Space-time Analytics of Human Physiology for Urban Planning

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Abstract

Recent advancements in mobile sensing and wearable technologies create new opportunities to improve our understanding of how people experience their environment. By analysing data collected from this type of sensors, we can study spatial variations in people's physiological response in relation to the surrounding environment, allowing us to provide urban planners objective metrics on how individuals experience urban design elements. Currently, an important urban design issue is the adaptation of infrastructure to increasing cycle and e-bike use. Using data collected from 12 cyclists on a cycling highway between two municipalities in The Netherlands, this paper presents a methodological framework for quantifying and analyzing spatiotemporal variations of emotion and their association with surrounding environmental features. We coupled location and physiological measurements of high spatiotemporal resolution to model and examine relationships between cyclists' physiological arousal (operationalized as skin conductance responses) and environmental characteristics (operationalized as visible land cover). We specifically took a within-participants multilevel modeling approach to determine relationships between different types of viewable land cover and emotional arousal, while controlling for speed, direction, distance to roads, and directional change. Surprisingly, our model suggests ride segments with views of more natural, recreational, agricultural, and forested areas were more emotionally arousing for participants. Conversely, segments with views of more developed areas were less arousing. The presented methodological framework, spatial-emotional analyses, and findings from hierarchical multilevel modeling provide new opportunities for spatial, data-driven approaches to portable sensing and urban planning research. Furthermore, our findings have implications for design of infrastructure to optimize cycling experiences.

Keywords: Spatial analytics, Physiology, Urban planning, Emotion, Portable sensing, Spatiotemporal metrics

1. Introduction

Emotions play a major role in our day-to-day lives, significantly contributing to how we perceive and experience the world. Emotions comprise intense, short-lived reactions to the context, and specifically the places, in which people live. Bumper-to-bumper traffic, large noisy crowds, and beautiful architecture, all will evoke emotional responses. While we may feel happy and secure in one place, we might feel worried and unhappy in another [1].

How we emotionally respond to a place depends on a wide variety of factors [2]. A great breadth of urban planning and design efforts focus on controlling these factors to make experiences of cities as positive as possible. Yet, research examining how emotions develop over urban spaces is limited. When research on emotions experienced during cycling in urban areas is, to our knowledge, nonexistent. Cycling's recent boom in popularity, and considerable efforts to redesign city transportation infrastructures around cycling, warrants researching regarding cyclists' experiences. The advent of electric bicycles highlights this need, as cities realize the need to adapt infrastructure more radically. Unfortunately, even the most basic predictors of cyclists' experiences remain unexplored. To address the gap seen in spatial-emotional knowledge, we use wearable location and emotion tracking of 12 cyclists on an intercity cycling highway to determine how the land cover within their field of view affects their emotions. Findings can inform urban-design approaches to build public spaces with spatial arrangements that stimulate positive experiences and emotions.

2. Background

Emotion is a biologically-based response to an external or internal stimulus [3]. Simply put, emotions are responses to the world around us. Evoked in situations that are seen as personally relevant, emotions constitute the main driving force of human behavior [4]. Physical characteristics of locations such as cities can evoke an emotion [5], causing them to be experienced as attractive, boring, dangerous or scary, for example [1]. Overall, emotions influence how people perceive and experience their environment. The present study focuses on the intensity of emotional reactions to viewing various combinations of physical characteristics while traveling on an intercity cycling highway.

Certain physiological measures–bodily changes that accompany emotions–have been shown to be especially sensitive to emotions [6, 7]. These measures are useful for studying whether the physical layout of an environment, along with its built and natural structures, can evoke particular emotions in its users and in turn, affect the way it is perceived and experienced [8]. One common and well-established physiological marker of emotion is skin conductance. Also termed electrodermal activity (EDA) or galvanic skin response (GSR), skin conductance refers to increases in the skin's ability to conduct electricity caused by an opening of the sweat glands. When the brain senses personally relevant stimuli, the nervous system then triggers sweat glands on the hands and feet, which in turn become damp. Two electrodes passing a weak current between one another, as those worn on the bottom of a wristband, can detect this change. Technologies such as the Empatica E4 [9], a wearable wristband designed to measure skin conductance, makes such measurement accessible in mobile field contexts.

Variations in skin conductance comprise psycho-physiological responses to discrete environmental stimuli. Hence, they are not only considered to be a reliable index of emotional arousal [10], but when combined with location tracking, offer a view into the spatiality of emotional experience [11, 12]. Coupling location measurements with physiological signals supports measuring the effects of urban design interventions such as cycling routes. Previously, research measuring the emotional effects of urban design research has been largely limited to one-time measurements through self-report-based questionnaires or qualitative methods. The combination of physiological emotion measurement with location tracking holds clear advantages over traditional self-report procedures: it is free from the well-known recall biases of self-report measures, it reduces burden on participants, avoids disrupting the experience being measured, is ecologically valid, and can log in-situ, continuous, high spatiotemporal resolution measurements of emotional arousal [13]. Ecological validity of most previous physiological research on emotions has suffered from participants' laboratory experiences being rather different than a real-life visit to an urban space. However, wearable recording equipment such as the Empatica E4 is now accessible to researchers. As a result, physiological measurements are increasingly being used in more ecologically-valid settings. The results of mobile in-situ emotion measurements are directly applicable to urban planning for decision support and the evaluation of ongoing planning processes [14]. Moreover, urban and city planners can gain valuable insight into which spatial configurations and environmental features (e.g., open green spaces, dense urban spaces) contribute to favorable physiological states of visitors and residents. Emotionally stimulating areas can be identified and then emphasized or removed, respectively.

Recent research has begun examining empirical prospects of integrating physiological sensing into spatial analytics for urban planning. Some of the more note-worthy studies involve the work of Nold (a pioneer in mapping skin conductivity patterns; [15]), Sagl and colleagues [16], and Resch and colleagues [14]. They present conceptual models of how the above-mentioned analytical methodologies can be used to explore a large breadth of theoretical questions. Unfortunately, empirical studies exploring physiological patterns of emotion and their spatial interactions are limited, although a few studies are still notable. For example, Zeile et al. [17] supplemented Nold's research by roughly aggregating individual physiological data on a grid. The interest in mapping emotion has since continued to grow as an area of interest within urban spatial analytics. This can be seen in the work from Birenboim [18, 19, 13], Kirillova [2, 20, 21], Shoval [22], and Zeile [17, 23, 24, 25], to name a few.

Emotions are subjective in nature. Thus, they warrant an adoption of analytical approaches involving subjective- and qualitative-based data practices. Kirillova [2, 20, 21] and colleagues for example, used qualitative assessments to examine tourists' experience. Employing 57 semi-structured interviews, they unearthed nine themes of aesthetic judgments of urban and nature-based tourist destinations: Scale, Time, Condition, Sound, Balance, Diversity, Novelty, Shape, and Uniqueness. These themes were then applied in the development of a framework for tourist experience. Most interestingly, Kirillova and colleagues' [21] longitudinal investigations revealed how people consider areas in nature to be the most aesthetically-pleasing, and urban destinations as less pleasing if not populous.

From a more quantitative side, Zeile and colleagues' research claims EDA to be the most reliable parameter for deriving and understanding emotions of citizens', as affected by their environment [23]. They supplemented EDA data with collections of ECG, SCR, skin temperature, and heart rate variability in efforts to objectively map emotion, specifically assigning emotional valence to environmental locations. Authors showed busy roads to reliably evoke stress, with streets containing low traffic and high greenery to evoke more calmed-states of emotion. More recently, Zeile and colleagues have also used more intensive data-acquisition techniques [25], using ECG, EDA, GPS, and GoPro video on a larger sample size to empirically unveil damaged road surfaces, dangerous intersections and crossing pedestrians as triggers for negative reactions. Findings were deemed inapplicable to ongoing urban-planning efforts by the authors, asserting that emotion-extraction processes must first become more robust before they can be applied to real-world urban planning efforts; calling even for fully automated emotion-extraction processes before such applications can be attempted.

The work most germane to the present study can be seen in Shoval et al. [22] as they reveal the potential for assessing more momentary discretized physiological-based environmental exposure. Four data collection techniques were used: location data (as collected from GPS), real-time surveying of experience through location- and time-triggered surveys, physiological response data (skin conductance levels, or tonic levels of electrical conductivity), and traditional self-report questionnaires. This ultimately lead to two interesting, and presently-relevant insights: (1) both ends of the emotional spectrum fell under two place categorizations–low SCL belonged to visually-aesthetic places or places of leisure, whereas high SCL was observed in places of either religious importance or ones with potential security risks.

Unfortunately, simply employing qualitative-quantitative methods does not guarantee that both spatial (residential, industrial, business areas) and temporal (e.g., daily, or yearly activity) dynamics of human behavior can be accurately and reliably identified. In fact, subjective judgements are not even required to match autonomous physical responses [17]. To understand fine-grained interactions between human experience and the environment, higher spatiotemporal data resolutions are needed. The spatiotemporal dynamics and features involved in these interactions require more than simplified uses of locations to approximate environmental influences on human behavior [26, 27]. Even well-established cognitive science methods, those which focus on affective, perceptual, and cognitive impacts of individual interaction with the environment, have limited potential for spatial-modeling of an individuals' perception and experience of their environment [28]. Thus, a fundamental methodological issue concerning this relationship at the individual level remains: different delineations of geographic context may lead to inaccurately-assumed relationships between environmental variables and behavior outcomes they are assumed to evoke. [29]. To address this problem, and further substantiate and enhance preexisting research efforts, we leverage emotional experiences of mobile human objects–cyclists commuting along a cycle-highway–state-of-the-art geospatial analytic techniques, and high resolution spatial data to investigate and empirically extract fine-grained, spatiotemporal dynamics of human behavior. Cyclists were chosen for our study sample since using a bicycle for transport involves more direct interaction with the environment than more isolating types of transport such as train and automobile. Thus, cycling highways form an ideal context for mobile emotion measurement to inform urban planning.

Cycle highways are a relatively new type of urban infrastructure that offer healthy and environmently-friendly alternatives to motorized transportation within and between nearby cities. Planning cycling highways for optimal rider experience is important for their overall emotional and physical well-being. This is due in short to stressful or unpleasant cycling experiences most likely to be recalled and as such, unlikely to be repeated, ultimately reducing cycling and possibly contributing to automobile use. Furthermore, the increased popularity of electric bicycles–larger in size, and capable of reaching higher velocities in a shorter time span–creates differing infrastructure requirements, and new challenges to solve. For example, conventional signposting are built for average cycling speeds of 15 km/h, whereas e-bikes can easily reach 25 km/h, with pedelecs nearing 45 km/h [30]. Current infrastructure includes rough paving, sharp turns, and small signs parallel to the direction of travel which are inadequate for navigating while riding at higher speeds. Thus, mapping and analyzing cyclists' experiences can help gather insights into natural spatiotemporal dynamics of people's behavior, and help city planners respond to changing infrastructure requirements. Specifically, we expect areas where infrastructure poses a known problem to lead to more emotional arousal in users. We also believe that uniquely positive or pleasant sights along the route will trigger emotions.

3. Challenges & Aims

Despite its empirical promise, and potential capability for informing current cycling infrastructure, research combining physiological and location data of cyclists is limited. This lacuna may be explained by the inability of traditional GIS systems to properly handle multilevel longitudinal geographic information, output by the movement of individuals within an environment, whose interaction with discrete environmental features changes over time. The closest pioneering effort to such a study, Zeile et al. [17] is limited by rather coarse spatial aggregation of data. For instance, how can skin conductance data be compared across individuals when SCRs can vastly differ from person to person? Thus, comparing each participant's experience against their own baseline in a multilevel model is necessary.

To address this need, we coupled location and physiological measurements of high spatiotemporal resolution (1Hz) to model participants' experiences (operationalized as skin conductance) as a function of environmental characteristics (operationalized as visible land cover).

Our model serves two goals:

1. Establish a methodology for spatiotemporal modeling of emotional reactions to urban experiences
2. Determine how environmental stimuli along a cycle highway influence electric bicycle users' emotions.

To carry out these objectives, we established the following research questions:

1. How does extent of a given land cover type in a electric bicycle rider's view affect her or his level of emotional arousal, while controlling for ride speed, direction, and distance to roads?

2. Do changes in direction (turns) explain additional variation in skin conductance when extent of viewable land cover type, ride speed, direction, and distance to roads are accounted for?

4. Methods & Data

4.1. Study Region

Our study took place on the F261 cycle highway from Tilburg via Loon op Zand to Waalwijk, Netherlands (see Figure 1). It has been established as a demonstration route for research on the effects of various traffic situations and bicycle infrastructure on cyclists' experiences. It is 18 kilometers long, is approximately evenly divided between urban and rural environments, and connects the municipalities of Tilburg, Loon op Zand and Waalwijk.

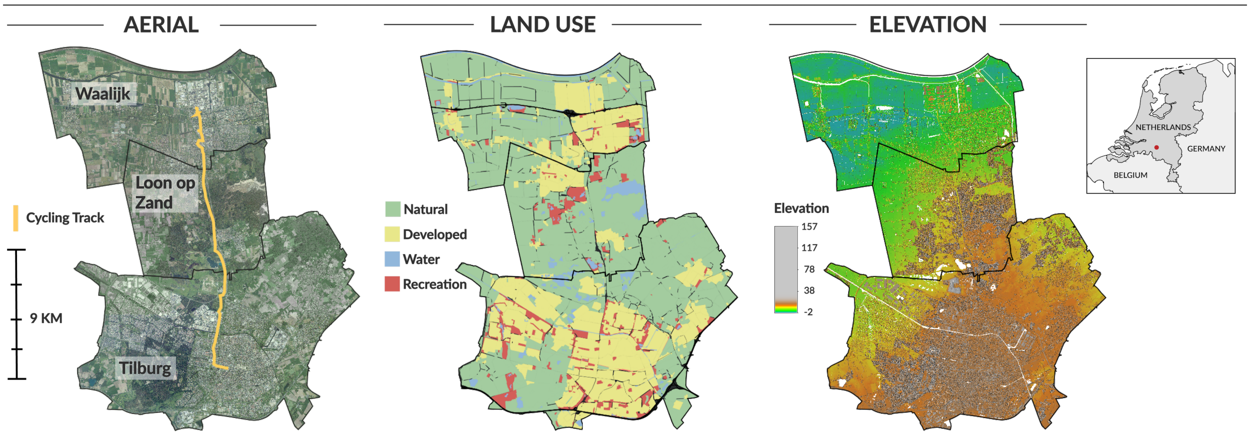

Figure 1: Cycling track on a bicycle highway participants took between the main municipalities of Tilburg and Waalwijk, Netherlands and static geospatial data layers used in the study.

4.2. Procedure & Participants

12 participants (4 female, 8 male) unfamiliar with the cycling route were recruited for this study. Half (N = 6) of participants' ages ranged from 18-24 years old (M = 21), while the remaining half were 55 years or older (M = 65). Participants were asked to provide information on their weekly cycling habits. Younger participants, mostly university students, reported cycling functionally three days a week (M = 20.4 minutes per day), while those 55 years or older cycled 2.5 days a week (M = 22.6 minutes per day). Recreationally, younger participants cycled roughly 1 day a week (M = 23.4 minutes per day) and older participants cycled 2 days a week (M = 4 hours per day).

Wearable physiological measurement and location tracking were combined to collect in-depth spatiotemporal information on participants' experiences. Participants cycled on an electric bicycle (electric support reaching up to 25 km/h) on the route between Tilburg and Waalwijk. They were assigned to follow the cycle highway. During their journey on the cycle highway, a researcher observed the participants. None of the participants were familiar with the route and they all used the signposting, infrastructural layout, and other indicators to find their way. Half of participants cycled in the direction from Tilburg to Waalwijk, while the other half cycled in the opposite direction.

4.3. Mobile Data Collection

4.3.1. Location and Speed

Location data were collected through a dedicated smartphone application. The application utilized both the smart phones' GPS and the cellular network location to record participants' whereabouts throughout their cycling trip as well as speed and elevation (see Figure 2). Collected time-stamps (Table 1) allowed for synchronization with skin conductance response data, a key aspect when analyzing skin conductivity as it allows for accurate logging of start- and end-times of specific physiological episodes.

The high sampling frequency of the location data (Table 1) resulted in an unrealistic, noisy speed variability. We used weighted moving average with 30 seconds backward and forward window to compute smoothed speed along the cycle highway for each participant. The weights were linearly decreasing from 1 at the current point to zero at

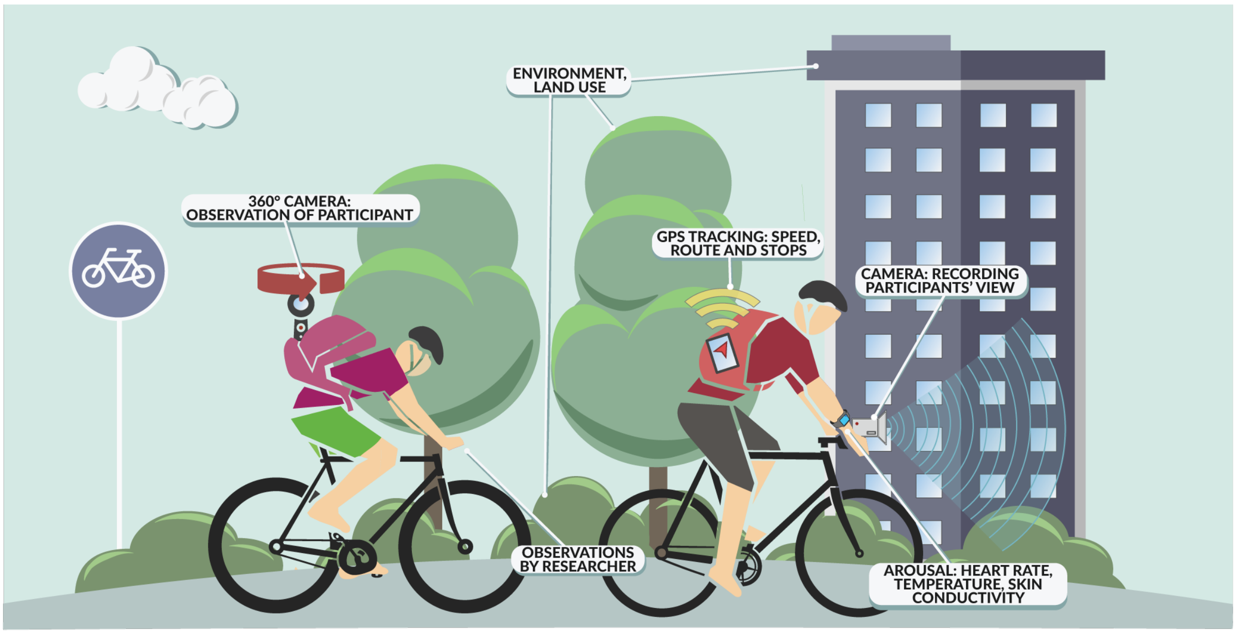

Figure 2: Data capturing process.

the window limits and subsequently the weights were re-normalized so that they summed to one. In this manner, the mean was unaffected while the noise decreased roughly by an order of magnitude and longer intervals of break in speed due to stops were still well represented.

4.3.2. Physiology

As cyclists biked along the track, their physiological arousal (operationalized as skin conductance) was measured using a wrist-worn Empatica E4 wearable, which uses two active electrodes on the bottom of the wrist. Skin conductance was recorded at a rate of 4 Hz. It is well-established that raw skin conductance signals result from two separate processes—rapid responses to emotional stimuli, and gradual change due to differences in temperature, physical activity, and the wearing of a sensor against the skin. The former component, known as phasic skin conductance or skin conductance responses (SCR), is the variable of interest in emotion physiology using skin conductance. Skin conductance responses were derived from the raw skin conductance signal in Ledalab [31], a MATLAB-based [32] software for the analysis of raw EDA data.

We first used a moving window of 20 seconds to identify deviations of 3 standard deviations or more as potential motion artifacts. These deviations were visually inspected and if they failed to conform to a standard, physiologically-plausible shape for a SCR, were replaced with linear interpolation. Cleaned data were then deconvoluted using the Ledalab toolbox into phasic and tonic components. After deconvolution, we proceeded with data representing the phasic component in R [33].

As mentioned earlier, the physiological data were georeferenced through a time-based synchronization of the SCR data with GPS location data. The entire data set, consisting of over 180000 georeferenced physiological measurements, was then re-projected to the local coordinate reference system (Amersfoort, EPSG: 28992) to facilitate integration with the geospatial data sets and efficient analysis.

Table 1: Descriptions, sampling devices, processing software, and sampling rates associated with various human movement, physiology, and environmental location data variables.

	Variable	Description	Device [Software]	Sampling Rate
Human Movement & Physiology	Init_time	Time stamp in Unix Time	Empatica [Matlab]	4Hz
	Init_time_mat	Time stamp in datetime format	Empatica [Matlab]	4Hz
	Fsample	Sample frequency	Empatica [Matlab]	4Hz
	Time	Sampled at a 4Hz frequency (s)	Empatica [Matlab]	4Hz
	Datatype	Type of data (SCR or GPS)	Empatica [Matlab]	4Hz
	Conductance	Raw Electrodermal Activity (EDA)	Empatica [Matlab]	4Hz
	Conductance_z	Z-transformed EDA	Empatica [Ledalab]	4Hz
	Tonic_z	Z-transformed SCL*	Empatica [Ledalab]	4Hz
	Phasic	Raw SCR	Empatica [Ledalab]	4Hz
	Phasic_z	Z-transformed SCR	Empatica [Ledalab]	4Hz
Environmental Location	Latitude	Coordinate data (northing)	Mobile GPS [R — GRASS]	16Hz
	Longitude	Coordinate data (easting)	Mobile GPS [R — GRASS]	16Hz
	Altitude	Height from sea level (m)	Mobile GPS [R — GRASS]	16Hz
	Distance	Meters from starting point	Mobile GPS [R — GRASS]	16Hz
	Speed	Current velocity (km/h)	Mobile GPS [R — GRASS]	16Hz

* Skin conductance level.

4.4. *Static Geospatial Data*

To develop digital surface model (DSM) and land use maps we used three geospatial datasets including orthoimagery, airborne lidar data, and vectorized buildings, roads, and other land use features downloaded from the official open data repositories (http://ahn.nl). See Figure 1 for an overview of the geospatial datasets used, and the Appendix[1] for the full Jupyter notebook environment that contains all used data and details cloud-executable code of the employed analyses.

4.4.1. *Elevation*

DSM was interpolated from first-return lidar points at half-meter resolution to provide input for computation of viewsheds along the cyclists path while capturing impact of buildings and other structures. We used a regularized spline with tension algorithm implemented in GRASS GIS [34] to balance the smoothness and approximation accuracy of the surface.

4.4.2. *Land Use*

Environmental features often have a significant impact on how cyclists value their environment and the trips themselves. Thus a detailed land use data set is essential for discrimination of fine-grained urban patterns (e.g., buildings, single trees, sidewalks) as related to variations in human physiological response. Within the current context, land use was split into the following seven classes: developed, natural, recreation, water, business, agriculture, and forest. These land cover classes were categorized based on re-classification of the public land use data classification. For example, developed areas were classified as any area with high levels of surrounding urban life. Natural areas in the vicinity of the cycle highway consisted of grasslands, herbaceous, unpaved surfaces, grass, orchards, meadows, and any other layers constituted by greenery. Recreation contained places frequented for leisure like parks, amusement parks (specifically Efteling, a fantasy-themed amusement park), soccer pitches, and camp sites. Any area described as containing a body of water was also defined. The polygon-based land use layer was then converted to 0.5 m resolution raster representation.

[1] https://colab.research.google.com/drive/14YzMIiYTjpYVBQi0vrlN-GRwU4vJOrDQ/

5. Analysis

5.1. Distance to Roads

Since our analyses are interested in any potential dependence between distance from environmental features and associated skin conductance values, we used v.distance[2], a GRASS GIS [35] module to map the distances between each cyclist's locational point and the closest roads. These were stored for later statistical analyses to determine possible relationships between how far away cyclists were from roads and observed levels of emotional arousal.

5.2. Viewsheds

Viewsheds, the portions of a landscape visible from a given point or set of points [36, 37], are computed on a DSM based on a line-of-sight method. To perform this analysis, we used the GRASS GIS r.viewshed[3] module, which employs a computationally efficient algorithm (line-sweeping method) suitable for deriving viewsheds on a high-resolution DSM [38].

The viewsheds were computed for 1739 viewpoints evenly distributed along the cycling highway at 20 m intervals. Considering the marginal increase in a person's height when riding a bike, the viewsheds were computed on the 0.5 m resolution DSM slightly above eye-level–1.75 m–to simulate a typical viewpoint while riding a bicycle. Cyclists' maximum range of visibility was set at 1000 m (1 km). Additionally, we limited cyclists' horizontal viewing angle to 180°. The viewing angles were computed based on the directions participants were traveling along the cycle highway, and were set in degrees counterclockwise (East is 0°), between 0°and 360°(Figure 3b).

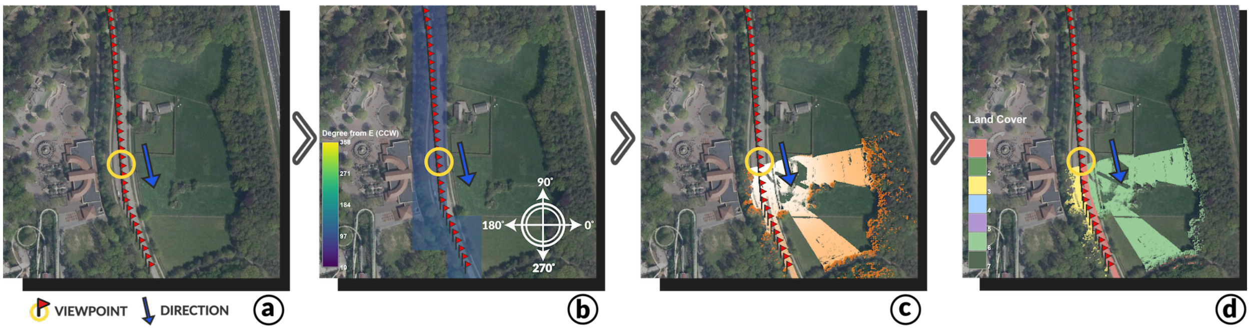

Figure 3: Procedure for computing viewshed for a single viewpoint: (a) viewpoints were set along the cycling highway at 20 m evenly distributed intervals; (b) riding direction angle was established with line direction in degrees counter-clockwise from east; (c) binary viewsheds generated on the DSM, horizontally limited to 180°; (d) viewshed maps were then intersected with land cover data layer to extract visible land cover classes.

Viewshed maps were then intersected with land cover data and zonal statistics were applied to extract proportional contributions of each visible land cover class (e.g., buildings, forest) within the total visible area, creating "visible land cover maps." These maps are high-resolution visualizations of participants' environmental interaction as it unfolds over time, within both natural and built conditions (Figure 3d). By coupling these with associated Z-transformed SCR data (phasic z), we can then statistically associate variations in the cyclists' perceptual and related mental states as they experience their environment.

5.3. Statistical Modeling

Because the data were nested within participants, we took a within-participants multilevel modeling approach using the lmer() function in R. The specific modeling approach used, within-participant random intercept models, model unique variance in a time-variant outcome as a function of time-variant predictors for an average participant, while controlling for baseline (intercept) differences between participants in the outcome variable. Because our central question (RQ1) was to determine the effects of environmental stimuli on experience, we used variables representing stimuli—viewable area in different land cover types, direction, distance to road, and speed—as predictors. We used a variable representing experience, quantified as phasic skin conductance responses, as the outcome. We compared this model using an F-test to a model with no predictors to establish its overall predictive value, before applying the Satterthwaite approximation of T-value to determine the statistical significance of each parameter.

[2] https://grass.osgeo.org/grass78/manuals/v.distance.html
[3] https://grass.osgeo.org/grass78/manuals/r.viewshed.html

We took a hierarchical approach to making the model more complex as a way of addressing our subsequent research question. As previous research based on the same participants emphasized the importance of turns during navigation to the overall experience, we added a measure of directional change to the model (RQ2), once again using the F-test to determine if this constituted an improvement in model fit.

5.4. Dynamic Visualization

To move beyond an aggregated consideration of space and time, we have developed a dynamic, interactive web-based mapping system capable of: registering linkages at individual and grouped levels; visualizing high-resolution spatiotemporal, geographically contextualized, interpretable data; and allowing researchers to investigate various aspects of environmental exposure and experience simultaneously.

The main view of this system and its user interface is shown in Figure 4. Its components, key views, and interactive features are described below. The implementation is mainly based on Mapbox GL JS, a JavaScript library that uses WebGL to render interactive maps.

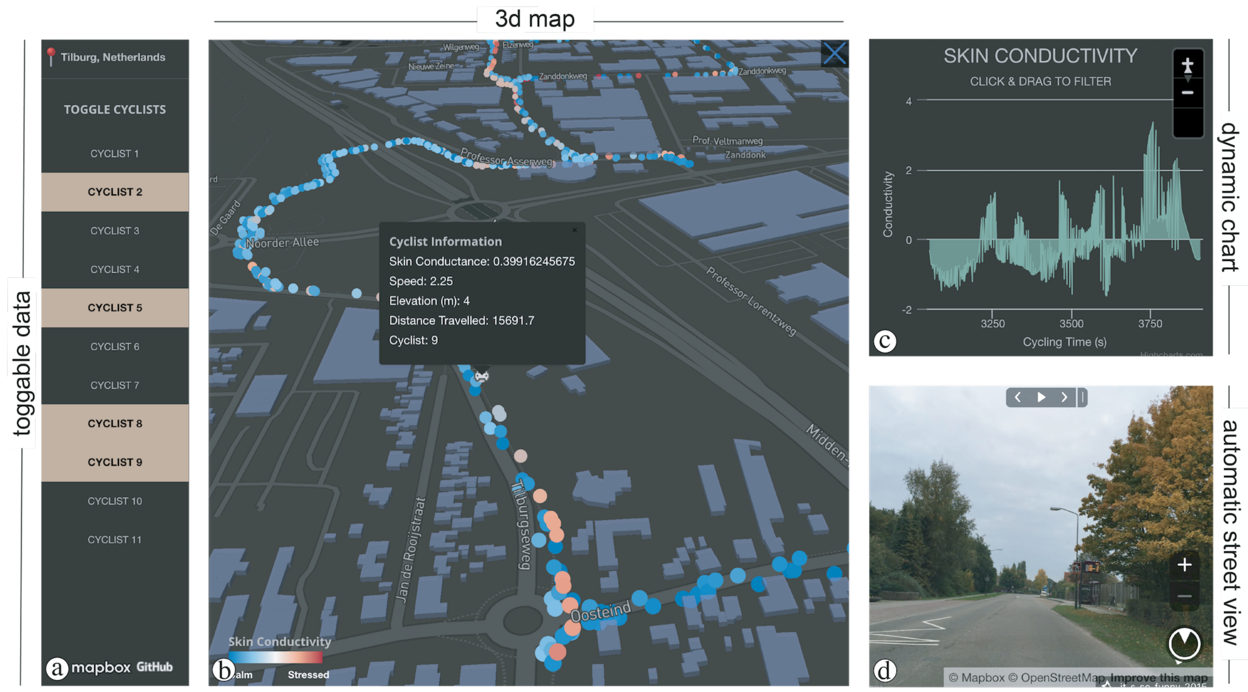

Figure 4: Web-based dynamic visualization of georeferenced physiological data: https://gcmillar.github.io/stress3d/

Toggable Data. With toggable data, we can seamlessly switch back and forth between different cyclists. This is important to explore variability in skin conductance that can be exhibited across multiple participants and can influence the statistical modeling. *3D Map.* The 3D map view provides an overview of the cyclists' physiological responses to and within the spatial context, including the effects of 3D buildings. It allows us to display the data as a 2D map or zoom-in and explore the details in a 3D perspective view. The 3D view facilitates visual assessment of the data location accuracy in relation to the buildings and transportation infrastructure, query all attributes associated with each point and visually analyze spatial patterns of attribute values using colored point symbols. The 3D mapping platform thus serves as a valuable feature for exploration, analysis, and interpretation of complex human physiology data across 3D urban landscapes.

Automatic Street View. The automatic street view allows us to more naturally and realistically inspect areas and their surrounding environmental features at a given time and provide insights into the complexities of moving through and directly experiencing 3D space.

Dynamic Graph. The dynamic graph shows the temporal distributions of cyclists' collective (or individual when only one cyclist has been selected) physiological patterns. This chart dynamically displays all data that is currently loaded into the map frame. As we zoom in and out and pan around in the map, the chart automatically updates with a spatiotemporal overview of complex, highly dynamic human physiological data.

Overall, the 3D viewer visualization and user interaction components enabled us to explore multiple data sources and related spatiotemporal details of fine-grained dynamics of human physiology. It was essential for informing the development of workflows for data processing and for interpretation of the results.

6. Results

6.1. Descriptive Statistics

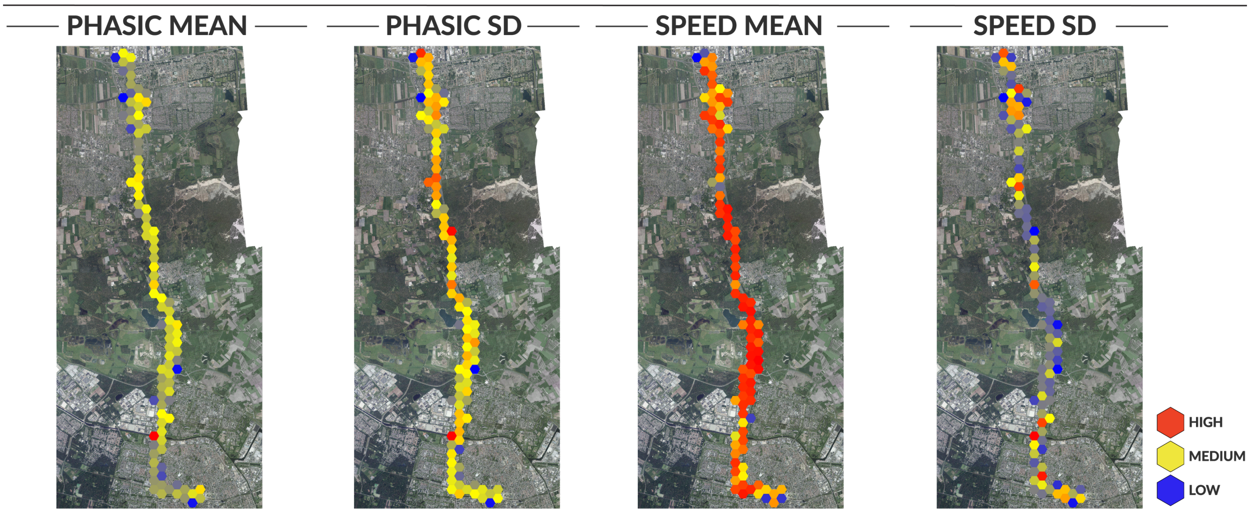

Figure 5: Hexagonal-binned maps indicating means and standard deviations (SD) of skin conductance response (phasic Z) and speed data variables across the entire cycling highway. Blue hexagons indicates lower statistical values while red hexagons show higher values.

To summarize and graphically represent descriptive statistical results from the measured data, we used a hexagonal binning process–a technique for synthesizing geographical data which groups pairs of locations based on their distance from one another across a spatial grid. Figure 5 shows the resulting gridded hexagons, generated at 300 m resolution. These display spatial distributions of the phasic skin conductance component and the speed variables along the cycling route used in our mixed-effects linear models (see Section 6.2), grouped by their respective average and standard deviations.

6.2. Multilevel Models

Our initial model (Table 2) examined the relationships between visible extent of seven different landcover types and emotional arousal while controlling for ride direction, speed, and proximity to roads. This model was significantly better than a null model (*AIC* = 356400; *LL* = -178187; *Chi-square* = 4143.1; p <0.001). Of the control variables, distance to roads was positively related to emotional arousal, while speed was negatively related to emotional arousal. Direction, namely whether participants cycled from Tilburg to Waalwijk or vice versa, was unrelated to emotional arousal. The visible extent of five landcover types had a significant effect on emotional arousal. The effects of viewable recreation, agriculture, and forest areas were positive, while the effects of developed and business areas were negative (all p's < 0.001). Thus, while holding distance to roads, speed, and direction constant, extent of viewable areas managed for natural resource uses were relatively more emotionally arousing, while human-built environments aroused relatively less.

We then entered the variable of directional change into the model, which captures the extent to which participants were turning rather than riding straight in a given moment. This addition resulted in a better fitting model (*AIC* = 355592; *LL* = -177782; *Chi-square* = 809.93; p <0.001). The effects of control variables on emotional arousal did not change in direction or significance. The effects of visible extent of landcover types also did not change in direction or significance, except the negative effect of business landcover became non-significant (p = 0.24). The variable of interest in this analysis, extent to which participants were turning, was negatively related to emotional arousal ($p < 0.001$). In other words, the more steeply participants were turning, the less emotionally aroused they were.

Table 2: Mixed-effects linear models of the connections among viewable land cover, speed, direction, distance to roads, direction changes, and emotional arousal.

	Predictor(s)	Fixed effect CE	SE	T	Model AIC
Model 1					356399.8
	Developed in View	-0.000002	0.0000002	-10.203***	
	Natural in View	-0.000023	0.000025	-0.903	
	Recreation in View	0.0000068	0.0000016	4.221***	
	Water in View	0.0000023	0.0000037	0.643	
	Business in View	-0.0000022	0.0000006	-3.418***	
	Agriculture in View	0.0000014	0.0000002	5.172***	
	Forest in View	0.0000378	0.0000017	22.171***	
	Speed (km/h)	-0.0145064	0.0003125	-46.416***	
	Direction	-0.2884326	0.2334752	-1.235	
	Distance to Road	0.0098596	0.0003992	24.693***	
Model 2					355591.9
	Developed in View	-0.0000016	0.0000002	-6.229***	
	Natural in View	-0.0000299	0.0000256	-1.170	
	Recreation in View	0.00000634	0.00000161	3.921 ***	
	Water in View	-0.00000002	0.00000368	-0.004	
	Business in View	0.00000077	0.00000065	1.182	
	Agriculture in View	0.00000070	0.00000028	2.531*	
	Forest in View	0.00003474	0.00000171	20.361 ***	
	Speed	-0.01495816	0.00031218	-47.916***	
	Direction	-0.28314307	0.23396383	-1.210	
	Distance to Road	0.00871448	0.00040035	21.767***	
	Direction Change	-0.00075514	0.00002650	-28.494 ***	

Note: Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

7. Discussion

The principal aim of the present study was to determine how the visible environment affects individuals' experiences of an inter-urban cycling highway. Twelve participants cycled the cycle highway between Tilburg and Waalwijk while their location and skin conductance were recorded. We used a multilevel model to determine the relationships between different types of viewable land cover and emotional arousal, operationalized as phasic skin conductance, while controlling for speed, direction, and distance to roads. We subsequently added a measure of directional change to the model, which significantly improved its fit. This definitive model suggested that ride segments containing relatively less developed and more recreational, agricultural, and forest land cover in view, were more emotionally arousing for participants. Conversely, segments which were more developed and less covered in visible recreational, agricultural, and forest land cover were less arousing. These patterns occur over and above the positive effect of distance from roads and negative effect of speed, as well as the negative effect of turning, on emotional arousal. Thus, in locations of similar land cover, slower, straighter segments which were further from roads offer higher emotional arousal.

Several studies have shown that emotional arousal is elevated with cities, usually being seen as exciting and stimulating places. This was seen in Zeile and colleagues' research [17, 23, 24, 25], which deemed less-busy streets as more calming. However, these studies relied too heavily on aggregate techniques for assessing spatial-emotional interactions at the individual level. Whereas our model, for the first time, incorporated multiple levels of environmental continuously collected interaction information into a single analysis. Specifically, by holding the environmental and human elements of speed, distance to roads, and turns constant, it more adequately models environmental exposure and interaction relations at both the individual and ecologic levels. Given confounds to emotional arousal held constant, it is very possible that the enjoyment of large, open, green views may comprise elevated emotional arousal, compared to a relatively functional approach to navigating the urban areas of Tilburg and Waalwijk. It is also important to remember that many Dutch cities, including Tilburg and Waalwijk, have a culturally-rich central core surrounded by large, more open commercial and industrial areas. Thus, these larger developed views may have been perceived as boring, and thus relatively low in emotional arousal. Another potential explanation is that the more arousing segments of the ride–which were recreational, agricultural, or forested in view–contain a lower quality of road infrastructure, decreasing cyclists' overall feelings of traffic safety and thus increasing states of arousal. It is more likely, however, that the emotional engagement as we measured it–according to phasic skin conductance, which spikes whenever an individual feels any emotional arousal, positive or negative–reflected a mix of positive and negative emotions.

"All perceptions start with the eye." [39]. That is, human sight is the main driver behind human perception [39] and related place-based experience. Past research has relied on qualitative assessments to establish aesthetic judgments of urban and nature-based locations [2, 20, 21]. Thus, our model, also for the first time, objectively incorporated the more influential perceptual variable of sight to explore relationships between environmental interaction and resulting physiological responses. Simple spatial proximity to an environmental feature does not imply true environmental interaction and experience. Specifically, one can be cycling past an amusement park with yet a low ability to view it due to surrounding tree coverage, speaking to the true value of viewsheds for establishing more accurate environment interaction metrics. This claim is made with caution however, as people still remain capable of developing experiences from multiple sensory inputs. For example, smell, sight, and sound, even when transmitted from long distances, can be simultaneously received, processed, and integrated for immediate experiential development [40, 41, 42, 43].

8. Limitations & Future Directions

This study has several important limitations, mostly stemming from the technical complexity of measuring emotional experiences as they unfold over space and time. While the wearable technology we used to measure skin conductance is increasingly accessible, it is still expensive. Thus, we were limited to a convenience sample of 12 participants, which excludes any possibility of analyzing between-participant differences, some of which strongly affect experiences. Even if budgets do not allow purchasing more wearable devices, it is possible to build up larger sample sized from using groups of participants to record data in "shifts." With such samples, future research stands capable of examining differences in how urban spaces are experienced based on individuals' gender, age, demographic status, and even personality traits.

Similar resource limitations were encountered from limitations in computing computer as required to calculate and generate analyzable viewsheds. While skin conductance was measured at 4Hz, location was only measured at 1Hz, whereas viewshed area and accompanying composition metrics were sampled and analyzed at a reduced spatial resolution, every 20 meters, which was roughly equivalent to temporal resolution of 4-5 seconds, depending on speed. If more powerful devices would be available to record GPS location data at the same 4Hz frequency in which skin conductance is sampled, with calculations of viewsheds matching this frequency as well, presented analyses would be far more precise. However, it is not clear whether this would offer higher statistical power within participants - a thorough analysis and optimization of spatial and temporal resolution should be performed to assess these issues.

Thus, we recommend future research to attend to technological considerations of needed developments and advancements in the implemented technologies–including computer systems such as GIS software and more streamlined, affordable mobile-sensing devices compatible across multiple data streams and spatiotemporal resolutions. That is, higher levels of precision in the collection and post-processing of relevant data streams must be made possible, as outcomes of such research could more robustly support urban planning decisions made for the development, sustainability, and betterment of our environment.

9. Conclusions

Our model incorporated multiple levels of environmental exposure, interaction, and experience into a single analysis. The novelty of our approach is specifically substantiated by holding environmental and human elements of speed, distance to roads, and turns constant, more adequately modeling environmental exposure at both individual and ecological levels. Furthermore, we demonstrated how accounting for a wider range of perceptual variables, specifically cyclists' line-of-sight, results in more accurate extraction of environmental interaction and experience.

This study demonstrated the possibility, potential, and utility in continuously monitoring cyclists with wearable sensors. A novel and complementary perspective has in result been established, which can be adopted to better understand the human experience as it unfolds over space and time, in its appropriate environmental context. In so doing, greater strides have been made toward supplying urban planners with highly-accurate, concrete, educated, and actionable insight which can be used to make just-in-time decisions and and investments; decisions and investments aimed toward making our environment not only a more beautiful place to be visited and traveled through, but one that functionally contributes to an optimized state of emotional and physical well-being.

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