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Tracing Individual Experiences of Everyday Greenness: Initial Results from the SpaceLog Mobile App

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Abstract

In this paper, we introduce a conceptual shift in how to investigate visual greenness as an important factor for individual wellbeing and self-reported health in everyday mobilities. Making use of controlled vocabularies of emotions, we discuss earlier approaches to data collection in everyday environments. We developed a new mobile diary app to collect multi-modal data that would allow not only for statistical spatial analysis, but also for a deeper analysis of individual sense-making of experiences in specific locations. From a limited first test sample, we evaluated the added value of the data collection process by conducting explorative data analyses of the visual greenness in user-generated imagery. We found that, in general, our method is able to relate different types of greenness observed on site to different emotional tags.

Keywords:

greenspace, health geography, self-reported health, image analysis, VGI

1 Introduction

Environmental health studies have long reported positive effects of visual greenness in one's everyday environment on self-reported overall health (see Twohig-Bennett & Jones, 2018), and have stressed the positive function of a green environment on physical activity and place-bound social cohesion (Markevych et al., 2017). These findings can be related back to earlier theories on the resilience-building effects of visual greenness, such as recovery from stress and restoring attention (Ulrich, 1983; Kaplan & Kaplan, 1989). In general, individuals who feel more connected to nature tend to be happier (Capaldi et al., 2014). Hakoköngäs and Puhakka (2021) report that interacting with nature leads to greater self-esteem, reduces anger, and improves general wellbeing. Urban green areas provide instant recreational functions. As individual experiences of a subjective connection to nature vary along a continuum (Capaldi et al., 2014), individual definitions of emotions are required. Hakoköngäs and Puhakka (2021) point to the relevance of routines and practices that provide or prevent the feeling of connectedness to nature. Even social cohesion may be fostered by green and blue spaces, by inducing a greater sense of trust, acceptance and belonging, while reducing a sense of loneliness (Hammoud et al., 2021).

Understanding how green spaces contribute to individual wellbeing calls for data collection processes that cover personal assessments of specific situations, as resilience-providing daily routines originate in individual biographical backgrounds as well as in the wider socio-cultural context (see Hakokӧngäs & Puhakka, 2021). This is in line with the concept of therapeutic landscapes (Kistemann, 2016), which highlights the importance of reflecting on place and identity (Lengen & Gebhard, 2016). While the concept is well established in other fields of GIS such as planning and geo-participation (e.g. Hennig, 2022), related work is still missing in the discipline of Health Geography.

In order to further investigate differences between objective and subjective wellbeing (Schwanen & Atkinson, 2015), initial approaches highlight the need for a mixed-method analysis that uses space as a medium of discovery more than as a domain of knowledge (Kremer & Walker, 2022). In this context, our exploratory study addresses the following research problems: (1) how to create a digitally enhanced data collection process suitable for recording subjective wellbeing in the very moment of sense-making, not in an ex-post scenario prone to memory bias, such that (2) automated data analysis flows can be easily applied to the data gathered.

After a thorough review of data collection processes currently used to identify relationships between individual observers and their surroundings, we derive the requirements necessary for a process that will record multi-modal data in the very moment of sense-making in everyday life. We report on the functionality of a mobile application which we developed to record these data. Drawing on our early limited data sample, we show how multi-modal data help with identifying links between different types of green spaces and individual self-reported emotions on site. Finally, we discuss prospects and limitations of our approach and provide perspectives for future research.

2 Method review and the approach derived

In general, previous studies examining effects on mental and social health induced or mitigated by the environment search for dependencies and differences between (1) demographic or socio-economic indicators, (2) available nearby features, and (3) self-reported or objective health indicators. Amerio et al. (2020) used an online questionnaire to identify effects of the built environment on mental health during the COVID-19 lockdown. Bjørndal et al. (2023) used survey data to assess relationships between self-reported factors of mental health, such as supportive social relations or fear of violence in the home neighbourhood, and the availability of environmental features (e.g. playgrounds). Findings have been based mainly on spatial-statistical analysis (Xu et al., 2023). When relying on additional qualitative data however, mixed-method approaches drawing on methodologies from the social sciences greatly improve the sensitivity and scope of empirical analysis (Lang et al., 2008).

Focusing specifically on the positive effects of green spaces, Cox et al. (2017) compared the availability of vegetation in a buffer area centered on the participants' home locations with data from an online survey indicating their stress, anxiety and depression levels. Wood et al. (2017) used questionnaires based on the Warwick Edinburgh Mental Well-being Scale (WEMWBS, Warwick Medical School, n.d.) to identify the effects of parks and green spaces in housing estates on new inhabitants. In a critique of mere availability of local environmental features as a key determinant of health, Brinkmann et al. (2022) propose an inverse viewshed analysis: they assess the visibility to the observer's eye of greenness at specific locations in urban settings. Van den Berg et al. (2015) additionally call for a deeper analysis of the effects of visible greenness on specific segments of the population, and of differential regional effects.

In order to address the limitations of traditional surveys and questionnaires, Mattila et al. (2008) used a mobile app to collect detailed mobile diaries from participants. MacKerron and Mourato (2013) report on the *Mappiness* app, which was used to assess participants' feelings of happiness at random moments during their daily lives. The app additionally recorded GPS positions, introducing detailed analysis of participants' movement patterns. A ready-to-use app named *Urban Mind App* to record diaries associated with generalized vocabularies of feelings, also used by Hammoud et al. (2021), was proposed by Bakolis et al. (2018) to examine the impact of the immediate built environment on wellbeing in daily life. The app allowed the combined recording of (1) individual assessments of the environment, (2) the geographical location, and (3) the user's current state of wellbeing. It, too, makes use of the WEMWBS (see Tennant et al., 2007), reducing it to five sub-scales in the version current at the time of writing:

- anxious-confident
- stressed-relaxed
- down-happy
- lonely-connected
- tired-energetic

However, for a dataset suitable for investigating individual experiences of visible greenness, a comprehensive methodology to collect and analyse image-based user-generated data is still missing. In essence, the Urban Mind App enabled users to upload photos, but only as a proxy for location. Nor can multiple images of a single location be tagged with different emotions by the same use. Other types of media (such as video or audio files) are not supported. Given that people's mental models of place and space are well understood to be cognitive collages (Tversky, 1993) composed of fragmented multi-modal experiences, we identified the need to develop a prototype for a new app with the capability of capturing a finer-resolution and more nuanced data snapshot of individual sense-making in everyday environments.

Using existing methods, (1) we gathered socio-economic data from our participants; (2) we carried out general tracking of geolocation; (3) we administered a mini-questionnaire allowing for the evaluation of situations of everyday life according to the WEMWBS. We then extended the scope of current apps supporting data collection by including a functionality to capture images, audio, video and text in order to represent diverse impressions and modes of communicating. The multi-modal data allow for a combined analysis of sites and situations together with participants' assessments of their health and wellbeing in situ.

We identified the following user stories for this new, enhanced, mobile app:

- Participants should be able to actively share basic sociodemographic information (age, self-identified gender, education and household size).
- Participants should be able to actively share single observations during their everyday routines, capturing the very process of sense-making of everyday environments. They should do this by recording multi-modal data (images, text, video and audio) of specific situations and assigning the emotion tags from a pre-existing list (adapted slightly from the Urban Mind app).
- Participants should be able to actively share GPS locations or tracks of their everyday mobility recorded by the app.

In accordance with local ethics guidelines and the requirements of the German law on data privacy (DSGVO; analogous to GDPR), we included the following functionalities:

- Data obtained must not include information that could be used to identify a participating individual (anonymity).
- All participants were required to provide informed consent[1] before installing the app.
- Participants were able to easily block GPS tracking at any time.
- Participants could end their participation at any time and have their data deleted.

Figure 1 illustrates the workflow of the resulting app, named SpaceLog.

[1] Institut für Geographie der Friedrich-Alexander-Universität Erlangen-Nürnberg (2022): Studie Individuelles Umwelterleben- Datenschutzerklärung. Retrieved Jul 23, 2023, from https://www.geographie.nat.fau.de/forschung/kulturgeographie/ag-digitale-gesundheitsgeographien-walker/studie-individuelles-umwelterleben/ (German only).

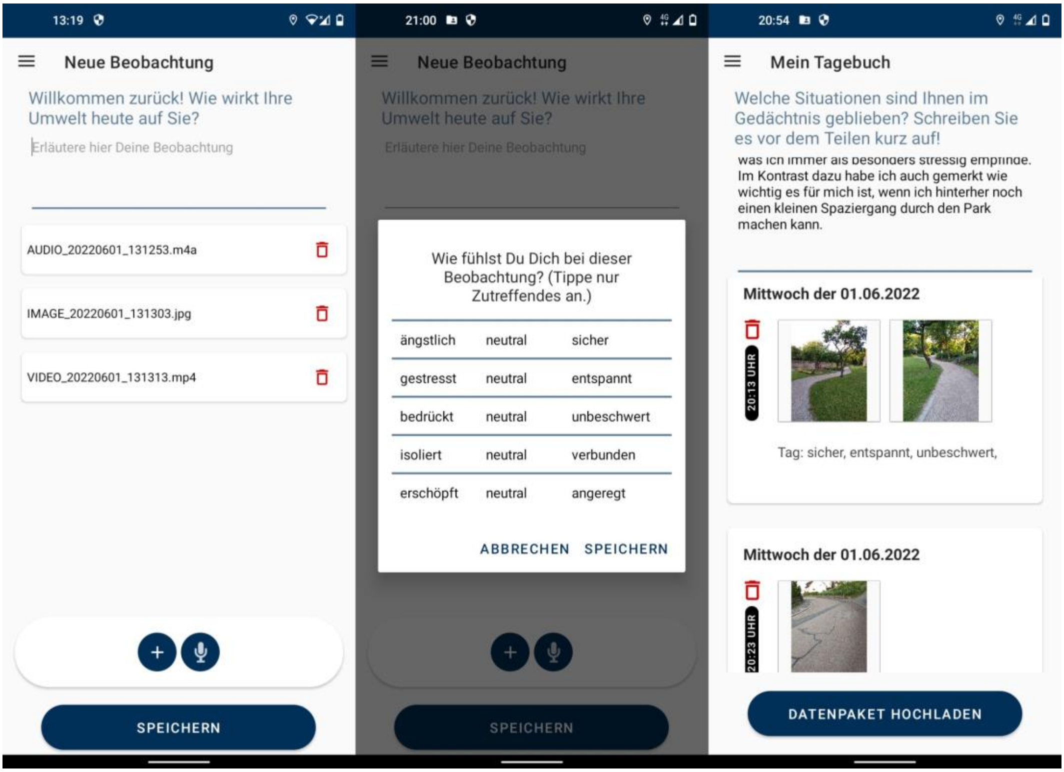


Figure 1: Basic workflow of the SpaceLog App (German only). Participants were asked to assess the influence of the built environment on them by recording multi-modal data and additional written or audio text (left), assigning the vocabulary of emotions (centre), and uploading their data to the project database (right).

3 Study setup and data collection process

In an initial exploratory study, the data collection process comprised three stages: (1) upon app startup, participants were asked to provide informed consent and, if applicable, were asked to agree to participate in an ex-post interview. They were presented with a short questionnaire collecting basic socio-economic data. (2) Participants were given their main task: to assess the emotional influence of their daily environment wherever and whenever they wished. Participants made recordings in a three-stage process: (a) collecting data in various media, with additional written or audio text; (b) assigning the vocabulary of emotions to their individual everyday situations; (c) uploading their data to the project database. Uploading prompted the user to consent again to sharing their data. Finally, based on close investigation of the data and exploratory analysis, (3) we selected candidates to invite for an ex-post interview.

In order to further protect participant anonymity, only one person from the project team was allowed to link the specific case IDs to participants' contact information until the related interviews were conducted. Furthermore, data were stored in a private cloud service2 hosted exclusively for this study at FAU Erlangen-Nürnberg. All data transfer to the private cloud was conducted using an encrypted connection.

Participants were recruited using a snowball sampling approach with the help of students. All participants regularly used roughly the same space within the metropolitan area of Nürnberg, Germany. In the initial experimental phase, 16 candidates provided informed consent. Three opted out after a few days, while the remaining 13 agreed to participate in an ex-post interview. Of the 13, only four participants used the app to provide a total of 34 photos, annotated with short diary entries and the emotion tags. While the resulting dataset for this pilot study cannot be considered representative, it enabled both methodological reflection and an exploratory evaluation of the added value of our data collection process.

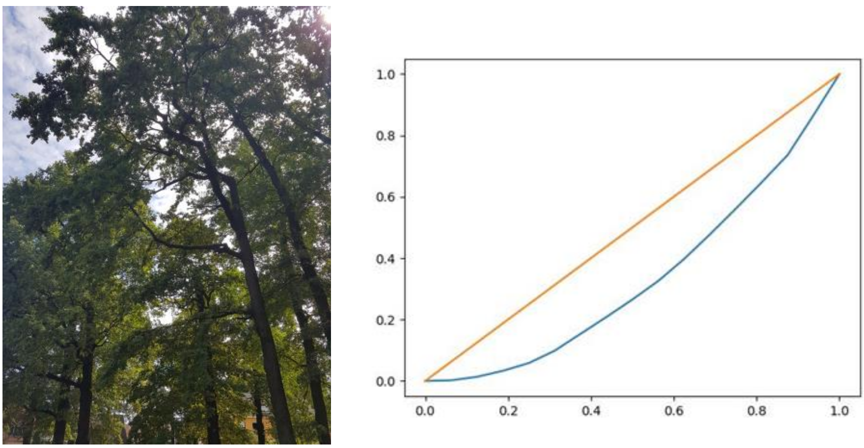
4 Preliminary results

We determined the overall greenness of each user-uploaded photo by using pixel-level classification for green, then calculated the proportion of green pixels per image. Next, we explored the approaches defined by Song et al. (2018) and Li et al. (2015). While Song et al. provide a classifier optimized for correctness that reduces the number of false negatives for pixels close to grey and yellow, the classification approach of Li et al. produced a number of false positives by detecting even small signal-to-noise ratios as green (see Figure 2). In the end, we obtained the best results with a simple HSV-range filter, which we used to identify and remove the outlier value of the two other approaches and to compute the average of the two remaining values.

[2] https://min.io/ (23.7.2023)

Figure 2: Greenness extraction: false negative (top; Song et al., 2018) and false positive (bottom; Li et al., 2015). For a better visualization of the classification process, we mask pixels classified as green (right) for each picture.

To better understand the distribution of green values across the photos, we computed the GINI coefficients of the distributions. This was done by segmenting each image into tiles and then computing the share of greenness of each tile. Aggregation was done by segmenting the images into smaller tiles, then sorting the tiles in ascending order according to their shares of greenness. Figure 3 shows example photos for high and low GINI coefficients.



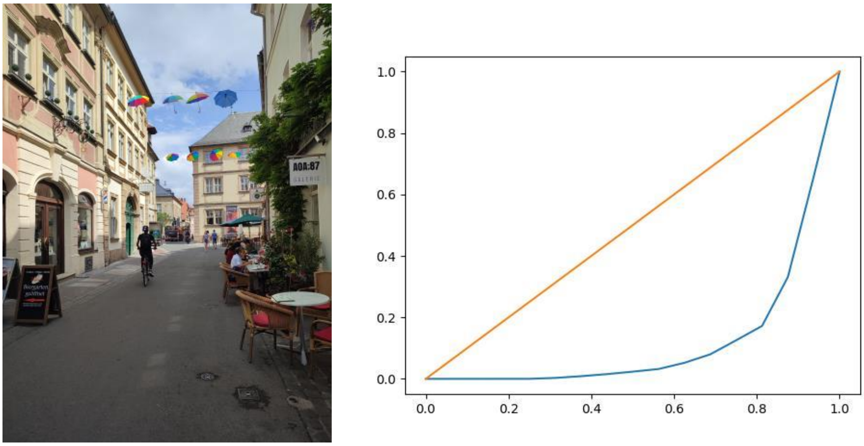


Figure 3: Lorenz diagrams for different distributions of greenness across the images

In the next step, we extracted the greenness from satellite images obtained from Google Earth, selecting a satellite image centred precisely on the GPS location at which a participant's photo was taken. We then applied the same classifiers and metrics as for the user-uploaded photos, as illustrated in Figure 4.

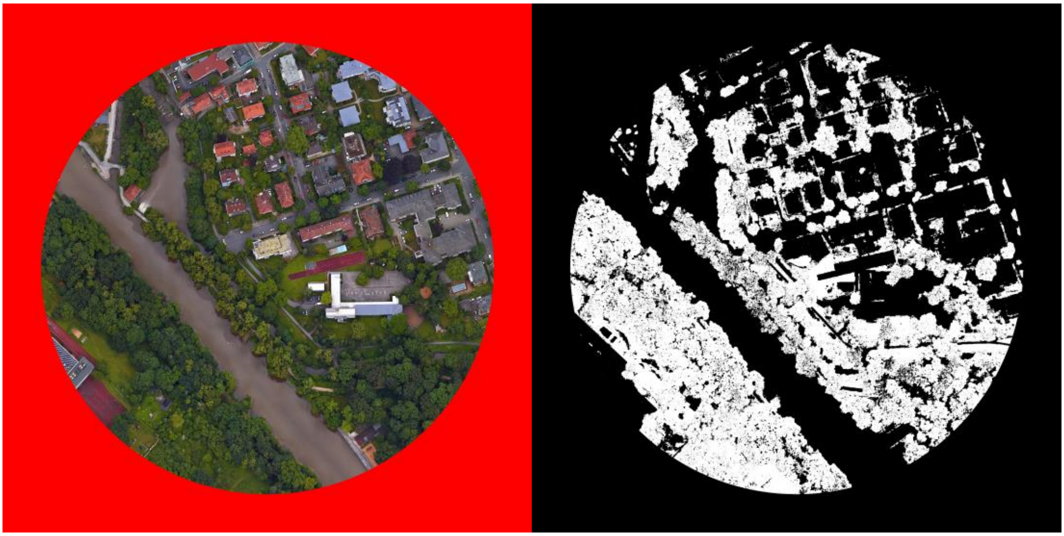


Figure 4: Greenness extraction in a 200m buffer around the location of an image

We were then able to compare the greenness extracted from the photos with the greenness extracted from the satellite images for each location.

As, at the time of writing, our dataset does not have a sufficient sample size, we were not able to produce statistically rigorous results. Our preliminary exploratory results, however, show that the proportion of greenness within the satellite images and user-generated photos correlated strongly, having a fit of 0.776 (Spearman pseudo-R^2). Interestingly, in a further step, we found that sub-scales of the emotions represented by the Urban Mind App vocabulary correlated strongly with the proportions of greenness for emotion-tagged images in the participants' specific situations, while others correlated strongly with the greenness as measured from the satellite imagery. For example, the tired-energetic scale correlated with the greenness of participants' photos, while down-happy exhibited a strong fit with the remotely sensed greenness, but only within a 50m buffer of the user's location.

5 Discussion

Thanks to the inclusion of multi-modal data for the individual emotional assessments of specific sites, our process provides significant complementarity to existing surveys, interviews and apps in the field of self-reported health. The data captured are fine-grained, allowing for individual differences, but can still be used for quantitative data analysis. Our results show that it is possible to combine the app-driven data collection process with the automated processing of image data, thereby adding substantially to existing frameworks such as the Urban Mind App. Thanks to the multi-modal data shared by participants, it is possible to pinpoint different emotional effects of different types of green features and green spaces.

Given the limited amount of data in our sample, we did not expect our preliminary analysis to provide measurable results. In order to assess the potential of this approach, ongoing and future work will seek to scale up the process to generate larger and more representative samples. However, by deriving conceptual requirements from current theory in the field of Health Geography, our approach serves as a proof-of-concept for image-based placial GIS (for text-based placial GIS, see Moura de Souza et al., 2022). This provides a number of advantages for GIScience research on how individuals make sense of green spaces:

- Greenness, in its relation to health, is not a simple, deterministic parameter that can be captured exclusively from objective measurements of environment, nor is it independent of environment and space. Rather, understanding the links between self-reported health and wellbeing requires researchers to adopt a mixed approach that leverages both objective measures of the environment and individual-level subjective indicators.
- This model is in line with a more phenomenologically informed approach to health geographies, framed by the concept of therapeutic landscapes (see Kistemann, 2016).
- Ultimately, our efforts address the need for geographic models of individual perceptions and conceptions of green environments that will allow more nuanced and sophisticated computational analysis. Both the new models and their capabilities will be better suited, epistemologically and ontologically, to capturing diverse discursive understandings of space and place.

6 Conclusion

Aiming at a deeper understanding of how individual experiences of greenness are obtained, constructed and mediated in everyday life, we underscore the need for a conceptual shift. Rather than simply searching for (spatial) correlations between scales of mental health and geofeatures, we propose a data collection process that embraces the phenomenological plurality of individual sense-making. In response to a requirements analysis revealing that current data collection processes, including mobile apps, lack the ability to provide these data, we introduce the SpaceLog app, which allows the multi-modal data needed to be recorded. Drawing from basic computational approaches that extract the share and spatial distribution of greenness in imagery, we see significant potential for linking different types of greenness to different emotions at the individual and community/sub-population scales.

Further research in this area will support mixed-method approaches to Health Geographies, as data on everyday sense-making will offer a rich source of explanations for individual differences when behavioural data are related to scales of mental health. Our next steps include (1) a larger-scale study to further examine and validate the data collection process presented here; (2) mixed-method analysis relating patterns in the behavioural data with information from the ex-post interviews; (3) relating the places of sense-making to everyday mobility patterns.

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