ways to cater for the needs of specific groups during unfavourable conditions or solutions that could mitigate conflicts between different user groups. Here we demonstrated a regression on the total observed users, but similar modelling applied to a number of users engaged in specific main or secondary activities or social situations could reveal further insights.

# CONVERTING BBAT DATA TO THE SOPARC FORMAT

Sometimes it might be potentially useful to convert BBAT data into the SOPARC format, which is a method of capturing activity intensity levels of users (McKenzie et al 2006) for comparison purposes and for calculating METs (Metabolic Equivalent of Task). Since the data collection rules have the same principles, it is an easy task. Firstly, SOPARC requires counts of visitors by age group, gender and activity level for each sub-area or behaviour setting. Subdividing the BBAT point data to sub-areas that can be determined at a later stage of analysis is a straightforward task of intersecting the point cloud with behaviour setting polygons in GIS. It is possible to start BBAT observations with less preparation and use the experience gained through the observations to refine the borders of the behaviour settings or sub-areas. Then the BBAT data points can be subdivided between these sub-areas, counted and analysed separately.

Secondly, BBAT captures a rather specific activity type for each user, while SOPARC observations only differentiate between three activity levels (McKenzie et al 2006): sedentary (lying down, sitting or standing); walking (at a casual pace and other moderate activities) and vigorous (any activity that requires more energy than casual walking). The activities captured in BBAT can obviously be reclassified to calm, moderate and energetic levels - a task that involves creating an extra column in the GIS database and using conditional logic to fill out the values based on other fields in the database. Table 2 provides a suggested conversion schema for performing the conversion.

*Table 2 Conversion schema of BBAT main activities into SOPARC activity intensity levels (S – sedentary activities; M – walking and other moderate activities; V – vigorous activities)*

| SOPARC intensity | BBAT Activity type: terrestrial | SOPARC intensity | BBAT Activity type: aquatic |
|---|---|---|---|
| Activity on foot | | Activities in the water | |
| <S> | A1 – lying down | <S> | iW1 – fishing |
| <S> | A2 – sitting or crouching | <S> | iW2 – feeding birds or fish |
| <S> | A3 – standing | <M> | iW3 – pond dipping / throwing rocks |
| <M> | A4 – walking quickly for transport | <M> | iW4 – paddling / splashing / wading |
| <M> | A5 – strolling | <V> | iW5 – bathing / dipping |
| <M> | A6 – walking with a dog | <V> | iW6 – (active) swimming |
| <V> | A7 – Nordic walking with poles | <V> | iW7 – diving / jumping into water |
| <V> | A8 – running / jogging | <V> | iW8 – snorkeling / scuba diving |
| Sports and games | | Activities on the water | |
| <V> | G1 – ball games (alone and teams) | <V> | oW1 – windsurfing |
| <V> | G2 – physical exercise / outdoor gym | <V> | oW2 – surfing on waves |
| <V> | G3 – frisbee, kite flying, disc golf | <V> | oW3 – paddleboarding |
| <V> | G4 – (child) playing on equipment | <V> | oW4 – wakeboarding (cable pulled) |
| <V> | G5 – (child) playing freely | <V> | oW5 – boating, rowing, pedalo |
| <M> | G6 – sand play | <M> | oW6 – boating (motor) |
| <M> | G7 – other games and informal sports | <V> | oW7 – kayaking/canoeing |
| <M> | G8 – playing with dog | <M> | oW8 – sailing |
| <V> | G9 – horse riding | | |
| Wheeled movement | | | |
| <V> | B1 – cycling | | |
| <V> | B2 – kick-scooter | | |
| <V> | B3 – rollerblading | | |
| <V> | B4 – skateboarding | | |
| <M> | B5 – using a wheelchair | | |

Figure 22 shows an example of proportions of activity levels on the study site, grouped by gender and sub-areas, where specific main activities from BBAT observation data have been converted into SOPARC activity intensity levels according to the conversion schema presented in Table 2.

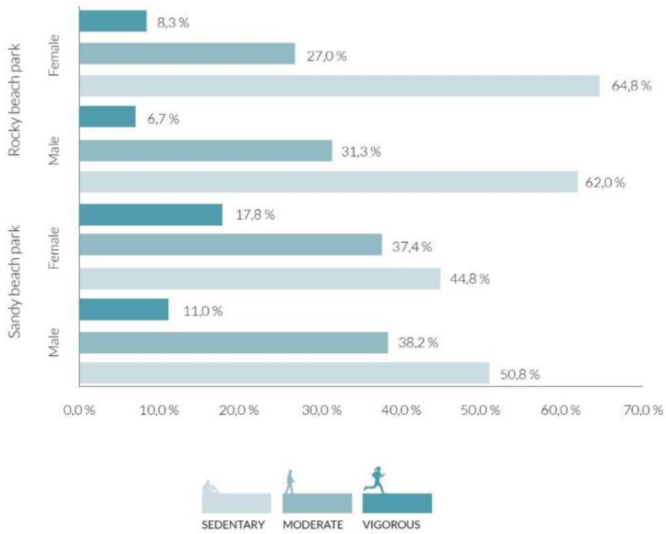


*Figure 22: Comparison of physical activity levels according to SOPARC activity levels by analysis sub-area (rocky beach and sandy beach of Pelgurand) and by gender.*

It is possible to assign metabolic energy expenditure rates to every activity and to use average METs (Metabolic Equivalent of Task) per person per observation episode as the analysis unit. Where the BBAT activities are used, the exhaustive list of MET values for various activities in the compendium of physical activities by Ainsworth et al. (2011) can be consulted, while if the activities have been reclassified to the three levels as in Table 2, then reference values for these can be used (see Vert et al. 2019). Figure 23 displays the distribution of the observed points grouped by SOPARC activity levels. An example of mean MET values per user per behaviour setting of the Pelgurand demonstration site is shown in Figure 24.

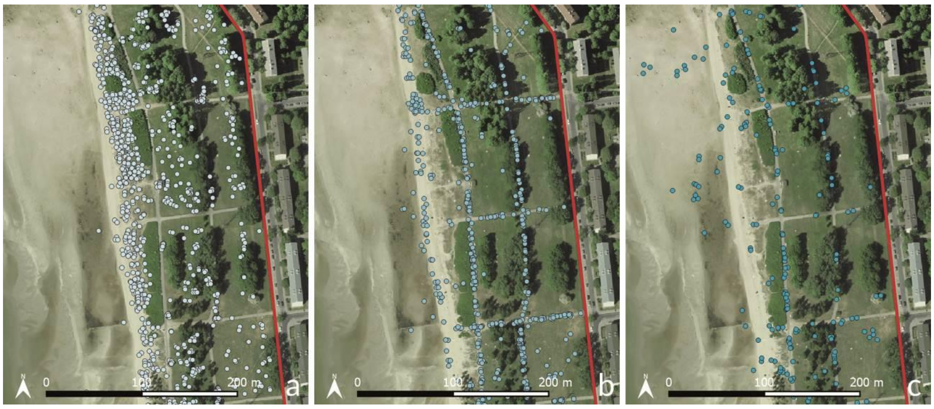


*Figure 23a-c: Map of sedentary (a), moderate (b) and vigorous (c) activities (Orthophoto: Estonian Land Board 2020).*

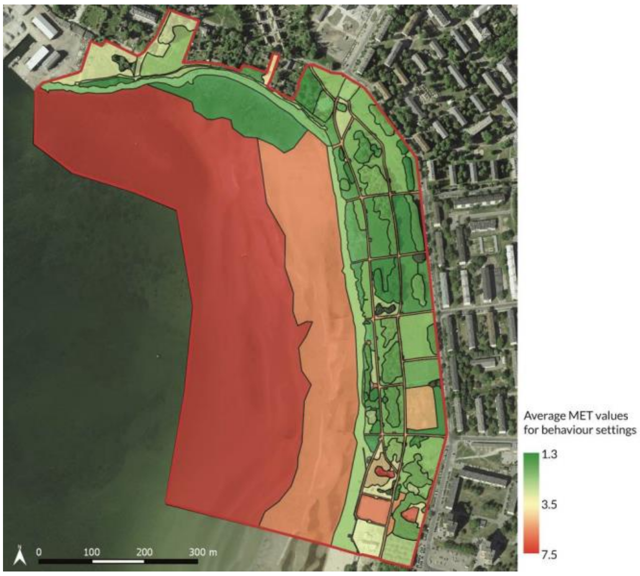


*Figure 24: A map showing the mean METs per minute per person calculated for each behaviour setting. Sedentary activities have been assigned 1.3 METs (green); moderate activities 3.5 METs (yellow); vigorous activities 7.5 METs (red) (Orthophoto: Estonian Land Board 2020).*

A limitation with applying METs in the context of BBAT or SOPARC data is the lack of a duration measurement – it is possible to estimate the potential to expend a certain amount of energy per minute, but it does not take into account the actual duration of visits. Many sedentary activities tend to last longer, so the total calorie budget may be higher than for some vigorous activities. Another limitation of using energy expenditure is that it discounts the quality of the sedentary experience as a source of psychological restoration as opposed to active physical exercise. We must look at these two aspects separately in terms of their respective health benefits.

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