

Nearby outdoor recreation modelling: an agent-based approach

Kevin Morelle, Matthias Buchecker, Felix Kienast, Silvia Tobias

Kevin Morelle, Swiss Federal Research Institute WSL, Zurcherstrasse 111, 8903 Birmensdorf, Switzerland, morelle.k@gmail.com

Matthias Buchecker, Swiss Federal Research Institute WSL, Zurcherstrasse 111, 8903 Birmensdorf, Switzerland, matthias.buecker@wsl.ch

Felix Kienast, Swiss Federal Research Institute WSL, Zurcherstrasse 111, 8903 Birmensdorf, Switzerland, felix.kienast@wsl.ch

Silvia Tobias, Swiss Federal Research Institute WSL, Zurcherstrasse 111, 8903 Birmensdorf, Switzerland, silvia.tobias@wsl.ch

Corresponding author: Kevin Morelle

Highlights

- Our ABM explains the spatial behaviour of recreationists
- both shortest-path and weighted-path strategies are used to access recreation areas
- The simulation mimics the recreationists' flow pattern well
- ABM can support the implementation of planned green infrastructure

This document is the accepted manuscript version of the following article:
Morelle, K., Buchecker, M., Kienast, F., & Tobias, S. (2018). Nearby outdoor recreation modelling: an agent-based approach. *Urban Forestry and Urban Greening*, 40, 286-298.
<https://doi.org/10.1016/j.ufug.2018.07.007>

This manuscript version is made available under the CC-BY-NC-ND 4.0 license
<http://creativecommons.org/licenses/by-nc-nd/4.0/>

Abstract

Modelling and simulating the movement of humans during outdoor nearby recreational activities can deliver important insight into the landscape services available to people in urbanized areas. Recreational activities such as walking, jogging and cycling are known to have a positive effect on people's mental and physical health, however in urban areas access to nearby recreation areas is sometimes lacking, under-developed or impeded by man-made infrastructures. In this context, understanding the spatial behaviour of humans during outdoor recreation is a crucial step towards implementing improvement measures. In this paper, we investigated the recreation strategies of multiple individuals and the flow in the movements of these individuals using a spatially-explicit agent-based model. The model combined information on the available infrastructures (roads, housing areas), the recreational potential of the landscape and rule-based movement strategies mimicking recreationists decision-making. At the individual level, we demonstrated that the shortest-path and weighted-path strategies were used the most during nearby recreation activities. At the population level, we successfully predicted recreationist flow patterns, highlighting gaps in path infrastructure and the most preferred path sections in a small town environment. We further illustrated the versatility of the model and its potential to support planning decisions to increase the accessibility of nearby recreation areas.

keywords: access, greenways, simulation, urban areas

Introduction

Today half of the world's population lives in urban areas (United Nations 2014). For most people nearby outdoor recreation activities represent an important part of their mobility

and access to good quality recreation areas in the neighbourhood or in close proximity is a crucial issue for urban-dwellers (Bell 2010). Indeed living in cities increases human daily stress (Kennedy and Adolphs 2011), and a lack of outdoor recreation can limit people's ability to recover from daily workloads (Degenhardt and Buchecker 2012). Nearby outdoor recreation refers to short-term (< 1 day) and close-to-home (< 8 km) activities that people perform in the natural environment around cities or villages during their leisure time, e.g. after work or at weekends (Buchecker and Degenhardt 2015). It potentially includes all nature-based activities, e.g. walking, jogging, cycling, Nordic walking and walking the dog, in easily accessible areas (in terms of distance, time and access routes). This paper specifically focuses on close-to-home recreation activities, involving convenience recreationists for whom the accessibility of nearby recreation areas is a crucial element in their pursuit of relieving tension from their everyday lives (Cohen 1979, Komossa *et al.* 2018).

The presence of people in nearby recreation areas is driven (1) by landscape attractors (e.g. rivers, forests, benches), and (2) by the attractiveness of the existing path network leading to recreation areas (Matsuoka and Kaplan 2008). The first aspect is well covered with research papers and recommendations for practice, e.g. highlighting the importance of size and quality of recreation areas (Roovers *et al.* 2002), as well as the individual's landscape preferences (Kienast *et al.* 2012, Boll *et al.* 2014). The second aspect - accessibility- has been found to be a key driver for decisions of people to engage into nearby outdoor activities (Koppen *et al.* 2014, Žlender and Ward Thompson 2017). Kienast *et al.* (2012) - based on an extensive empirical study in Switzerland - recommend that attractive green spaces should be provided within a 5-10 min walking or cycling distance

from home, suggesting that not only the recreation site in itself, but also the path leading to it has a recreational value and should therefore be included in assessments of recreational potential (Kienast *et al.* 2012, Bögli 2015). This finding is implemented in most pragmatic recreation planning as a basic principle. However leisure research is far from understanding and modelling the dynamic flow patterns of recreationists in urban environments. A spatially explicit agent-based model (ABM) can be a powerful tool to reduce this gap in current knowledge.

ABMs consider a bottom-up approach to simulate the behaviour of discrete decision-making entities, referred to as 'agents', evolving in a landscape, and explore the emerging properties of the whole system (DeAngelis and Grimm 2014). The analysis of interactions among the agents and/or between the agents and the landscape reveal system properties and processes that influence agents decision-making. ABMs have been applied in all fields of natural and social sciences, in which interactions between individuals and system properties are observed (Tang and Bennett 2010, Conte and Paolucci 2014). With the emergence of spatial data and GIS resources, ABMs have progressively included more spatial realism in their simulations (Wallentin 2017), providing powerful tools to explore complex and more realistic spatial systems (Heppenstall *et al.* 2012). Moreover, with the inclusion of network analysis tools, ABMs enable the investigation of movements of agents along linear infrastructures and can therefore easily be applied in research transport systems and human mobility research. This is in fact demonstrated by numerous studies on vehicle and bicycle traffic (Wallentin and Loidl 2015, Leao and Pettit 2016), crowd behaviour (Helbing 2012) and walking behaviour in public health research (Yang *et al.*

2011). In the field of recreation science, ABMs have mostly been applied to investigate the use of outdoor recreation areas, such as investigating the number of visits (Gimblett *et al.* 2001, Vries and Goossen 2002) or a site's carrying capacity (Shelby and Heberlein 1984). Most of these studies focused on large recreational areas in natural environments, e.g. national parks. The use of ABMs to explain spatial recreation patterns in urban environments has largely been neglected so far, despite its great potential in recreation management and planning (but see Gimblett and Skov-Peterson (2008)). In this study we used the potential of ABMs to investigate recreational spatial patterns and wayfinding strategies in a small-town context at two levels: i) the level of individuals and ii) the level of a population. While most other wayfinding studies focus on route-choice behaviour in inner-city environments, this study investigates route choice behaviour from the point of view of recreationists moving at the transition of urban to natural environments. At the level of the individual person the following research questions were investigated: 1) What movement strategies do people use when engaging in nearby outdoor recreation activities?, 2) How strongly does the use of particular strategies depend on the distance travelled? At the population level, we assessed the flow of people engaging in recreational activities. We hypothesized that the strategies identified by research question 1 would best mimic the recreational flow.

We derived our movement strategies from concepts of wayfinding and human route-choice behaviour (Golledge 1995, Borgers 2005, Agrawal *et al.* 2008). According to Golledge (1995) wayfinding is the “process of determining and following a path or route between an origin and a destination”, in which humans use cognitive maps of their environment. The

basic assumption in wayfinding research is that people try to minimize the distance or travel time between two locations (Seneviratne and Morrall 1985). However numerous studies have demonstrated departures from this basic assumption (Agrawal *et al.* 2008, Rodríguez *et al.* 2009, Guo and Loo 2013), assuming that people select roads or paths that are attractive in terms of their immediately surrounding environment and structure (e.g. road surface, width, traffic, signalisation) (Žlender and Ward Thompson 2017). We tested the following movement strategies: the shortest-path strategy corresponding to distance-optimization, the weighted-path strategy, i.e. maximizing the quality of the route, and the combined-path strategy, i.e. maximizing a composite variable combining route length and quality. Alongside the above-mentioned strategies, we also included a random movement strategy which serves as a control. We hypothesized that the recreationists make more use of the weighted-path strategy, but with increasing length of the trip the shortest-path strategy would be used more frequently (Kienast *et al.* 2012).

We developed a spatially-explicit agent-based model of mobile agents moving around in a realistic environment composed of a road network, residential areas and surrounding landscape with recreational qualities. The ABM served to test how well a simple rule-based ABM could mimic the recreational flow of people. With this we developed a practical tool that aims at improving accessibility to nearby recreation areas. We analysed and validated the behaviour of the model by comparing model outcomes with real movement data of inhabitants of the city of Wil (SG) in Switzerland.

Material and methods

Study area

The model was developed and implemented for the city of Wil located in the canton of St. Gall, East of Switzerland (47° 28' North 9° 03' East) (Fig. 1). Wil is a mid-sized Swiss town with 24,022 inhabitants and a population density of 1,137 inhabitants km⁻², located 571 m a.s.l. The average age of inhabitants is 41.8. People under 20 years old constitute 19.9% of the whole population, 20-64 years old 61.6% and senior (those above 64 years old) 18.5%. Most working opportunities in the city of Wil are to be found in the tertiary sector (services), with 53.1% of the active population working in this sector, followed by secondary (43.0%) and the primary sector (3.9%). The area of Wil covers 20.8 km² of which 30.1% is occupied by buildings and roads. The city is embedded in a landscape of agriculture and forest covering 50.2% and 19.1% of the landscape respectively. Mobility in and out of the town is ensured by dense railways, regional and inner-city bus connections as well as direct access to the A1 motorway (connecting Geneva to St. Gall). With its close by forest areas, open landscapes, riversides and inner city parks, the town offers numerous recreational opportunities, yet the mentioned highway, roads and railways hinder access to most of these areas. Moreover the municipality is involved in a larger regional transport planning project, one of the aims of which is to improve path connections from residential areas to recreational areas in the context of green corridor development. Examples of planned measures are: developing new access paths to nearby high value recreation areas,

creating passages above and under barriers (e.g. highways and railways), and improving the attractiveness of the existing path network.

[Figure 1]

Model development

Here we describe the model principles; a complete description of the model is presented in the appendix and follows the ODD (Overview, Design, Details) (Grimm *et al.* 2006), and the ODD+D (including human-decision making elements) (Müller *et al.* 2013) protocols. The spatially-explicit agent-based model is based on a nearby recreation suitability map (Kienast *et al.* 2012), a road network and buildings areas (SwissTLM3D). The model assumes i) people are not moving randomly but are conscious of their decisions, i.e. they select recreation areas based on their preferences (in terms of “recreational value” and road attributes), ii) individuals move according to given strategies, iii) recreational behaviour observed in a population can be represented with a probabilistic approach. In the model, the agents have to make three decisions: i) Where to go?, ii) Which path to take to get there? and iii) Which path to take to get back home?

To take their first decision (Where to go?), the agents are informed of the “recreational value” of the landscape surrounding their dwelling area. This value is assessed and extracted from the recreational suitability model developed by Kienast *et al.* (2012). In this model, potential recreation use was forecasted based on data from surveys in several mid-sized Swiss towns. Surveys combined mapping exercises (i.e. indicating preferred recreational places on the map grid) with a detailed questionnaire about outdoor recreation

behaviour and site preferences. Our ABM is distance-based, i.e. the agents select a destination within an arbitrarily user-defined distance radius from their home.

To take their second decision (which path to take to get to the selected destination?), we implemented four rule-based movement strategies that agents can use. The first strategy is the random movement, which assumes that the actor has no control over his movement and this was used as a control case. Under this strategy, the agents randomly choose at every crossroad which direction to travel in next. The second strategy is the shortest-path strategy representing an extreme target-orientation. It is based on the Dijkstra (1971) algorithm, which computes the shortest route to get to a destination. The shortest distance between two points (origin and destination) is assessed through a network analysis, based on the length of each road segment and the accumulated distance between origin and destination for alternative routes. The third strategy is the weighted-path strategy, in which the access quality is accounted for the agent's route choice. To assess how people value road attributes, a deterministic approach, based on consultation with experts, was used to parameterize the decision-making processes (see Appendix for details on the implementation of this strategy). The fourth and last strategy is a combination of the shortest and weighted-path strategies, i.e. agents decide on the basis of a linear combination of the segment length and the segment quality.

To take their third decision (which path to take to get back home?), we assumed that agents used the same strategy as the one used to access the recreation site chosen, but that they varied in retrace (recreationists following the same or partly the same route back home) and loop (recreationists using a different route) behaviour (Taczanowska et al. 2006). For

the return process we allowed agents to either select the same route or a totally different route to the one used to reach their destination. We calculated a posteriori the “avoid-used-path” parameter to ascertain the proportion of retrace and loop behaviour within our population of agents.

The model was implemented in the Netlogo modelling environment (Wilensky 1999) using the *network* and the *GIS* extensions of NetLogo to import and adapt real world data sources.

Simulation design

For each movement strategy we ran 100 repetitions to control the natural stochasticity of the model stemming e.g. from the initialization or the selection of the movement rules. The literature (Auchincloss and Garcia 2015) suggests 20-30 runs; hence we are well above the suggested threshold. In each repetition the following actions occurred sequentially: i) creation of 200 agents. This number is equivalent to the number of observed routes extracted from the survey, ii) selection of a recreation destination for each individual, iii) selection and implementation of a movement strategy to get there. In our modelling design, we limited the distance radius to search for potential destinations to 2 km. In an empirical study conducted in six Swiss cities 20-60% of the interviewees had nearby recreation areas 2 km from their home. Given the fact that this included pedestrians and cyclists, the value of 2 km is considered appropriate and realistic (Kienast *et al.* 2012, Bögli 2015). During the simulations, we collected data on the routes taken by each agent. This allowed us to calculate the number of agents travelling on each road/path segment. We further converted this number to a relative use intensity measure.

Independent survey

It is essential to ensure model validity by “ground-truthing” the simulation results with empirical presence/absence data of recreational activities. We conducted a survey in Wil and collected independent data on people’s recreational activities. This survey was focused on the north-western part of the town (47.470N, 9.034E), which is located at the interface of the town centre and the nearby landscapes of interests for recreationists (see Study area section). 1,000 questionnaires were distributed to households within this area. In these questionnaires, we asked the respondents to inform us on their recreational habits in terms of use intensity, timing and mode of visits. The questionnaire included a section in which participants were asked to mark on a 1:20,000 topographical paper map up to three of their most used/preferred recreational routes, starting from their home and ending at their home. Recreational routes of visitors have been recorded in a similar way in recent studies (Vejre *et al.* 2010, Klain and Chan 2012, Bögli 2015), but they were not used as an empirical basis for modelling outdoor recreational behaviour.

The recreational routes were digitized in the Geographic Information System QGIS. For each route, the following metrics were extracted and used later to compare and validate the model outcomes: total distance travelled, maximum distance from home, route shape (round-trip or both trips using the same route) as well as information on the characteristics (road width, road cover and road label, see Table A of the Appendix) of the route used. This independent dataset was used to evaluate the model both at the individual (*micro-validation*) and the aggregated scale (*macro-validation*).

Validation procedure

Micro-validation (Individual movement strategies)

To validate the individual movement strategy, we compared the observed and modelled recreational routes. We selected the real points of origin of the observations and considered the locations half-way along the recreationists tracks as their destination points. We then applied the model to this set of origin-destination points using the different movement strategies. We finally assessed the similarity between the observed and modelled routes by measuring the proportion of identical road segments used (Manley *et al.* 2015). The similarity values have been categorized into 4 classes: < 25% 25-50, 50-75 and 75-100% of similarity. We are well aware of the fact that the longer a trip, the more alternative routes exist, i.e. typically for a 500m trip fewer alternative routes will exist than for a 2km trip. Thus the chance that the ABM predicts the correct route is larger for shorter trips than for longer trips, simply because there are fewer alternatives. We correct for this phenomenon by comparing model performance only in given length ranges of travel distance, i.e. 0-1.5km, > 1.5km.

Macro-validation (recreational flow assessment)

Once the strategies were verified, i.e. they could reasonably portray the recreation patterns, we tested the model at the scale of the surveyed area. To this aim we took into account the total number of routes described by the respondents to generate a map of observed relative road use intensity. For each strategy we then simulated the movement of 200 agents simultaneously performing the following actions i) selection of a recreation destination, ii)

selection of an access route according to the tested strategy, iii) movement to the destination and back home. For each strategy, we performed 100 repetitions of this process. Comparative analysis between the observed and the simulated spatial patterns of road use intensity was then carried out. Furthermore, we compared the density distribution of two spatial metrics, total travelled distance and maximum distance from home, to assess how well the model matched the observed patterns. We assessed the quality of the model by performing an equivalence test. Equivalence tests formulate an inverse null hypothesis, which assumes that two sets of data are inherently different, and check whether this assumption could be verified. Such tests are particularly suited for model validation (Robinson *et al.* 2005). To assess the model performance, we took the relative use intensity of each accessible road segment, i.e. segments encompassed in a 2 km buffer area around simulated agents. We compared this value to the relative use intensity obtained from the survey, used as reference values. We performed a two one-sided t-test (TOST) (Wellek 2010). We used $\pm 25\%$ of the standard deviation as the interval, also called region of indifference, within which differences between the observed and simulated values can be considered negligible (Robinson *et al.* 2005). Taking this threshold value allowed us to ensure a statistical power of 0.9 for the probability of detecting significant similarities. This equivalence test was performed using the TOSTER package in R (Lakens 2017).

Results

A total of 107 questionnaires were completed and sent back to us yielding 218 correctly mapped recreational routes, of which 180 were walking routes, 30 were cycling routes and 8 routes were used for both walking and cycling (for the same individual) (Table 1).

[Table 1]

Micro-validation (individual movement strategies)

From the 180 recreational walking routes received, 107 were used for modelling and comparison purposes, after excluding recreational routes which extended beyond the map extent ($n=28$) and routes that encompassed informal paths ($n=45$), i.e. paths not represented in the SwissTLM3D data source. We used the origins and mid-points of the 107 routes as start and endpoints (see Methods section) and tested the real routes against the four different movement strategies. We found that on average, the weighted-path and the combined strategies revealed the highest similarities to real data ($45.0\pm 28.0\%$ and $44.6\pm 28.9\%$ of the same paths were used respectively), followed by shortest-path strategy ($39.8.0\pm 27.9\%$ of the same paths were used) and random strategy ($18.1\pm 16.2\%$ of the same paths were used). To check whether the strategies that fit best are equally represented in all similarity levels we plotted all 107 routes according to their similarity class and identified the best fitting strategy for each route (Fig. 2). We observed that in general the weighted- and shortest-distance strategies perform best, with the shortest-distance strategy performing best in the highest similarity class ($75-100\%$ of the same paths were used). As expected the random strategy performs the worst.

[Figure 2]

The length of the recreation route has a decisive effect on the model fit (Fig. 3). The shorter the trip the higher the similarity value, i.e. 69.1% (sd=22.2%, n=20) for routes shorter than 1.5 km and 40.4% (sd=25.1%, n=17) for routes longer than 3 km. However, we have to keep in mind that for shorter trips not as many alternative routes are available and thus the similarity value must be slightly higher than for longer trips. In the following, we therefore compare model performance within distance segments to correct for this effect (<1.5km; >1.5km). Our result suggests that the quality of the simulation greatly considerably depends on the length of the trip and this, for all strategies (Fig. 3).

[Figure 3]

Macro-validation (recreational flow)

For this section, we shifted from an individual level perspective to a population level perspective, considering the simultaneous movements of multiple agents. At this level we noted that our ABM simulation captured the pattern of route use intensity shown by the respondents and these were the three more realistic strategies (shortest-path, weighted-path and combined-path) but not for the random strategy. Comparing the total distance travelled and the distance from home metrics between strategies, we showed that the shortest-path, the combined-path and the weighted-path strategy performed relatively similarly, i.e. these strategies match the observed distance metrics well (Figs. 4 and 5). In both cases, for total distance travelled and distance from home, the shortest-path strategy revealed the highest overlap with the observed metrics in the density distribution curve,

although no significant difference was observed between the above mentioned strategies (Table 2).

[Table 2]

In terms of density distribution, the shortest-path strategy again presented the better overlap value with the observed data (84% of overlap for total distance and 84% for distance from home). However the weighted-path strategy (78% and 82% of overlap, respectively) and the combined-path strategy (80% and 83% of overlap, respectively) also matched the observed data closely (Figs. 4 and 5).

[Figure 4 and figure 5]

Spatially explicit macro-validation was performed using road use intensity as a comparative measure. Visually our simulation revealed a relatively good similarity between the simulated intensities of all strategies and the observed intensities, with the exception of the random strategy which was our control case (Fig. 6).

The results of the equivalence test showed that the null hypothesis of dissimilarity can be rejected for the shortest-path and the combined-path strategies, but not for the weighted-path and the random path strategies (Table 3).

[Table 3]

Applications of the ABM for improving accessibility to nearby recreation areas

After having shown that the ABM mimics nearby recreation patterns with medium (at the individual level) to high (at the population level) accuracy, we present a practical

application of the model in the spatial planning field. This application concerns a planned passage over the railway to increase accessibility from the north-western part of the city to the closest nearby recreation area. We ran the model both with and without the described improvement measure and predicted how the flow of people would be impacted by this improvement.

The model demonstrated a considerable change in the flow of recreationists following the implementation of a new passage over the railway (Fig. 7). In particular we observed that the new passage would have a high probability of being used frequently. The planned development may additionally increase the use of the Oberholz recreation area and of the northern recreation areas. This new passage has a potential positive impact within a range of 500m around it (see flow changes on the eastern part of Fig.7).

[Figure 7]

Discussion

By designing and developing an agent-based model in the field of nearby recreation, our objectives were: i) to elucidate movement strategies used during nearby outdoor recreation activities at an individual scale, and ii) at the population scale, to test how well a simple rule-based ABM could mimic the recreational flow of people living in small-town environments.

At the individual scale, we showed that no single movement strategy prevailed, but that multiple strategies co-existed in our surveyed population: i) shortest-path; ii) weighted-path and, iii) to a lesser extent, a combined strategy of shortest- and weighted-path.

Assuming that the shortest-path strategy is an expression of target-focused recreation, i.e. accessing a recreation site quickly, and the weighted-path strategy corresponds to focusing on the path quality, our results suggest a relative even balance of using these two strategies. This co-occurrence of multiple strategies can be explained by the numerous motives for nearby outdoor recreation (Degenhardt *et al.* 2011, Conedera *et al.* 2015) but also by results of studies which highlight the importance of both distance and quality of the path during nearby outdoor recreation (Roovers *et al.* 2002, Taczanowska *et al.* 2008, Irngartinger *et al.* 2010, Kienast *et al.* 2012). Kienast *et al.* (2012) confirm that target orientation is one of the main components of decision-making in nearby recreation activities, which supports the choice of the shortest-path strategy. However, their results also suggest that recreationists consider the path used as an inherent part of their recreational activities, which is why they also tend to choose the weighted-path strategy. Irngartinger *et al.* (2010) further showed that people prefer paths with natural surfaces, which again indicates the use of a weighted-path strategy. Accordingly, Bögli (2016) found that recreationists rated easy and attractive access to recreation areas a more important selection criterion when selecting outdoor recreation routes than short access distance.

Our results extend the concepts of route-choice behaviour observed with inner-city walkers and outer-city walkers or urban dwellers in search of leisure in the surrounding green landscape. Inner-city walkers are indeed known to primarily use the shortest-path and

weighted-path strategies when moving within a city environment (Golledge 1995, Borgers 2005, Agrawal *et al.* 2008). The combined-path strategy, i.e. combining short access-length with high route-quality, seemed to be used less for access routes at the scale of our model. This strategy may be more suitable for larger distances, as the relative use of this strategy increases when the recreational trip becomes longer. The longer the distance, the more the variability of road quality increases, offering the recreationists more options for their decisions. Hence, our results indicate that recreationists' route-choice strategies change with increasing trip-length: the use of the shortest-path strategy declines and the use of the combined strategy increases, whereas the use of the weighted-path strategy remains roughly the same, independent of the trip length.

Our results concur with the basic wayfinding assumption that the shortest-path strategy is the most commonly used strategy in human walking behaviour (Golledge 1995). Although similar results previously highlighted the importance of road-link length in people's route choice in an urban environment (Seneviratne and Morrall 1985), our results extend this observation to recreational behaviour at the interface of urban and natural landscapes. Several studies however contradict this starting assumption and point out the importance of spatial structures and environmental cues in human decision-making, e.g. the built and the aesthetic environment (Agrawal *et al.* 2008, Guo and Loo 2013), which is also suggested by our observations highlighting that weighted- and combined-path strategies are used by recreationists as well. Borst *et al.* (2009) found that for older people only 20% of the chosen routes were the shortest ones, the choice of the remaining 80% of routes was influenced by multiple factors such as pavements, slopes, stairs, green strips, front gardens, blind walls,

litter on the street, dwellings, shops, parks, traffic volume, and link length. Seneviratne and Morrall (1985) explained people's deviation from the shortest-path strategy by other influential factors such as route attraction, number of crossings, degree of crowding, weather protection, noise, and safety. Degenhardt and Buchecker (2012) found that recreationists decide intuitively on their routes, particularly when they have more time for example at the weekend. Rodríguez *et al.* (2009), finally, showed that pedestrian use intensity was associated to the quality of road segments (measured in terms of land-use, sidewalk width, sidewalk continuity, rubbish bins, crossing aids, crossing density and road density).

Although we observed a relatively high similarity between the observed and the simulated routes, 35% of the simulated routes had a similarity value lower than 50%. Recreationists may therefore choose their routes according to other criteria, such as old routines, non-visible place meanings, social factors (friends, bad experiences with people, lack of knowledge of the area or false beliefs that a particular route is shorter when this is not the case) (Seneviratne and Morrall 1985, Degenhardt and Buchecker 2012). Moreover, while analysing the survey, we noticed - in agreement with other studies (Taczanowska *et al.* 2014) - that some route sections used by surveyed people were not indicated in the road dataset (these were defined as informal paths in the methods section). Aerial image analysis and in-situ observations showed that these segments were routes along or across fields, or forest borders joining existing pathways. Using such informal paths indicates the desire of recreationists to freely do what they want to do - which would - in the words of Kaplan and Kaplan be the compatibility component of restorative landscapes (Kaplan and Kaplan

1989). This compatibility component is an important driver of outdoor activities and is for example reported from freeriding and snowshoeing (Freuler and Hunziker 2007). This explorative behaviour can also be seen as a means for recreationists to discover new areas or to use known shortcuts between marked paths to facilitate or accelerate access to a particular point of interest or a particular activity (Taczanowska et al. 2006, Taczanowska 2009).

At the population scale, ABM successfully represented the overall flow of recreationists. One single strategy could not accurately mimic the overall pattern of nearby recreation in a small-town environment. The shortest-path and the combined-path strategies were similar to the observed patterns. Interestingly, the weighted-path strategy was not effective at the population level, possibly due to the implemented method for assessing the weights. The weighted approach was based on consultation with experts (see Appendix), assuming an average recreationist's and idealistic perception of the considered variables. As such this approach was probably not able to encompass the overall pattern of the recreational flow at the population level. Our results should therefore be interpreted more in terms of relative use rather than a real flow of people at any given time (Gimblett and Skov-Peterson 2008). The advantage of our model is that it provides a fine understanding of spatial, rather than temporal, patterns of recreational behaviour. Compared to situations where temporality might play a role in the decisions of agents to visit an area or not, e.g. overcrowding issues in national parks during the peak season (Skov-Petersen 2008a), we focused rather on overall use or non-use of recreational routes and sites for a particular time-independent context.

Model limitations

To ensure a successful application of the presented methodology, we further discuss several critical points of our work which should be considered before applying the approach in, for example, spatial planning.

Low response rate. Although the response rate obtained (10.7%) for our postal survey is relatively low, it is still within the margin of response rates for similar types of surveys that require simple mapping skills of the respondents (Brown 2003). Further, the sample has been found to be representative for the population of the canton of St. Gall in terms of a number of demographic characteristics (see online statistics <https://www.statistik.sg.ch/home/STADA.html> and Table 1). Finally the empirically obtained recreation pattern (type, frequency of activities) fits very well with the results obtained in a large survey conducted over multiple Swiss towns (Buchecker et al. 2012). While we could have opted for an online survey to increase the number of respondents, this method has often the disadvantage of a biased sample, and, as shown by Brown (2016) and Pocewicz et al. (2012) random paper-based surveys have higher response rates, better spatial data quality, reduced respondent's bias and greater mapping participation when simple mapping skills by participants are required.

A distance- and not time-based approach: in the proposed model we used a distance-based and not a time or time-distance based approach. Hence time aspects have not been included explicitly in the model, neither in the starting time (all agents start their activities simultaneously) nor in the overall activity time (since activity is based on origin-destination

distance). This means that the decision-making of the agents on where to go is only based on the actual distance of a set of potential recreation areas within an arbitrary distance (2 km). Although recreation activities and accessibility are often described in terms of time, e.g. recreation areas should be accessible within a 15-min walk from dwellings (Kienast *et al.* 2012), using a distance-based approach has two main advantages. It facilitates the use of an ABM and reduces the running time of each simulation (Wilensky 1999). It also enables the focus to be set on the selected path strategies of people (both as individuals and as a population) independent of when displacements may occur, i.e. simply assuming that per se recreational activities are performed after work or at the weekend (Degenhardt *et al.* 2011).

Only static a-priori landscape preferences included: our model uses the map of recreation potential from Kienast *et al.* (2012) as static input for the agent's selection of the target destination. In contrast to many ABMs reported in the literature (see next text section), the implementation of this a-priori knowledge is needed to model everyday recreation in areas where people have an accurate idea of where "their" attractive landscape spots are located. To keep the ABM simple, our agents do not store landscape information from previous visits and do not improve local knowledge as described by Cavens *et al.* (2004). Whilst their study covered hikers in mountain terrain, we argue that in our small-town study site, the "unexpected" landscape experience, which would lead to a "learning effect", is by far not as important as for day hikers in the mountains. Thus we are confident that our simple behavioral rules without learning effect are sufficient. They are comparable to the motivation behavior algorithm used in the MASOOR model (Jochem 2008).

No group-specific landscape preference included: The implemented spatially explicit a-priori knowledge (map of recreation potential from Kienast *et al.* (2012)) is based on an average preference profile of inhabitants in peri-urban and urban areas of the Swiss lowlands. As a consequence, our model is unable to directly predict the behaviour of specific user groups such as elderly people or young families. Rather we assumed that the variety of recreationist types (Van Marwijk 2006) is included implicitly in the recreation potential map, which provides us with a comprehensive picture of the recreationist variety, both in terms of demography and recreational preferences (Taczanowska *et al.* 2008).

This implicit mix of user profiles and the time independency distinguishes the current approach from traditional ABMs developed for recreation research, e.g. RBSim (Gimblet 2000), MASOOR (Jochem 2008), ALPSIM (Cavens 2004), KVINTUS (Skov-Petersen 2008b) models. Incorporating time constraints and rules (e.g. speed of movement, time spent at a landscape feature, time spent resting, memory effect) would indeed be a further improvement of our approach, as it would allow us to include a wider diversity of agent profiles. We could also imagine implementing social interactions (Gimblet *et al.* 2000, Bishop and Gimblett 2000) or encountering rates between different agents' groups to analyze and possibly predict user conflicts.

Only basic properties of routes included: Given the fact that the quality of the routes may play a considerable role in path selection, our quality rating of the route segments might be too simplistic and thus lower the quality of the model output. As we used available route characteristics, our approach has the advantage of being directly applicable to other areas using the same reference data. To increase the understanding of route-choice, we would

nevertheless suggest including more detailed information on scenic view and landscape quality along the chosen routes (Taczanowska et al. 2008, Rodríguez *et al.* 2009). By including these elements in the weighting approach of the weighted-path strategy, one could investigate other route-choice algorithms such as algorithms based on landmarks, decision points, or route structures (e.g. route minimizing turning angle) (Jochem *et al.* 2008, Schwering *et al.* 2017). The use of other data sources such as smartphone GPS tracking of people during recreation activities (Korpilo *et al.* 2017) also opens promising perspectives to improve the understanding of spatial recreational behaviour.

Model does not correct for more alternative routes with longer travel distance: As mentioned in the Methods chapter and throughout the paper, we recognize the fact that the longer a trip, the more alternative routes exist, and that the changes of the ABM to pick the correct route decreases as a matter of a normal chance probability. When picking the best routing strategy of the ABM we strictly compare the same trip length segments. Thus recommendation of a routing strategy must always be seen in the context of trip length.

Conclusions

The main novelty of this work lies in modelling human spatial behaviour at the interface of urban and natural landscapes. So far, most of the recreational flow models focused on visitor behaviour within specified recreational destinations (e.g. urban parks, forests, protected areas) or traffic models depicting travelling patterns within urban infrastructure. However, modelling human behaviour within the nearby recreation context requires a broader view including the entire space between home and the final destination. The paper

fills this gap by proposing an agent-based model to investigate fine scale behaviour and patterns of recreationist movements in and around a midsized town environment. The main conclusions of this study are the following:

- (1) People seeking nearby recreation are sensitive to distances but also to the quality of roads and paths leading to attractive recreation areas. Accordingly, planners should not only ensure recreation areas for inhabitants within accessible distance, but they should also take the quality of access paths to recreation areas into account when planning new developments.
- (2) As barriers and corridors for reaching attractive outdoor recreation areas appeared relevant, a potential application of the ABM-based approach is to simulate the flow of people under various different planned accessibility routes. As such the simulation model can be helpful to identify the routes that are most intensively used by inhabitants to reach their destinations according to different strategies. Effects of improvement measures, e.g. through enhancing the existing network or creating new access routes, can thus directly be assessed by the model as demonstrated in our study case.

Acknowledgements

This project was funded in the frame of the Swiss Model Project on Sustainable Spatial Development: “ Attractive Access Network to Nearby Recreation Areas”. The authors are grateful to Sarah Radford for proofreading and editing the language of former version of the

manuscript. We are also grateful to the anonymous reviewers for their comments which helped improving the manuscript.

Appendix. ODD model documentation

The SiReMo model is a spatially-explicit model of agents (“the recreationists”) moving in a realistic GIS-based environment along the existing linear infrastructures (“the network”). The base for the model is a recreation suitability map (Kienast *et al.* 2012) which serves as basis for the selection of recreation areas by the agents. The model is documented following the ODD+D protocol which is an extension of the initial ODD protocol (Overview, Design, Details) by Grimm *et al.* (2006) adapted for ABM including human decisions (Müller *et al.* 2013).

Model Overview

Purpose

The model aims to simulate the movement of humans travelling to recreational activities/areas by foot in a small-town environment, in order to assess movement flows and gaps along the mobility network with a particular focus on greenways. The spatial distribution frequency of recreationists in the city of Wil (Switzerland) emerge as the main outcome of the model. The results of this model are expected to i) improve knowledge on where people actually go for recreation, ii) inform planners on the current state of the greenway network, i.e. if it needs to be improved and optimized to provide urban-dwellers

with attractive access to recreational spaces, iii) support planners in assessing how the recreational potential is used, i.e. assess areas which are over- or under-used, and how a better balance can be achieved. The model can be used to generate and test hypotheses on factors driving people's decisions during their recreational activities, e.g. to test the effect of reducing car traffic on some roads and its implications for people's decisions.

To represent recreational behaviour at the population level we used a probabilistic approach, i.e. assuming in the model that the variability of recreationist behaviour and personality can be encompassed by the decision-making of agents on where to go based on probability (the higher the recreational value of an area, the greater the chance that it will be visited) (Kienast *et al.* 2012, Bögli 2015). We assume this approach allows consideration for numerous and diverse recreationist types and their associated behaviour, as the underlying recreation suitability map, used in the ABM, is built from different recreational user groups and therefore intrinsically encompasses the existing variability and diversity in behaviour and preference. Once the agents have decided where to go, they decide which strategy to use to access their chosen nearby recreation site.

Entities, state variables and scales

The model is composed of four entities: a spatial recreation map, a network of edges and links (the linear transport infrastructures), human individuals and visual elements. The model processes take place on a raster map representing the recreational potential of the environment. Each cell thus represents a classification of the landscape denoting its

recreational value. This value is based on the study of Kienast *et al.* (2012) elucidating preferences of people in terms of nearby recreation. The recreational value of a cell is the linear combination between the following characteristics of that cell (in bracket the sense of the relationship indicated, “+” indicates a positive effect on the recreational value, “-” a negative effect on the recreational value:

- proximity to forest areas (+)
- proximity to humid area (+)
- proximity to rivers (+)
- proximity to hilly areas (+)
- view/open scenery (+)
- landscape diversity (+)
- noise pollution (-)

The cells are 70 m x70 m large and the total area encompassed by the model is 7 km x 7 km (this can be modified). Linear transport infrastructure (roads not railways) is superimposed over this recreation map. In the NetLogo environment, linear elements are converted into a network made of links (linear elements) connected by edges (junctions and crossroads). Links are composed of several attributes indicating the type of path they represent, ranging from highways to 1 meter wide paths, attributes also indicate path surfaces (from gravel to asphalt) and whether it is part of a dedicated walkable network.

The third model entities are the individual humans. Although the model is intended to model both agents moving by foot and by bike, in this version of the model only walking agents were considered. In our model, we decided to consider the variety of recreationists and the variety in preferences or perceptions of the landscape and road attributes using a probabilistic and a stochastic approach rather than a deterministic one. Firstly, variation in recreational preference was considered under a probabilistic framework, while differences

in individual preferences or perceptions of the network were accounted for by a stochastic variation in the weight of road segments. There is thus one type of walking human agents, referred to as “recreationists” who walk along the road and path network of the city of Wil. State variables of the agents are a starting location (“home”), which denotes an edge located close to a living area and a recreational destination (see recreational area selection procedure). Furthermore, the agents have a recreational status (“recreated?”) indicating whether they had already reached their destination target or not. The last entity of the model is the dwelling/residential area, which serves as the starting location of the agents. Number of agents and their initial location is based on a population density map (resolution 1 ha).

Process overview and scheduling

The model starts with the agents making decisions on their recreational destinations. Once decided, the agents assess the path/route to be used to reach the destination based on the movement strategy they are arbitrarily assigned at the beginning of the simulation (the same strategy for all agents, either random, shortest-path, weighted-path or combined-path). The model further proceeds in abstract time-steps which represent a unit of movements along the network. At each of these steps, the agents assess their current position (e.g. time step t) and their next position (at time step $t+1$). If this next position is still within the same link, then the agent simply moves to this next position according to its own speed. In cases where the next position is a junction, i.e. a crossroad, then the decision on where to go next is based on the movement strategy in use. Once they have reached their destination, the agents return to their home, either via the same path or by using a different

path (i.e. avoiding already used paths). Agents stop moving once they arrive back at their starting position (home).

Design concepts

Spatial patterns of recreationists' movement from their living area to the nearby recreation areas emerge from individual behaviour. This individual behaviour is the result of both the following decisions: *Where to go?* and *Which path to take to get there?*. The first decision is a weighted stochastic procedure based on the recreational value of each cell of the spatial environment. The second decision is a user-based decision enabling the testing of various movement strategies and their effect on the spatial patterns of recreationists' movements.

Theoretical and empirical background. In the model, agents are assumed to be knowledgeable about the landscape covered, i.e. they know where areas with high/low recreational value are and their decision making is based on this knowledge. The procedure of selecting a recreational destination is based on cognitive theory, i.e. assuming agents make their decisions based on their beliefs or preferences (see Kienast *et al.* 2012). The movement strategy sub-model is underlined by the space theory (for shortest-path strategy, assuming agent decision-making is based on distance) and calibration-based rules (for the weighted path strategy, see model calibration section). For this latter strategy, the relative importance of road attributes were assessed by means of an expert-based weighting method (see calibration section).

Individual decision making. At the initialization phase, the agents make a decision on which recreation area to move to. By making this decision, agents are expected to fulfil their

need or interest for recreational activities (see introduction section). Decision-making of the agents is a stochastic process, involving: i) assessment of the recreational value of all grid cells in the direct vicinity (a user-based parameter defining the search radius from their starting location), ii) selection of one of these cells according to a probability-rule based on the recreational value (the higher the value, the higher the probability). The movement strategy taken by the agents is a user-defined parameter, meaning that during a particular run, all agents use the same strategy. The shortest- and weighted-path strategies are deterministic processes in which agents select the shortest path and the path minimizing the weight of the road/landscape attributes of the road segments (links) to get to the destination, respectively.

The agents are able to adapt their behaviour under exogenous changes by re-assessment of the most effective path to get to their destination. This process however requires restarting the model. Social norms and cultural values do not play a direct role in decision making. These features are incorporated indirectly in the recreational potential map as this map is based on survey results delineating human preferences in terms of recreation (Kienast *et al.* 2012).

Spatial aspect plays a role in the decision process, principally in the shortest-path decision-making where agents have to find out which path minimizes the distance to the selected destination. Temporality takes the form of an agent's memory of the previously visited links and plays a role in the return (to home) phase, depending on whether re-use of similar links are enabled or not (by the *way-back* and *avoid-used-path* model parameters).

Uncertainty is not explicitly included in the agent's decision rule.

Learning. There is no (collective) learning implemented in the model.

Individual sensing. Individuals sense the recreational quality of the environment and they sense the attribute (length, road type). Based on this sensing they make their decision on where to go and which path to take to get there. The sensing process is assumed to be non-erroneous; however it should be considered that it is based on aggregated or expert-based data. The spatial scale of sensing is determined based on the *home-range* (HR) parameter. Agents are not able to sense each other and as such move independently of each other. The calculation of the shortest-path and the weighted-path is modelled explicitly. Costs for cognition and for gathering information are not explicitly included in the model.

Individual prediction. There is no individual prediction implemented in the model.

Interaction. No interactions between agents are implemented in the model.

Collectives. Collectives are not implemented in the model.

Stochasticity. The decision on an initial location (home) is partially random, except in the case of micro-validation where initial locations had to be deterministic.

Observation. Spatial distribution of recreation routes emerges from individual behaviour and can be directly visualized in the model interface. For analysis, during the multiple simulation runs, the memory of visited links of each agent is collected at the end of its recreational activity. From the model, a distinct pattern in the frequency of use of each road segment (link) emerges depending on the movement strategy used.

Details

Implementation details. The model was implemented in NetLogo modelling platform. The model will be made available upon request.

Initialisation. The model landscape represents an area of 7 km x 7 km with its centre covering the centre of Wil city. The area is composed of a 100 x 100 grid such that each cell covers a surface of 70 m x 70 m. The recreational value of each cell is derived by extracting the value of the underlying raster of the recreational potential (raster created in R). The network is built based upon a shapefile of the Swiss road system (source: strasse features of the SwissTLM3D). Each street segment is associated with information on its length, route weight, legal restrictions and regulations. In the NetLogo software these street segments were then rearranged to a routable network dataset. Routes were calculated using the Dijkstra algorithm of NetLogo's network extension weighted by a street-segment criterion (see calibration section). Buildings are also included based on SwissTLM3D, the starting location for each recreationist is generated randomly from these data. Agents are released on edges close to buildings. A user-defined number of agents (number-of-recreationists) are created. For the model validation, initial values are based on available literature and on existing data.

Input data. The recreational background raster grid is based on Kienast *et al.* (2012). The R-built raster is prepared in R and imported into NetLogo in the setup phase. The road network and buildings come from the SwissTLM3D and are imported as a shapefile. Prior to import in NetLogo, projection of spatial files, were transformed from the Swiss coordinate

system (Oblique Mercator, CH1903/LV03, epsg:21781) to Universal Transverse Mercator (WGS 84/UTM zone 32, epsg:32632), the projection accepted by NetLogo.

Submodels. The following sub-models are included: i) selection of *recreational destination selection*, ii) determination of *path to destination* and iii) determination of *path to return home*.

- i) *Selection of recreational destination:* Agents make a probabilistic decision on where to go according to the values of the underlying recreational map within their accessible home-range. This decision is implemented in NetLogo using the *rnd:weighted-one-of-list* function of the *rnd* extension, where the recreational value of the cell is used as the weighting factor.
- ii) *Determination of path to destination:* Based on the user's assigned movement strategy, each agent calculates the list of links (=road segments) to visit to get to its destination.

Possible strategy:

a. Shortest-path strategy

With this strategy, agents implement the Dijkstra algorithm (Dijkstra 1971), i.e. find the route minimizing the distance between a starting and a destination point. In NetLogo, this algorithm is implemented through the *nw:weighted-path-to* function of the Network extension using the attribute segment "length of the links" as the weighting factor.

b. Weighted-path strategy

With this strategy, agents find the route minimizing the road and landscape based attribute weight, i.e. they try to avoid unfriendly roads while maximising usage of walker-friendly roads (see calibration section). In NetLogo, this algorithm is implemented through the *nw:weighted-path-to* function of the Network extension using an additive combination of the following attributes: weight-belag (type of road/path surface), weight-objekt (type of road/path) and weight-ww (indicating whether the path is a hiking trail or not) of the links as the weighting factor. To assess how people value road attributes, a deterministic approach, based on consultation with experts, was used to parameterize the decision-making processes. We organised a workshop with a panel of nine experts representing perspectives of Swiss authorities and organisations active in the field of pedestrian mobility. During the workshop we asked the panel of experts to score a set of road attributes (see Table 1) on a Likert scale (McIver and Carmines 1981) according to their importance for recreationists decisions on route selection. The scale ranged from 1 indicating a strong preference by the respective users to 5 indicating a strong avoidance. To weight the different road attributes, we used the geometric mean for each criterion, which is considered to represent human preferences more realistically (Tofallis 2014).

Table A. Expert-based weighting scores (summed scores of experts on the left and geometric mean on the right) for the weighted movement strategy. Data on the geometric mean were extracted from the SwissTLM3D system.

	Criteria	Sum	Geometric mean
Road type (width indicated in meter)			
	1m path	8	1.00

	2m path	8	1.00
	track	11	1.30
	3m street	12	1.41
	4m street	24	2.91
	6m street	26	3.18
	8m street	29	3.59
	10m street	32	4.00
	Cantonal road	40	5.00
Road label			
	Designated path	15	1.77
Road cover			
	Gravel road	20	2.16
	Asphalt road	28	3.36
Particular structures			
	Tunnel	24	2.77
	Stairs	29	3.59

c. Combined-path strategy

The fourth and final strategy is the combined strategy. This strategy is a combination of the shortest-path and the weighted-path strategies. It works on the same basis as the weighted approach, but the weight of each segment is multiplied by the length of the segment. This strategy is implemented in a similar way to the two previous ones, simply it differs in that the weight is based on the multiplicative interaction between segment-length and the attributes used in the weighted-path approach.

d. Random strategy

With this strategy, agents simply move along the network and make a random decision each time they reach a crossroad to decide on their next location (e.g. go straight, turn left or turn right).

iii) *Determination of the path to return home*: the process is similar to that of the sub-model to get to the destination, with the exception that it is possible to weight previously used links, meaning that the agent would avoid taking a similar route home. Introduction of this avoidance concept is based on empirical observations of human behaviour during recreational activities, suggesting that people usually prefer to make a circular trip as opposed to a linear trip following the same path in both directions. We did not include slope as a constraining factor in the model since people engaging in sport activities have been shown to prefer to use sloped areas (Degenhardt and Buchecker 2012).

References

Agrawal, A.W., Schlossberg, M., Irvin, K., 2008. How Far, by Which Route and Why? A Spatial Analysis of Pedestrian Preference. *Journal of Urban Design* 13, 81–98. <https://doi.org/10.1080/13574800701804074>

Auchincloss, A.H., Garcia, L.M.T. 2010. Brief introductory guide to agent-based modeling and an illustration from urban health research. *Cadernos De Saude Publica* 31, 65-78. <https://doi.org/10.1590/0102-311X00051615>

Bell, S., 2010. Forest recreation and nature tourism. *Urban Forestry & Urban Greening*, Special section on “Forest recreation and nature tourism” 9, 69–70. <https://doi.org/10.1016/j.ufug.2010.03.001>

Bishop, I.D., Gimblett, H.R., 2000. Management of Recreational Areas: GIS, Autonomous Agents, and Virtual Reality. *Environment and Planning B: Planning and Design* 27, 423-435. <https://doi.org/10.1068/b2637>

Boll, T., Haaren, C. von, Ruschkowski, E. von, 2014. The Preference and Actual Use of Different Types of Rural Recreation Areas by Urban Dwellers—The Hamburg Case Study. *PLoS ONE* 9. <https://doi.org/10.1371/journal.pone.0108638>

Borgers, T., A., 2005. Modelling pedestrian behaviour in downtown shopping areas, in: *Proceedings of Cupum 05 Conference, Computers in Urban Planning and Urban Management*. Centre for Advanced Spatial Analysis, University College London, London, pp. 83–97.

- Borst, H.C., Vries, S.I. de, Graham, J.M., Dongen, J.E. van, Bakker, I., Miedema, H.M., 2009. Influence of environmental street characteristics on walking route choice of elderly people. *Journal of Environmental Psychology* 29, 477–484. <https://doi.org/10.1016/j.jenvp.2009.08.002>
- Bögli, K., S., 2016. Welchen Stellenwert haben Gewässer bei der Naherholung? *Wasser Energie Luft* 118, 303–307.
- Bögli, S., 2015. Naherholung im suburbanen Raum. Untersuchung der Erholungsnutzung um den Glattpark in Opfikon (Master thesis). Basel, Basel, Switzerland.
- Brown, G., 2003. Mapping Spatial Attributes in Survey Research for Natural Resource Management: Methods and Applications. *Society & Natural Resources* 18, 17-39. <https://doi.org/10.1080/08941920590881853>
- Brown, G., Schebella, M.F., Weber, D., 2014. Using participatory GIS to measure physical activity and urban park benefits. *Landscape and Urban Planning* 121, 34–44. <https://doi.org/10.1016/j.landurbplan.2013.09.006>
- Brown, G., 2016. A Review of Sampling Effects and Response Bias in Internet Participatory Mapping (PPGIS/PGIS/VGI). *Transactions in GIS* 21, 39-56.
- Buchecker, M., Degenhardt, B., 2015. The effects of urban inhabitants' nearby outdoor recreation on their well-being and their psychological resilience. *Journal of Outdoor Recreation and Tourism, SI: Health and Well-being* 10, 55–62. <https://doi.org/10.1016/j.jort.2015.06.007>

Cavens, D., Gloor, C., Nagel, K., Lange, E. and Schmid, W. A. (2004). A Framework for Integrating Visual Quality Modelling within an Agent-Based Hiking Simulation for the Swiss Alps. *Working Papers of the Finnish Forest Research Institute 2*.

Cohen, E., 1979. A Phenomenology of Tourist Experiences. *Sociology* 13, 179–201. <https://doi.org/10.1177/003803857901300203>

Conedera, M., Del Biaggio, A., Seeland, K., Moretti, M., Home, R., 2015. Residents' preferences and use of urban and peri-urban green spaces in a Swiss mountainous region of the Southern Alps. *Urban Forestry & Urban Greening* 14, 139–147. <https://doi.org/10.1016/j.ufug.2015.01.003>

Conte, R., Paolucci, M., 2014. On agent-based modeling and computational social science. *Frontiers in Psychology* 5. <https://doi.org/10.3389/fpsyg.2014.00668>

DeAngelis, D.L., Grimm, V., 2014. Individual-based models in ecology after four decades. *F1000Prime Reports* 6. <https://doi.org/10.12703/P6-39>

Degenhardt, B., Buchecker, M., 2012. Exploring Everyday Self-Regulation in Nearby Nature: Determinants, Patterns, and a Framework of Nearby Outdoor Recreation Behavior. *Leisure Sciences* 34, 450–469. <https://doi.org/10.1080/01490400.2012.714706>

Degenhardt, B., Frick, J., Buchecker, M., Gutscher, H., 2011. Influences of Personal, Social, and Environmental Factors on Workday Use Frequency of the Nearby Outdoor Recreation Areas by Working People. *Leisure Sciences* 33, 420–440. <https://doi.org/10.1080/01490400.2011.606780>

Dijkstra, E.W., 1971. A short introduction to the art of programming. Techn. Hogeschool.

Freuler, B., Hunziker, M., 2007. Recreation activities in protected areas: Bridging the gap between the attitudes and behaviour of snowshoe walkers. *Forest Snow and Landscape Research* 81, 191–206.

Gimblett, H., Richards, M., Itami, R., 2001. RBSim: Geographic Simulation of Wilderness Recreation Behavior. *Journal of Forestry* 99, 36–42.

Gimblett, H., Skov-Peterson, H., 2008. Monitoring, simulation, and management of visitor landscapes. University of Arizona Press.

Gimblett, R., Daniel, T. & Meitner, M. J. (2000). An Individual-Based Modeling Approach to simulating Recreation Use in Wilderness Settings. In D. Cole & S.F. McCool (Eds.), *USDA Forest Service Proceedings RMRS-P-15-VOL-4* (pp. 99-106). Ogden, UT: U.S. Department of Agriculture, Forest Science, Rocky Mountain Research Station, USDA Forest Service.

Golledge, R.G., 1995. Path selection and route preference in human navigation: A progress report, in: *Spatial Information Theory A Theoretical Basis for GIS, Lecture Notes in Computer Science*. Springer, Berlin, Heidelberg, pp. 207–222. https://doi.org/10.1007/3-540-60392-1_14

Grimm, V., Berger, U., Bastiansen, F., Eliassen, S., Ginot, V., Giske, J., Goss-Custard, J., Grand, T., Heinz, S.K., Huse, G., Huth, A., Jepsen, J.U., Jørgensen, C., Mooij, W.M., Müller, B., Pe'er, G., Piou, C., Railsback, S.F., Robbins, A.M., Robbins, M.M., Rossmanith, E., Rüger, N., Strand, E.,

Souissi, S., Stillman, R.A., Vabø, R., Visser, U., DeAngelis, D.L., 2006. A standard protocol for describing individual-based and agent-based models. *Ecological Modelling* 198, 115–126. <https://doi.org/10.1016/j.ecolmodel.2006.04.023>

Groot, R.S. de, Alkemade, R., Braat, L., Hein, L., Willemsen, L., 2010. Challenges in integrating the concept of ecosystem services and values in landscape planning, management and decision making. *Ecological Complexity, Ecosystem Services – Bridging Ecology, Economy and Social Sciences* 7, 260–272. <https://doi.org/10.1016/j.ecocom.2009.10.006>

Guo, Z., Loo, B.P.Y., 2013. Pedestrian environment and route choice: Evidence from New York City and Hong Kong. *Journal of Transport Geography* 28, 124–136. <https://doi.org/10.1016/j.jtrangeo.2012.11.013>

Helbing, D., 2012. Self-organization in Pedestrian Crowds, in: *Social Self-Organization, Understanding Complex Systems*. Springer, Berlin, Heidelberg, pp. 71–99.

Heppenstall, A., Crooks, A., See, L., Batty, M., 2012. *Agent-Based Models of Geographical Systems*. Springer.

Iringarter, C., Degenhardt, B., Buchecker, M., 2010. Nearby outdoor recreation behavior and associated demands in Swiss agglomerations. Results of a survey in St. Gall in 2009. Eidg. Forschungsanstalt WSL, Birmensdorf, Switzerland.

Jochem, R., Marwijk, R. van, Pouwels, R., Pitt, D.G., 2008. MASOOR: Modelling the transaction of people and environment on dense trail networks in natural resource settings, in:

Monitoring, Simulation and Management of Visitor Landscapes, 15th Ser. The University of Arizona Press, Tucson, Arizona, USA.

Kaplan, R., Kaplan, S., 1989. The experience of nature: A psychological perspective. Cambridge University Press.

Kennedy, D.P., Adolphs, R., 2011. Social neuroscience: Stress and the city. *Nature* 474, 452–453. <https://doi.org/10.1038/474452a>

Kienast, F., Degenhardt, B., Weilenmann, B., Wäger, Y., Buchecker, M., 2012. GIS-assisted mapping of landscape suitability for nearby recreation. *Landscape and Urban Planning* 105, 385–399. <https://doi.org/10.1016/j.landurbplan.2012.01.015>

Klain, S.C., Chan, K.M.A., 2012. Navigating coastal values: Participatory mapping of ecosystem services for spatial planning. *Ecological Economics* 82, 104–113.

Komossa, F., Zanden, E.H. van der, Schulp, C.J.E., Verburg, P.H., 2018. Mapping landscape potential for outdoor recreation using different archetypical recreation user groups in the European Union. *Ecological Indicators* 85, 105–116. <https://doi.org/10.1016/j.ecolind.2017.10.015>

Koppen, G., Sang, Å.O., Tveit, M.S., 2014. Managing the potential for outdoor recreation: Adequate mapping and measuring of accessibility to urban recreational landscapes. *Urban Forestry & Urban Greening* 13, 71–83. <https://doi.org/10.1016/j.ufug.2013.11.005>

Korpilo, S., Virtanen, T., Lehvävirta, S., 2017. Smartphone gps tracking—Inexpensive and efficient data collection on recreational movement. *Landscape and Urban Planning* 157, 608–617. <https://doi.org/10.1016/j.landurbplan.2016.08.005>

Lakens, D., 2017. Equivalence Tests: A Practical Primer for t Tests, Correlations, and Meta-Analyses. *Social Psychological and Personality Science* 8, 355–362. <https://doi.org/10.1177/1948550617697177>

Leao, S.Z., Pettit, C., 2016. Mapping Bicycling Patterns with an Agent-Based Model, Census and Crowdsourced Data, in: *Agent Based Modelling of Urban Systems, Lecture Notes in Computer Science*. Springer, Cham, pp. 112–128. https://doi.org/10.1007/978-3-319-51957-9_7

Manley, E.J., Addison, J.D., Cheng, T., 2015. Shortest path or anchor-based route choice: A large-scale empirical analysis of minicab routing in London. *Journal of Transport Geography* 43, 123–139. <https://doi.org/10.1016/j.jtrangeo.2015.01.006>

Matsuoka, R.H., Kaplan, R., 2008. People needs in the urban landscape: Analysis of Landscape And Urban Planning contributions. *Landscape and Urban Planning* 84, 7–19. <https://doi.org/10.1016/j.landurbplan.2007.09.009>

McIver, J., Carmines, E.G., 1981. *Unidimensional Scaling*. SAGE.

Müller, B., Bohn, F., Dreßler, G., Groeneveld, J., Klassert, C., Martin, R., Schlüter, M., Schulze, J., Weise, H., Schwarz, N., 2013. Describing human decisions in agent-based models – ODD + D,

an extension of the ODD protocol. *Environmental Modelling & Software* 48, 37–48.
<https://doi.org/10.1016/j.envsoft.2013.06.003>

Pocewicz, A., Nielsen-Pincus, M., Brown, G., 2012. An Evaluation of Internet Versus Paper-based Methods for Public Participation Geographic Information Systems (PPGIS). *Transactions in GIS* 16, 39-53. <https://doi.org/10.1111/j.1467-9671.2011.01287.x>

Van Marwijk, R., 2006. Managing the transaction of nature and recreational behaviour: Experiences in dwingelderveld np (working paper). Wageningen University, Wageningen, The Netherlands.

Robinson, A.P., Duursma, R.A., Marshall, J.D., 2005. A regression-based equivalence test for model validation: Shifting the burden of proof. *Tree Physiology* 25, 903–913.

Rodríguez, D.A., Brisson, E.M., Estupiñán, N., 2009. The relationship between segment-level built environment attributes and pedestrian activity around Bogota's BRT stations. *Transportation Research Part D: Transport and Environment* 14, 470–478.
<https://doi.org/10.1016/j.trd.2009.06.001>

Roovers, P., Hermy, M., Gulinck, H., 2002. Visitor profile, perceptions and expectations in forests from a gradient of increasing urbanisation in central Belgium. *Landscape and Urban Planning* 59, 129–145. [https://doi.org/10.1016/S0169-2046\(02\)00011-7](https://doi.org/10.1016/S0169-2046(02)00011-7)

Schwering, A., Krukar, J., Li, R., Anacta, V.J., Fuest, S., 2017. Wayfinding Through Orientation. *Spatial Cognition & Computation* 17, 273–303.
<https://doi.org/10.1080/13875868.2017.1322597>

Seneviratne, P.N., Morrall, J.F., 1985. Analysis of factors affecting the choice of route of pedestrians. *Transportation Planning and Technology* 10, 147–159.

<https://doi.org/10.1080/03081068508717309>

Shelby, B., Heberlein, T.A., 1984. A conceptual framework for carrying capacity determination. *Leisure Sciences* 6, 433–451.

<https://doi.org/10.1080/01490408409513047>

Skov-Petersen, H., Meilby, H., Jensen F.S., 2008a. Monitoring, simulation, and management of visitor landscapes, in: R. Gimlett, H.S.-P. (Ed.), University of Arizona Press, pp. 123–142.

Skov-Petersen, H., Kefaloukos, P., & Snizek, B., 2008b. Kvintus.org - a choice based agent-based simulation model integrated with Google Maps. In A. Raschi, & S. Trampetti (Eds.), *Management for protection and sustainable development* National Research Council (CNR-IBiMet).

Song, C., Qu, Z., Blumm, N., Barabási, A.-L., 2010. Limits of Predictability in Human Mobility. *Science* 327, 1018–1021. <https://doi.org/10.1126/science.1177170>

Taczanowska, K., Muhar, A., Arnberger, A., 2006. Exploring spatial behaviour of visitors in peri-urban recreational areas - multi-attribute analysis of individual route profiles. In: Schrenk, M.: CORP 2006 & Geomultimedia06, 13.2.-16.2.2006, Wien, 315-323; ISBN 3-9502139-0-2 p. 315-323.

Taczanowska, K., Muhar, A., Arnberger, A., 2008. Monitoring, simulation, and management of visitor landscapes, in: Gimblett R., S.-P.H. (Ed.), University of Arizona Press, pp. 159–174.

Taczanowska, K.(2009): Modelling the Spatial Distribution of Visitors in Recreational Areas. 199; Universität für Bodenkultur Wien.

URL: https://zidapps.boku.ac.at/abstracts/oe_list.php?paID=3&paSID=7284&paSF=-1&paCF=0&paLIST=0&language_id=DE

Taczanowska, K., González, L.-M., Garcia-Massó, X., Muhar, A., Brandenburg, C., Toca-Herrera, J.-L., 2014. Evaluating the structure and use of hiking trails in recreational areas using a mixed gps tracking and graph theory approach. *Applied Geography* 55, 184–192. <https://doi.org/10.1016/j.apgeog.2014.09.011>

Tang, W., Bennett, D.A., 2010. Agent-based Modeling of Animal Movement: A Review. *Geography Compass* 4, 682–700. <https://doi.org/10.1111/j.1749-8198.2010.00337.x>

Tofallis, C., 2014. Add or Multiply? A Tutorial on Ranking and Choosing with Multiple Criteria. *INFORMS Transactions on Education* 14, 109–119. <https://doi.org/10.1287/ited.2013.0124>

United Nations, P.D., Department of Economic and Social Affairs, 2014. *World Urbanization Prospects: The 2014 Revision, Highlights (ST/ESA/SER.A/352)*.

Vejre, H., Jensen, F.S., Thorsen, B.J., 2010. Demonstrating the importance of intangible ecosystem services from peri-urban landscapes. *Ecological Complexity, Ecosystem Services – Bridging Ecology, Economy and Social Sciences* 7, 338–348. <https://doi.org/10.1016/j.ecocom.2009.09.005>

Marwijk van, R., Taczanowska, K.(2006): Types of Typologies – From Recreationists and Tourists to Artificial Agents In: Siegrist, D., Clivaz, C., Hunziker, M., Iten, S. (Eds.), Exploring the Nature of Management. Third International Conference on Monitoring and Management of Visitor Flows in Recreational and Protected Areas, University of Applied Sciences Rapperswil, 498-501, ISBN: 3-033-00953-2 [http://mmv.boku.ac.at/refbase/files/van_marwijk_ramona-2006-types_of_typologies.pdf];

Vries, S. de, Goossen, M., 2002. Modelling recreational visits to forests and nature areas. Urban Forestry & Urban Greening 1, 5–14. <https://doi.org/10.1078/1618-8667-00002>

Wallentin, G., 2017. Spatial simulation: A spatial perspective on individual-based ecology— a review. Ecological Modelling 350, 30–41. <https://doi.org/10.1016/j.ecolmodel.2017.01.017>

Wallentin, G., Loidl, M., 2015. Agent-based bicycle traffic model for Salzburg City. GI_Forum – Journal for Geographic Information Science 2015, 558–566.

Wellek, S., 2010. Testing statistical hypotheses of equivalence and noninferiority, second edition. CRC Press.

Wilensky, U., 1999. NetLogo.

Yang, Y., Diez Roux, A.V., Auchincloss, A.H., Rodriguez, D.A., Brown, D.G., 2011. A spatial agent-based model for the simulation of adults' daily walking within a city. American Journal of Preventive Medicine 40, 353–361. <https://doi.org/10.1016/j.amepre.2010.11.017>

Žlender, V., Ward Thompson, C., 2017. Accessibility and use of peri-urban green space for inner-city dwellers: A comparative study. *Landscape and Urban Planning* 165, 193–205.
<https://doi.org/10.1016/j.landurbplan.2016.06.011>

ACCEPTED MANUSCRIPT

Figures legends

Figure 1. Location of the town of Wil in Switzerland and an illustration of Wil in the context of its infrastructure and the surrounding environment. Data source: Swisstopo.

Figure 2. Relative frequency of the similarity classes (i.e. percentage of same road used between observed and simulated routes) for the four tested strategies.

Figure 3. Similarity value in relation to the trip half distance (grouped in distance above and under 1.5 km) according to the four tested strategies. The value above the boxplots corresponds to the sample size.

Figure 4. Density distribution of the total distance travelled by the agents (according to the different strategies) as well as for the observed behaviour (survey data).

Figure 5. Density distribution of maximal distance from the starting point (home) to the destination (according to the different strategies) and comparison with observed behaviour (survey data).

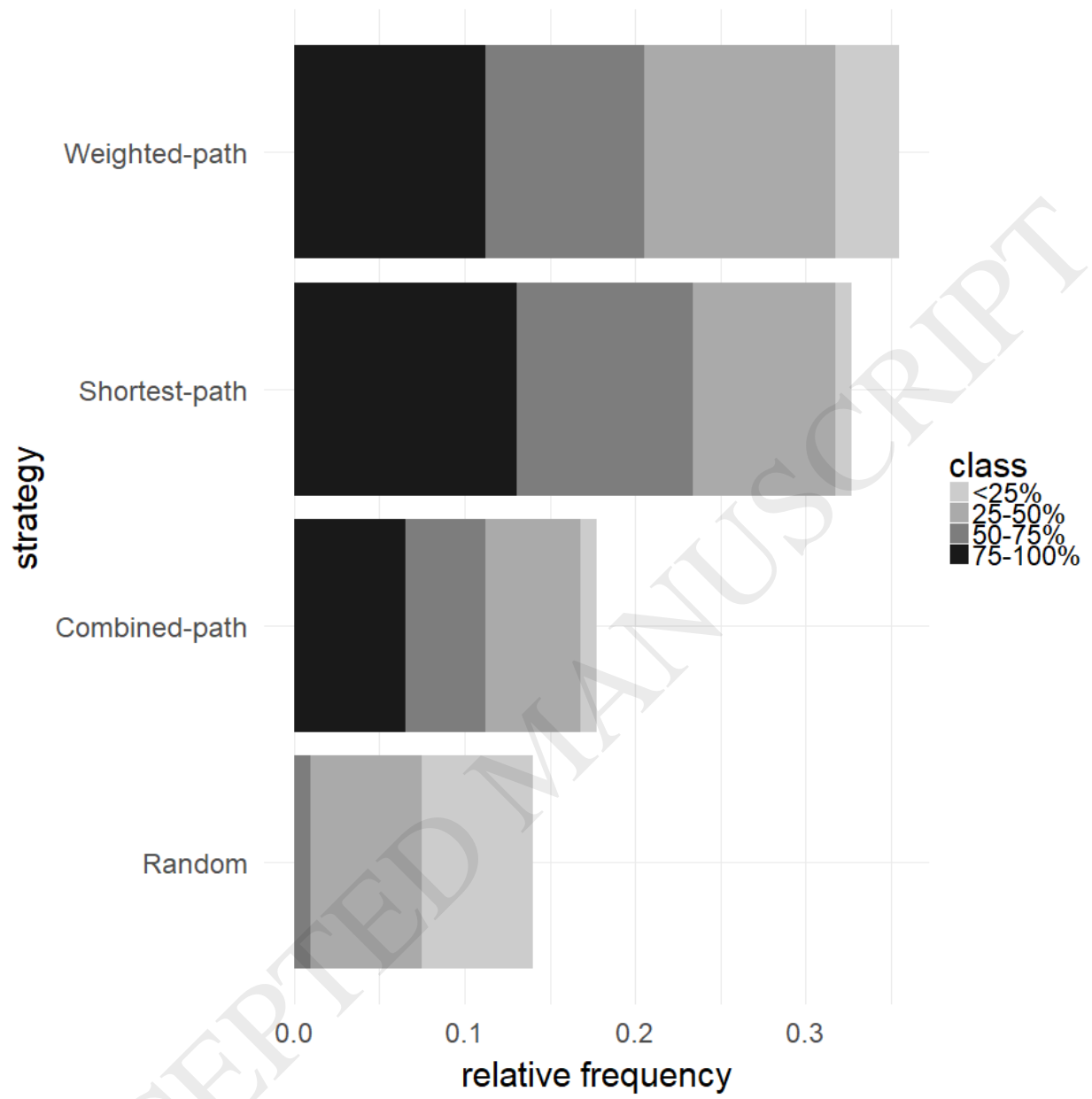
Figure 6. Use intensity of different road/path segments in the north-western area of Wil. The level of use intensity is indicated by the colour and width of the road/path segments.

Figure 7. Effect of the planned passage over the railway (indicated by blue arrow on the right map) on the movement flow of recreationists.

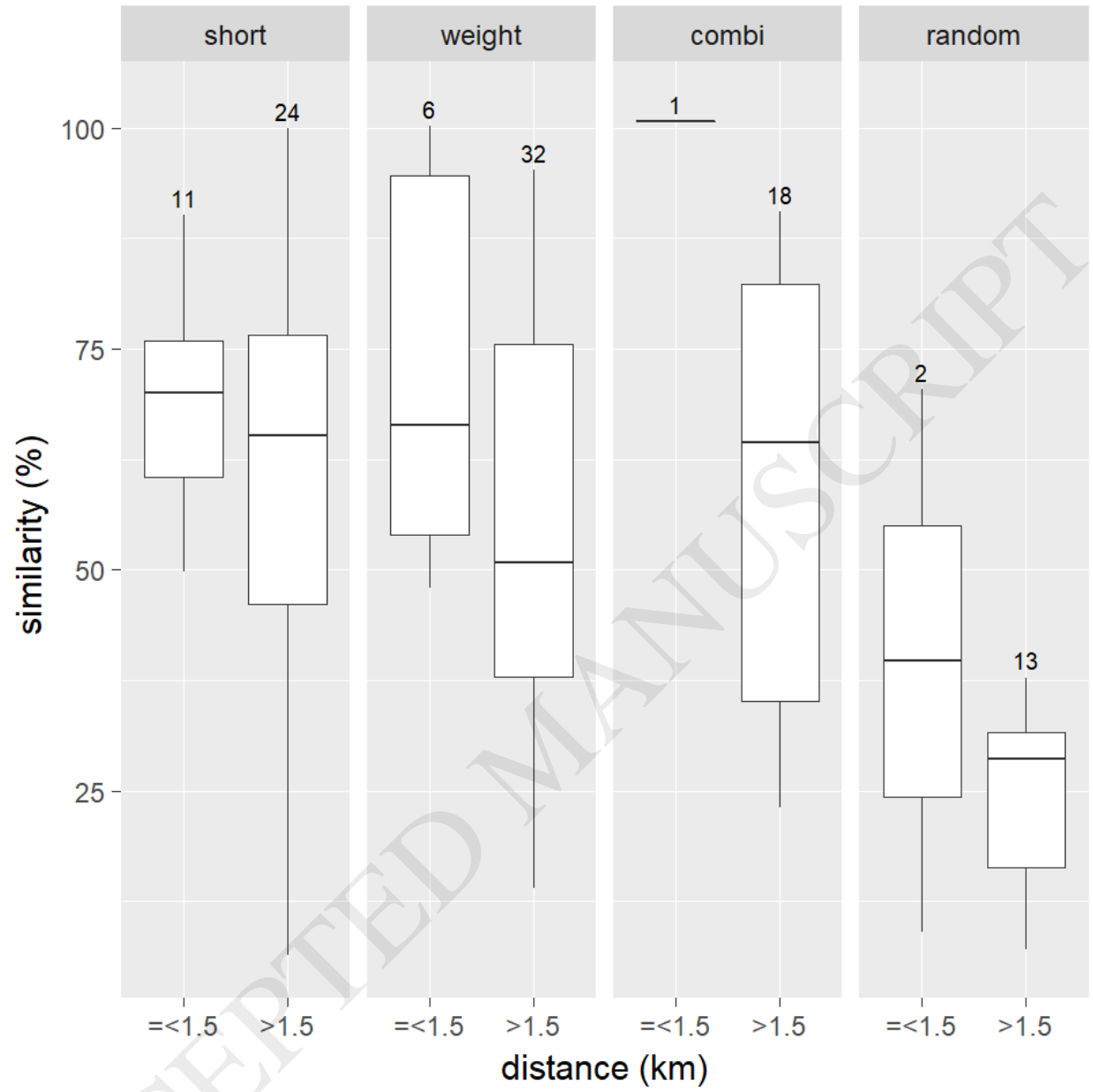
Figures



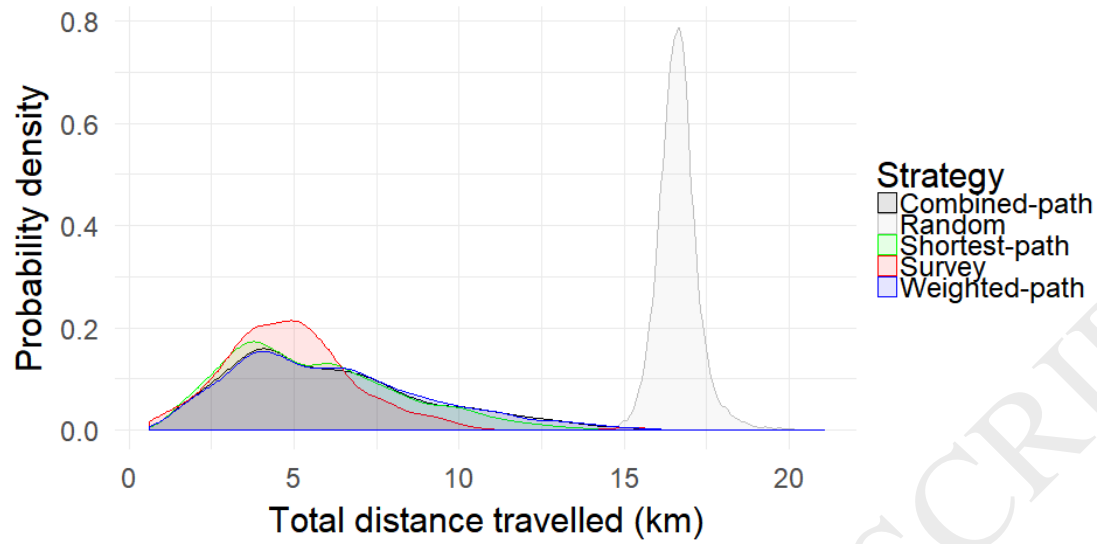
Morelle, Buchecker, Kienast, Tobias. Figure 1.



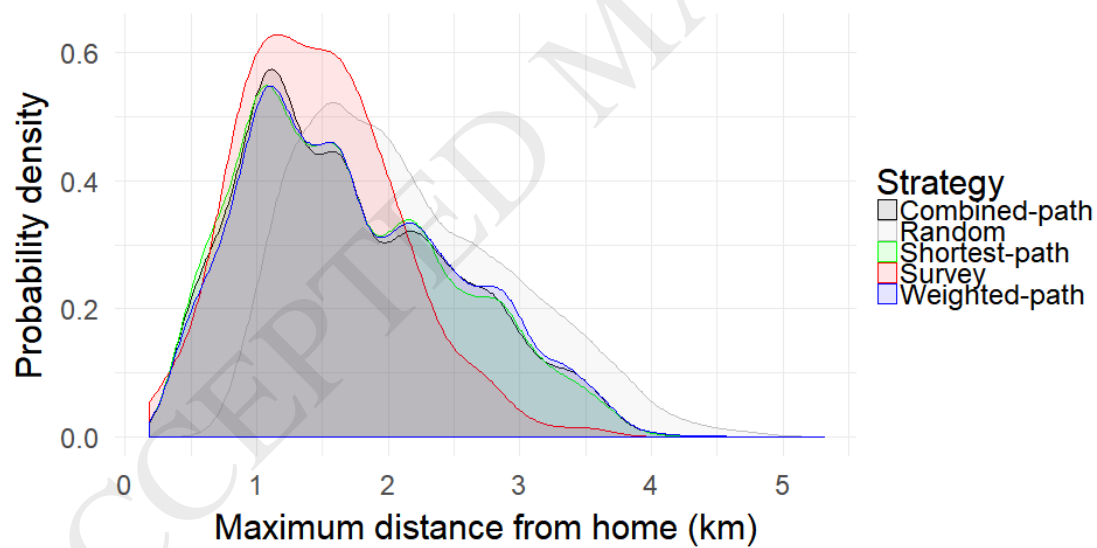
Morelle, Buchecker, Kienast, Tobias. Figure 2.



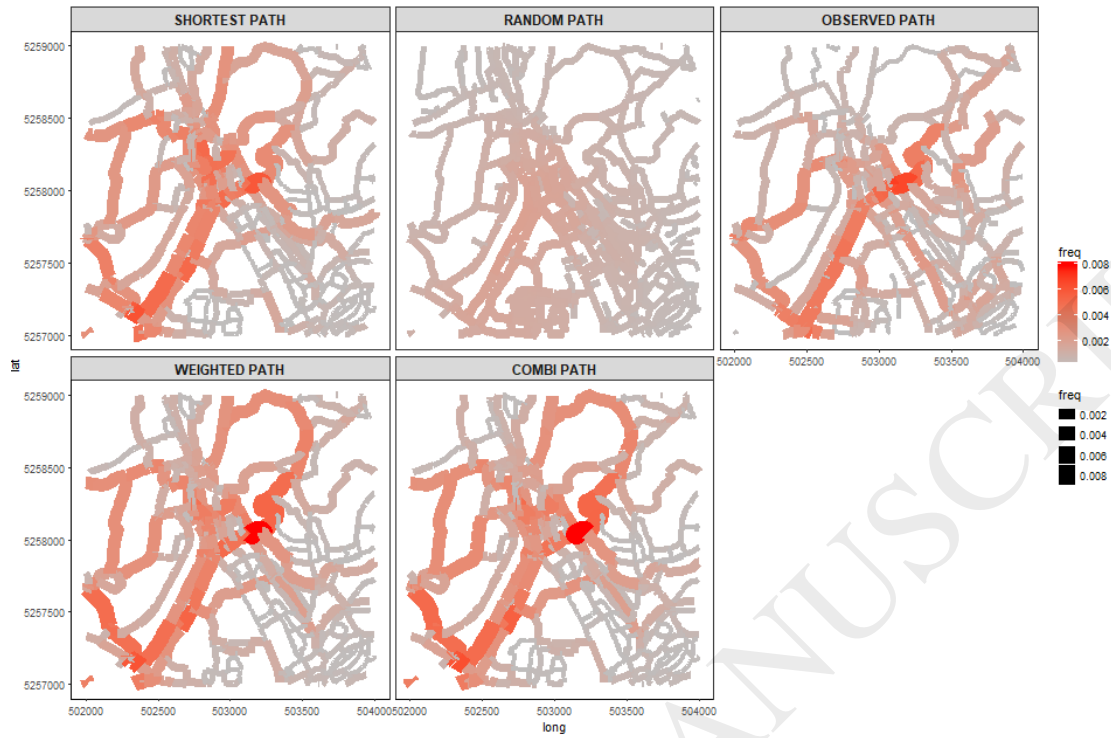
Morelle, Buchecker, Kienast, Tobias. Figure 3.



Morelle, Buchecker, Kienast, Tobias. Figure 4.



Morelle, Buchecker, Kienast, Tobias. Figure 5



Morelle, Buchecker, Kienast, Tobias. Figure 6.



Morelle, Buchecker, Kienast, Tobias. Figure 7.

Tables

Table 1. Characteristics of the respondent to the post survey realized in Wil (SG), Switzerland. Note that for the question on type of activities pursued during recreation, the respondents were not limited in the number of answers.

Population characteristics	All respondents (n=107)	Women (n=58)	Men (n=49)
age			
min	18	23	18
mean (sd)	54.4 (16.9)	53.5 (17.1)	55.5 (16.8)
max	84	84	83
frequency of activity n (%)			
daily	35 (35)	20 (37)	15 (33)
1-2/week	49 (49)	26 (48)	23 (51)
monthly	9 (9)	5 (9)	4 (9)
seldom	3 (3)	2 (4)	1 (2)
type of activity n (%)			
walking	83 (84)	42 (78)	41 (91)
jogging	22 (22)	11 (20)	11 (24)
walking the dog	6 (6)	5 (9)	1 (2)

biking	57 (58)	25 (46)	32 (71)
enjoying nature	32 (32)	17 (31)	15 (33)
playing	16 (16)	9 (17)	7 (16)
to grill	13 (13)	6 (11)	7 (16)

ACCEPTED MANUSCRIPT

Table 2. Summary statistics of the spatial metrics obtained for the different strategies, with distances in kilometres and the overlap representing the percentage of overlap of the probability distribution curve for observed and simulated data.

strategy	Distance total			Distance to home		
	mean	sd	overlap	mean	sd	overlap
Survey	4.9	2.0	NA	1.5	0.6	NA
Random	16.6	0.6	0.00	2.2	0.8	0.68
Shortest-path	5.6	2.6	0.84	1.7	0.8	0.84
Weighted-path	6.1	3.0	0.78	1.7	0.8	0.82
Combined-path	6.0	3.0	0.80	1.7	0.8	0.83

Table 3. Summary of the regression-based equivalence test for the different strategies tested against observed data.

strategy	n	dissimilarity	mean	sd	p	power
Random	1531	not rejected	0.0005	0.0005	0.0000	0.9
Shortest-path	1398	rejected	0.0007	0.0009	0.3586	0.9
Weighted-path	1275	not rejected	0.0008	0.0012	0.0006	0.9
Combined-path	1410	rejected	0.0007	0.0010	0.4643	0.9

All test were performed at $\alpha=0.05$.

The p-value denotes the value of the t statistic against the cut-off delimited by the region of indifference.