

Smart Phones for a Smart City: Requirements for Context Aware Mobile Application for Landscape and Urban Planning

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Abstract

Technologies collecting location-based data in the real world have advantages over traditional methods for landscape perception research. The possibility to relate geo-referenced responses of inhabitants to the physical and social data in expert GIS databases can lead to new insights into the difference between laymen and expert opinions and may result in adjustments of policy forming. To date, the use of Social Sensing in Landscape perception and valuing is limited. This research presents the set of requirements for a mobile application for landscape and urban planning, discusses some of the main challenges, and concludes that a number of evaluated existing mobile applications just partly meet those requirements.

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1. Introduction

Knowledge about people's perception of the urban landscape is important for spatial and environmental planning and can be used in a number of ways to support both operational and strategic decisions. Within the concept of smart cities, citizen involvement in decision-making becomes even more valuable since the way the cities could deal with environmental problems can be more efficient if the policy is tailored to citizens needs. In this vision, smart cities "sense" behavior and use citizen feedback to manage urban dynamics and fine-tune services (Hajer and Dassen, 2014).

It is an established practice in spatial decision-making to act in accordance with an expert-based interpretation of the citizens' needs, originating either from literature studies or empirical research. Nevertheless, in many cases, citizens' experiences can differ from an expert one (Kaplan, 1985; Kytta, 2011; Price, 2013). There is a belief that more and varied data and direct involvement of citizens in the decision-making process can overcome this problem, as many practical examples of participatory decision-making show. One of the ways citizens can be involved in decision-making is to ask them to deliver data, information or opinions by using mobile computing devices. This type of data collection is termed *crowd sensing* or *social sensing* and involves engaging people to collect and share data to measure and map phenomena. Social sensing as is seen as a promising method for rapid collection of localized data that allows administrations to react adequately, timely, and efficiently to problems in specific locations. The use of such data to improve the environment, sustainability and the quality of life of citizens forms a part of the smart city concept and can also stimulate planning innovation.

This paper discusses the potential of social sensing to provide real time geo-referenced data on perception and valuing of metropolitan landscapes. For the purposes of this study we will use the term 'landscape' to describe the total physical environment or urban areas, and the term metropolitan to refer to the particular focus of this study: the urban region. We believe that the information obtained by social sensing can overcome weaknesses of traditional landscape perception research methods used to input metropolitan policy forming. This paper proposes a set of requirements for a mobile app to gather citizen data on environmental perception in metropolitan areas. The data is also intended to provide broader insights into citizen perception of metropolitan landscapes. The provisional name of the app is "Landscapiness".

2. Requirements based on landscape perception research and policy forming

In this section we introduce the concept of metropolitan landscape and explain the problems specific to perception research related to metropolitan areas. We identify the problems of the most commonly used methods for landscape perception research, and use this as input to define the requirements for the app which would satisfy needs of researchers and urban/landscape planning experts.

2.1 Metropolitan Landscape

Metropolitan landscapes commonly comprise of a combination of both urban and non-urban features. Industrial, residential, peri-urban and mixed-use urban tissues in metropolitan areas are characterized by varying densities and forms of built and un-built space which differ markedly from that of compact (historical) urban tissues and open countryside. In recent years, various terms have been used to describe the process of spreading of built up areas and the space which appears as a result of that process. Urbanization, urban sprawl, suburbanization, dispersion, or fragmentation lead to new spatial forms termed urban fringe, peri-urban areas or territories-in-between (Wandl *et al.*, 2014). Generally these processes are considered as negative from the point of view of landscape protection, while the perception of these heterogeneous landscapes has not yet been specifically studied. As the majority of the world population lives in metropolitan regions and the most leisure time is spent in or around the city, it is important to understand how people perceive and value these landscapes.

2.2 Landscape Perception Research for Policy Forming

Landscape perception research is considered an important input for landscape policy forming. Nevertheless, the problem of understanding human landscape perception is often associated with the subjectivity and reliability of the research methods used (Colin, 2013). Traditional methods for researching landscape perception rely on surrogate landscapes represented by landscape drawings, physical landscape models, static photos or virtual 3D models (see, for instance, studies of Bryan, 2003; Catwright *et al.*, 2004; Crampton, 2001; Lange *et al.*, 2008; Lange and Hehl-Lange, 2010; Pettit *et al.*, 2011; Williams *et al.*, 2007). The majority of landscape perception research mainly looks at visual perception while other very important experiences are under-represented (sound, smell, touch, possible movement, etc.).

Another way to research visual landscape preferences is with the use of indicators. For example, the nine key concepts describing visual landscapes identified by Tveit *et al.* (2006) and Ode *et al.* (2008) - stewardship, naturalness, complexity, imageability, visual scale, historicity, coherence, disturbance and ephemera. These indicators originate from rural landscape perception studies and have been studied in an urban situation (Tveit, 2014), but have not yet been extended with indicators adequate for mixed metropolitan areas.

In the last decades, the fascination with new visualization technologies, on-line visualization tools such as Google Earth and augmented reality has resulted in numerous research papers on that subject (Appleton and Lowett, 2003; Bishop and Lange, 2005; Ghadirian and Bishop, 2007; Lovett, 2005; Sheppard and Cizek, 2009; Wu *et al.*, 2010). In contrast to technological challenges, perceptual and societal issues of visualization have hardly been touched in landscape visualization research (Lange, 1999; Bishop *et al.* 2001). This is an important issue, as in some situations expert opinion does not match citizens' perception. One example is to illustrate this is the protection of landscape openness, which has a long tradition in Dutch national and regional policy on landscape protection. The concept of openness – used to argue the protection of rural areas from urbanization - has a direct impact on decision-making on the local level, resulting in protection of the open landscape not only from being built-up but also from being redesigned for recreational needs. Research on preferences for recreation and attractiveness of rural landscape types however shows that the open landscapes are found the least attractive and have the least number of visitors compared to small-scale enclosed landscapes such as dunes and forests (Sijtsma *et al.*, 2013).

Another established conviction in planning practice is that urban density has a negative effect on the quality of urban environment. Nevertheless, studies of happiness and child-friendliness in the Helsinki metropolitan area revealed that the relationship between urban density and the perceived quality of living environment does not appear to be negative or linear (Kyttä, 2011). Average perceived environmental quality would seem to continue to rise until the density level reaches around a hundred housing units per hectare, before falling again (Kyttä, 2011). Studies concerning the child-friendliness of various types of urban environment have also highlighted the positive aspects of urban density. A dense urban structure promotes active (e.g. walking or cycling) journeys to school, increases independent access, and guarantees that locations meaningful to children are only a short distance away (Kyttä, 2011). Finally, despite the criticism of the reliability of the landscape perception research methods, the results of

inquiries are often used as argument in policy forming. Some of the examples are landscape protection policy in U.S.A. (described in Kaplan, 1985) or Dutch landscape protection policy (Weitkamp *et al.*, 2012).

Development of open GIS and internet technology in recent years such as the Soft GIS approach to collect data on citizens' preferences is seen as a tool that can address the above-mentioned problems. As some of the examples show (hotspotmonitor.eu; <http://www.daarmoetikzijn.nl>; mapita.fi) Soft GIS enables the combination of 'soft' subjective data provided by citizens via Internet with 'hard' objective GIS data of urban planners. Yet it misses one important feature that mobile technology has: location-based response. Although technically possible in practice it is not a part of Soft GIS applications. Looking at the possibilities that smart phone app can offer such as easily responding on a location and repeated responses in different moments of a day and seasons, we believe that the two technologies combined together can create a powerful tool for the research and planning purposes.

2.3 Requirements for the App Based on research and policy forming needs

On the basis of the above analysis we can define the following requirements for a crowd-sensing application (app):

- Situated data creation: citizens to contribute data on how they experience an outdoor space *while* they are situated in that space; therefore the app should be location-based and provide geo-referenced data.
- Participatory sensing: as we are interested in people's subjective experience of spaces, we need people to actively participate and contribute data. This is distinct from opportunistic sensing, which concerns contribution of data that is generated anyway for other purposes.
- High resolution data: data needs to be collected with high spatial resolution to cover a wide variety of metropolitan spaces (landscape types), if possible in a wide variety of conditions (e.g., time of the day, day of the week, season, etc., weather, activity, company, state of mind, crowdedness, space, population).
- Data to be reliable/accurate
- Data to incorporate multiple sensorial aspects:
 - visual experience
 - auditory experience
 - olfactory
- Support objectivity
- Be multi-purpose – for instance, related to generic landscape typology

- Effective in visualization / representation of results and feedback to user
 - combined with other information sources such as Internet
- Allow follow-up questions (e.g. for evaluation)
- Provide continuity in time and space (wouldn't stop after one enquiry but continue to grow)
- Permanent learning tool: adjustments and calibration of questions based on response
- Stimulating citizens participation in planning and decision making

3. Users Behavior and Crowd Sensing Methods

In order to employ crowd sensing for collecting data for use in urban planning, we need to understand how people can be engaged to collect the required data. This concerns both enrolling as a (potential) participant (installing the app), as well as contributing data (using the app). In this paper, we will focus mainly on the latter.

A main consequence of social sensing is that contributing data requires effort from people, particularly when data creation is situated. People are required to contribute while they are carrying out another activity, e.g., commuting, shopping or doing sports. Since participating comes with costs for people, when developing a software framework for social sensing, it is particularly important to address how the long-term *sustainability of the social sensing system* can be ensured. If people quickly stop participating (nearly 60 per cent of apps downloaded are briefly used and then discarded (Ofcom, 2014), this will negatively affect the quality and resolution that can be obtained and the ability to conduct (follow-up) experiments as the need arises.

3.1 Incentives, Efforts and Data Quality

Designing a system with the desired properties of sustainability and high quality data requires that people be approached in the right way. For this two components go hand-in-hand:

1. An accurate user model representing user motivation and incentives;
2. Optimal system decision-making which takes this user model into account;

The design of system to make optimal decisions given a user model is studied in the field of mechanism design, such as Inverse Game Theory. Current challenges here are to relate short and long-term goals and deal with a changing environment (Nisan, 2007; Parkes *et al.*, 2010). The chal-

lenge is to balance costs and benefits while obtaining the required data (at the right location and with the right quality) for the requesting party, while minimizing costs for the requesting party.

It seems intuitive that taking into account user models as beneficial for the result. However, what is needed here exactly? Are simple models enough? And can we use social rewards (reputation, four-square, scrip systems)? We expect the perceived effort for real-time social sensing to be higher than for other systems, because real-time social sensing on demand interrupts the normal flow of activities, in contrast with for instance contributing product reviews which can be done in your own time.

Another issue is data quality: since the sensing concerns an observation regarding a certain place and time, it is difficult to check whether this was accurate (e.g. compared to a product review). In addition, subjective versus objective sensing information needs to be addressed, i.e. collecting opinions versus facts (for instance comparing sensing experience of a space and weather sensing). With subjective data the goal is to check internal consistency, not objective “truth”.

3.2 User Models and Requirements

Accurately modeling of behavior is a long-standing challenge. In the context of optimal decision-making, this is mainly studied by behavioral and experimental economists. Straightforward user models express a user’s utility by costs and benefits (Neumann and Morgenstern, 1944). Costs and benefits need to be balanced: if higher costs are incurred, a higher reward is needed to entice people to act. These costs and benefits are typically expressed as utility functions mapping everything to a single dimension, usually in terms of money, but also reputation and recognition (e.g., Four-square) and scrip systems in which points can be earned that can be used later. Costs incurred by contributing people in social sensing are for example effort, time, money and battery life of their mobile device. Various incentives may be considered as benefits. An inherent benefit can be to influence actions or policies of institutions, for example motivating them to repair public property or improve a public green space. Some users may be interested in a log of their own activities, or an overview of all entries by all users, or eventually see the possibility of their report influencing the environment.

In the literature, phenomena arising from the interaction of groups of people have also been studied, for example, *Tragedy of the Commons* (Hardin, 1968) which concerns usage of a common resource by multiple people. In social sensing, this translates into people wanting to use the data that other people collect, but not contribute themselves. If too many people

act like this, the social sensing system does not function effectively. Another aspect regarding studies of behavior concerns a situation where costs are incurred now and benefits are obtained later. This is relevant for social sensing systems, since contributing data now may give benefit later, e.g., when the collected data lead to policy decisions.

Simple utility-based user models often do not match real behavior, because they ignore omnipresent personal traits such as for example altruism (Rahn, 2013; Trivers, 1971) and reciprocity (Cox *et al.*, 2007; Falk and Fischbacher, 2006; Axelrod, 1984; Fehr and Gächter, 2000), and bounded rationality (Rubinstein, 1997). In the context of social sensing, people may want to collect data because they want to contribute to a greener, healthier and safer environment, or because they are interested in the phenomenon that is being studied.

The challenge of developing an effective social sensing system is that we need to understand how to model behavior in this setting, i.e., what kind of model is appropriate, and how behavior can be effectively influenced in this domain (De Weerd *et al.*, 2014). Finally, from the considerations discussed in this and previous sections we can define the following user requirements:

- Effectiveness in relation to effort, time and money
 - incentives (rewards)
 - easy to install and to use
 - minimum disturbance of ongoing activities
 - configurability (preferences for when or by whom to be approached)
- Effective visualization of
 - own contributions
 - direct feedback
 - insight in aggregated data
- Information about the long term use of provided data
- Effect on decision making process and outcomes

4. Analysis of Existing Smart Phone Apps that Can be Used to Study Landscape Perception

To the best of our knowledge, very little research has been done on the intersection of social sensing and landscape and urban planning. In the last decades, data from mobile phones have been implemented as innovative tools in geography and social science research mostly focusing on a common format called 'Call Data Record' or CDR. Empirical studies of complex city systems which use CDR already provide new insights to develop

promising applications for supporting smart city initiatives (Steenbruggen *et al.*, 2014). By contrast, knowledge about how smart phone apps can be used for gathering data on landscape perception relevant for landscape and urban planning is scarce. In the following section we will analyze and compare a number of apps that we have found in the spatial and landscape planning literature. We do not aim at full coverage, but rather at providing a representative sample of current state-of-the-art of the mobile phone apps which can be used to study landscape perception.

4.1 Generally used apps versus planning specific apps

Smartphone apps have already been used for various purposes in urban planning and by urban planners. In the analysis presented in this section though we make a distinction between apps that are generally used by planners from **planning specific apps**. According to Evans-Cowley (2014), urban planners use many generally available apps, but her survey among 237 planners from the US, mainly employed in the public sector, shows that less than one third of the respondents ever used planning specific apps. Evans-Cowley does not explain further what planning specific apps are. In our case, we consider planning specific apps as those that are matching (or partly matching) the requirements presented in sections 2 and 3 of this paper.

From the long lists of the apps presented in the overviews of Evans-Cowley (<http://www.planetizen.com/node/66853>) and Cyburbia (<http://www.cyburbia.org/content.php?r=134-10-apps-that-every-planner-should-have>) we will just mention some of those that we **do not take** in consideration to illustrate the range of planners activities they cover: for data collection (LocalData; ArcGis; Collector), providing information about the space (LayAR) or about spatial plans and projects (Sustainable Rotterdam); informing about city services (SmartSantanderRA), or providing statistical data (MetroPulse, Dwellr). Planners also use many social networking apps such as LinkedIn and Facebook, but also those for exchange of information between the members of specific communities like Ushahidi. A bit closer to what we have defined as planning specific apps are, for example, apps for emergency warnings (CFA Fire Ready), for reporting problems (City of Boston) or for reporting code violations (You the Man, City of Phoenix, MyDelaware, Civic Duty).

Finally, we found seven crowdsourcing apps, i.e., Mapiness, Color you space, EpiCollect, LocalData, Ushahidi, Stereopublic, and Widenoise that come close to meeting the requirements from the previous sections. Each is discussed below and they are compared (Table 1) deriving criteria from requirements presented in sections 2 and 3. We also compared these

seven apps with the more generic survey tools such as Google forms (<http://www.google.com/forms/about/>). The comparison is made by reading description on the developers website and by installing and testing the app on the iPhone.

- Mappiness (<http://www.mappiness.org.uk/>) is an app that "maps happiness across space in the UK". The app becomes active a number of times a day (users can set a maximum) and asks users how they are feeling and where they are. If the user is outside, it is also possible to upload a photo. A website provides maps with aggregated data on how people are feeling in the whole UK or London area. Users also get personal feedback and can see the result of the inquiry on the related website.
- Color your space (<http://coloryourspace.com/>) is an app that aims "to analyse the users' perception of spaces". The app asks users to rate their experience in a specific (predetermined) place. At the moment of writing, it is used for five public spaces in the UK and the Netherlands. The app can be integrated with Facebook.
- EpiCollect (<http://www.epicollect.net>) is an app for "the generation of forms (questionnaires) and freely hosted project websites for data collection". The app distinguishes itself from survey-based tools because it also collects GPS and possibly media data and that it can present the (aggregated) results of the surveys using Google Maps.
- Local Data (<http://localdata.com>) is a web-based app that "helps cities and communities make data-driven decisions by capturing and visualizing street-level information in real time." This web app also allows users to fill in questionnaires. Aggregated data gathered by social crowdsourcing is used to enrich other open data projects, for example, for a cartographic map of Los Angeles or a historic map of New York.
- Ushahidi (<http://www.ushahidi.com>) helps people building crowdmaps. A crowdmap is a simple map-making tool, built on an open API, that allows users and the world to collaboratively map their worlds. The idea behind is to "bring together organizations across the private and public sectors to foster innovation, manage large funds and build communities". One interesting example of Ushahidi community is BOSKOI, an open source mobile app that helps people explore edible landscapes in the Netherlands.
- Stereopublic (<http://www.stereopublic.net/>) is a project supported by Australian government that "asks participants to navigate through their city for quiet spaces, share them with social networks, take audio and visual snapshots, experience audio tours and request original compositions made using own recordings".

- WideNoise (<http://www.widetag.com/widenoise>) is a mobile app that “helps people understand the soundscape around them”. The idea is to make people aware that sound is also a kind of pollution. With WideNoise it becomes possible to monitor the noise levels for a given area. Users can check an online map to see the average sound level of the area around them.

4.2 Evaluation criteria and results of the analyses

Requirements described in the previous sections form the point of view of research, planning practice and users are in this section integrated in the ten criteria and then used to evaluate seven apps. The criteria are:

1. *Location based*: indicates if the collected data is tied to a specific location. For example, if a survey is sent back and the survey contains GPS coordinates then the data is location based. This typically does not hold for (web based) surveys.
2. *Coverage*: indicates the quality of the coverage in multiple dimensions:
 - a. *spatial* (how many data points for a given area),
 - b. *temporal* (how many data points over a time period),
 - c. *population* (how many people use the app, and are these a representative sample of the population at a given location),
 - d. *senses* (can you only fill in a survey, or also upload pictures, sound or other media form a location) and
 - e. *generic* (is the mobile app developed for a specific purpose or can others also use it for their own goals).
3. *Feedback*: this indicates what type of feedback is given to end-users and how aggregated data are presented.
4. *Follow up Question*: is it possible to ask the user more questions after they have collected data, i.e., can we ask for more information to the same user based on the first data entry?
5. *Configurable*: is it possible to configure mobile apps, such as Mappiness, that ask users multiple times a day if they can provide information, for example, is it possible to indicate that you only want two request for data a day and no questions between 8 p.m. and 8 a.m.
6. *Request driven*: is it possible for the mobile app owner or others to request that data is collected for specific locations or time intervals?

Table 1 shows that pure survey-based approaches, i.e., on paper or via a website, do not capture enough data for complex problems from the perspective of citizens’ spatial perception. In cases where surveys do not have to be filled in at a particular location (Color your space for instance), the connection (both spatial and temporal) with the urban space is loose at

best. Most other apps, i.e., not Color your space or web based surveys, perform much better, but do not provide a very high spatial or temporal coverage. None of the apps provide support for follow-up questions, and none of them are request driven. These are the key features that can help one receive more information about urban spaces: follow-up questions can be used to get more information about a particular location (If people are unhappy in a space can we try to figure out why?) and by requesting information from users in a particular location (geofencing, see Sheth *et al.*, 2009) or time instance it becomes possible to increase both the spatial and temporal resolution (coverage) without having a very large user base. Such features basically allow us to use the available resources, i.e., volunteers that use the app, in a more efficient manner and by allowing users to configure how many times and when they are disturbed, the irritation threshold of users is hopefully not met.

Although two apps – Mapiness and Color your space - come the closest to our requirements, none of them can be directly used for the study of metropolitan landscape perception as defined in section two. Mapiness because the level of happiness can result from many non-spatial reasons and therefore cannot be directly associated with the landscape perception by the respondent. Color your space, on the other hand, has very low coverage and it is not location based.

Table 1. Evaluation of mobile apps for urban planning with respect to the requirements discussed in Section 2 and 3

App name	Location based		Coverage				Feedback	Fol- low up Q	Configu- rable	Request driv- en
	spatial	temporal	population	senses	generic					
Mappiness	gps data collected	gps data - low	low	62,819 participants (25/2/2015)	photo, sound	special purpose	website/map/ status	no	# requests per day, time intervals	limited, app asks a few times a day for data
Color your space	predetermined	gps data - average	low	hundreds	none	all surveys	facebook page	no	N/A	no (survey)
Ushahidi	gps data collected	gps data - average	low	depending on topics fro a few to hundreds		all surveys	map	no	no	No
Epicollect	predetermined	gps data - low	low	hundreds	photo	survey	website/maps	no	N/A	no (survey)
Stereopublic	gps data collected	gps data - average	low	hundreds	sound, photo	specific	webiste/map	no	no	no (survey)
Widenoise	gps data collected	gps data - average	low	hundreds	level of noise	specific	website/map	no	no	no (survey)
Web app Local-Data	predetermined	gps data - low	low	hundreds to thousands	unclear	survey/focus on urban infra	website/maps/twitter	no	N/A	no (survey)
Generic survey via website	no	low	low	varies, potentially ten thousands	none	survey	varies	no	N/A	no (survey)

5. Social sensing app for Landscape Perception Research – “Landscapiness”

In this section we will describe the basic concepts that are derived from the literature review and requirements definition which we intend to apply in development of the Landscapiness app. The first important issue to mention is that the data collected by social sensing will be related not to a single area but to a generic landscape typology.

The amount and location of various landscapes within the metropolitan region makes perception data intensive and difficult to gather, therefore using a landscape typology as a basis for research is a helpful approach. This is also important for the integration of social aspects of landscape planning, as suggested by Ryan (2011). Another advantage of using landscape typologies is that relating landscape perception to a particular landscape type extends the applicability of the results to metropolitan areas that share the same spatial conditions. For this study, we will use landscape typology developed for the Rotterdam metropolitan area by Tisma *et al.* (2015). In the next step of this research we plan to use the Landscapiness app (currently under development by the authors of this paper) to acquire citizens' perception of these landscape types.

The Landscapiness app will ask participants located in a character type to send a picture and respond to a set of questions about their perception of that environment. The participants will be asked to provide their answers in time of the day, day of the week, weather conditions, etc. This will ensure that the dataset is sufficiently representative for the character types under a wide range of circumstances. By linking the collected data (including GPS coordinates) with the landscape types from the Metropolitan Landscape Characterization we can validate the perception of experts, as well as track the perception and valuing of that character type by metropolitan inhabitants. To stimulate users engagement several ways of feedback and rewards will be implemented.

For the transparency of the process, the data stored in the back-end database will be analyzed and aggregated and the results made available on a related website. An example of how such data could be used is shown on the figure 1. The map shows how perception of pleasure varies per landscape type within the protected recreational areas of the southern part of the Province of South Holland.

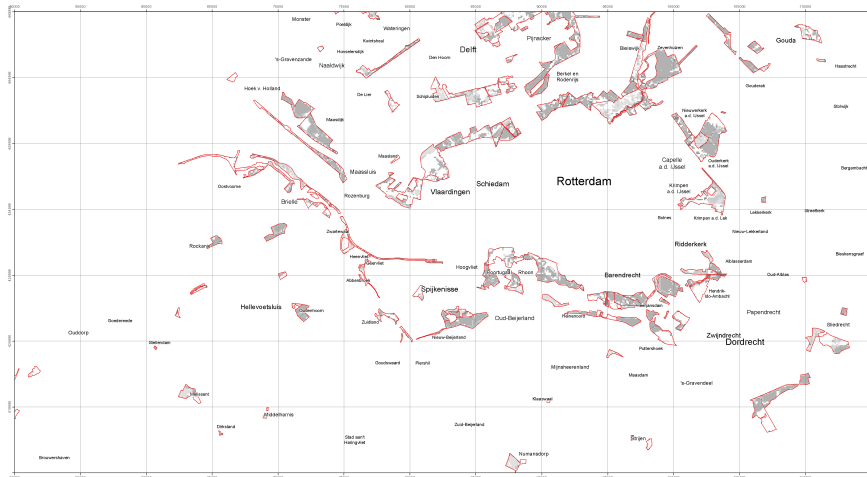


Figure 1. Perception of pleasure within the recreational areas protected by the Province of South Holland (Tisma et al., 2015). The darker the color the less pleasant the landscape.

The statistics have shown that only about 30% of the recreational areas are perceived as pleasurable, 30% as neutral and 10% as unpleasant (for the remaining 30% of the areas there is no data). This map is constructed on the basis of expert opinions. We can imagine that the value would be much higher if we would have citizens responses.

6. Conclusions

When studying landscape perception technologies collecting location-based data in the real world have advantages over traditional methods used in perception research. Social sensing using smart phone devices allows for potentially larger responses with improvements in accuracy and coverage. The possibility to relate geo-referenced responses of inhabitants to landscape typologies developed by experts can lead to new insights into the difference between laymen and expert opinions and result in adjustments in policy forming.

As the analysis of the existing planners specific apps showed, the use of social sensing in landscape perception research and in planning practice is limited. None of the seven apps that were found to partly match requirements defined by this research is fully and directly usable for landscape perception research and for the enrollments of citizens in policy forming. The steps toward smart use of data for the future apps should respond to the requirements of researchers, urban planners and users as described in the previous sections. In summary:

- Researchers: improve the methods for landscape perception research and improve understanding of location-based experiences of the metropolitan landscape.
- Urban planners: better understanding of what citizen's perception is when designing metropolitan landscapes.
- Users short-term: minimum effort and direct feedback about their own and aggregated location-based experiences.
- Users long-term: permanent insight into aggregated data on location-based experience for the whole city/region and the way that policy makers use these data to improve spatial planning policy.

In policy forming, knowledge about human perception of landscape has been mainly used for the purposes of landscape or environmental protection. Better understanding of metropolitan landscape perception can form the input for targeted policies which can be also part of common action of planners and citizens. We believe that request-driven social sensing can help realize this ambition.

References

Appleton, K., & Lovett, A. (2003). GIS-based visualisation of rural landscapes: defining 'sufficient' realism for environmental decision-making. *Landscape and Urban Planning*, 6, 117–131.

Axelrod, R.M. (1984). *The evolution of cooperation*. Basic Books

Bishop, I.D., & Lange, E. (2005). *Visualization in Landscape and Environmental Planning. Technology and Applications*. Taylor and Francis, London.

Dodge, M., Doyle, S., Hudson-Smith, A. & Fleetwood, S. (1998). Towards the Virtual City: VR & Internet GIS for Urban Planning. In: (Proceedings) Virtual Reality and Geographical Information Systems Workshop.

Bennett, P.G. (1995). Modeling decisions in international relations: Game theory and beyond. *Mershon International Studies Review*, 39(1):pp. 19–52

Bryan, B.A. (2003). Physical environmental modelling, visualization and query for supporting environmental planning decisions. *Landscape and Urban Planning*, 65(4), 237–259.

Cartwright, W., Miller, S., & Pettit, C. (2004). Geographical visualization: past, present and future development. *Journal of Spatial Science*, 49(1), 25–36.

Colin, P. (2013). Subjectivity and objectivity in landscape evaluation: an old topic revisited. In C. Van der Heide, C.M. and Heijman, W.J.M. (Ed.) *The Economic Value of Landscapes* (pp. 53 – 77). London and New York: Routledge

Cox, J. Friedman, D. and Gjerstad, S. (2007). A tractable model of reciprocity and fairness. *Games and Economic Behavior*, 59(1):17 -- 45, 2007.

Crampton, J.W. (2001). Maps as social constructions: power, communication and visualization. *Progress in Human Geography*, 25(2), 235 – 252.

De Weerd, M.M., Dignum, V. Van Riemsdijk, B. and Warnier, M. Request-Driven Social Computing: Towards Next Generation Crowdsensing Systems. In *Proceedings of the 3rd international workshop on Human-Agent Interaction Design and Models*, 2014.

Evans - Cowley, J. (2014): The Best Planning Apps for 2014
<http://www.planetizen.com/node/66853>

Falk, A. and Fischbacher, U. (2006). A theory of reciprocity. *Games and Economic Behavior*, 54(2):293 - 315

Fehr, E. and Gächter, S. (2000). Fairness and retaliation: The economics of reciprocity. *Journal of Economic Perspectives*, 14(3):159--181

Ghadirian, P., & Bishop, I. (2007). *Exploring environmental changes using integration of augmented reality and GIS*. Paper Presented at Spatial Sciences Institute Biennial Conference. Hobart, Tasmania.

Hajer, M. and Dassen, T. (2014): Smart about cities. Visualizing the challenge for 21st century urbanism. NAI 010 Publishers.

Hardin, G., (1968). The Tragedy of the Commons. *Science* 162, no. 3859, 1243-1248.

Kytta, M. (2011). SoftGIS Methodology. Building bridges in Urban Planning. http://www.gim-international.com/issues/articles/id1677-SoftGIS_Methodology.html4

Lange, E. (2001a). The limites of realism: perceptions of virtual landscapes. *Landscape and Urban Planning*, 54, 163-182.

Lange, E., Hehl-Lange, S., & Brewer, M.J. (2008). Scenario-visualization for the assessment of perceived green space qualities at the urban-rural fringe. *Journal of Environmental Management*, 89(3), 245–256.

Lange E., & Hehl-Lange S. (2010). Making visions visible for long-term landscape management. *Futures*, 42(7), 693-699.

Lovett, A. (2005). Futurescapes. *Computers, Environment and Urban Systems*, 29(3), 249–253.

Neumann, J. and Morgenstern, O. (1944) *Theory of Games and Economic Behavior*. Princeton

Nisan, N. (2007). Introduction to mechanism design (for computer scientists). In *Algorithmic Game Theory* (pp. 209-242). Cambridge University Press.

Pettit, C.J., Raymond, C.M, Bryan, B.A., & Lewis, H. (2011). Identifying strengths and weaknesses of landscape visualization for effective communication of future alternatives. *Landscape and Urban Planning*, 100, 231-241.

Sheppard, S. R. J., & Cizek, P. (2009). The ethics of Google Earth: Crossing thresholds from spatial data to landscape visualisation. *Journal of Environmental Management*, 90, 2102-2117.

Sijtsma, F.J., Farjon, H., van Tol, S., van Kampen, P. Buijs, A. and van Hinsberg, A. (2013). Evaluation of landscape impacts – enriching the economist’s toolbox with the HotSpotIndex In C. Van der Heide, C.M. and Heijman, W.J.M. (Ed.) *The Economic Value of Landscapes* (pp. 53 – 77). London and New York: Routledge

Ofcom (2014). Adults’ Media Use and Attitudes Report 2014.
<http://stakeholders.ofcom.org.uk/market-data-research/other/research-publications/adults/adults-media-lit-14/>

Parkes, D. C., Cavallo, R., Constantin, F., & Singh, S. (2010). Dynamic incentive mechanisms. *AI Magazine*, 31(4):79-94.

Rahn, M. and Schafer, G (2013). Bounding the inefficiency of altruism through social contribution games. *Conference on Web and Internet Economics*, Boston, MA, USA.

Rubinstein, A. (1997). *Modeling Bounded Rationality*, volume 1. The MIT Press, 1 edition.

Ryan, R.L. (2011). The social landscape planning: Integrating social and perceptual research with spatial planning information. *Landscape and Urban Planning*, 100, 361 – 363.

Smith, E.L., Bishop, I.D., Williams, K.J.H., & Ford, R.M. (2012). Scenario Chooser: An interactive approach to eliciting public landscape preferences. *Landscape and Urban Planning*, 106(3), 230-243.

Steenbruggen, J. et al. (2014). Data from mobile phone operators: A tool for smarter cities? *Telecommunications Policy*.

Tisma, A., van der Velde, R., Nijhuis, S. & Pouderoyen, M. (2014). Beyond the Urban-Rural Paradigm: A Method for Metropolitan Landscape Characterization. *SPOOL journal*, 1(1). 201-224.

Tisma A., Van der Velde, R., Pouderoyen, M. , Wilbers, J. (2015). Metropolitan Landscape Characterization: Pilot study Province of South Holland. Delft, Faculty of Architecture and Built Environment.

Trivers R.L. (1971). The evolution of reciprocal altruism. *The Quarterly Review of Biology*, 46:35--57, 3

Tveit, M. S. Ode, S. (2014). Landscape assessment in metropolitan areas – developing a visual indicator-based approach. *SPOOL*, p. 301-316.

Wandl, A.D.I, Nadin, V. Zonneveld, W., Rooij, R. (2014). Beyond urban-rural classifications: Characterising and mapping territories-in-between across Europe, *Landscape and Urban Planning*, 130, 50-63.

Williams, K.J.H., Ford, R.M., Bishop, I.D., Loiterton, D., & Hickey, J. (2007). Realism and selectivity in data-driven visualisations: a process for developing viewer-oriented landscape surrogates. *Landscape and Urban Planning*, 81, 213-224.

Weitkamp, G., Van den Berg, A. E., Bregt, A.K., Van Lammeren, R.J.A. (2012). Evaluation by policy makers of a procedure to describe perceived landscape Openness. *Journal of Environmental Management* 95, 17 -28.

Wu, H., Zhengwei, & H., Gong, J. (2010). A virtual globe-based 3D visualization and interactive framework for public participation in urban planning processes. *Computers, Environment and Urban Systems*, 34, 291–298