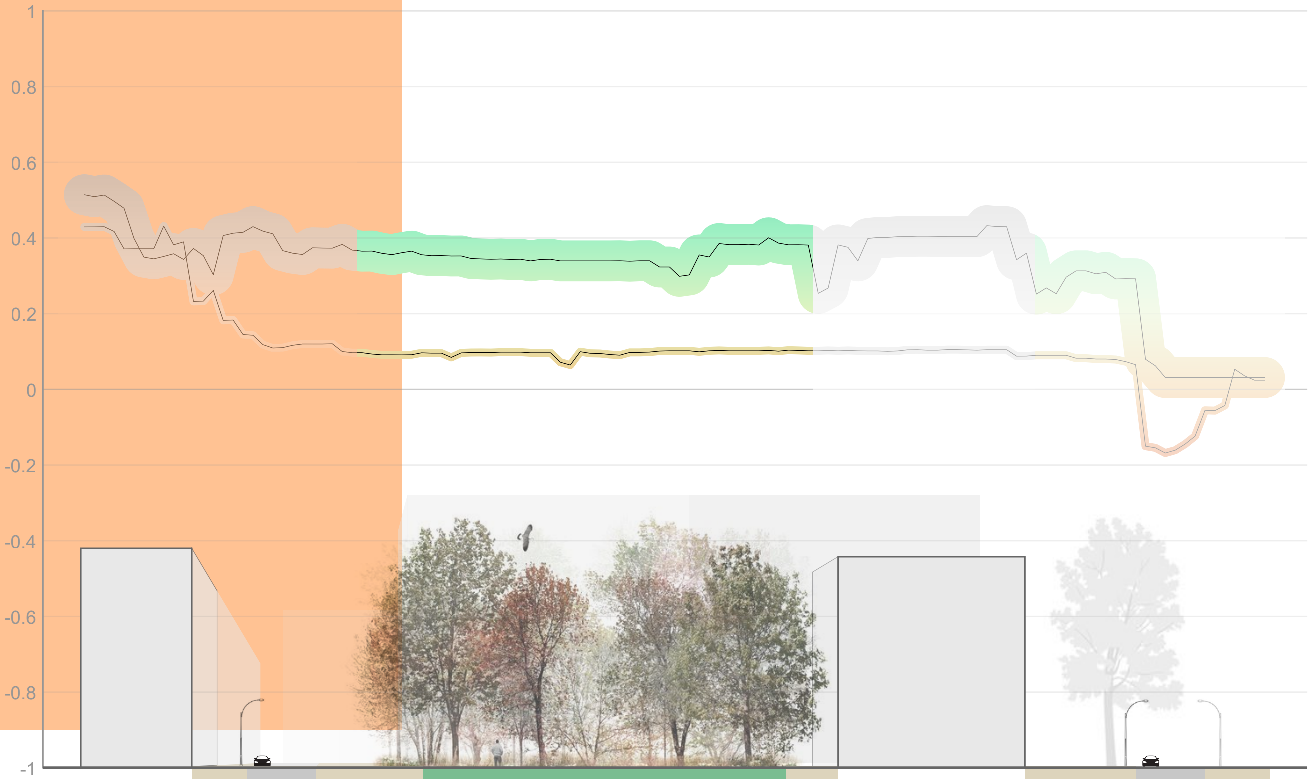
Beyond Noise

A Framework for a Design Tool Predicting and Optimizing Soundscape Design



MSc Thesis

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‘k Sluit m’n ogen als de zon schijnt

Want geluid is soms genoeg en

Kom je me halen uit de speeltuin?

Oh, het klinkt hier als vroeger

(Froukje, 2024)

Abstract

Despite its importance to public health, environmental noise and soundscapes are a forgotten topic in urban design. This study crates a framework for a design tool for soundscape design. The aim of this framework is to bridge the knowledge gap of soundscapes for urban designers. This is done by looking at the relationship between design elements and the percevied pleasantness in the soundscape. This pleasantness will be predicted by machine learning methods.

Machine learning methodologies present a promising approach for predicting and evaluating the efficacy of potential solutions aimed at improving urban soundscapes. By analyzing datasets that include environmental factors, noise levels, architectural designs, and community preferences, machine learning algorithms can help identify optimal interventions. Predictive models can also streamline decision-making processes by forecasting the potential impact of proposed solutions on soundscape quality.

This paper investigates the complexities of urban soundscapes, examines the feasibility and limitations of using machine learning to predict viable solutions, and proposes a data-driven framework to guide decesion-making in urban development. The goal is to enhance auditory environments in urban areas without the necessity of consulting soundscape experts.

The random forest regressor that was used for the prediction model in this research had an R2 of 0.41, explaining 41% of the variance of the model. This framework is tried and tested on a new location to verify its use. The prediction maps and section are a helpful tool in communicating the value of the soundscape pleasantness and understanding the effect that the design elements have on its prediction.

Acknowledgements

I am very grateful for all the help and support I received during my graduation process and with completing my Master's Thesis

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Contents

Chapter 1 Introduction

Motivation and Problem Statement

In urban environments, the prevalence of high-density areas has led to an increasing concern regarding the quality of soundscapes. The persistent noise pollution in these environments poses a challenge in creating harmonious, pleasant living and working spaces. Despite efforts to mitigate noise, the selection and implementation of effective solutions remains a complex and subjective task.

In this context, the exploration of soundscapes in busy, noisy environments emerges as a crucial aspect of urban development. Identifying and evaluating solutions that effectively address noise pollution require a comprehensive understanding of the various contributing factors, human perceptions, and the interplay between environmental characteristics and acoustic properties.

Machine learning methodologies offer a promising avenue to predict and assess the efficacy of potential solutions for improving soundscapes in new urban development. Leveraging machine learning algorithms to analyze diverse datasets encompassing environmental factors, noise levels, architectural designs, and community preferences can facilitate the identification of optimal interventions. Additionally, the utilization of predictive models can streamline decision-making processes by forecasting the potential impact of proposed solutions on soundscape quality.

However, the application of machine learning in predicting effective solutions for soundscapes in urban development necessitates addressing several challenges. These include but are not limited to the interpretation of subjective human perceptions, the integration of multi-dimensional data sources, and the ethical considerations surrounding community inclusivity and diverse stakeholder interests.

Therefore, the central aim of this thesis is to investigate the complexities of soundscapes in busy, noisy environments, explore the feasibility and limitations of machine learning in predicting viable solutions, and propose a framework for leveraging data-driven approaches to guide decision-making in new urban development for improved auditory environments without the need of consulting soundscape experts.

Background

Environmental noise impact

After fine particulate matter, traffic noise, including road, rail and air traffic, has been classified as the second environmental threat to public health in western Europe(EEA, 2020). In the western part of Europe every year at least one million healthy years of life are lost from traffic-related noise. Sleep disturbance and annoyance, mostly related to road traffic noise and impact on the cardiovascular and metabolic system, comprise the main burdens of long-term exposure to environmental noise (WHO, 2023). Noise pollution in urban areas has become a serious public health concern.

While Noise annoyance is one of the main burdens of traffic noise, Research on sound quality indicates that merely 30% of the irritation caused by noise stems from its physical attributes, such as sound energy. Therefore, only focusing on reductions in sound levels will not directly translate to an improved quality of life (Acun, 2021). While traffic and industrial activities often limit the possibility of substantial sound level reductions in urban environments, other strategies exist to mitigate stress and annoyance by exploring other potential modifications that enhance the overall satisfaction of residents in these settings.

Soundscapes

From soundscape research and literature we can find that different factors can play a role in the acoustical comfort of participants. The International Organization for Standardization (ISO) defines a soundscape as a "[the] acoustic environment as perceived or experienced and/or understood by a person or people, in context" (NEN-ISO 12913-, 2014) It is not merely the physical acoustical context. It is the relationship between human beings and the acoustic environment, based on four elements: sound, space, people and the environment (Zhang and Kang 2007). Alleta et al (2018) found through a systematic literature review that positive soundscapes were associated with faster stress-recovery processes in laboratory experiments, and better self-reported health conditions in large-scale surveys (Aletta and Kang, 2018). Soundscape research is essential for understanding and optimizing the interplay between environmental acoustics and human well-being, providing insights crucial for designing spaces that promote positive auditory experiences and health outcomes.

Machine Learning

Traditional approaches to enquire data for soundscape research have often relied on manual analysis and subjective assessments. However, the integration of machine learning techniques offers a transformative potential to enhance the efficiency, accuracy, and depth of understanding in this field. Machine learning presents an opportunity to analyze complex acoustic data collected from diverse urban environments, identify patterns, and predict the efficacy of different interventions or designs in mitigating noise pollution. However, the application of machine learning models to evaluate and predict the effectiveness of these solutions in new urban development contexts remains an underexplored area.

In the context of the Netherlands, a country renowned for its commitment to sustainable urban development and environmental conservation, the soundscape plays a pivotal role in shaping the urban experience. With densely populated cities and a strong emphasis on environmental sustainability, understanding and managing the acoustic environment is crucial for ensuring a harmonious and livable urban landscape.

Research definition

Research objective

The objective of this research is to develop a comprehensive framework for a design tool that can anticipate and evaluate perceived sound quality in emerging urban (re) developments.

The proposed approach involves the training and validation of an existing soundscape quality prediction model for analyzing existing urban environments, specifically chosen for its adaptability to analyze the perception of the acoustic environment of new urban developments. The selected model will be repurposed and trained on a modified dataset tailored to the nuances of soundscape research.

The ultimate deliverable will be a well-trained model capable of generating predictions regarding soundscape quality for novel urban designs. The output will be presented in the form of an accessible and user-friendly soundscape map.

Research questions

With this research objective my main research question will be:

Main Research Question:

How can soundscape design, and urban acoustical comfort, be integrated in the early stages of the design process of urban (re)development, in an accessible and intuitive way, without relying on the need of experts?

To be able to answer this question I will be looking at the following sub questions to provide some insights:

Quality of sound and soundscapes

What is 'good' soundscape design?

Perception and Soundscape Components:

What correlations exist between the identified soundscape indicators and descriptors of human perception of comfort or discomfort within urban environments?

Computational Design Integration

To what extent can computational design tools, in the shape of machine learning models, incorporate soundscape data to inform and shape urban design elements for improved soundscapes?

Soundscape of Design Iteration

How do design iterations impact the perceived quality of soundscapes within urban environments?

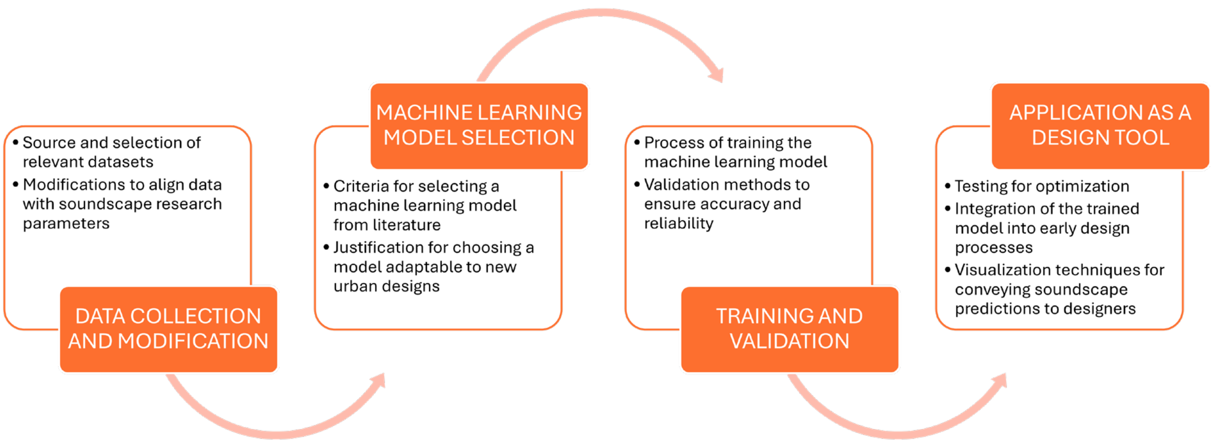


Figure 1 Methodology process, by author

Research outline

My first two research questions can be answered with findings in existing literature. For my literature research I have looked at the following fields.

I have used the search queries:

soundscapes AND urban AND design

soundscapes AND "machine learning"

soundscapes AND mapping

"machine learning" AND urban design

With this research I found +- 8 studies that had a similar direction as the proposed plan of this thesis project. In the literature studies these will be shown and analyzed. Figure 2 shows the different fields research for this thesis.

The responses to the latter two research questions will unfold within the design process outlined in the methodology. Chapter 1.3 offers a comprehensive description of the methodology, explaining the sequential steps undertaken to address the research questions and providing an in-depth explanation of each phase. The four phases are: Data collection, machine learning model selection, training and validation and application as a design tool.

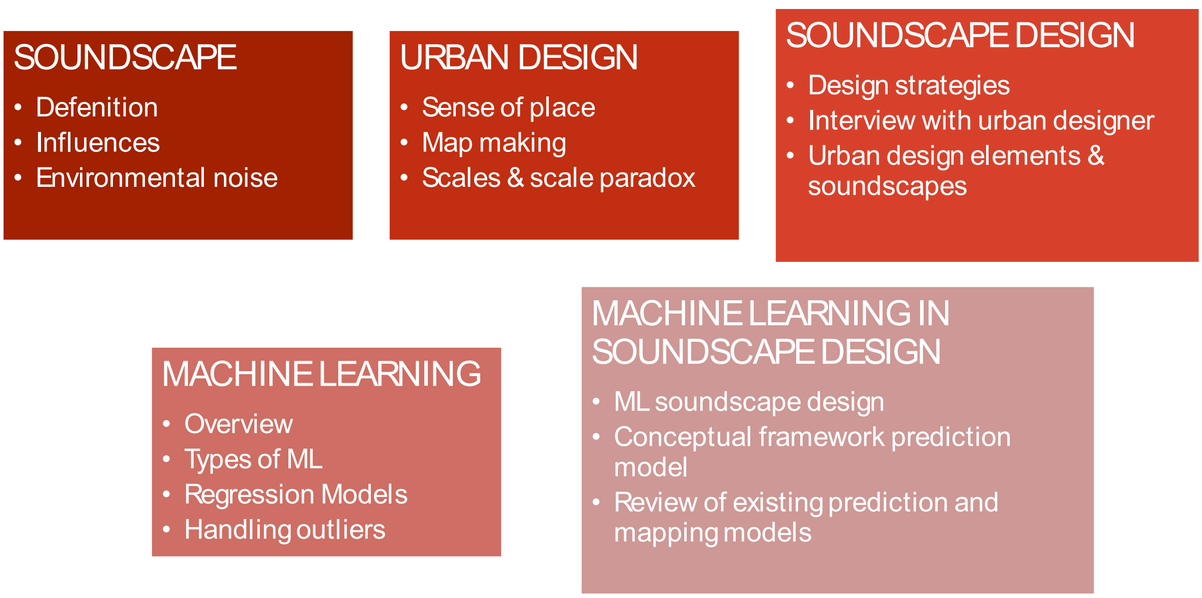


Figure 2 Literature Review

Methodology

The framework for the design tool

In urban design there is a gap in the awareness and understanding of the design decisions and their impact on the perceived sonic environment, namely the soundscape. The research focusses on bridging this gap by creating a comprehensive framework tailored to equip urban designers with the right tools for navigating and designing soundscapes. By developing this toolkit, designers will be empowered to conduct early-stage assessments of the acoustic environment, facilitating more informed and efficacious design decisions.

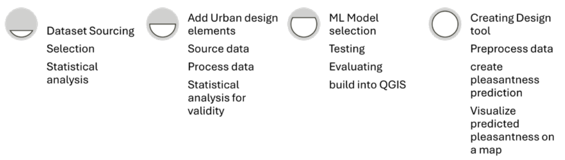


Figure 3 Methodology, by author

The methodology for this research and design project involves a sequential process encompassing literature studies, data selection and analysis, machine learning model selection, machine learning model training and validation, and the subsequent creation and application of the chosen model as a design tool.

Data Selection and Availability

Data selection and availability are critical considerations in model development. The dataset that is selected, should contain comprehensive information regarding the assessment of perceptual quality in acoustic environments and the perceived presence of diverse sound sources. The dataset that is chosen is the dataset from the international soundscape database (SSID). This dataset contains information on the perception of the pleasantness of the acoustic environment and the perceived sound sources, as well as coordinates.

The dataset has undergone a statistical analysis, to find patterns in the dataset itself and outliers are removed.

Sourcing georeferenced urban design data

Additionally, geographical data, including coordinates, enrich the dataset by facilitating precise mapping of points, thus enhancing spatial understanding. The additional data was sourced from OpenStreetMap (OSM) and other publicly available databases. This data, alongside the SSID dataset, is loaded into QGIS to prepare and modify the dataset.

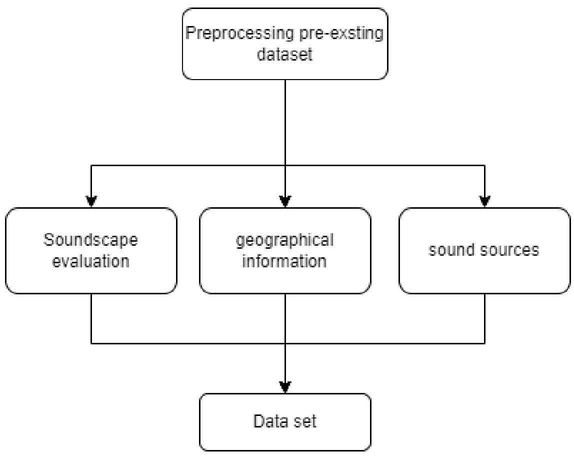


Figure 4 Data modification, by author

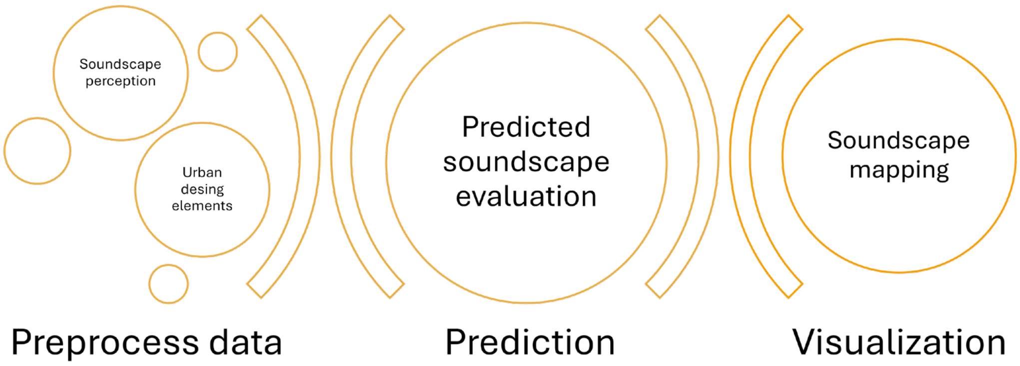


Figure 5 Framework visualization process, by author

Machine Learning Model Selection

The machine learning model selection involved studying various models and their characteristics, and also a process of trial and error, in which multiple models were tested for accuracy and compatibility.

For this research multiple regression models were compared. Another path that was looked into was an image recognition model. However it was opted not to choose such a model.

The first reason why this method is not chosen, is the data availability. For this type of modeling a large dataset is needed. For smaller datasets a regression model can be trained more effectively. Regression models are less complex to implement and interpret than image recognition models, especially with smaller datasets. The next reason is the datatype. The descriptor Pleasantness is a numerical value, this is more suited for regression. This output for the regression model might also be easier to interpret, than classification labels. Overall for this research opting for regression models, seemed to be the best option.

For fast comparisons the PyCaret Library was used. This is a user-friendly python library for quick ML model comparisons, of 25 different regression models. From there 3 with the highest R2 and lowest errors were selected. These were examined further. This was done with some extra literature studies, and attempts in optimizing and tuning the models. Based on the characteristics of the models, and their performance, the most suitable one was selected.

Application as a Design Tool

To create the framework for the design tool, the tool needs to be created. The practical application phase comes after successful training and validation of the model. The models is then also built into a QGIS function. The model is created to be user-friendly, so easy to use for people with no background in soundscape design.

This function preprocesses the georeferenced urban design elements, such as the roads, buildings and parks, and adds this data to a grid for which a pleasantness value is predicted. To visualize this data a raster is created with these predicted values.

This Design tool was then optimized with multiple alterations, by testing the application on locations of the sourced dataset, and by applying it into new designs.

Chapter 2 Literature

Environmental Noise & Health

The World Health organization (WHO) defines environmental noise as "noise emitted from all sources except for noise at the industrial workplace" in the Guidelines for community noise (WHO,1999) The European Union Directive 2002/49/EC on the management of environmental noise has a slightly different definition of environmental noise. It defines environmental noise as "unwanted or harmful outdoor sound created by human activities, including noise from road, rail, airports and from industrial sites".

Health Effects

After fine particulate matter, traffic noise, including road, rail and air traffic, has been classified as the second environmental threat to public health in western Europe. Long-term exposure to noise that exceeds certain levels can lead to non-auditory health effects. This includes annoyance, sleep disturbance and impact on the cardiovascular and metabolic system (EEA, 2020). Environmental noise is an important public health issue, featuring among the top environmental risks to health (WHO, 2023).

Merely 30% of the irritation caused by noise stems from its physical attributes, such as sound energy . Therefore, it is challenging to assert that a reduction in sound levels will inevitably translate to an improved quality of life (Acun, 2021). Together with sleep disturbance, noise annoyance is one of the main burdens of traffic noise (WHO, 2011). Annoyance is not classified as a "health effect", but it does effect the wellbeing of many people, and falls within the definition of The WHO of health as 'a state of complete physical, mental, and social well-being, and not merely the absence of disease of infirmity'.

From soundscape research and literature we can find that different factors can play a role in the acoustical comfort of participants. While traffic and industrial activities often limit the possibility of substantial sound level reductions in urban environments, avenues exist to mitigate stress and annoyance by exploring other potential modifications that enhance the overall satisfaction of residents in these settings

Regulations

The European parliament and of the council defines Lden in Directive 2002/49/ by formula 1: in which: $L_{day,}$ $L_{evening}$, and L_{night} are A-weighted long-term average sound levels, defined in ISO 1996-2:1987, calculated across day, evening, and night periods throughout a year respectively. The EU Member States choose the start times for day, evening, and night periods, consistent for all noise sources. Typically, defaults are 07:00-19:00, 19:00-23:00, and 23:00-07:00 local time (EEA, 2002). The WHO (2011) recommends reducing traffic noise levels to be below 53 dB Lden. As for night exposure, L_{night} should be below 45 dB.

According to the Dutch 'Wet Geluidshinder', homes built within a restructuring, planned densification of an existing residential area, or adjacent to an existing residential area with limited expansion may have a maximum allowable noise level of up to 60 dB(A). For new homes replacing existing ones or other sound-sensitive buildings may set a maximum noise level of up to 65 dB(A). This is in regards to industry noise

The maximum allowable noise level at the facades of homes in an area due to road traffic is set at 48 dB. However, for future homes in urban areas not yet planned,

$$L_{den} = 10\log\left[\frac{1}{24}\left(12*10^{\frac{L_{day}}{10}} + 4*10^{\frac{L_{evening}+5}{10}} + 8*10^{\frac{L_{night}+10}{10}}\right)\right] \quad dB$$

Formula 1 Lden: Directive 2002/49

a maximum noise level of 63 dB from an existing road can be established. Similarly, for existing or under-construction homes in urban areas, the future noise levels from a road not yet planned can also be set at a maximum of 63 dB.

The emphasis on setting maximum noise levels for dwellings in the Netherlands, as outlined in the 'Wet Geluidshinder,' stems from the direct impact of noise on residents' well-being and quality of life. Dwellings, serving as personal sanctuaries, warrant stringent regulations to ensure a peaceful living environment. The flexibility in noise regulations for urban areas acknowledges the dynamic nature of these spaces, allowing for a balance between development and noise control to accommodate diverse activities and functions. For 2024 the legislation has been updated.

Table B: Noise levels applicable to noise sensitive residential development proposed in areas of existing noise

Dominant Noise Source	Assessment Location	Design Period	LOAEL (Green)	LOAEL to SOAEL (Amber)	SOAEL (Red)
Anonymous noise such as general environmental noise, road traffic and rail traffic –	Noise at 1 metre from noise sensitive façade/free field	Day	<50dB $L_{Aeq,16hr}$*	50dB to 72dB $L_{Aeq,16hr}$*	>72dB $L_{Aeq,16hr}$*
		Night	<45dB $L_{Aeq,8hr}$ <40 dB $L_{Aeq,8hr}$**	45dB to 62dB $L_{Aeq,8hr}$* >40dB L_{night}**	>62dB $L_{Aeq,8hr}$*
	Inside a bedroom	Day	<35dB $L_{Aeq,16hr}$	35dB to 45dB $L_{Aeq,16hr}$	>45dB $L_{Aeq,16hr}$
		Night	<30dB $L_{Aeq,8hr}$ 42dB $L_{Amax,fast}$	30dB to 40dB $L_{Aeq,16hr}$ 40dB to 73dB $L_{Amax,fast}$	>40dB $L_{Aeq,8hr}$ >73dB $L_{Amax,fast}$
	Outdoor living space (free field)	Day	<50dB $L_{Aeq,16hr}$	50dB to 55dB $L_{Aeq,16hr}$	>55dB $L_{Aeq,16hr}$
Non-anonymous noise	See guidance note on non-anonymous noise				

*LAeq, T values specified for outside a bedroom window are façade levels
**Lnight values specified for outside a bedroom window are free field levels

Figure 6 Noise levels for outdoor living spaces, (Camden Local Plan, n.d.)

In London, in the Camden district there are values for 'anonymous noise' such as environmental noise from road or rail traffic. In the green zones, the noise is considered to be at an acceptable level. For an outdoor living space (a garden) this is less than 50dB $L_{aeq,16hr}$. from 55dB $L_{aeq,16hr}$ the SPL does have an adverse effect, this is in the red zones.The amber zones have a value in-between. For healthy outdoor living spaces a weighted SPL of less than 55dB, and ideally 50 dB is required.

Exposure / In practice

According to research from the European Environmental Agency (2020), in the Netherlands 19.3 % of the population inside urban areas is exposed to Lden > 55dB, which is less than in other European countries.

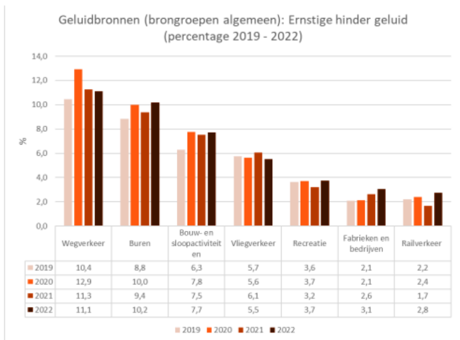


Figure 7 Noise annoyance (Poll and Simon, 2023, p. 16)

The RIVM report of Poll and Simon (2023) found the main sources of noise annoyance ('geluidshinder'). Sound originating from road traffic is, and remains, the primary source of annoyance at 11.1 percent (Confidence Interval: 9.8-12.4%). The percentage is the part of the population that is 16 years and older experiencing the annoyance. Noise from 50 km/h roads cause the most annoyance (7.3%; CI 6,2-8,4%). Other main sources of noise annoyance are noise from: neighbors, construction and demolition activities, air and rail traffic, recreation, and factories.

Soundscapes

The International Organization for Standardization (ISO)defines a soundscape as a “[the] acoustic environment as perceived or experienced and/or understood by a person or people, in context” (NEN-ISO 12913-1, 2014). It is not merely the physical acoustical context. It is the relationship between human beings and the acoustic environment, based on four elements: sound, space, people and the environment (Zhang and Kang 2007).

Perception and experience

Schulte-Fortkamp et al. (2023) describes soundscapes as a perceptual construct of an acoustic environment and, therefore, it must be distinguished from the actual physical environment.

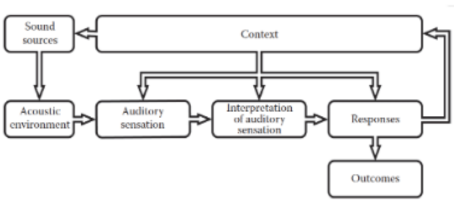


Figure8 Elements that influence the perceptual construction of soundscape experience. (From ISO-12913-1. Acoustics—Soundscape—Part 1: Definition and Conceptual Framework, April 2014.)

Figure 8, in the ISO standard on defining the concept of soundscapes has this diagram for clarification. This biggest influence on the soundscapes is the context. The context facilitates sound sources. They create and mold the acoustic environment. The acoustic environment influences the personal auditory sensation, this sensation is then interpreted. By the meaning given to this sensation, in regards to the context, a response is formed by individuals. For example, if a person would evaluate a soundscapes negatively, a choice can be made to leave and not return to this site. It is interesting to note that context plays a role in interpreting auditory sensations, and our response to them. Non-acoustic factors can influence the way we perceive and react to acoustic environments, like the character of the place (a park), and the timing (on a sunny Sunday afternoon). (Hong and Jeon, 2015) (Haberl, 2018), (Lugten et al., 2017), (Schulte-Fortkamp et al., 2023). Therefore a holistic approach is recommended when studying soundscapes.

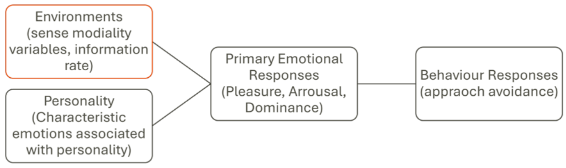


Figure 9 experience of soundscapes P34 Schulte-Fortkamp et al. (2023)

The importance of soundscapes

The soundscape approach in urban design looks beyond noise control. Reducing environmental noise can bring economic and societal benefits, but it doesn’t always directly improve well-being and quality of life, because sounds serve as information carriers, and loudness can be desirable in specific contexts. Systematic reviews by Alleta et al (2018) indicate that positive soundscapes were associated with faster stress-recovery processes in laboratory experiments, and better self-reported health conditions in large-scale surveys (Aletta and Kang, 2018). Therefore adopting a soundscape based approach might be viable for scenarios where high noise levels appear inevitable.

For each of the 8 scales below, to what extend do you agree or disagree that the present surrounding sound environment is...
Please tick off one reponse alternative per scale

	Strongly agree	Agree	Neither agree, nor disagree	Disagree	Strongly disagree
- pleasant	☐	☐	☐	☐	☐
- chaotic	☐	☐	☐	☐	☐
- vibrant	☐	☐	☐	☐	☐
- uneventful	☐	☐	☐	☐	☐
- calm	☐	☐	☐	☐	☐
- annoying	☐	☐	☐	☐	☐
- eventful	☐	☐	☐	☐	☐
- monotonous	☐	☐	☐	☐	☐

Figure 10 Questionnaire Likert scales for Perceived Affective Qualties (PAQ's) (From ISO- 12913-1. Acoustics—Soundscape—Part 2: Data collection and reporting requirements, 2018.)

Assessment of Soundscapes: Descriptors

In a soundscape study, a descriptor refers to a term or set of terms used to characterize and describe specific acoustic qualities or attributes of the auditory environment. There are many ways to evaluate a soundscape and different descriptors for this are used. Descriptors in soundscape analysis are perception based so they are collected through the use of questionnaires or interviews. The descriptors play a crucial role in capturing the diverse and subjective nature of the soundscape by providing a vocabulary to express the perceptual aspects of the acoustic experience.

The most common way in soundscape literature to assess the soundscape quality is through the use of the pleasantness & eventfulness axis defined by Axelsson (2010).

Another more straightforward descriptor is to directly ask people their perceived soundscape quality, like Hong and Yeon (2017), Ricciardi et al. (2015), Boes et al. (2018). Respondents questionnaires can also ask a question similar to this one: Overall, how would you describe the present surrounding sound environment. And gave this a score on the Likert scale from 'very good', to 'very bad'. This can also be used as a valid input for a machine learning model.

Pleasantness from the ISO standard

Axelsson et. al (2010) proposed a model to use as a framework for future soundscape research, and is the most referenced model in other soundscape literature. shown in figure 11. It has a two-axis framework encompassing Pleasantness and Eventfulness dimensions. The third dimension, Familiarity, exhibited low variance and, consequently, has been omitted from subsequent investigations. The descriptors employed in characterizing affective quality are rooted in the model proposed Mehrabian and Russell. (1974), utilizing the dimensions of Valence and Arousal to capture emotional responses to environmental stimuli. Additional descriptors utilized in related research include Calmness and Vibrancy (Cain et al., 2013), Pleasure and Activation (Andringa and van den Bosch, 2013), as well as Appreciation and Dynamism, with Monotony as a third separate descriptor (Tarlao et al., 2019).

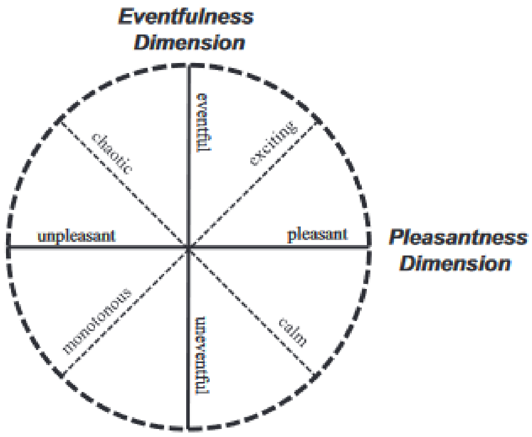


Figure 11 from Schulte-Fortkamp et al., Soundscapes. Two-dimensional representation of the affective quality attributed to acoustic environments

Soundscape prediction models have been measuring pleasantness according to Axelsson's (2010) definition, or have come up with their own descriptor. Another more straightforward descriptor is to directly ask people their perceived soundscape quality, like Hong and Yeon (2017), Ricciardi et al. (2015), Boes et al. (2018) did.

Data Collection

To calculate the pleasantness survey data from a questionnaire is collected via SSID Protocol based on ISO 12913 standard. This is based on a five point Likert scale, as shown in figure 10.

Calculating ISO pleasantness

ISO Pleasant is a descriptor of a soundscape. It is calculated based on 6 survey responses (perceived attribute qualities, PAQ's) that each respondent gives (ISO/TS 12913-3:2019(E), 2019). pleasant, annoying, calm, chaotic, vibrant, and monotonous are perceived effective qualities related to the environment or experience being assessed. These could be subjective ratings given by individuals about how they perceive certain aspects of their environment.

The formula calculates ISO Pleasant by combining three different factors: pleasantness vs annoying, calmness vs chaotic , and vibrancy vs monotony, and normalizing it to a value between -1 and 1 (shown in formula 2). The part inside the square brackets calculates the weighted sum of these factors: The part (pleasant-annoying) measures the difference between how pleasant and how annoying the environment is perceived to be. In the formula cos(45°) Is used with the pairs (calm-chaotic) & (vibrant-monotonous) to adjust for the 45° rotation in the two dimensional model (Figure 1). The denominator 1/ (4 sqrt(32) normalizes the result to ensure that the Pleasant value falls within a the range (-1 to 1).

Probabilistic distribution

In their recent study, Mitchell and colleagues (2022) introduce a novel approach to conceptualize soundscapes as probabilistic distributions. They assert that this framework offers a versatile toolkit for broader application. Viewing soundscape evaluations through the lens of distribution analysis reveals both the mean perception and the variability in auditory experiences. To use this in design the focus should be on shifting the distribution. Figure 10 shows all the possible outcomes of the ISOPleasant score with all the different inputs in the questionnaire.

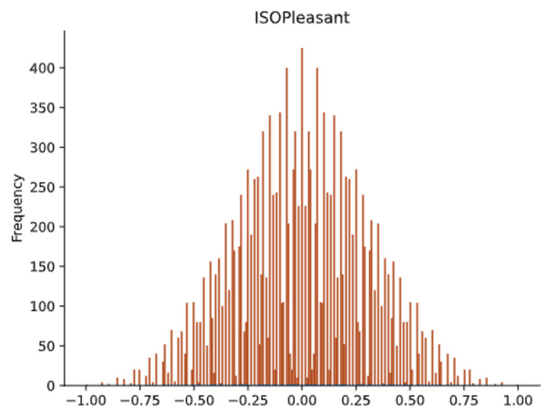


Figure 12 Distribution chances for all soundscape pleasantness scores, by author

Why use Pleasantness from ISO

For this research the Pleasantness score according to the ISO standard will be used as the descriptor. The data for this descriptor is collected by ISO standards through questionnaires, and is based on 6 PAQ's.

$$ISOPleasant = \frac{[(pleasant - annoying) + \cos 45° * (calm - chaotic) + \cos 45° * (vibrant - monotonous)]}{(4 + \sqrt{32})}$$

Formula 2 Pleasantness from (ISO/TS 12913-3:2019).

Comprehensive assessment

the ISO Pleasant formula takes into account multiple dimensions of the environment, including pleasantness, calmness, and vibrancy. By considering these factors simultaneously, the formula offers a more comprehensive assessment of the environment compared to a simple ranking system, which may only capture one aspect at a time.

Precision and Sensitivity:

The precision and sensitivity of the ISO Pleasant formula captures subtle differences in the environment. The weighted combination of factors, along with normalization, ensures that small variations in the environment are reflected in the calculated index. In contrast, a 1 to 5 ranking system may lack the granularity to detect these nuances effectively.

Consistency and Reliability:

the ISO Pleasant formula promotes consistency and reliability in measurement across different contexts and individuals. Since it is based on a standardized mathematical model, the interpretation of the ISO Pleasant index remains consistent regardless of who is assessing the environment. This consistency is crucial for conducting reliable comparisons and drawing meaningful conclusions. It also makes it favorable when collecting new data.

Practical Applications:

the ISO Pleasantness score could be valuable in practical applications, such as urban planning, architecture, environmental psychology, and user experience design. A standardized measure like the ISO Pleasant index can facilitate decision-making and optimization in these domains.

To what extend do you presently hear the following four types of sounds?
Please tick off one reponse alternative per type of sound

	Not at all	A little	Moderately	A lot	Dominates completely
Traffic noise (e.g. cars, buses, trains, air planes)	☐	☐	☐	☐	☐
Other noise (e.g. sirens, construction, industry, loading of goods)	☐	☐	☐	☐	☐
Sounds from human beings (e.g. conversation, laughter, children at play, footsteps)	☐	☐	☐	☐	☐
Natural sounds (e.g. singing birds, flowing water, wind in vegetation)	☐	☐	☐	☐	☐

NOTE The first scale has the heading "traffic noise" and the second completes the category with the heading "other noise." The term "noise" is used instead of "technological sounds". The term "noise" is not intended as a value judgement.

Figure 13 Questionnaire Likert scales for presence of sound source types (From ISO- 12913-2. Acoustics—Soundscape—Part 2: Data collection and reporting requirements, 2018.)

Indicators

Indicators, in the context of soundscapes, refer to measurable parameters or factors that provide information about the acoustic environment. These indicators help quantify and describe various aspects of the soundscape, allowing for a systematic analysis and assessment of the auditory surroundings. Indicators play a crucial role in influencing how we perceive and understand soundscapes. Perceptual indicators, visual and contextual cues, along with the temporal dynamics, collectively offer a more accurate prediction of the overall soundscape quality. Other less effective indicators are physical measurements and, demographic and psychological information. These are the categories under which most indicators fall:

Perceptual indicators

Perceptual indicators are automatically assessed or evaluated by the participants, for example: Subjectively evaluated sound level, and Sound source identification. Other Perceptual indicators are: subjective perception of acoustics, sound source prominence assessment, and subjective preferences.

Sound source identification

Sound sources identification response and the perceptions of the acoustic environment show significant correlations in previous studies(Hong and Jeon (2015). The NVN-ISO/TS 12913-2:2018 Identifies source sources into three main types:

- Sounds of Technology
- Sounds of Nature
- Sounds of Human Beings

The most widely used classification of sound sources suggested by Axelsson, Nilsson, and Berglund (2012). has 5 types of sound sources: Traffic noise, fan noise, other noise (construction, industry, machines, sirens, music), sounds from human beings, and natural sounds. These categories are easy to understand whilst working with people with no background knowledge in acoustics.

These are incorporated in the ISO standard ISO/TS 12913-2:2018(E), 2019 for soundscape data collection, as illustrated in Figure 13. The standard poses the question: "To what extent do you currently hear the following four types of sounds?" The four types of sounds are

- Traffic noise (e.g cars, buses, trains, airplanes),

- Other noise (e.g. sirens, construction, industry, loading of goods),
- Sound from human beings (e.g. conversation, laughter, children at play, footsteps),
- Natural sounds (e.g. singing birds, flowing water, wind in vegetation).

Most soundscape research on this topic finds that sounds of technology (traffic noise and other noise) have a negative impact on the perceived pleasantness. Natural sounds have a positive impact (Lavendier, 2016) (Hong & Jeon, 2017), (Yin et al., 2023).

Visual and contextual information.

Individuals who rate visual comfort highly tend to provide more positive evaluations of acoustic comfort, whereas low visual comfort significantly increases the likelihood of giving a negative assessment of acoustic comfort as well (Lionello et al., 2020). For example: the percentage of blue, the percentage of natural and contextual features in the visual context are visual or contextual indicators that can predict the soundscape quality. Changing visual features can positively affect the soundscape perception of places exposed to traffic noise (Lugten et al., 2017). Mainly adding vegetation had a positive effect.

Acoustic and Psychoacoustic indicators

Acoustic indicators are acoustic metric that can be measured. For example: The Sound Pressure Level (A weighted, or C weighted). Psychoacoustic indicators refer to measures or parameters that capture the psychological and perceptual aspects of sound, reflecting how humans subjectively experience and respond to auditory stimuli.. These are derived from recordings using standardized models to calculate them. Psychoacoustics can analyze in detail the acoustic composition of a soundscape and the signal properties that elicit specific auditory sensations; however, a comprehensive interpretation of the results requires feedback from the listeners. (Schulte-Fortkamp et al., 2023) Psychoacoustic factors are measured using sound level meter data. They are converted to different metric which explain different characteristics of the acoustics. The four most important ones are explained below.

Loudness

Loudness is a psychoacoustic metric measuring the subjective perception of sound pressure. which is calculated according to Eberhard Zwicker and standardized in the ISO 532-1 (ISO, 2017,-06). It connects the physical sound event to the hearing sensation. (Haberl, 2018). The loudness metric is soneGF. Sone is the unit of loudness. The G shows that the loudness was determined from 1/3 octave bands. The F says that the sound field was in the free field condition. The Loudness N5 percentile is the loudness value which is met or exceeded in 5% of the measurement time (Rhode & Schwarz, 2017) . It is used as a ISO standard to determine the overall perceived loudness. N10_90 is also the Loudness however this is the value that is exceed 10% of the time.

Roughness

Roughness of sounds is determined by slow temporal changes at about 70Hz in loudness, and it's a modulation based metric that can be defined as quackers, squaller and harsh. They usually have an unsatisfactory effect. (Aydin and Yilmaz, 2016, p. 88)

Sharpness

"The psycho-acoustic metric Sharpness indicates the spectral balance between low and high frequencies(Kang, 2007)" (Aydin and Yilmaz, 2016, p. 88).

Relative Approach 2D

The relative approach in 2D acoustics involves evaluating sound environments based on their spatial characteristics and relationships to surrounding features (Bray, 2004). This method considers how sound propagates and interacts within a two-dimensional space, providing a detailed understanding of acoustic landscapes.

Urban design

Urban design describes the process of designing cities with the goal of creating urban areas consisting of a high quality of life (Haberl, 2018). A good urban design varies depending on the context, much as a soundscape is best when it meets the needs of its specific stakeholders (Schulte-Fortkamp et al., 2023).

Sense of place

The sense of place is the sensory experience of people including the meaning of the place. That means sense of place also indicates the way we see, interpret and interact with our environment. The sense of places can vary among people, and even in people in different stages of their lives (Haberl, 2018).

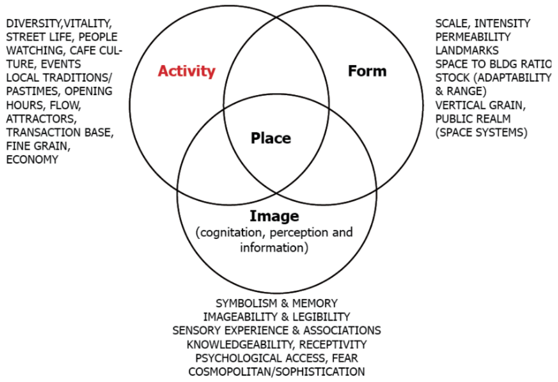


Figure 14 Sense of place from Montgomery (1998), taken from (Haberl, 2018)

When analyzing soundscapes not only the objective environment is important, but also the internal representation of it. (Schulte-Fortkamp et al., 2023). There are similarities between this sense of places and the soundscape experience.

Visual representation

In Urban design, Conceptually creating a map is creating a visual representation landscape (de Jong, 2008). Maps can be seen as a form of visual communication — a special-purpose language for describing spatial relationships.

Map analysis and interpretation

Abstraction and reduction play an important role in urban design, due to size and scale of the projects. When analyzing maps, a reduction of information is needed, depending on the information you want to focus on. Figure 15 shows an example of the alteration from a satelite images using abstraction (left), and reduction (right).

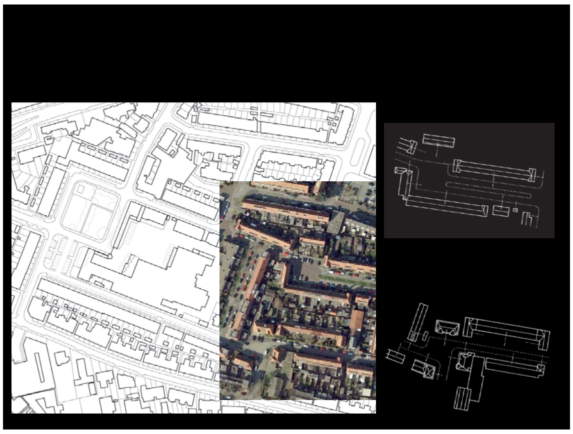


Figure 15 Abstraction and Reduction (From bk1gr2 Stedebouw Inleiding 120218, p103)

Legends

The legend is the vocabulary of design, and tells us how to read a map(de Jong, 2008). There are three types of legends, Scale representations, how much is the reality scaled down. The scale of a map can be defined simply as the relationship between distance on the map and the distance on the ground, expressed as a proportion, or representative ratio. Labels, for example, a certain color is assigned a certain meaning. Symbols, for example the placement of a certain function.

Urban design scales

Urban design is designing through different scales. Different scales have a different concept of 'environment' (De Jong, 2008). De Jong (2008) describes 2 dimensions of scale. Time and Space. What seems true or right in terms of weeks may be false or wrong in terms of months. This could relate to the temporality and dynamics of the sonic environment as well. When analyzing or designing a soundscape, it might be good to consider the scale timewise as well as the spatial scale.

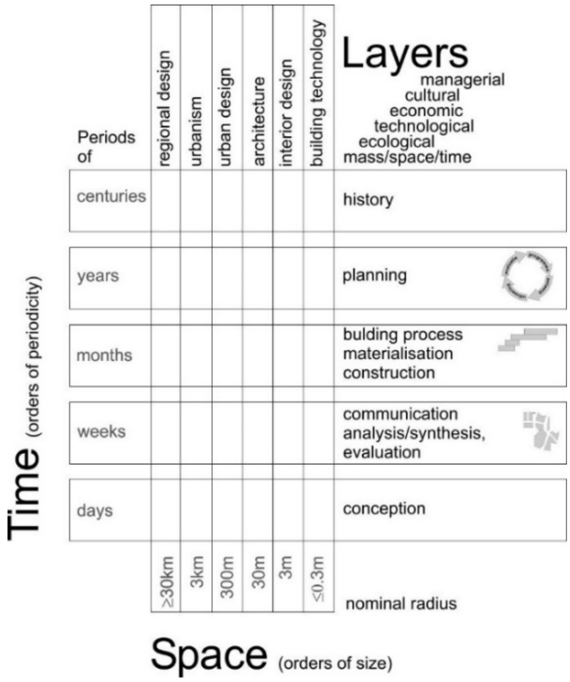


Figure 16 Scales of urban design (De Jong, n.d.)

Scale paradox

The scale paradox is that conclusions made on a specific scale, can be opposite to conclusions that are drawn on another urban scale. Conclusions drawn at one scale cannot be applied to another scale without any concern. As Figure 17 shows that conclusions could be different depending on the scale that is analyzed, this is called scale forgery. To avoid this scale articulation is important.

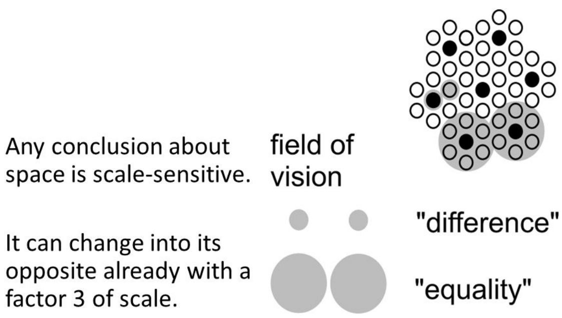


Figure 17 The scale paradox (de Jong, 2008 Scale Articulation)

Since soundscapes are by definition experienced, this experience should not be extrapolated or averaged to scales that are bigger than that.

Urban scales for soundscapes

Based on the literature by de Jong (2008), three major design scales are identified that are crucial for soundscapes. These scales are not rigidly distinct, and effective urban design integrates and navigates through these various scales.

Human experience

At the most intimate level lies the human/street scale, where soundscape design takes center stage, as soundscapes are intimately perceived through personal encounters. Temporally, it also has a very small scale, because sounds are perceived only when they occur. Once a sound stops it cannot be experienced the same way anymore. Materiality can play a role in this scale. Street profiles are also around this scale. When relating this to a human activity, this could be related to sitting or standing around.

Building block / Neighborhood scale

The second scale is the building/neighborhood level. This could be a urban design project where the building footprint, building lots and functions are located. Even though a soundscape is experienced locally we can still have an understanding of other places in the close context, that might be contrasting. The impact of the design here lies in the layout of the building blocks and how movement is created through them. Temporally this is a slightly bigger space as well. Like we can understand the relativity of spaces we can also understand the relativity of time. Different physical context are experienced differently because there might be different sound sources. In the same way we can understand that at different times of the day there can be different sounds present, like rush hour traffic, or a café being open at night. Relating this to a human activity would be walking, or biking for short distances.

District scale

The third and biggest scale discussed here is a bit more variable on the context, but here is called the district scale. On this scale a lot of reduction and abstraction takes places when making maps. The human activity that is important here are bigger traffic flows, such as cars and public transport. On this scale the direction and magnitude of these flows can be planned and designed. This scale is related more to bigger urban planning projects, which take a much longer time to realize and to implement.

Human Experience

(3-30m)

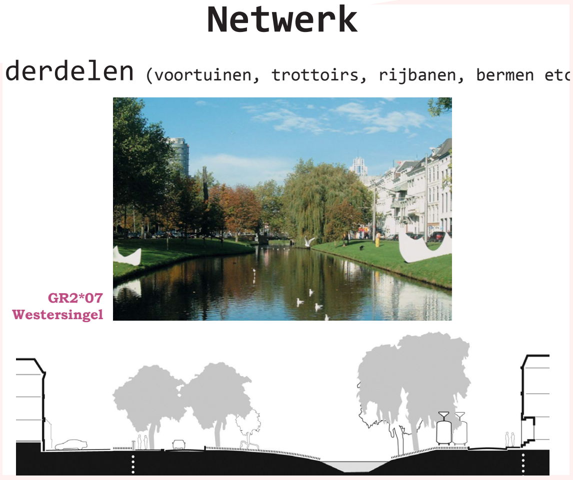


Figure 17 Human Experience (From bk1gr2 Stedebouw wk2 190218, p22)

Building Block

(30-300m)

Figure 18 Building Blocks (From bk1gr2 Stedebouw wk2 190218, p19)

District

(300+m)

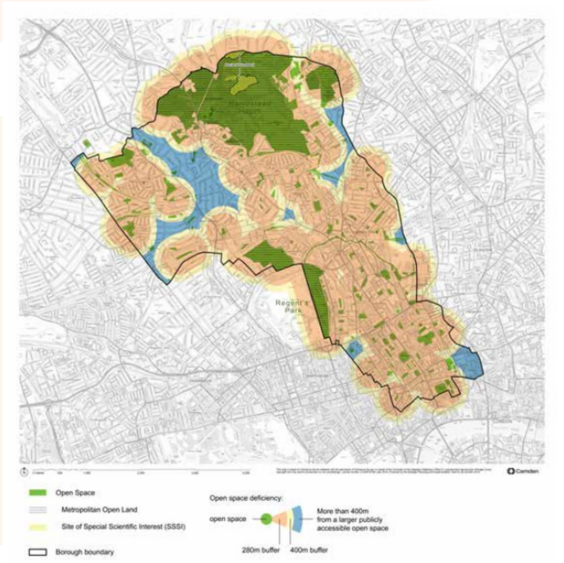


Figure 19 Access to public green spaces (Camden Local Plan, n.d.)

Soundscape design

Good soundscape design involves creating environments where the acoustic qualities contribute positively to the well-being, comfort, and intended activities of individuals. It considers context-specific qualities, embraces positive auditory features, minimizes unwanted noise, and aligns with the preferences and needs of the community or users. Ultimately, a well-designed soundscape enhances the overall experience and character of a space.

lack of information about soundscapes in urban design

Current research within the soundscape discipline is mainly focused on academic studies of individual spaces or methods of data collection and analyses, with only a few examples of applications on a large urban or city-wide scale. (Schulte-Fortkamp et al., 2023).Individuals and communities can benefit from improving the urban soundscape. Many current objectives in urban design such as pedestrian-friendly districts and mixed-use neighborhoods, have good opportunities for soundscape design to be implemented (Schulte-Fortkamp et al., 2023). However in practice very little is done to improve the acoustical conditions.

Tools for Soundscape design

The Cambridge dictionary defines a framework as a system of rules, ideas, or beliefs that is used to plan or decide something (Framework, 2024).

Figure 20 Symbol for three action strategies, by author

Cerwén (2017) created a model for landscape architects, which has three action categories to consider in noise-exposed developments. These categories were found through workshops about soundscape design in different contexts with different participants, and is focused on actions that can be implemented for improving soundscapes. The categories are: 1) localization of functions, 2) reduction on unwanted sounds, and 3) introduction of wanted sounds.

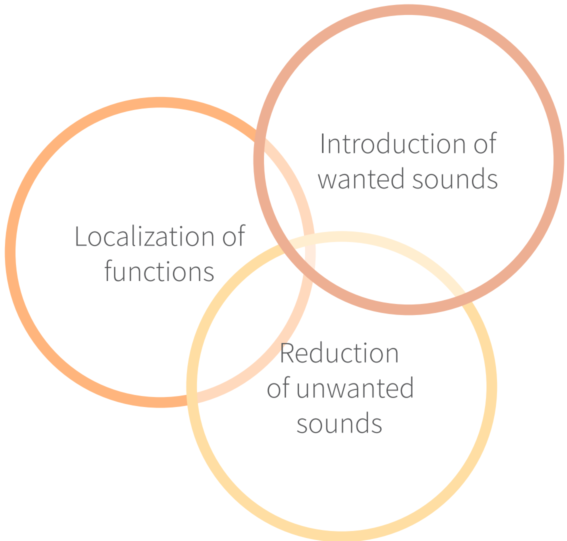


Figure 21 Soundscape design action categories, by author inspried by Cérwen (2017)

Localization of functions

This first step in the design strategy is looking at which function have different requirements for their soundscapes. Some functions should be localized away from noise sources, while others could 'embrace unwanted sounds' as part of their urban character. The importance of a good soundscape design is relevant at places where a lot of human activities occur. This may include, but is not limited to parks, other recreational spaces, schools and other educational institutions, and around healthcare facilities. Places where improvements in soundscape are not the most relevant are: on heavy roads where a lot of vehicles are passing, and other more transit oriented places

The human sensory experience strongly responds to contrast, which is a good thing to take into account when designing a place. Variation in soundscapes increases the possibility of people being able to choose which soundscape to attend too (Cerwén et al., 2017). For example, a quiet park can be experienced as more tranquil when it is surrounded by a noisy environment. Different soundscape can reinforce each other's character, when they are well designed or planned. Some places already have existing noise pollution. On this scale it can be decided to relocate or redesign a noise source, so for example creating alternative road networks, where some roads facilitate the heavy traffic, so other places are spared from this noise source. Or otherwise it can be decided that a place where unwanted sounds cannot be mitigated are not suitable for certain urban functions

This category relates the most to strategic thinking and overall planning. On the bigger scales in urban design from district, to city to regional scale. this localization of functions can be realized.

Reduction of unwanted sounds

Reduction of unwanted sounds, such as road noise are important if the noise levels exceed 53dB Lden (WHO, 2023), because from that level public health is affected. Reducing the presence of unwanted sounds can be done with noise screens, reducing the source activity, or adding absorbing materials to the space. By strategically placing them, buildings can also function as sound screens. Buildings can have a substantial effect, because they are generally larger than sound screens. Reducing the sound source activity could, for example, be that the speed limit of a certain street is lowered, or the traffic could be replaced to a different route.

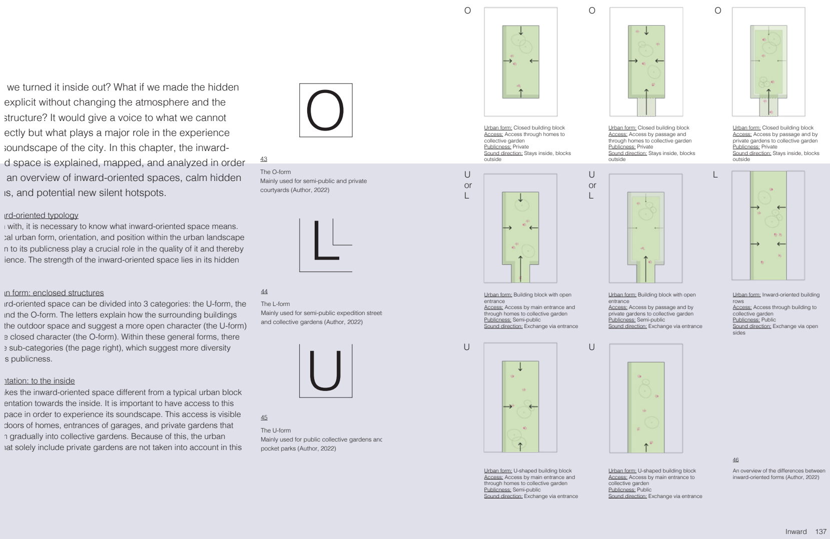
This strategy step is relevant to the urban design scale of the building block or the neighborhood. This could be a urban design project where the building footprint, building lots and functions are developed. The impact here lies in the layout of the building blocks and how movement is created through them. Street network and layout design can have a big impact in road noise reduction.

Introduction of wanted sounds

To improve the soundscape, wanted sounds can be introduced using auditory and visual masking techniques Auditory masking is the effect that occurs when one sound is introduced to reduce impact or shift focus from another sound. Visual masking shifts the focus away from the noise source, by hiding an unwanted sources visually, or adding elements that attract attention. The experience of sound depends not only on auditory information but on many contextual cues, such as visual input, expectation and relevance (Hong and Jeon, 2014).

A few strategies for introducing wanted sounds using auditory masking are introducing water elements, vegetation, and biotope design which attracts animals such as birds. Other wanted sounds could be introducing human propagated sounds such as social activities, or pavements that enhance the sound of walking.

This third strategy relates to the human/street scale. On this scale design choices can have a substantial impact, for how people perceived their environment, because soundscape are shaped through perceiving them. The strategy of adding wanted sounds contributes to a more holistic and proactive approach to urban soundscape design, aiming to create spaces that not only


we turned it inside out? What if we made the hidden explicit without changing the atmosphere and the structure? It would give a voice to what we cannot ectly but what plays a major role in the experience soundscape of the city. In this chapter, the inward-d space is explained, mapped, and analyzed in order an overview of inward-oriented spaces, calm hidden ıs, and potential new silent hotspots.

ırd-oriented typology
with, it is necessary to know what inward-oriented space means. cal urban form, orientation, and position within the urban landscape n to its publicness play a crucial role in the quality of it and thereby ience. The strength of the inward-oriented space lies in its hidden

ın form: enclosed structures
ırd-oriented space can be divided into 3 categories: the U-form, the ınd the O-form. The letters explain how the surrounding buildings the outdoor space and suggest a more open character (the U-form) e closed character (the O-form). Within these general forms, there e sub-categories (the page right), which suggest more diversity s publicness.

ntation: to the inside
kes the inward-oriented space different from a typical urban block entation towards the inside. It is important to have access to this pace in order to experience its soundscape. This access is visible doors of homes, entrances of garages, and private gardens that n gradually into collective gardens. Because of this, the urban nat solely include private gardens are not taken into account in this

O

43
The O-form
Mainly used for semi-public and private courtyards (Author, 2022)

L

44
The L-form
Mainly used for semi-public expedition street and collective gardens (Author, 2022)

U

45
The U-form
Mainly used for public collective gardens anc pocket parks (Author, 2022)

O
Urban form: Closed building block
Access: Access through homes to collective garden
Publicness: Private
Sound direction: Stays inside, blocks outside

O
Urban form: Closed building block
Access: Access by passage and through homes to collective garden
Publicness: Private
Sound direction: Stays inside, blocks outside

O
Urban form: Closed building block
Access: Access by passage and by private gardens to collective garden
Publicness: Private
Sound direction: Stays inside, blocks outside

U or L
Urban form: Building block with open entrance
Access: Access by main entrance and through homes to collective garden
Publicness: Semi-public
Sound direction: Exchange via entrance

U or L
Urban form: Building block with open entrance
Access: Access by passage and by private gardens to collective garden
Publicness: Semi-public
Sound direction: Exchange via entrance

L
Urban form: Inward-oriented building rows
Access: Access through building to collective garden
Publicness: Public
Sound direction: Exchange via open sides

U
Urban form: U-shaped building block
Access: Access by main entrance and through homes to collective garden
Publicness: Semi-public
Sound direction: Exchange via entrance

U
Urban form: U-shaped building block
Access: Access by main entrance to collective garden
Publicness: Public
Sound direction: Exchange via entrance

46
An overview of the differences between inward-oriented forms (Author, 2022)

Inward 137

Figure 22 Urban Pockets: Section from thesis van den Berg (2022)

mitigate unwanted noise but also actively promote a positive and enjoyable auditory experience

Interview Urban designer with soundscape experience

To validate the creation of my framework I interviewed an urban designer Anne van den Berg. She helped giving me a perspective from an urban designer on soundscape design. The interview was an hour long, and a lot of things were mentioned that are already discussed, these will not be mentioned. Some interesting moments will be highlighted in the next paragraph.

In urban design it is important to use the existing differences as contrast, or create new places that contrast the existing ones (for example hofjes). Combining information on how sound creates different experiences in urban design with information about the other senses. Routing and sightlines are important in urban designs and this can also be enhanced with sounds. So draw people to certain places where a certain sound is coming from, like chatter. Using pattern language was also mentioned.

Designing these 'urban pockets' can give a sense of privacy and tranquility in a busy city and can shape or create a new soundscape environment, as shown in figure 22.

Urban design elements in relation to soundscapes

The framework of this design tool aims to look at urban design elements and their ability to predict urban acoustical comfort. In this section these elements will be defined, and motivation is given why each of these elements should be included in the prediction model.

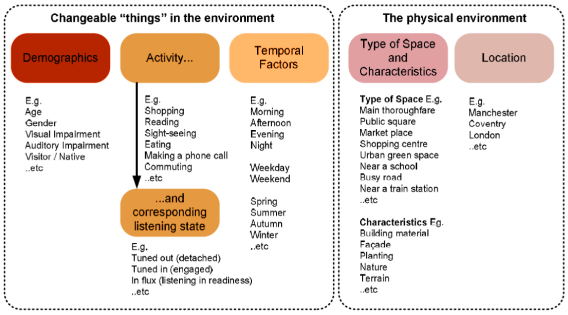


Figure 23Model of the changeable factors of the environment (taken from (Haberl, 2018)) by Cain (2013)

As our soundscape design expert stated it is important to note that some of the objects that urban planners design are not the objects that emit sounds, they just facilitate the sound propagation. A road unused does not propagate traffic noise, this is caused by the vehicles using the road. A park bench is not having conversations, it is the people that sitting on the bench from whom you can hear the chatter. Trees do not chirp, the birds in the trees do. Exceptions will also be discussed, for example fountains, which can be a good design element in creating a soundscape composition. Cain (2013) defined elements in the environment that can be changed. Different acoustic requirements are needed for different functions and activities in the space (Haberl, 2018).

Buildings

The buildings can dampen or amplify the effects of different types of sound sources. Firstly, buildings can act as a shield, shielding from noises such as road noise. This can also be the case for natural sounds. Secondly, it can amplify the sounds. When a sound source is surrounded by buildings it reflects on all the facades. Environmental noise is especially further transmitted by the hard materials that are mostly used for façades. (Niesten et al., 2021). Facades consisting of hard-sound reflective materials can cause urban noise levels to be 3-8dB higher than in a free field situation.

Sky view factor

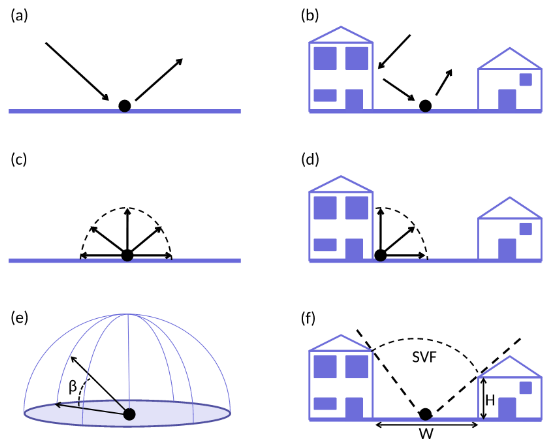


Figure 24 Explanation on the Sky View Factor (Dirksen et al., 2019)

One way to analyze the effect of building shapes between buildings is the sky view factor The Sky View Factor (SVF) defines the ratio of sky hemisphere visible from the ground , which is not obstructed by buildings (Bernard et al., 2018), as shown in figure 24. The SVF is an important parameter in urban planning because of its relationship to the UHI. A higher SVF, means lower long-wave radiation is emitted by buildings during the night time. And crucial to describe the urban climatology at scales below 100m. (Dirksen et al., 2019)

The study conducted by Silva et al. (2017) delved into the impact of Sky View Factor (SVF) on the transmission of traffic noise in urban environments, particularly in Paris. The research compared different urban sites in Paris near roads, taking into account their geometric shapes, to the measured sound pressure level at the same location. The research found that in urban areas with a low sky view factor, the highest noise levels were found. They conclude that the SVF can potentially be used in research on urban noise.

This seems to align with the formula for sound levels in an open field:

$$L_p = L_w - \left|10 \cdot log\left(\frac{Q}{4\pi \cdot r^2}\right)\right|$$

Formula 3 Sound in a free field

This formula incorporates factors such as the directivity factor (Q), reflecting how the spreading of sound waves diminishes with distance and obstruction. In urban settings, where buildings and other structures can obstruct sound propagation, SVF serves as a proxy for the extent of obstruction, thereby influencing the observed noise levels.

Roads

As discussed in the section ‘Environmental Noise & Health’ the health effects from road noise are significant, and can lead to irritation and annoyance. One way to model the impact of road noise is simulating the Lden.

Parks, Trees and other vegetation

Research by Lugten et al. (2017) underscores the significant influence of vegetation on the perceived pleasantness and overall acoustic quality. Additionally, investigations into the correlation between visual context and soundscape perception reveal that the presence of trees or vegetation positively enhances the reported acoustic quality in regions affected by road traffic noise. Therefore using the visibility of trees can serve as an indicator for the prediction of the quality of soundscapes. In city parks the majority of people would experience hearing road-traffic noise. Good soundscape quality in city parks during daytime can only be attained when exposure to traffic noise remains below 50 dBA. (Nilsson & Berglund, 2006).

Water sounds / Fountains

Fountains create the sound of running water, associated with a lot of positive features like calmness, health and cleanliness (Calarco & Galbrun, 2024). Additional it also has other benefits such as cooling its surrounding through evaporative cooling. You et al.(2010, p. 477) found that under conditions of road traffic noise registering at 55 or 75 dBA, water sounds that had a 3dB smaller SPL were found to make the urban soundscape more subjectively pleasant. Water sounds with more low frequency sound are preferred for masking road traffic noise. Through use of materials, speed through which the water travels through the fountain, and using multiple fountain sources the composition of the sound can be crafted to elevate the surroundings

Machine Learning

Machine learning (ML) is a subset of artificial intelligence (AI), that involves the development of algorithms and models that enable computers to learn and make predictions based on data. ML uses algorithms that iteratively learn from data, identify patterns, and make data-driven predictions or decisions, and improve and learn from experience without being explicitly programmed. Acun, (2021)

ML algorithms require large datasets to learn from. So, the first step is to acquire or develop a dataset and to assess the quality of the data. The algorithm learns patterns and relationships from the data. During the training phase the algorithm is exposed to the data and learns the patterns and relationships. The main types of algorithms are supervised and unsupervised learning. After the model is trained it needs to be validated with a test dataset, to assess how well it generalizes to new unseen data. After the model is trained and validated it can be used to make predictions on new unseen data.

A good performing ML model has a small training error and a small difference between the test and the training error. A training error is the error of performance on the dataset the model was trained on. The test error is the error of performance on a new unseen dataset. A low training error means the model can closely replicate the target outcomes in the training data. A low test error means that the model can make an accurate prediction for new data. A ML model is overfitted when it performs well on training data, but poorly on test data. The patterns identified in the model are too specific. Overfitting occurs more in nonlinear and non-parametric models. A ML model is underfitted when it cannot obtain a low error rate on the test and on the training data.

Types of ML

The two main subtypes of machine learning are supervised learning and unsupervised learning, as shown in figure 25. Unsupervised learning uses unlabeled data in the training process.

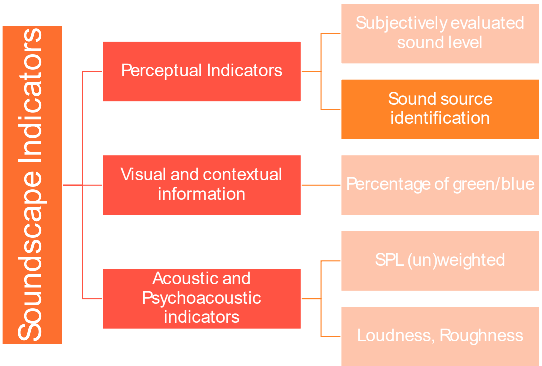


Figure 25 Overview of types of Machine Learning by author inspried by https://www.geeksforgeeks.org/types-of-machine-learning/

Supervised learning is the process of training the ML structure based on labeled data. A supervised learning model predicts the label of a new data sample, after training on a sample of labeled data instances. This research will focus on using labeled data. It is most commonly used for classification and regression problems. Regression models are used with problems with quantitative response, and are designed to predict continuous outcomes. Classification models are used for problems with categorical variables.

PyCaret: Classification & Regression

PyCaret is as an open-source, low-code Python library for machine learning that streamlines the entire ML workflow. By automating tasks and simplifying complex processes, PyCaret accelerates experimentation and enhances productivity significantly. Compared to other open-source ML libraries, PyCaret stands out as a low-code alternative, enabling users to achieve results with minimal code.

Metrics for regression model analysis

PyCaret allows users to train and test different machine learning models and easily compare them. When training regression models they can be compared on these metrics:

R2 (Coefficient of Determination) indicates the proportion of the variance in the target variable that is predictable from the independent variables. The Mean Absolute Error (**MAE**) measures the average absolute difference between the predicted and actual values. The Mean Squared Error (**MSE**) measures the average of the squared differences between the predicted and actual values, penalizing large errors more than MAE. The Root Mean Squared Error (**RMSE**) is the square root of the MSE and represents the standard deviation of the errors

Random Forest Regressor

A random forest regressor (RF regressor), is a supervised learning algorithm, using ensemble learning method for regression. It is a bagging technique meaning that the trees run in parallel and there is no interaction between these trees.

Random Forest Regressors are known for their robustness, flexibility, and ability to handle high-dimensional datasets with noisy features. They are less prone to overfitting compared to individual decision trees and often provide good performance with minimal hyperparameter tuning.

Light Gradient Boosting Machine

Light Gradient Boosting Machine (LightGBM) is a machine learning algorithm that belongs to the family of gradient boosting methods. A LightGBM regression model can be sensitive to outliers, they can disproportionately influence the decision boundaries. The model uses leaf-wise growth, and can be prone to overfitting, especially when the dataset is small and noisy. Therefore it is more suitable for large datasets, with around 10,000+ rows (Gupta, 2019)

Multiple linear regression model

With a multiple linear regression the relationship can be estimated between variables (two or more independent variables and one dependent variable), following a linear regression.

Handling outliers

there are different ways to identify outliers for machine learning. Firstly it is important to verify in what way datapoints can be outliers and how that can impact the model as a whole.

Contextual outliers

Contextual outliers are outliers within specific contexts or subgroups of data. Contextual outlier detection considers local characteristics of datapoints. n. Contextual outlier detection can identify anomalies in specific subsets of the data, rather than in the data as a whole. This is opposite of conventional outlier detection, which detects outliers considering the whole dataset. This is shown in figure 26.

Z-score method

A commonly used statistical method for detecting outliers is the z-score method. Z-scores are a metric for assessing how odd an observation is within a dataset, when it has normal distribution. The z-score is the number of standard deviations from the mean for each value. A z-score of 1, tells that the observation lies 1 std away from the mean. The z-score can be calculated with this formula:

$$z = (X - \mu) / \sigma$$

formula 4: calculating the z-score

The higher the absolute value of the z score is the bigger the outlier is. A standard cutoff value for outliers is a z-score of 2- 3. Having a low Z-score for contextual outliers means that datapoints are removed where there are unusual conditions for the certain context. The variance is so extreme that it cannot be related to the factors that are outlined in this research.

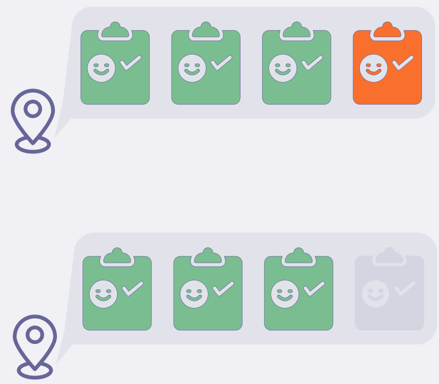


Figure 26 Contextual outliers

Addressing contextual outliers facilitates the refinement and optimization of machine learning models used for predictive modeling, ultimately improving the accuracy and effectiveness of future analyses and applications.

Ensemble learning model

Ensemble learning combines the predictions from multiple machine learning algorithms. This helps to create more accurate predictions, compared to the individual models.

Bagging vs Boosting

Bagging can reduce variance and minimize overfitting (Ensemble Models, n.d.).

Boosting is a sequential ensemble learning technique where hard to classify instances are given more weights. This weighting mechanism facilitates subsequent learners in focusing their learning efforts on these misclassified instances. The final model is derived through the weighted aggregation of these weak learners. (Gupta, 2019)

Small datasets

When using small datasets, there are a few factors that need to be taken into account. (Dealing with Very Small Datasets, n.d.). Overfitting becomes harder to avoid, and the impact of outliers can increase to a point where it makes the general prediction inaccurate. With small datasets it is advised to use simple models.

Machine Learning in soundscape studies & design

Why ML in soundscape studies?

In contemporary soundscape studies, the predominant focus revolves around gathering data that captures individual reactions to the acoustic surroundings directly experienced by individuals in situ. This approach commonly relies on a restricted range of methodologies including soundwalks, questionnaires/interviews, non-participant behavioral observations, among others Aletta, Obermang & Kang, 2018).

Asking people how they perceive the acoustic environment is a laborious task, so if a model can predict this, it is not needed. An accurate model can reveal underlying causes of the perceived properties (Alleta and Kang, 2016). This can be used for design purposes. And therefore subsequently improve human wellbeing in noise affected areas

Conceptual framework prediction model

Lionello et al. (2020) conceptualized the process of modelling soundscape in three components, indicators, descriptors and the set of rules, as illustrated in figure 27.

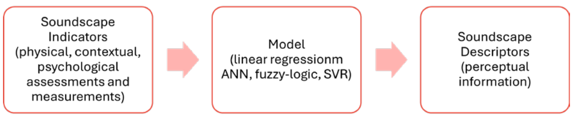


Figure 27 Conceptual Framework Prediction Model from (Lionello et al., 2020)

Review of existing prediction models

Aumond et al. (2016) created their own indicator, the TFSD(f,t); the normalized Time and Frequency Second Derivative, representing the deviations of each recorded sample: which is best correlated, among a large set of calculated physical indicators, with the perceived time presence of birds and voices” . The full review will be added in the appendix

Hong and Jeon (2015) found different relations of indicators to soundscape quality for different functions in urban areas. These four classified functions have been used again in the research of Hong and Jeon (2017).

Machine learning in design

The prediction models of soundscape evaluation can be used in preliminary design stages, to indicate and evaluate the soundscape design. Only Yue et al. (2023) has explicilty attempted to use Machine learning to improve the quality of urban parks. This will be discussed later in this section.

Design optimization

Radziszewski (2018) discovered through research that Machine Learning Algorithm-Based tools exhibit potential in replacing traditional daylight simulations during the preliminary stages of architectural design evaluation. The algorithm was faster than daylight simulations and was max 2.8% off. Instead of running three simulations for three daylight metrics, a model is trained to predict those values.

Soundscape mapping

As a complementary approach to noise maps, soundscape maps can be useful tools for urban planning and design because they provide more information than conventional noise maps to reflect perceived acoustic environments. (Hong et. al., 2017). Maps are a widely used method by urban designers to convey their message, so in order to communicate with them, it could work to try to speak their language. In addition of creating 2d maps of the site, in the next chapter, section drawings are proposed as well, because they present the opportunity to visualize both the data, and the experienced design.

Legends and labeling

Lavandier et. Al (2016) created a color scale intended be used for soundscape mapping, as shown in figure 28. Their methodology involved collecting a questionnaire where respondents were asked to select colors suitable for their perception of 'Pleasant' and 'Unpleasant' acoustic environments. The collective average of these subjective color selections was combined with the existing color scale for European noise maps. In the interest of coherence and accessibility, a comparable color scheme will be employed in this research for of soundscape maps. The scales on which the maps will be created will be discussed later on in this thesis.

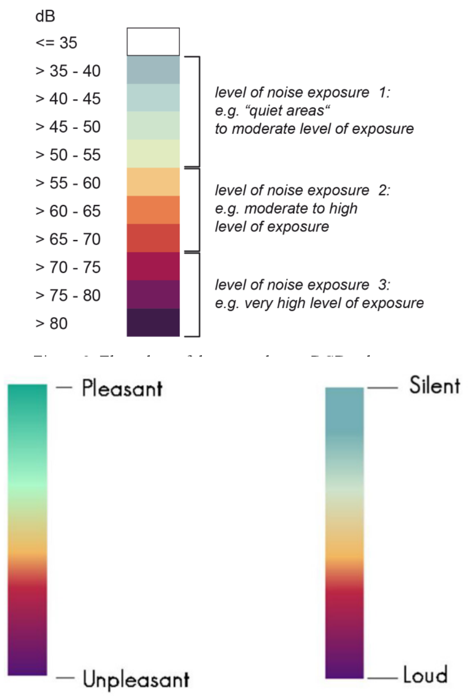


Figure 28 Color Scales, from Lavandier (2016)

Interpolation methods

The following research papers have attempted to visualize soundscape data, they have used different methods for calculating the data, and/or visually represent the soundscape.

Soundscape approach integrating noise mapping techniques: a case study in Brighton, UK. Aletta and Kang, 2015

Perceptual questionnaire and measurement of sound pressure levels during a sound walk, with 21 participants. The prediction surface is mapped using the kriging interpolation method, as shown in figure 29.

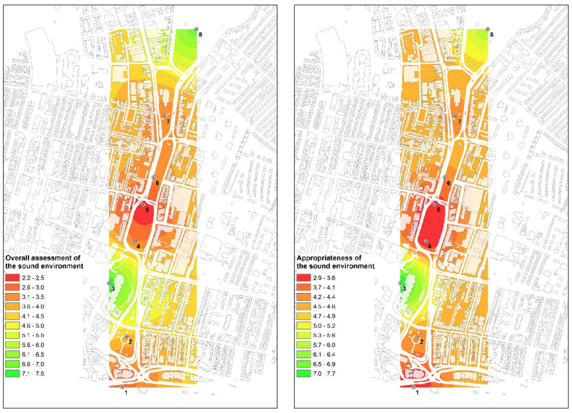


Figure 29 Kriging Interpolation map, Soundscape Pleasantness Aletta and Kang (2015)

Exploring spatial relationships among soundscape variables in urban areas: A spatial statistical modelling approach. Hong and Jeon, 2017

Perceived sound source dominance measured with 5 point interval scale by 8 observers.

The geographically weighted regression (GWR) is used to explore geographically varying relationships, dependent and independent variables. The GWR analyses was conducted using the software gwr4. The mapping process was done in GIS, with the kriging interpolation method, with the circular semi variogram model, as shown in figure 30.

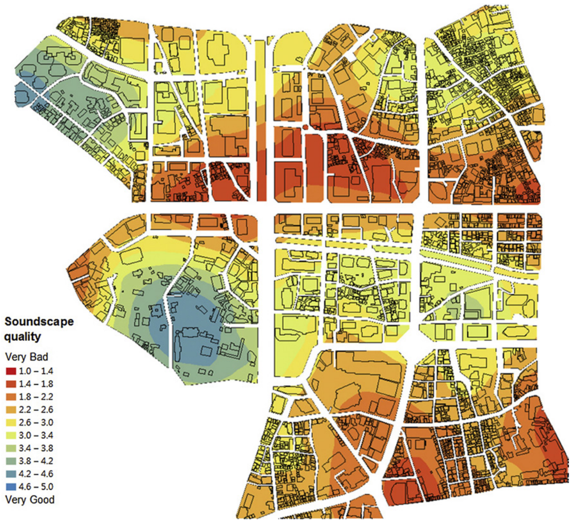


Figure 30 Predicted Soundscape Quality using GWR. Hong and Jeon (2017)

Urban soundscape maps modelled with geo-referenced data. Lavandier et al., 2016

The final aim of this study is to propose predictive sound quality maps that can be built by any city which has these georeferenced data already collected in GIS. Perceptual data modelled with geo-referenced data. 89 urban sites 20 people per location. Linear regression with an R2 of 0.68. The prediction was based on the time presence of certain sound sources. A scale from “rarely present” to “frequently present” was used to collect data on the presence of these types of sound sources. (Lavandier et al., 2016). The kernel density method with gaussian distribution is used to distribute georeferenced data on each mesh of the map, as shown in figure 31.

Figure 31 Predicting Soundscape pleasantness from georeferenced data from Lavandier (2016)

A visualized soundscape prediction model for design processes in urban parks. Yue et al., 2023.

This paper uses the soundwalk method, with and experimental group consisting of 10 observers, to collect data.The paper focuses on categorizing the presence of different sounds, and predicting them with the Gaussian Mixture Model method. The predictions are used to analyze design alterations. The visualizations are not very strong as shown in figure 32.

Figure 32 Soundscape prediction classes visualization Yue et al. (2023)

Evaluation of Soundscapes in Urban Parks in Olsztyn (Poland) for Improvement of Landscape Design and Management (Jaszczak et al., 2021)

This paper has a more artistic appraoch to soundscape mapping, which combines numerical data from SPLs and symbology to represent the sound source types present, as shown in figure 33.

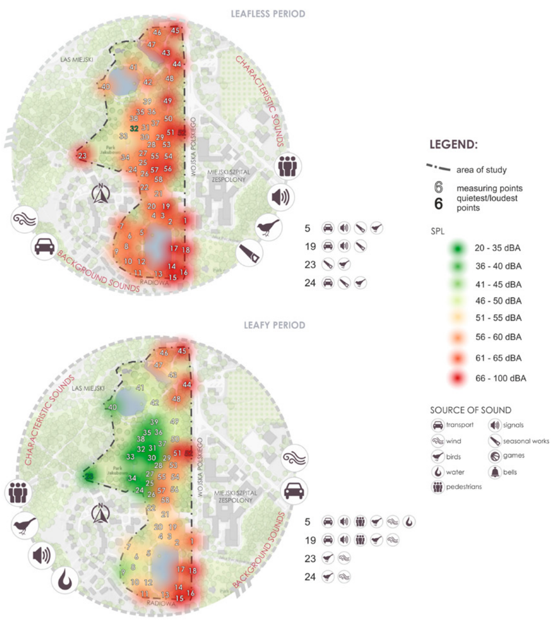


Figure 33 Artistic visualization of Soundscape mapping from (Jaszczak et al., 2021)

Soundscape Optimization Strategies Based on Landscape Elements in Urban Parks (Tian et al. 2023)

This study collected soundscape data, like SPL values, sound source presences and soundscape evaluation. This visualization which combines the SPL and the section is very illustrative on what the locations look like to the visitors and relates that to a numeric scale. Differences in soundscape pleasantness score could be visualized in a similar way.

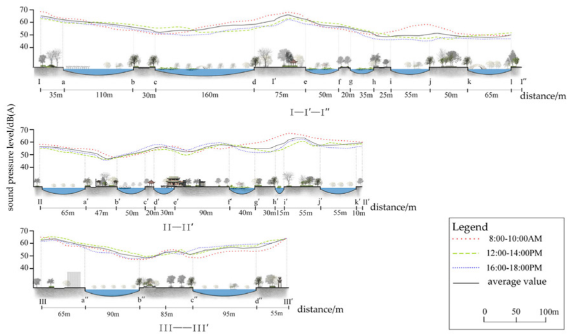


Figure 34 Visualization of SPL on a section of the surroundings from (Tian et al., 2023)

Inward, The Silence is within. (van den Berg, 2022)

This Urban Designer Approach shows how sections, combined with maps can really link to the human experience very well. Words mimicing sounds are used to convey the soundscape as well as shown in figure 35.

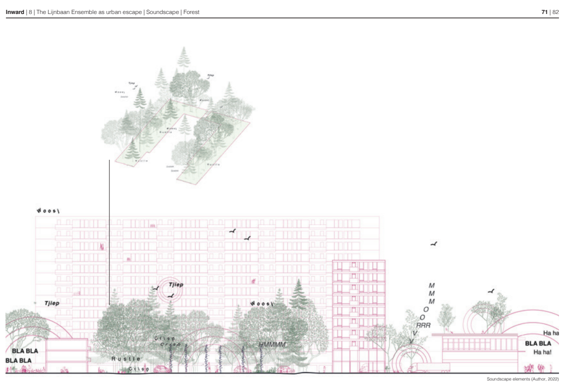


Figure 35 Visualization of Sound on a section of the surroundings from (van den Berg, 2022)

Soundscape design alterations

Only Yue et al. (2023) focused on design alterations. Their grid of 50 meters contains design urban design elements. With a Gaussian mixture method the soundscape evaluation prediction model is developed based on SPL prediction, sound source prediction and soundscape evaluation prediction. The SPL can be predicted from the minimal distance to roads, with an accuracy of 67%. With computer vision, visual perception elements are analyzed, to predict the presence of different sound sources with an accuracy of 77.4%. Inputs for soundscape evaluation included geographic information, visual perception data, and sound source perception data obtained from surveys, although the reliability of the latter was limited due to a small sample size (10 participants). This model reached an overall accuracy of 74.2%. Altering the grid size (20-100m), causes the accuracy to fluctuate.

For the next step, this research applied the model to a new design, incorporating predictions of dominant sound sources rather than soundscape evaluation. Design modifications included adjustments to entrances and pathways, as shown in figure 36.

Prediction pleasantness from urban design elements

To date, there has been a notable absence in predicting the pleasantness of soundscapes in new urban design. To bridge the gap between academia and practice this seems to be a crucial step, for enhancing the field and the practical applicability of research findings.

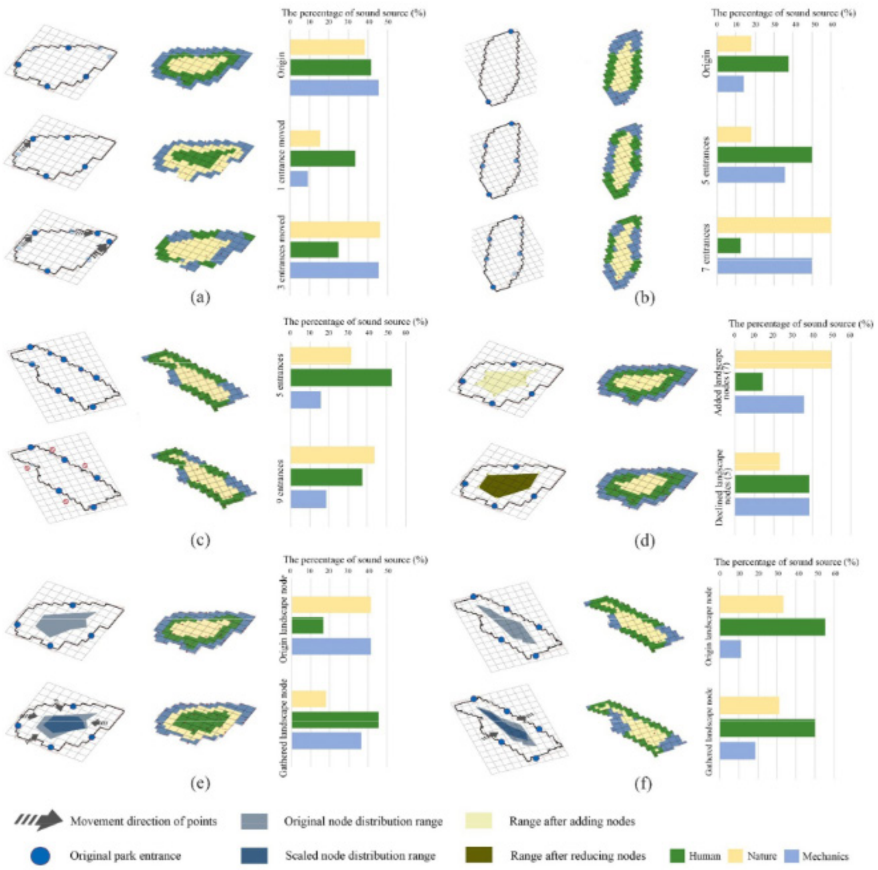


Figure 36 Prediction of the most dominant present sound source type Yue et al. (2023)

Datasets for Soundscape quality prediction

There are different datasets available to use to train a model. In this section I will be looking at different datasets and I will define what kind of information the dataset preferably should contain.

Requirements

Most importantly the dataset should have information on the perceptual evaluation of their urban acoustical environment. This will be the descriptor in the prediction model. So a rating or emotion attached to certain soundscapes.

Given the aim of this research to translate this data into a design tool for predicting the comfort of urban designs, it is preferable that the collected data originates from urban settings. Ideally, this information should be geo-referenced, providing coordinates, so that the urban context in which the evaluations were conducted can be accurately depicted

To apply it as a design tool, architectural elements must be linked to the perceptual evaluations. For instance, roads could be associated with noise emission or propagation arising from traffic, while vegetation might be linked to emissions from natural sound sources. These links enable a more nuanced understanding of how specific architectural features contribute to the overall acoustic environment which facilitates targeted design interventions aimed at optimizing acoustic comfort. Examples of databases are shown in the table below.

choice of dataset

The chosen dataset to use in this research is the dataset from the international soundscape database, which has information on the pleasantness, the perceived sound sources and the geographical location of the respondent.

The International Soundscape database (SSID)	Soundscape assessment campaigns carried out across Europe, conducted according the SSID protocol. With in situ questionnaires, binaural recordings, sound level meter readings and 360 degree video.
DeLTa Deep Learning Techniques for noise Annoyance detection) Dataset	The Deep Learning Techniques for noise Annoyance detection (DeLTA) dataset includes 2,980 15-second binaural audio recordings from urban public spaces in London, Venice, Granada, and Groningen, sourced from the International Soundscape Database. A remote listening experiment was conducted using Gorilla Experiment Builder, involving 1,221 pre-registered participants. Participants listened to ten 15-second binaural urban environment recordings, identifying sound sources and providing annoyance ratings (1 to 10). A list of 24 labels was provided for sound source recognition. If two or more participants identified a source, it was considered present. Each binaural audio recording, in MP3 format, has 3.2 identified sound sources on average. The dataset includes a 2890 by 24 data frame, representing recordings with identified sound sources and average annoyance ratings.
Chattymaps	An urban sound dictionary and a Sample of sound-related Flickr photo identifiers for Barcelona and London
Freesound	Freesound is a collaborative database for audio recordings released under Creative Commons License. It aims to be a open database of sounds available for scientific research.
Emo-Soundscapes	a dataset of 1213 6-second Creative Commons licensed audio clips named Emo-Soundscapes. The dataset is created by curating 600 soundscape recordings from Freesound.org and combining 613 audio clips from these recordings. Ground truth annotations of perceived emotion in the soundscape recordings were collected through a crowdsourcing listening experiment involving 1182 annotators from 74 different countries, ranking the audio clips based on perceived valence/arousal. This dataset enables the exploration of emotion recognition in soundscapes and the impact of mixing various soundscape recordings on their perceived emotion. Two evaluation protocols for machine learning models are also proposed in the project.

Discussion and Conclusion Literature studies

What is 'good' soundscape design?

Good urban design, and therefore good soundscape design has the aim of creating urban areas consisting of a high quality of life. Good soundscape design involves creating environments where the acoustic qualities contribute positively to the well-being, comfort, and intended activities of individuals. It considers context-specific qualities, embraces positive auditory features, minimizes unwanted noise, and aligns with the preferences and needs of the community or users. Ultimately, a well-designed soundscape enhances the overall experience and character of a space.

To reach the goal of a high quality soundscape the action categories from the soundscape design strategy by Cerwén (2017) can be taken into account.

The first step in the design strategy is the localization of functions. Determine which areas have different requirements for their preferred soundscape. The importance of a good soundscape design is relevant at places where a lot of human activities occur, like parks or other recreational spaces. By focusing on specific areas and leaving others out contrast is created. This is relevant to the bigger scales in urban design from district, to city to regional scale. On this scale this localization of functions can be realized.

The second step of the soundscape design strategy is the reduction of unwanted sounds. Reduction of unwanted sounds, such as road noise are important if the noise levels exceed 53dB Lden. Reduction of unwanted sounds, in this scenario from road noise can be most effectively done by using buildings as a sound barrier. For example when designing a building with a small public space on a plot next to a busy road, placing the building in between the busy road and the public space can improve the soundscape quality there. Van den Berg (2022) also analyzed building block shapes in regards to soundscapes and found that creating urban pockets created the most optimal soundscapes, while also creating a feeling of enclosure. Another aspect for the urban design can be to create contrast, like van den Berg said during the interview. In urban areas with a lot of traffic noise, creating small pockets that are more quiet can make the city soundscape more livable overall and contribute to a better acoustical comfort. This strategy action is relevant to the urban design scale of the building block or the neighborhood. This could be a urban design project where the building footprint, building lots and functions are developed. The impact here lies in the layout of the building blocks and how movement is created through them. Although this research has mentioned the importance of urban morphology, this field could has been explored more by other researches. Buildings shape, height, and façade materials can impact how people perceive their soundscape.

The introduction of wanted sounds, which is strategy action step 3, can mask or distract from the perceived presence of the unwanted sounds. In cases where traffic noise levels persistently high, it is recommended to incorporate a fountain within the urban area. Fountains not only offer potential benefits for masking traffic noise levels, but they also contribute positively to urban heat regulation and the overall ambiance. Adding vegetation such as parks and trees can invite natural sounds such as rustling leaves, and birdsong, which ultimately people will find more pleasant acoustically, as well as visually. This third strategy relates to the smallest urban design scale discussed in this research: the human/

street scale. Here soundscape design is the very important, because soundscapes are perceived through personal experience.

Furthermore, it is important to propose methods to integrate these considerations into a broader holistic model that encompasses various sensory experiences to improve the experience of urban design overall. Good sound quality should not reduce other urban design qualities in the area.

What correlations exist between the identified soundscape indicators and descriptors of human perception of comfort or discomfort within urban environments?

Different studies have found correlations between the human perception of soundscape comfort and different indicators. Perceptual indicators such as perceived sound source types seem to have strong correlations to the perceived quality of the acoustic environment. There is a clear negative correlation with perceived exposure to traffic noise, and other noise sources such as railroad traffic or air traffic and noise annoyance or unpleasantness. On the other hand natural sound sources for example the presences of birds, or fountains can have a positive effect on the perceived quality, and can even distract from the presence of noise sources in the area.

For acoustic parameters, the Lden is relevant to take as a boundary measurement level. The WHO recommends an Lden lower than 53, to reduce the public health impact. According to the RIVM people find roads with a 50km/h speed limit the most annoying. In order to test a soundscape design the starting point could be an urban area that has a busy road of the same order nearby that can negatively impact the perceived acoustical comfort of the people there.

To what extent can computational design tools, in the shape of machine learning models, incorporate soundscape data to inform and shape urban design elements for improved soundscapes?

For new designs collecting soundscape data from people is impossible. And for existing sites collecting soundscape data is a laborious task, including taking soundwalks, collecting surveys and doing sound meter recordings. Through computational design methods, such as machine learning, the soundscape quality can be predicted and optimized with knowledge on soundscape design strategies. This saves time and energy, which can make this type of information more accessible to designers with lesser knowledge on the topic.

To date, there has no research been done that focused on the applicability of soundscape prediction on new urban design. Focusing on this practical application could bridge the gap between research and the design world.

The dataset that will be used is from the international soundscape database and has information on the pleasantness, the perceived sound sources and the geographical location of the respondents. In the chapter of the data analysis, the choice for this dataset in this research will be further examined and motivated

The additional data that is needed for the prediction model can be taken from standard urban design elements, such as buildings roads and parks, and optionally fountains. There are different ways to compute their relationship to their environment, which are briefly discussed in this chapter. For roads, Lden can be a good indicator for soundscape quality. For vegetation, visibility is an important aspect that affects the perceived pleasantness of a soundscape, and can mask unwanted sound, and mitigate the negative effects of traffic noise. For parks, the distance from the periphery can play a role, since further away from it more natural sounds, such as bird sounds can be perceived. Fountains can also be used to mask unwanted, dependent on their sound pressure level, as modeled as such.

To visualize this data the predicted pleasantness can be represented in a map. Maps can allow for easy interpretation of data, presented in a more visual way related to specific location. Soundscape perception is very location based, so therefore this approach would be suitable to communicate this type of data. Maps are also a widely used tool for urban designers to show their ideas, and one of their main forms of communication.

Chapter 3 Choosing a dataset

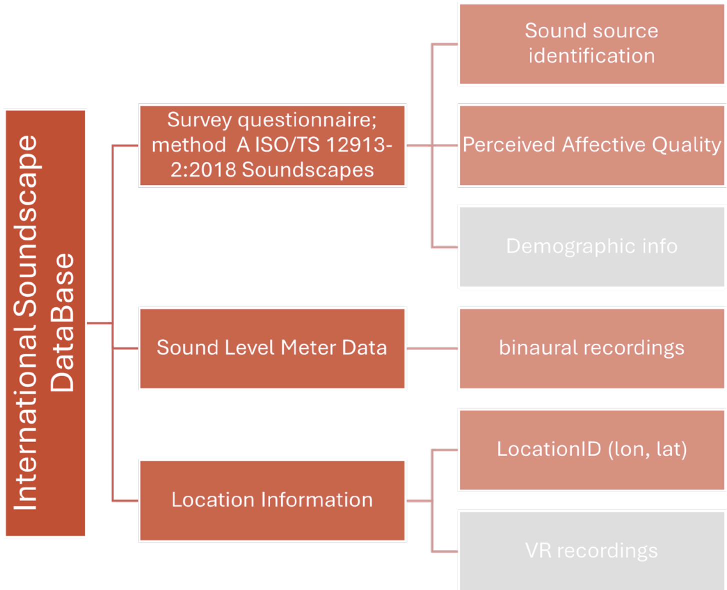


Figure 37 Representation of the used content in the dataset from Mitchell et al. (2020), by author

The International Soundscape Database (Mitchell et al., 2020), comprises a comprehensive collection of individual questionnaires from over 3,500 participants residing in urban centers across Europe and China. The dataset includes psychoacoustic analysis of 30-second binaural recordings, providing valuable insights into the auditory experiences of diverse urban environments.

The collection method is intended for future augmentation with new locations, cities, and contexts. The responses are collected on multiple days in 2-5 hour sessions, for each location at least 100 response are collected This subjective soundscape data from the survey includes soundscape descriptors, sound source presence & identification, and assessment of the overall environment.

The data also includes personal information per respondent. The respondent also fill in the WHO-5 well-being index, rate their self-reported well-being and give background information on themselves such as their demographic and socio-economic data. The objective measurements included are spatial, audio-visual recordings, binaural recordings and other acoustic and psycho-acoustic factors. Figure 37 shows which data from the Internation Soundscape database is used for the statistical analysis.

Data collection

Here briefly will discussed how the data is collected for this dataset.

Pleasantness

The SSID questionnaire collected the following data on the perceived Pleasantness. This data collected according to ISO standards (ISO/TS 12913-2:2019(E), 2019). To calculate the pleasantness survey data from a questionnaire is collected via SSID Protocol based on ISO 12913 standard. This is based on a five point Likert scale. Pleasantness is calculated by using formula 2.

To what extend do you presently hear the following four types of sounds?

Please tick off one reponse alternative per type of sound

	Not at all	A little	Moderately	A lot	Dominates completely
Traffic noise (e.g. cars, buses, trains, air planes)	☐	☐	☐	☐	☐
Other noise (e.g. sirens, construction, industry, loading of goods)	☐	☐	☐	☐	☐
Sounds from human beings (e.g. conversation, laughter, children at play, footsteps)	☐	☐	☐	☐	☐
Natural sounds (e.g. singing birds, flowing water, wind in vegetation)	☐	☐	☐	☐	☐

NOTE The first scale has the heading "traffic noise" and the second completes the category with the heading "other noise." The term "noise" is used instead of "technological sounds". The term "noise" is not intended as a value judgement.

Figure 38 Questionnaire Likert scales for presence of sound source types (From ISO- 12913-2. Acoustics—Soundscape—Part 2: Data collection and reporting requirements, 2018.)

Sound source types

The SSID questionnaire collected the following data on the perceived presence of sound sources. This data collected according to ISO standards (ISO/TS 12913-2:2019(E), 2019), as shown in figure 38.

It asked the question: To what extend do you presently hear the following four types of sounds? The four types of sounds are:

- Traffic noise (e.g cars, buses, trains, airplanes),
- Other noise (e.g. sirens, construction, industry, loading of goods),
- Sound from human beings (e.g. conversation, laughter, children at play, footsteps),
- Natural sounds (e.g. singing birds, flowing water, wind in vegetation).

This is subjective ordinal level data. It is not about the physical measured presence of sound sources, but of their perceived presence. This still however could tell a lot on how people experience sounds

A correlation between presence of certain sound sources and the perceived quality of the soundscape

Investigating the correlation between the presence of specific sound sources and the perceived quality of the soundscape is essential for understanding of their effects on perceived soundscape quality. By examining whether certain sound sources, such as natural elements or human activities, are associated with higher or lower perceived quality, insights can be gained into the factors that shape individuals' experiences of their surroundings.

a correlation between the perceived presence of a sound source and architectural objects in a virtual 2d space

Exploring the relationship between perceived presence of sound sources and objects in a virtual 2D space offers valuable insights into spatial perception and audiovisual integration. Understanding whether individuals perceive sound sources as spatially correlated with virtual objects can inform the design of immersive environments and virtual experiences, enhancing their realism and effectiveness. Both inquiries contribute to our understanding of how auditory and visual cues interact to shape our perception of the environment, with implications for fields ranging from urban planning to virtual reality design.

Psycho-acoustic factors

Acoustic data are collected during the survey sessions, via a stationary class 1 or 2 Sound Level Meter as defined in IEC 61672-1:2013 (Mitchell et al., 2020). The psycho-acoustic data for Loudness and sharpness is collected according to ISO standard 532-1

Location data

Each survey response includes coordinates. Although Mitchell et al. (2020) recorded additional location details such as architectural typology and visual openness, this data was not disclosed in their publication

The data points are situated in two cities: London and Venice. For the statistical analysis, all data points will be utilized. However, when examining urban design elements, only the data points located in London will be considered. The majority of the locations, 11 out of 13, are in London. These datapoints are shown in figure 39. Additionally, more supplementary data, such as road maps and a tree database, is available for this location.

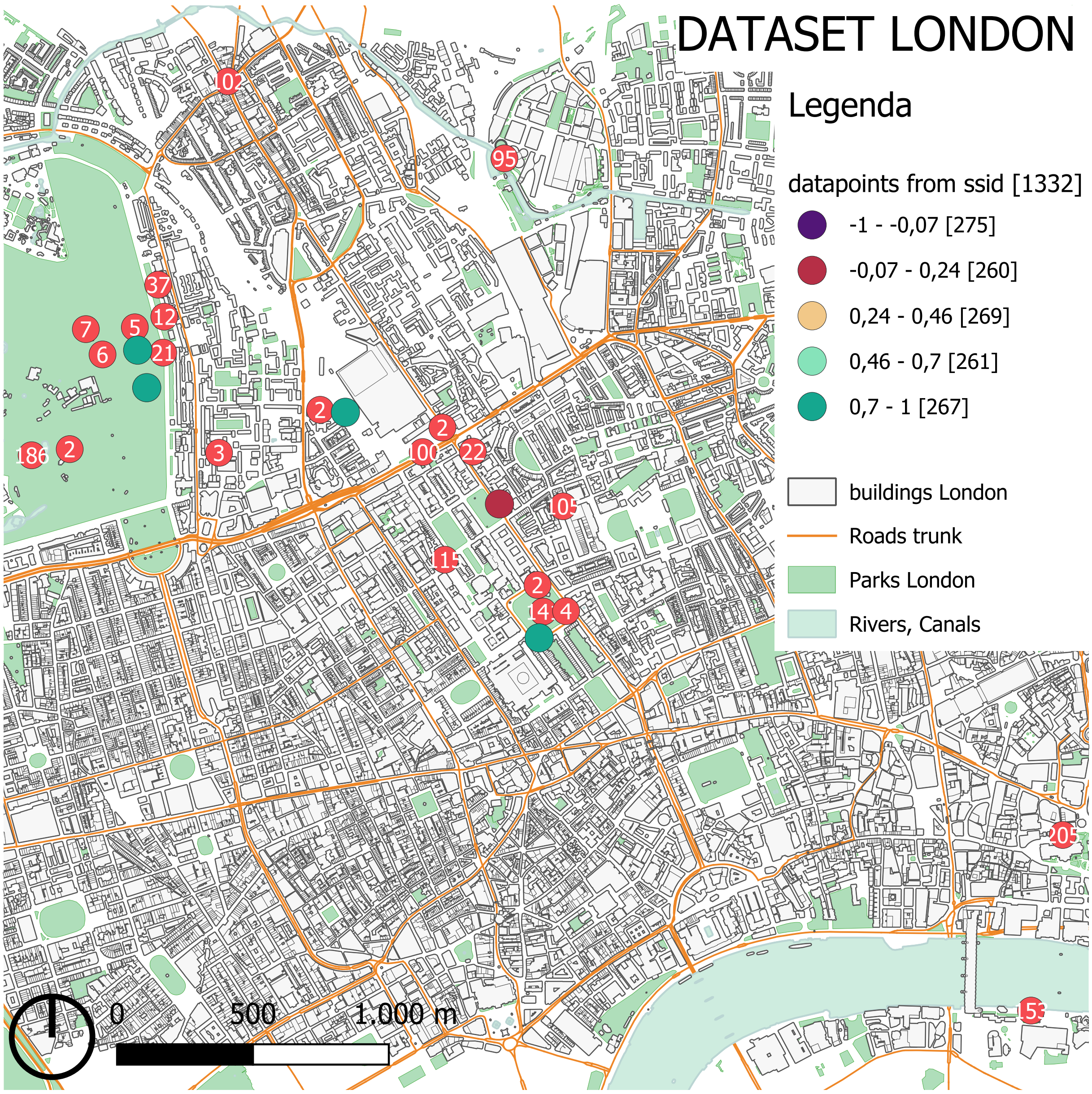


Figure 39 All the points in the dataset (excluding points located in Venice), plotted on a map of London. (Bulidings, water, roads, and parks from OpenStreetMap) , created by author

Chapter 4 Statistical Analysis of the Dataset

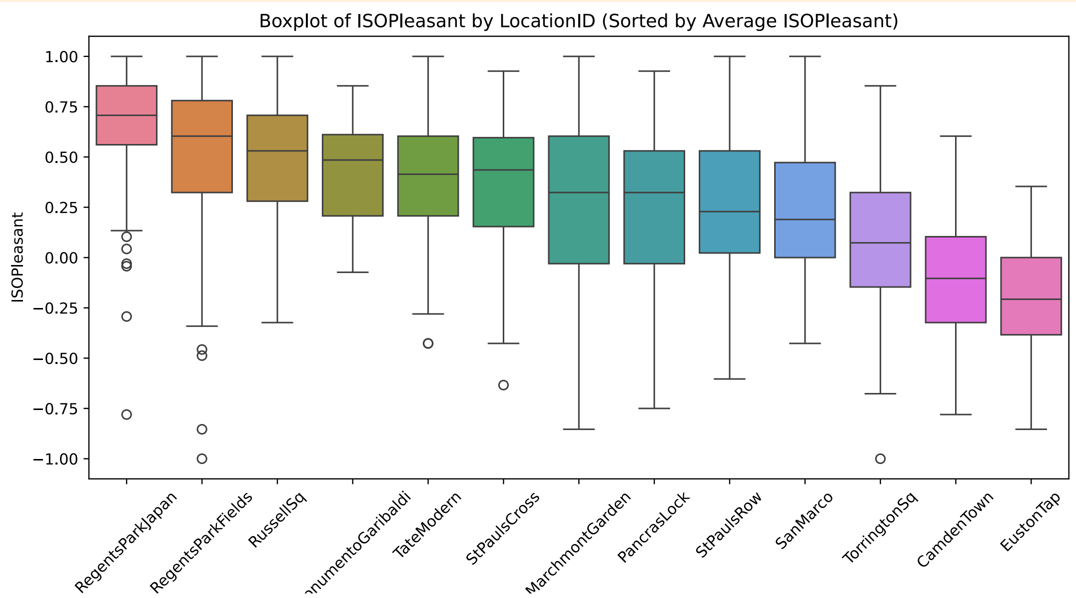


Figure 40 Boxplot of average Pleasantness per location, by author

To check the validity of the dataset a statistical analysis is done on features inside the dataset. Outliers removal options are also discussed in this chapter. The conclusions drawn at the end of this chapter will be used later on in this research.

Statistics per location

The examination of mean values per location enables the systematic investigation of variations across the different spatial environments within the dataset. By finding the mean value for the variables from each location, the influence of personal preferences, and temporal differences is diminished.

Pleasantness per location

When looking at the average of the perceived Pleasantness per locations, some disparities emerge. This is shown in figure 40. The location of 'Regents Park Japan' exhibits the highest mean Pleasantness score, registering at 0.66, while 'Euston Tap' has the lowest mean Pleasantness, recorded at -0.21. Notably, only two locations have mean pleasantness values below 0: 'Camden Town' with -0.10 and 'Euston Tap' with -0.21. Conversely, all other 11 locations manifest mean pleasantness scores surpassing 0, indicating a predominantly positive perception across the dataset.

'Euston Tap' and 'Camden Town' exhibit relatively low standard deviations (std) in perceived Pleasantness, measuring at 0.28 and 0.29, respectively. Those are the lowest std among the locations. 'Marchmont Garden', 'Regens Park Fields' and 'Pancras Lock' are locations with the highest std, with a std of 0.42, 039, and 0.39 respectively. Given the method of calculating pleasantness, it is expected that mid-range scores would exhibit the greatest distribution. It is unusual that 'Regent's Park Fields' has a high std as well. However, the locations with the two highest evaluations also have the most outliers, resulting in a higher std.

Seeing these differences per location

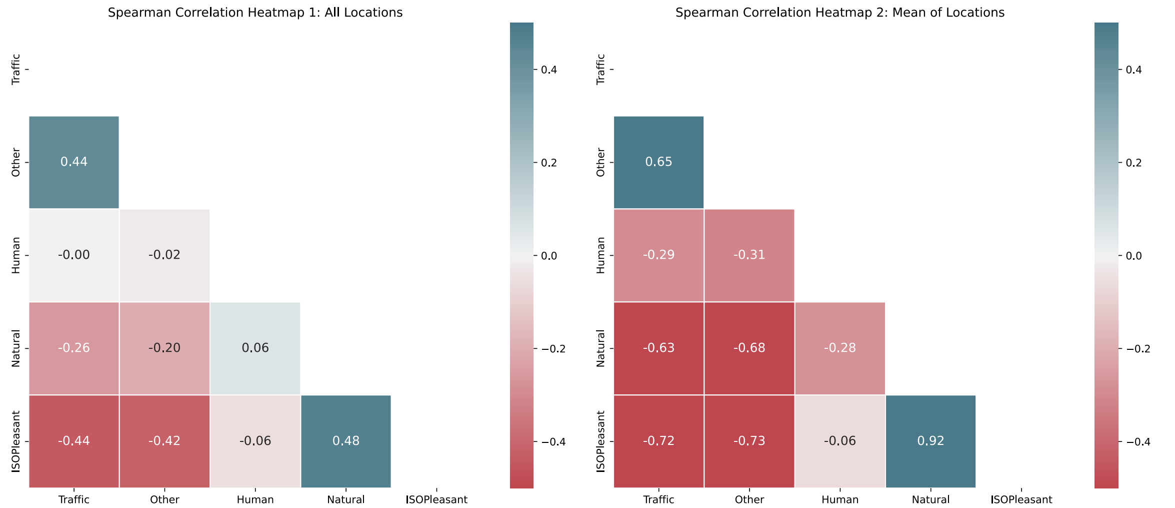


Figure 41 Correlation matrix for Spearmanr ISOPleasant and presence of different types of sound sources on the whole dataset (left), and on average per location (right), by author

suggests that besides personal preferences there are other factors that are spatially dependent that have influence on how sound is perceived.

Correlations between Sound sources and perceived Pleasantness

The first analysis was conducted on the full dataset (with removing contextual outliers wit a z-score> 2). Next, The same analysis conducted taking the averages per location.

Because the perceived pleasantness and the perceived presence of the sound sources are ordinal data, a spearman correlation was applied. The results are shown in figure 41.

There is a strong negative correlation for traffic sounds , rs[1282] = -0.44, $p < 0.001$, and for sounds in the category 'Other' rs[1282] = -0.42, $p < 0.001$. The negative correlation with traffic sounds and the rating of the soundscape quality is already established in previous literature research. It has also been correlated with increased annoyance.

There is a strong positive correlation with the pleasantness and the presence of Natural sounds rs[1282] = 0.47 $p<0.001$. The presence of Natural sounds and the positive correlation with a positive soundscape evaluation is also supported by previous findings in the literature.

The correlation with presence of human sounds and pleasantness is very weak amd not statistically significant: rs[1282] = 0.05, $p > 0.1$.

Correlation between Pleasantness and sound sources per location

The table presented shows the calculated means for each location's Likert scale responses in the dataset. Furthermore, the correlations observed are particularly robust, especially between different variables and the ISOPleasant measure. With a rs[13] = -0.71, $p < 0.001$ for the correlation between the presence of Traffic noise and the Pleasantness, and a rs[13] = 0.92, $p < 0.001$ for the correlation between the presence of Natural sounds and the Pleasantness.

Another interesting number that appears here is the negative correlation with the perceived presence of Natural sounds in relation to the perceived presence of Traffic and Other noise rs[13] = -0.62, $p < 0.001$, and rs[13] = -0.67, $p < 0.001$. That suggests that when natural sounds are more prevalent, the presence of intrusive noises like traffic becomes less prominent in people's perception. Conversely, in environments dominated by traffic and other urban noises, the presence of natural sounds tends to be perceived as less prominent.

Understanding these relationships can be valuable for urban planners, architects, and policymakers interested in creating healthy environments. Incorporating more natural elements into urban spaces, such as greenery and water features, could potentially mitigate the negative impact of urban noise pollution on people's perceptions and overall quality of life.

Correlations between pleasantness and psycho-acoustic factors

Psycho-acoustic factors are measured using sound level meter data. They are converted to different metric which explain different characteristics of the acoustics. The three most important ones are explained below. Loudness, Sharpness and Roughness are examples of psycho-acoustic metrics to measure the sensory experience of different characteristics of sounds. THe correlations with all the (psycho)-acoustic factor and Pleasantness is shown in figure 42.

Higher values of Loudness or roughness in the sound recordings are correlated with lower scores of perceived pleasantness among respondents. There is a negative correlation between Pleasantness (ISOPleasant) and the loudness that is exceeded 5% of the measurement time, Loudness_N5 rs[1282] = -0.37, p < 0.001, and the loudness that is exceeded 10% of the measurement time N10_90(SoneGF): rs[1282] = -0.46, p < 0.001.

The correlation between pleasantness and the Roughness of the sound is negative: rs[1282] = -0.44, p < 0.001. This finding is consistent with prior research, such as Aydin and Yilmaz (2016, p. 88), which has linked psycho-acoustic indicators like loudness and roughness to heightened levels of annoyance or unpleasantness.

Acoustic measurements characterized by elevated levels of loud and rough sounds tend to coincide with a perceived absence of natural sounds. The correlation between the perceived presence of Natural sounds and Loudness (N10_N90(soneGF)) is rs[1282] = -0.44, p < 0.001. The correlation between the perceived presence of Natural sounds and Roughness (Rough_HM_R(Asper)) is (rs[1282] = -0.48, p < 0.001. These correlations between loudness or roughness and pleasantness, exhibit a similar magnitude to those observed between pleasantness and psycho-acoustic measures. Loudness and roughness have a similar effect on the

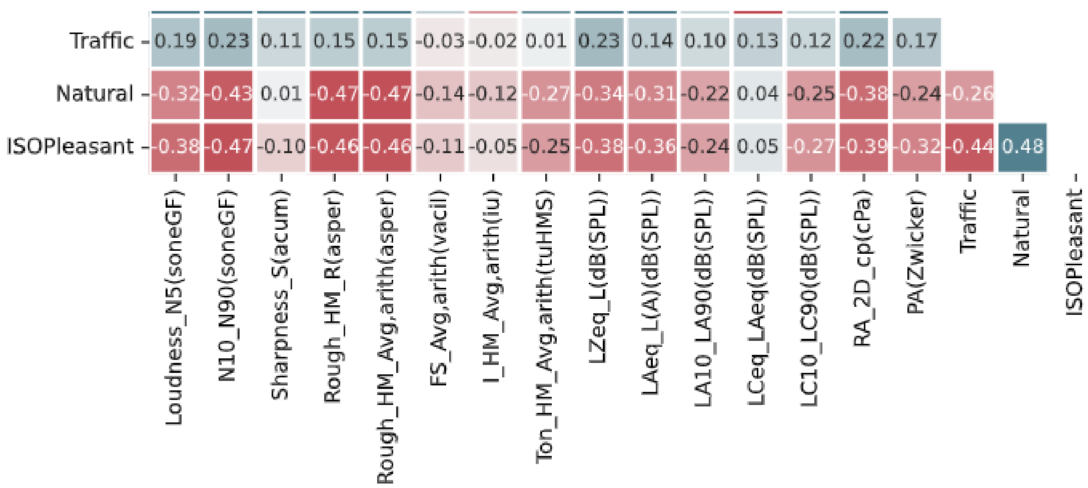


Figure 42 Spearman correlation matrix (cutoff) for the ISOPleasant and the psycho-acoustic factors taken for the whole dataset, by author

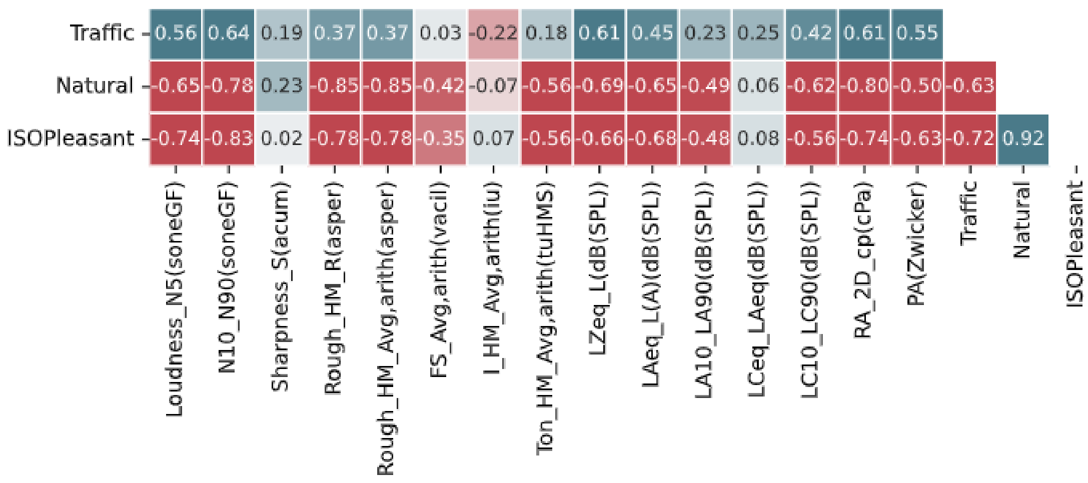


Figure 43 Spearman correlation matrix (cutoff) for the ISOPleasant and the psycho-acoustic factors for each average from each location, by author

perception of those two factors.

Psycho-acoustic features per location

For the Psycho-acoustic factors, the averages per locations are also analyzed and compared to the perceived pleasantness. Again this is done to account for the variation in the responses which is not location based. All the correlations are shown in figure 43.

There is a negative correlation between some (psycho-)acoustic factors, like the Loudness, Roughness and L_{Zeq}, and the ISOPleasant. These correlations are in the same magnitude as the negative correlation between the perceived presence of Traffic noise and the perceived pleasantness rs[13]=-0.73, $p < 0.001$

A higher value of Loudness (N10_90) correlates with a lower ISO pleasant score, with a strong correlation of rs[13] = -0.84, $p < 0.001$.

Looking at the correlation between the psycho acoustic features and the presence of Traffic noise one thing to note is that a higher Loudness value or LZeq correlates with a higher perceived presence of Traffic noise, rs[13] = 0.56 , $p < 0.05$, and rs[13] = 0.60, $p < 0.05$ respectively. These correlations are not strongly present when looking at the correlations of the entire dataset.

There is a strong negative correlation between the perceived presence of Natural sound sources and pyscho-acoustic features such as Loudness: Loudness_N5 rs[13] = -0.65, $p < 0.00$, and 1 N10_90(SoneGF) rs[13] = -0.78, $p < 0.001$. As well as a strong negative correlation between the perceived presence of Natural sound sources and Roughness rs[13] = -0.85, $p < 0.001$.

The positive correlation between the 2D approach and perceived pleasantness, evidenced by a Spearman correlation coefficient of rs[13] = 0.73, $p < 0.001$, suggests that areas with more favorable acoustic spatial configurations tend to be perceived as more pleasant. This strong correlation indicates that the spatial arrangement and interaction of sound sources and barriers significantly influence how people experience and evaluate the pleasantness of an environment.

This tells us that these factors could also be suitable for use to predict the urban acoustical comfort. However in this research these factors will not be used in the prediction model, because they cannot be obtained for new designs

Discussion

This chapter of the research checked the validity of the chosen dataset through statistical analysis.

People experience soundscape more positively when they experience a higher prevalence of Natural sounds rs[1282] = 0.46 $p<0.001$, and more negatively when they experience a stronger presence of Traffic noise rs[1282] = -0.44, $p < 0.001$. The data in the model seems to align with previous findings in the literature research (Hong & Jeon, 2017), (Aumond et al., 2017). The correlation with presence of Human sounds is very weak. In previous studies, human sounds were correlated both positively and negatively, or not correlated at all to the soundscape evaluation. Because the correlation with the presence of Human sounds is very weak in this dataset with the perceived pleasantness, and the p value is too high, it will not be taken into account further on in this research.

When correlating the mean values per location for perceived pleasantness and perceived presence of Natural sounds and Traffic Noise these correlations become even stronger. rs[13] = 0.91, $p < 0.001$, and rs[13] = -0.73, $p < 0.001$ respectively. This suggests that the variables that impact the urban soundscape pleasantness are location based.

This dataset is also used in the research where the pleasantness and eventfulness are predicted from psycho-acoustic factors (Mitchell, 2022). This had an R2 of 0.85. for predicting the Pleasantness. This research also found that sound level reduction does not always increases pleasantness, but sound source composition is important This statistical analysis also found some strong correlations between the psycho-acoustic factors and the perceived pleasantness, so this aligns with the literature. The psycho-acoustic parameters were not chosen to be used in the prediction model in this research because this does not fit into the design model framework. Mitchell (2022) also researched the correlation between pleasantness and eventfulness and demographic information. There were no strong correlations between those factors. In their ML model demographic information explained 1.4% of the variance in the model. Including the location context increased the R2 of the models, suggesting that context accounts for the majority of the variance

Limitations

Even though the dataset is very extensive and contains most of the information that is needed for the experiment in this master thesis, there are some limitations to the dataset that require to be mentioned.

Size

The dataset only has 1330 respondents. More data would make the model make more accurate predictions. However for this experiment the size is fine.

Only for image classification: To increase the sample size maps (images) can be rotated, to add to the data. Non-linear algorithms need more data.

Likert Scales and the PAs

The Pleasantness based on the ISO standard is calculated by the input of answers of the questionnaire based on a Likert scale. (formula 2) .There is some discussion on whether these Perceptual attributes have exactly the same effect as in the formula (Mitchell, 2022).

Locations

The locations in the dataset are rather limited. These mostly consist of public spaces in urban parks in big cities. The current dataset only has data in London and Venice. Acoustical comfort can have some differences between countries because of cultural differences. Because most of the datapoints are collected in these urban park areas, the predictions used will be the most accurate in similar environments. The newer set of data will also have data on a city in the Netherlands (Groningen). and other cities in Europe and China.

more positive responses than negative

Among the surveyed locales, only 2 of the 13 exhibited an average pleasantness score below zero, indicating inadequate soundscape quality. Applying this dataset to enhance soundscapes necessitates acquiring additional data on both adverse and favorable sound environments. Given the prevalence of positive soundscapes, exploring their positive attributes is paramount.

Different points at the exact same location

Human perception is inherently subjective, also in regards to acoustics. Datapoints sharing the same geographic location can still have differences in the perceived pleasantness due to this subjectivity. The presence of multiple points sharing identical geographic coordinates but exhibiting variations in the ISOPleasant column and other attributes underscores a limitation inherent in the dataset. At the same time, because of its subjectivity it is important to collect a lot of data at the same spot to validate the data.

This may result in some generalization challenges when training the machine learning model later in this research. If the dataset contains a wide range of perceptions for the same location the model may struggle to discern underlying patterns or trends, making it less effective when applied to new unseen instances.

Lavandier et. al (2016), tried to predict pleasantness in a somewhat similar fashion. The research started with 3409 real individual sound pleasantness data points, which they then condensed down to 204 urban situations for analysis. Following this example, this research could explore a similar strategy to streamline the dataset and reduce any unwanted noise.

Another approach would be removing the outliers per location. For usage in training a machine learning model, outliers per location can be removed to improve the model, and help against overfitting to these outliers

Accuracy of the location coordinates

When inputting the geographical coordinates from the dataset into the QGIS software and visualizing them on a map, certain datapoints exhibit indications of potentially erroneous location data. The accompanying images illustrate instances of points situated within or atop buildings. Additionally, the final image depicts points where survey respondents appear to be positioned within the River Thames. It is assumed that these anomalous coordinates are likely a consequence of input error during the data entry process. These points will not be taken into account during the machine learning process to make sure the model is trained properly. The points that have been removed are shown in figure 44.

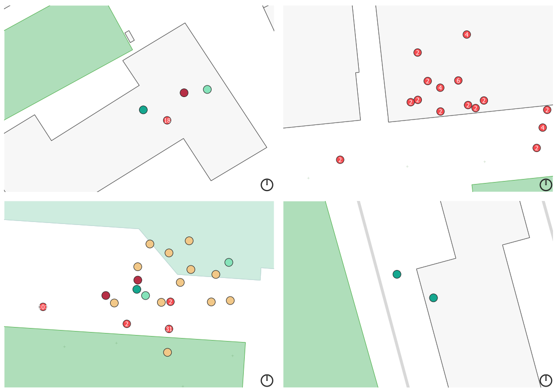


Figure 44 Four places in the dataset (Mitchell et al. 2020) where datapoints are taken out because of faulty placing, Made in QGIS with OpenStreetMap background, by author

Time of the day Temporality / Dynamics of acoustics

The time of recording is not evenly spread throughout the day. Figure 45 shows that the majority of the recordings are done between

11 am and 2 pm. Acoustics are a very temporal dynamic experience. Therefore on different times of the day the assessment could be different. For example during rush hour, there might be an increased experience of Traffic noise.

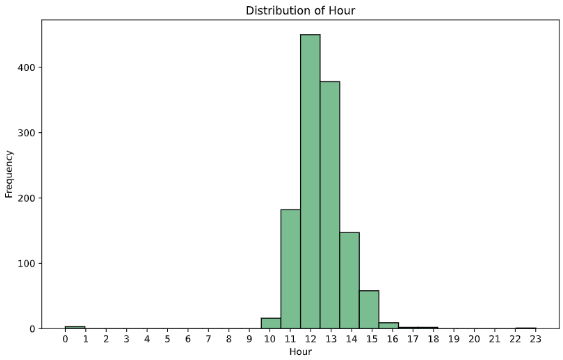


Figure 45Hisotgram showing which hours of the day the surveys were collected, graph made by author

The dataset contains a column for annotations, which are filled in when there are remarks during the survey. For example some notes show that there are helicopters flying over a park, something that impacted the perceived acoustic quality of the area for the respondents

Age & inclusivity

Figure 46 shows the ages of the respondents. The age group of respondents in the survey are on average 31 years old (median 29). This might not be representative of a mixed population in an urban area, consisting of all ages. In terms of inclusivity and accessibility, it would be better to question a broader age group. Studies found that for example elderly (Baquero Larriva & Higueras García, 2023) experience soundscape differently than their younger peers.

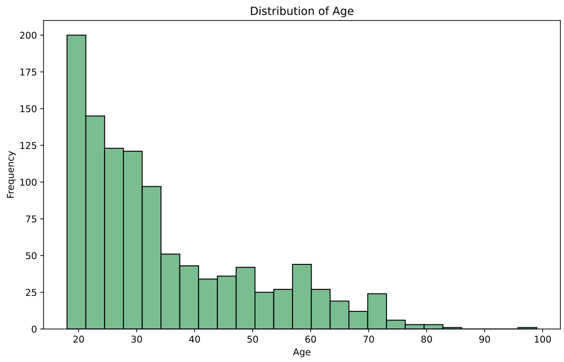


Figure 46 Histogram showing the ages of the respondents (bins of 5 years), graph made by author

Conclusion

In conclusion, while the dataset utilized in this master's thesis is extensive and provides valuable insights into urban acoustics and perceived pleasantness, several limitations must be acknowledged.

Firstly, the size of the dataset may limit the precision of predictions, particularly in non-linear algorithms where more data could enhance accuracy. The dataset's geographical scope, primarily focused on public spaces in urban parks in London and Venice, introduces potential limitations regarding generalizability, as acoustical comfort can vary across different locations and cultures.

The dataset's inherent subjectivity, reflected in variations in perceived pleasantness even within the same geographic coordinates, poses challenges for training machine learning models. The uneven distribution of recordings throughout the day further complicates temporal dynamics in acoustics assessment, potentially impacting the accuracy of predictions. Furthermore, demographic considerations, such as the age distribution of respondents, and methodological aspects, including the use of Likert scales for perceptual attribute assessment, warrant careful consideration to ensure the robustness of findings.

Despite these limitations, the dataset aligns with previous literature, highlighting the influence of the perceived presence of natural sounds and traffic-related noise on soundscape pleasantness. Therefore this dataset will be used as input for the machine learning model for this research.

Chapter 5 Expansion of Dataset & Statistics

In this section, other additional data sources will be explored and their relationship to variables in the dataset will be tested. At the end of this chapter, a few soundscape design strategies will be discussed, based on the findings in this chapter.

In order to conduct a comprehensive analysis of the dataset, additional datasets from the city of London were acquired to facilitate comparative assessments. The decision to focus solely on London for dataset expansion was driven by several factors. Firstly, the dataset already contained a significant proportion of survey locations within London, comprising approximately 11 out of 13 locations, yielding around 1100 datapoints. This concentration of data within London facilitated robust statistical analyses and ensured a representative sample of urban dynamics. Conversely, the inclusion of only two survey locations in the city of Venice limited the availability of public data for comparative purposes, since similar data for the city of Venice were publicly unavailable. Consequently, the research scope was narrowed to exclusively examine the urban landscape of London, thereby enhancing the depth and reliability of the analytical findings.

L_{den} for road Traffic London

The municipality of London (Department for Environment Food & Rural Affairs, "Noise Pollution in London - London Datastore.", 2012) has a map with the Lden of road and rail noise for the city. The Lden map has similar noise levels as the LAeq levels that are already available in the dataset, as discussed later in this chapter.

Some datapoints in the dataset will not be included in this part of the statistical analysis. The points that are left out have a Lden from Road Noise that is lower than 55dB. They did not overlap with the Lden map created by the municipality of London. 798 of the points fall into this group. By excluding these points, the dataset becomes more focused on capturing the nuances and effects of higher levels of road noise. Consequently, the remaining 534 data points, which exhibit a higher range of road noise exposure in terms of Lden, are utilized in the subsequent statistical analysis.

L_{den} & Pleasantness

The Spearman correlation between the NoiseClass cateogries for L_{den} and the Pleasantness have a spearman rank correlation coefficient of rs[534] = 0.58 $p<0.01$. This is a strong correlation which is statistically significant. This correlation is even stronger than the correlations between acoustical measurements in the dataset and the pleasantness.

The L_{den} only captures road noise and punishes noise in the evening (+5dB) and at night (+10dB) (see formula 1). These penalties might impact Lden's effect, since the questionnaires are conducted at specific times of the day, mostly around noon, even if there is a predicted surge of Traffic noise at night.

When comparing the L_{den} with the L_{Aeq}, the L_{den} has a higher correlation with the Pleasantness. The L_{Aeq} is recorded during the interview sessions, and includes road noise as well as all other sounds. The Lden is not representative for the SPL as a whole but rather emphasizes the presence of Traffic noise as discussed in the next section.

The strong correlation between the Lden and the Pleasantness and the likeliness of the L_{den} to the acoustic measures in the dataset seem to indicate that creating predicted L_{den}

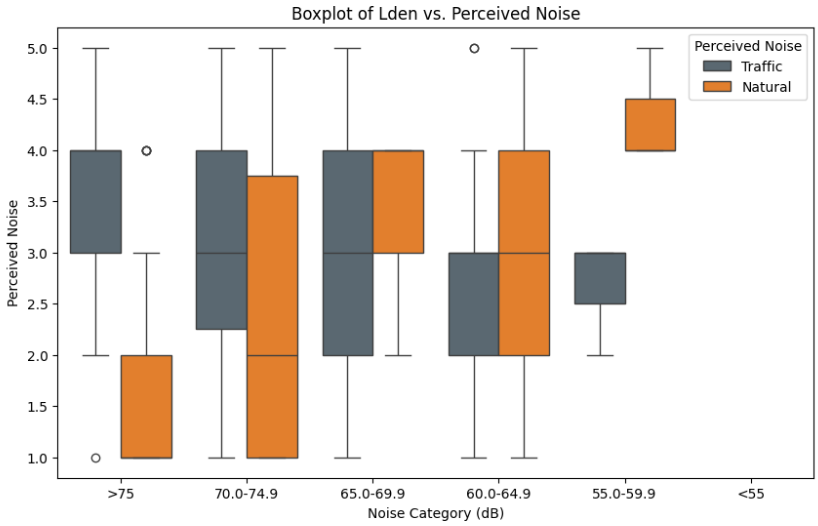


Figure 47 Lden from GLA (2017) and the perceived presence of Natural Sounds and Traffic Noise, by author

maps for future designs is a good input for predicting the urban comfort in that area, as shown in figure 48.

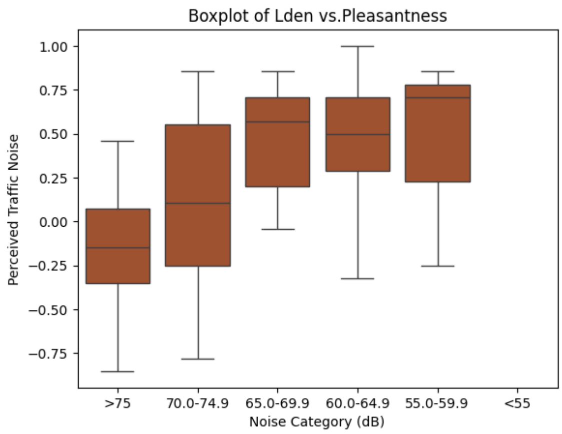


Figure 48 Boxplot of ISOPleasant and the L_{den} from GLA (2017) , made by author

Perceived Traffic Noise

The average perceived presence of traffic noise increases when the L_{den} level increase. The difference between 55-59.9 and 60-64.9 is very little. The difference between >=75 and the step below is the biggest.

There is a correlation between the perceived presence of Traffic noise and a higher L_{den} value. the Spearman correlation is rs[534] = -0.51 $p<0.001$, which is a moderately strong correlation. Points were removed that did not fall into the categories in the L_{den} map, so when the estimated value is lower than 55dB. There is more variety in the perceived presence of Traffic noise in this group.

The general perceived presence of Traffic noise might be more sensitive to changes in noise levels in L_{den} once a certain threshold is reached. Below this threshold, the L_{den} from road noise might not be perceived as significantly different, but once road noise levels surpass this threshold, people become more aware of and affected by the noise, leading to a stronger correlation between measured noise levels and perceived Traffic noise presence.

Areas with L_{den} noise levels below 55dB include quieter residential zones or parks where the background noise level is generally low. In such environments, temporal variations in Traffic noise levels may have more impact on perceived Traffic noise presence, in comparison to busy areas when the Lden is consistently higher.

When checking all the points in the dataset the Spearman correlation coefficient is rs[1327] = -0.33 with $p<0.001$. This is a moderately weak correlation, which is statistically significant.

Perceived Natural Sounds

Spearman correlation coefficient: rs[534]=-0.45 p<0.01 between the L_{den} and perceived presence of Natural Sounds. This is a stronger correlation then the correlation between L_{den} and Traffic Noise. So, the absence of Road Noise measured in Lden suggests a higher presence of Natural Sounds.

Again this is with leaving out the datapoints having a L_{den} lower than 55dB, with including those datapoints the spearman correlation rank is : rs[1332] =-0.21 p<0.01. The stronger negative correlation rs[534]= -0.45 suggests a more consistent and pronounced relationship between road noise levels and the perceived presence of natural sounds when focusing on areas with higher noise levels. Instances where road noise is more dominant and has a greater potential to overshadow natural sounds, leads to a stronger negative correlation between the two variables. the L_{den} does not account for temporal changes in the acoustic environment, which can be perceived as more prominent when the background noise levels are lower.

LAeq, LZeq & Lden

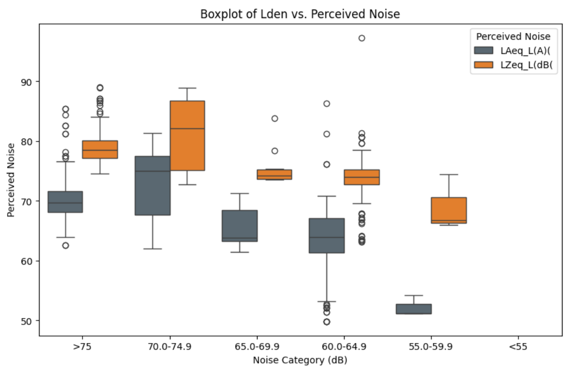


Figure 49 boxplot of Laeq, LZeq and Lden, by author

The L_{den} and the L_{aeq} have a Spearman correlation coefficient rs[534] = -0.64 with p<0.01, which is a moderately strong negative correlation, which is statistically significant. In the places where the L_{den} is higher in general the L_{Aeq} is also higher. The spearman correlation coefficient between the L_{zeq} and the L_{den} rs[534] = -0.68 with p<0.01. Also a moderately strong correlation, which is statistically significant. Figure 48 shows the distribution of recorded SPL at locations with the corresponding L_{den} level from the GLA map

Biodiversity

The biodiversity map shows different land use types. It is called the Living Habitat map of England

The majority of the points fall into the category of Built Areas. Generally this group also scores lower on the Pleasantness, then the other categories.

In the areas labeled 'Built up Areas and Gardens' the perceived presence of Natural sounds is the lowest. With 678 points in this category this category also makes up the largest part of the dataset.

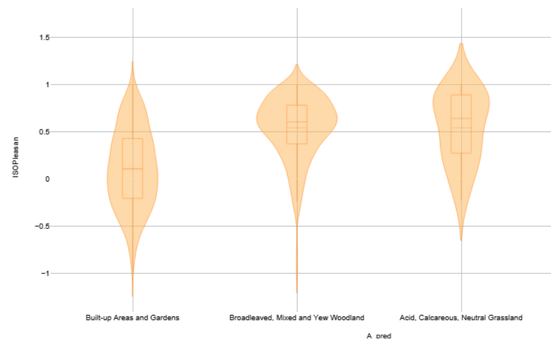


Figure 50 Violin plot ISOPleasantness for Built-Up and Gardens (left), Broadleaved (middle) and Neutral grassland (right) , by author

OpenStreetMap

Why use OSM data

The utilization of OpenStreetMap (OSM) data offers several advantages. OSM is a free publicly accessible geographic database collaboratively developed by volunteers worldwide, aimed at providing comprehensive and up-to-date street maps. To goal of the international OSM project is to create a free map of the world. (OpenStreetMap Blog | Supporting the OpenStreetMap Project.) Given its community-driven nature, OSM maps undergo frequent updates, ensuring the accuracy of spatial information pertaining to the built environment. Geographical data from OSM can give an indication of the closeness to a certain sound source, in addition it can also somewhat give an indication of the visual imagery of the surroundings. Therefore OSM data serves as a reliable presentation of geographical features and infrastructural elements.

Roads

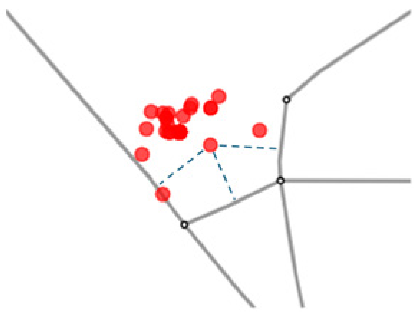


Figure 51 Visualization of datasetpoints and roads from OSM, by author

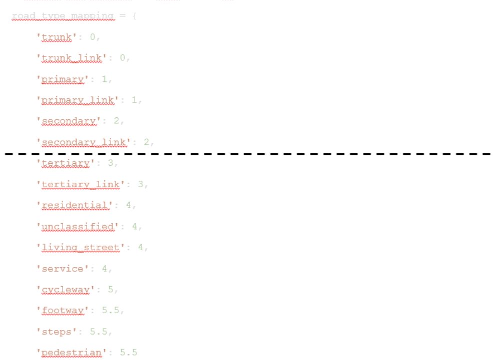
This part of the research aims to find a correlation between the distance between the dataset objects placed on their respective coordinates and the nearest road, and their perceived pleasantness and the perceived presence of Traffic sounds. The road network is loaded from OpenStreetMap (OSM). For every point the distance to the closest street edge is calculated, illustrated in figure 51. The correlation between the distance to the nearest road and the perceived presence of Traffic noise is rs=0.32 $p<0.01$. Such a correlation implies an increase in the perceived intensity of traffic-noise as distance from the roadway increases. However, this inference appears counterintuitive given the conventional understanding of sound propagation dynamics in free field environments, where sound pressure levels typically diminish with distance from the source.

$$L_p = L_w - \left| 10 \cdot log\left(\frac{Q}{4\pi \cdot r^2}\right) \right|$$

The relation between the distance to the nearest road and the perceived pleasantness the correlation has a correlation coefficient (rs) of =-0.13 $p<0.01$. This correlation coefficient suggests a very weak tendency for individuals to perceive acoustic environments as more pleasant when in close proximity to a road, which also appears counter intuitive.

During the data analysis phase, a negative correlation coefficient of -0.43 was detected between the perceived presence of traffic sounds and the perceived level of pleasantness. This finding indicates a tendency for individuals to perceive a decrease in pleasantness when heightened levels of traffic noise are perceived, suggesting a potentially adverse impact associated with closer proximity to this auditory source.

Focusing solely on the proximity to the nearest road may suggest that emitted sound is confined solely to that nearest road. However, this perspective overlooks the differential noise emission and propagation patterns associated with various types of roadways. It is essential to recognize that busier thoroughfares, characterized by higher volumes of vehicular traffic such as cars and similar vehicles, 50km/h roads, are primary sources of traffic noise, and for example footpaths or bicycling paths have a smaller impact on the perceived presence of Traffic noise.



```
road_type_mapping = {
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    'trunk_link': 0,
    'primary': 1,
    'primary_link': 1,
    'secondary': 2,
    'secondary_link': 2,
    'tertiary': 3,
    'tertiary_link': 3,
    'residential': 4,
    'unclassified': 4,
    'living_street': 4,
    'service': 4,
    'cycleway': 5,
    'footway': 5.5,
    'steps': 5.5,
    'pedestrian': 5.5
```

Figure 52 List of road types in OSM with cut off line for busy roads, by author

In order to delineate various categories of roads, a systematic compilation was undertaken, incorporating weighted factors corresponding to distinct traffic patterns. Roads experiencing heavier traffic volumes were assigned higher values within the list. For example, roads for walking are labeled 'footpath' and roads for cars can be labeled as 'trunk' or 'primary.

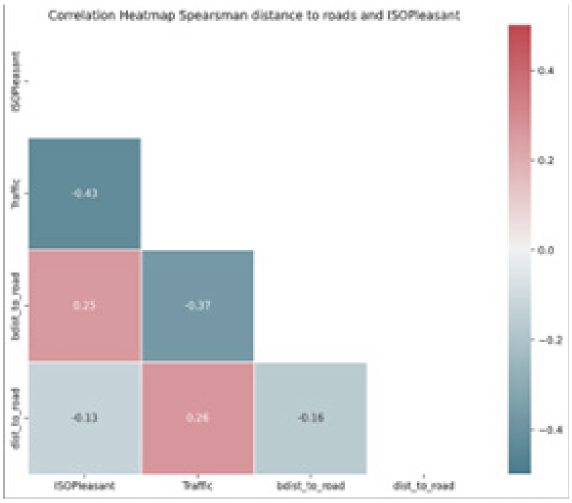


Figure 53Spearman correlation matrix ISOPleasant and distances to busy roads, by author

The correlation between the distance to the nearest 'busy' road and the perceived presence of traffic noise is observed to be rs= -0.37. This seems more intuitive, that there is a tendency to experience more traffic noise when proximity to a busy road decreases.

The correlation analysis reveals a statistically significant coefficient rs[1282] = 0.25 ($p < 0.001$) between perceived acoustic pleasantness and proximity to the nearest busy road. This result indicates that perceived pleasantness increases as distance from a busy road increases, aligning well with both our statistical findings and prior research in the field.

This correlation of rs[1282] = 0.26 $p<0.001$ of ISOPleasant and the proximity to the nearest busy road is a moderately weak correlation. However contrasting this with the stronger negative correlation of -0.43 observed between traffic noise and ISOPleasant . This suggests the expected correlation between roads as a noise source and their influence on the perceived pleasantness is not expected to be higher than 0.43 in absolute value. This indicates the potential for approximately half of the variance in pleasantness to be accounted for by respondents' distance from a busy road.

Partial correlations

In statistical analysis the partial correlation finds the unique relationship between variable X and Y, when other variables have been considered (Field, 2018). Partial correlations are useful in situations where multiple variables can influence the relationship between two variables of interest. When looking at the correlation between factor X and Y it takes into account the correlations between X and Z and Y and Z, to find what their impact is on the correlation.

By isolating the relationship between these two variables from the influence of other variables a better understanding of the relationship of those isolated variables can be found. If the partial correlation differs a lot in value from the original correlation, the relationship between the variables X and Y might be indirectly influenced by the variable Z. If the correlation coefficient stays somewhat the same, the correlation between X and Y has a smaller influence from the variable Z. (This is not to say that then there is a causal relationship between the factors, they could still be indirectly influenced by other factors.).

This is the formula to calculate the partial correlation:

$$r_{xy|z} = \frac{r_x y - r_{xz} r_{yz}}{\sqrt{1 - r_{xzy}^2} \cdot \sqrt{1 - r_{yz}^2}}$$

Formula 5: Partial correlations (Field, 2018)

In this case X is the perceived acoustic Pleasantness, and Y is the perceived presence of Traffic noise. The variable Z that is accounted for is the distance to a busy road. This is shown in figure 54. The spearman rank correlations between the variables are r_{xy} = -0.44, r_{zx} = 0.25, r_{yz} = -0.37.

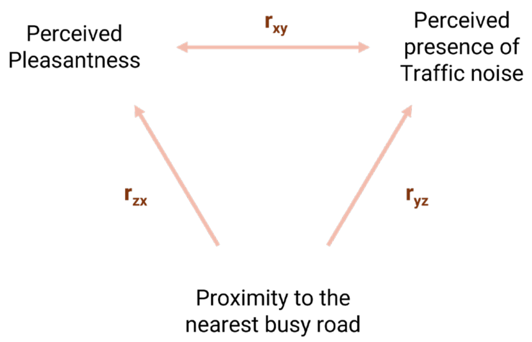


Figure 54 Visualization for partial correlations, by author

$r_{xy,z}$ is the partial correlation coefficient between ISOPleasant and Traffic controlling for the variable bdist_to_road. The partial correlation $r_{xy,z}$[1131]= -0.413, the p-val < 0.01, which indicates that there is indeed a significant partial correlation between ISOPleasant and Traffic when controlled for distance to a busy road.

	n	r	CI95%	p-val
spearman	1074	-0.44		<0.01
partial	1074	-0.41	[-0.46 -0.36]	<0.01

Table 2 the Partial correlation between Pleasantness and Traffic Noise when controlled for the distance to a busy road.

The reduction in the correlation coefficient from -0.44 to -0.41 indicates that factoring in the variable "distance to nearest busy road" slightly weakened the strength of the relationship between perceived pleasantness and perceived presence of Traffic noise. Even though the correlation can partly be explained by this third variable, a bigger part of the correlation cannot be explained by controlling for distance to nearest busy road.

The propagation of traffic noise within urban areas does not adhere to a linear pattern across cities. The current model solely considers the proximity to the nearest busy road, neglecting the natural dispersion of sounds throughout the urban landscape. Moreover, it fails to account for the presence of other multiple nearby roadways that may also contribute substantially to road noise emissions. Furthermore, the model assigns equal weight to all busy roads, disregarding variations in traffic densities and the wide-ranging emissions of road noise among different road segments. Additionally this model does not take into account the temporality of road noise with the presence of traffic throughout the day. Thus, a more comprehensive approach that incorporates the complex spatial distribution of traffic noise sources and considers the heterogeneous characteristics of urban road networks, like Lden simulations, is warranted for accurate assessment and prediction of urban noise exposure levels.

	n	r	CI95%	p-val
spearman	1074	0.25		<0.01
partial	1074	0.11		0.941

Table 3 The correlation between pleasantness and the distance to busy roads, when controlled for the Perceived presence of Traffic Noise

The spearman rank correlation between the distance to a busy road and the perceived pleasantness is rs=0.25. However, when accounting for the perceived presence of traffic noise, the partial correlation coefficient diminishes to rs = 0.11. This suggests that a substantial portion of the correlation observed between pleasantness and proximity to the nearest busy road can be attributed to the influence of perceived presence of traffic noise. Additionally, the p-value is very high. Therefore this correlation is not statistically significant and will not be used in the further research and design.

Nature (vegetation)

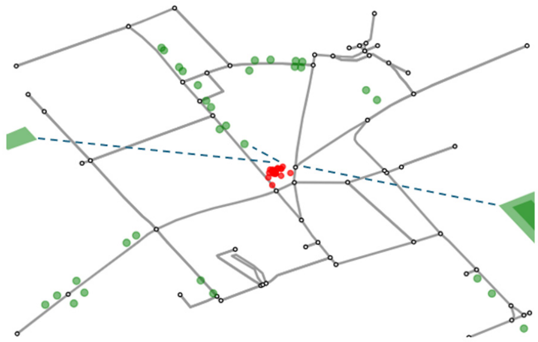


Figure 55 Visualization for distance from vegetation from OSM, by author

This part of the research aims to find a correlation between the proximity to the nearest park and an increased perceived presence of natural sounds, and a positive influence on the perceived pleasantness of the acoustical environment for respondents. In our dataset there is a strong positive correlation with the pleasantness and the presence of Natural sounds rs[1282] = 0.46 $p<0.001$. Therefore modeling the sound source of natural sounds can give insights on how this plays out in an urban environment.

The data for parks is loaded from OSM. From each point the proximity to the nearest park is calculated, as shown in figure 55. If the location of the survey respondents is inside a park the distance will be set to 0.

The correlation analysis reveals a moderately strong relationship between proximity to vegetation and the perceived presence of natural sounds $rs = -0.38$, $p < 0.001$. Specifically, as respondents were closer to parks, there is an observed increase in the perception of natural sounds.

Similarly, the analysis indicates a moderately strong correlation between proximity to vegetation and perceived pleasantness $rs = -0.33$, $p < 0.001$. This suggests that a shorter distance to parks is associated with a more favorable perception of acoustic environments. These findings corroborate previous research and align with our prior observations, highlighting the consistent influence of vegetation proximity on both natural sound perception and perceived pleasantness.

The proximity to parks had very little effect on the perceived presence of Traffic Noise rs=0.04, p < 0.10.

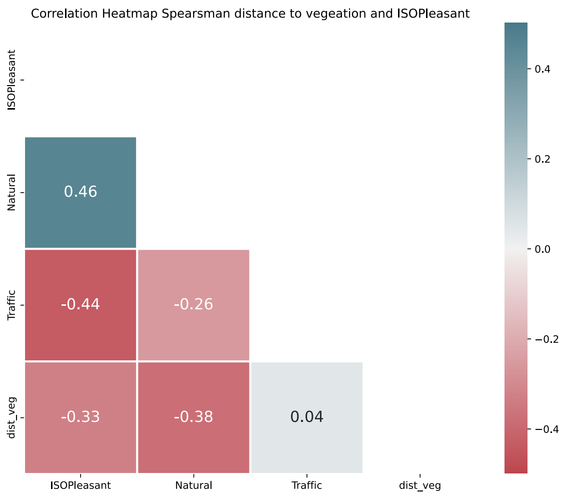


Figure 56 Spearman correlation matrix for ISOPleasant and distance to vegetation, by author

In urban settings like the city of London, parks are often situated within densely populated areas, surrounded by busy roads and high traffic density. Therefore, even though respondents may have been physically close to parks, the pervasive urban infrastructure, like roads with heavy traffic, still contribute a lot to the overall composition of the soundscape

Additionally the design of these urban parks in the city center of London might not effectively buffer against traffic noise. While green spaces provide some degree of respite from urban environments, they may not offer sufficient acoustic insulation to shield park users from the sounds of nearby traffic.

While natural elements like grass and trees do offer some degree of acoustic absorption, they may not be as effective as solid structures like buildings in attenuating traffic noise. Natural elements like grass and trees are porous and have low density on average, which may limit their capacity to absorb and attenuate traffic noise, particularly low-frequency noise produced by vehicles. Solid structures such as buildings typically have denser and thick construction materials, which are more effective in blocking and absorbing sound waves.

Considering these factors, in urban planning different strategies may need to be employed. Adding wanted sound sources like natural sounds by, for example, adding vegetation, can definitely improve the soundscape. However in high density urban places people still could experience traffic noise. Therefore the other soundscape strategy, limiting the perceived presence of unwanted sounds, should also be implemented. This can be by shielding the urban areas from roads, limiting their exposure to traffic noise.

Partial correlations proximity to vegetation

	n	r	CI95%	p-val
Spearman correlation	1254	0.46		<0.001
Partial correlation	1254	0.38	[0.33 0.43],	<0.001

Table 4 The Spearman correlation and partial correlation between Natural & ISOPleasant

The reduction in the correlation coefficient from -0.46 to -0.38 indicates that factoring in the variable “distance to nearest parks” slightly weakened the strength of the relationship between perceived pleasantness and perceived presence of Natural sounds. While the inclusion of the distance to nearest parks variable can account for a portion of the correlation observed between perceived pleasantness and perceived presence of natural sounds, a significant portion of this correlation remains unexplained even after controlling for distance to parks. This suggests that there are other factors beyond the proximity to parks that influence the relationship between perceived pleasantness and perceived presence of natural noise.

	n	r	CI95%	p-val
Spearman correlation	1276	-0.33		<0.001
Partial correlation	1276	-0.19	[0.24 0.13],	<0.001

Table 4 Spearman correlation and partial correlation between the distance to the nearest park, and the ISOPleasant. The partial corrrelation is controlled for the percevied presence of Natural Sounds

This could have several reasons. One of them could be that this type of analysis does not take into account the quality of the parks. Size, amenities and biodiversity are different factors that have not been taken into account while looking at these parks. Additionally this analysis did not take into account other urban and environmental factors such as nearby roads or buildings.

Conclusion

Considering the previous analysis of the dataset and the added data, there is no simple solution to designing a good urban landscape. A multifaceted approach is needed.

To what extent can computational design tools, in the shape of machine learning models, incorporate soundscape data to inform and shape urban design elements for improved soundscapes?

A high L_{den} has a strong negative impact on the perceived pleasantness of the acoustic urban environment, even higher than acoustic recordings in the dataset. Furthermore greater distance from busy roads correlates with an enhancement in the perceived pleasantness of the surrounding environment and a reduction in the perceived presence of traffic noise. However when controlling for the presence of traffic noise, the partial correlation between proximity to a busy road and pleasantness became very small. Consequently, utilizing distance from roads as a sole design parameter may not yield favorable outcomes.

Instead, employing simulation mapping techniques to predict L_{den} levels derived from road emissions emerges as a more prudent approach for anticipating the perceived presence of traffic noise, the perceived absence of natural sounds, and the overall perceived pleasantness of the soundscape

Proximity to vegetation correlates with enhanced pleasantness, and a heightened perception of natural sounds. The relation between the distance to the nearest park and the perceived pleasantness is slightly lower when controlled for the perceived presences of natural sounds. While this approach proves adequate, alternative methods for predicting the presence of natural sounds will be further investigated for comprehensive analysis.

The distance from vegetation exhibited minimal impact on the perceived presence of traffic noise. Consequently, while the addition of vegetation may enhance acoustic pleasantness by augmenting the perceived presence of natural sounds, it does not improve soundscape pleasantness by mitigating the presence of traffic sounds.

In examining strategies for enhancing urban soundscape design, referencing Cerwén's (2017) soundscape design strategy is beneficial.

Reduction of unwanted sounds

Soundscape design aims to look beyond noise reduction. However Traffic noise emissions still remain an important part in the perceived pleasantness in the dataset. In places where the Lden level exceeds 60dB the pleasantness is heavily impacted. Therefore if at a a selected location the Lden exceeds this level, reduction methods should be implemented, before looking at other strategies.

Introduction of wanted sounds

The introduction of wanted sounds through adding vegetation can definitely improve soundscape design by inviting more vegetation not only adds aesthetic value but also contributes to acoustic comfort by absorbing and diffusing sound waves, thus mitigating the impact of unwanted noise.

Overall the findings in this chapter helped with creating the framework for the design tool that is created in this research, and help focus on which subjects are important

Chapter 6 Modification of the dataset

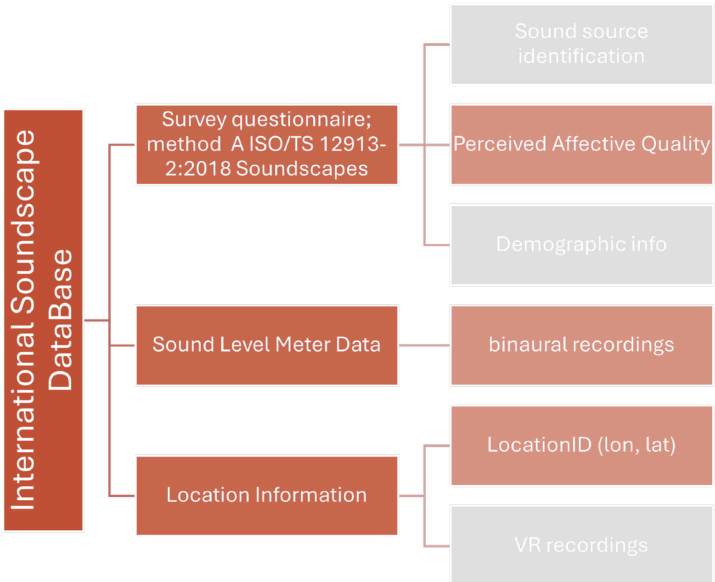


Figure 57 Representation of the used content in the dataset from Mitchell et al. (2020), by author

Modification of the dataset

After the statistical analysis, to check the validity of the dataset, the information that is needed as input for the machine learning process is compiled

Filtering data

The dataset used is the previously discussed International Soundscape Database dataset: Below is shown what data the dataset includes and what data is used to train the model eventually. Data that is included in the dataset are the perceived affective qualities (PAQs), which lead to a pleasantness score with the formula from the ISO standard (formula 2). Other data from the dataset that is used are the coordinates. With the latitude and longitude the point can be located geographically.

Sound source identification was employed in the statistical analysis to inform decisions regarding the design tool framework. Alternative studies, exemplified by Lavandier et al. (2016) and Hong and Jeon (2017), attempted predicting the presence of different sound source , distinguishing between natural and technological or traffic-related sounds. However, because of the unavailability of subjective data for new designs, it will not be included for training a ML model.

Sound level meter data is also left out of the ML model, since this is hard to reproduce for new designs. The same goes for VR recordings. Additionally, demographic information is left out of the dataset for the machine learning model.

Identify outliers

contextual outliers per geographical location

The literature section has discussed methods for identifying outliers, with this research opting to focus on contextual outliers. In the context of the dataset used in this research, the geographical location serves as the relevant context for identifying contextual outliers. The contextual outliers are the datapoints in the same location, which have a very different ISOPleasant score. Removing conventional outliers, so looking at the dataset as a whole, removes the variance that can be attributed to differences in physical and sensory environment. Since this research looks at the differences per location, it would not be beneficial to remove conventional outliers.

Z-score method

The z-score method, previously discussed in the literature chapter, will be used to remove contextual outliers. Having a low Z-score can take into account contextual outliers per geographic location that may not solely be attributed to their physical environment. This approach considers additional factors such as temporal fluctuations, such as for example the presence of helicopters, and wellbeing of the respondent, which can significantly impact the perceived quality of the acoustics (Mitchell, 2022). Addressing contextual outliers facilitates the refinement and optimization of machine learning models used for predictive modeling, ultimately improving the accuracy and effectiveness of future analyses and applications.

Outlier removal process

Given the amount of contextual outliers affecting perceived pleasantness within the dataset, the decision was made to remove the most significant outliers. For each group of data points sharing identical longitude and latitude coordinates, datapoints were removed with z-score exceeding 2.0 for their ISOPleasant value. The datapoints have a column with the latitude and longitude coordinate, that is ow they are determined. This removed 41 outliers, out of 1332 datapoints.

Eliminating additional outliers

As discussed in the chapter where the dataset is analyzed, some points in the dataset are located on odd locations. For example, certain data points are situated in unconventional locations, such as inside or atop buildings. These locations introduce

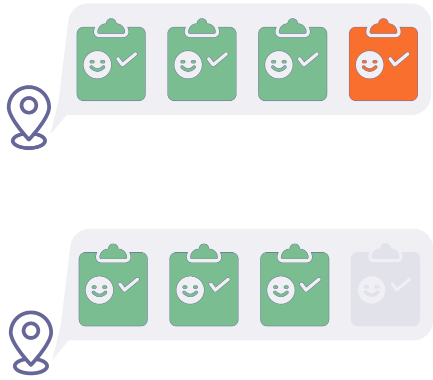


Figure 58 Contextual outliers

distinct input values for the supplementary data discussed later in this chapter. Therefore, these datapoints will also be removed for more accurate results

Failed attempt

Although an attempt was made to replicate Lavandier's (2016) methodology of averaging across different locations, this approach did not result in an improvement in the machine learning model's performance. There are approximately 200 different locations in the dataset based on coordinates. Some of these coordinates have 1 data entry while others have +100. By taking the average of every location, the locations with only 1 entry have as much weight in the model as locations with 100 data entries. This discrepancy likely contributed to the inefficacy of this methodology for the current dataset.

Additional data

Once the dataset is filtered and the outliers are determined, other data can be added to the dataset. Data that is added to the dataset is in regards to the previously discussed urban design elements, such as buildings, road and vegetation/natural elements, to see if they can accurately predict urban acoustic pleasantness.

Buildings

During the statistical analysis phase, buildings were not initially considered. However, upon completion of the analysis, it became apparent that buildings may have a significant influence on sound propagation and ultimately shape the experience of the soundscape. Moreover, buildings are integral to the creation of the predicted Lden maps, which are used to predict traffic noise. These buildings are initially sourced from OpenStreetMap data for inclusion in the analysis.

Building height

Building height data was sourced from the municipality of London dataset (GLA, 2017), providing information for the majority of buildings in the area, although not all buildings are included. For buildings lacking height data, interpolated values from neighboring buildings were employed to estimate their heights. Notably, the generated map of building heights does not consider variations in elevation levels throughout the city. In a city like London this is not a problem, but in other places this should also be taken into account. If such data is accessible, it could be integrated into a raster format along with the building height data to enhance the accuracy of the analysis. The raster map that is created is shown in figure 59.

Sky view factor, Visible Sky and Average View distance

The Sky View Factor (SVF) defines the ratio of sky hemisphere visible from the ground , which is unobstructed (Bernard et al., 2018). The research from Silva et al. (2017), found that in areas with a low sky view factor, the highest noise levels were found.

The input needed to create the following maps with this plugin is a Digital Elevation Model (DEM) file, and a radius, which here was set to 100m. The Skyview Factor plugin in SAGA performs this computation, for the sky view factor. (Böhner & Antonić, 2009). The SAGA-plugin also calculates the 'Visible sky'.

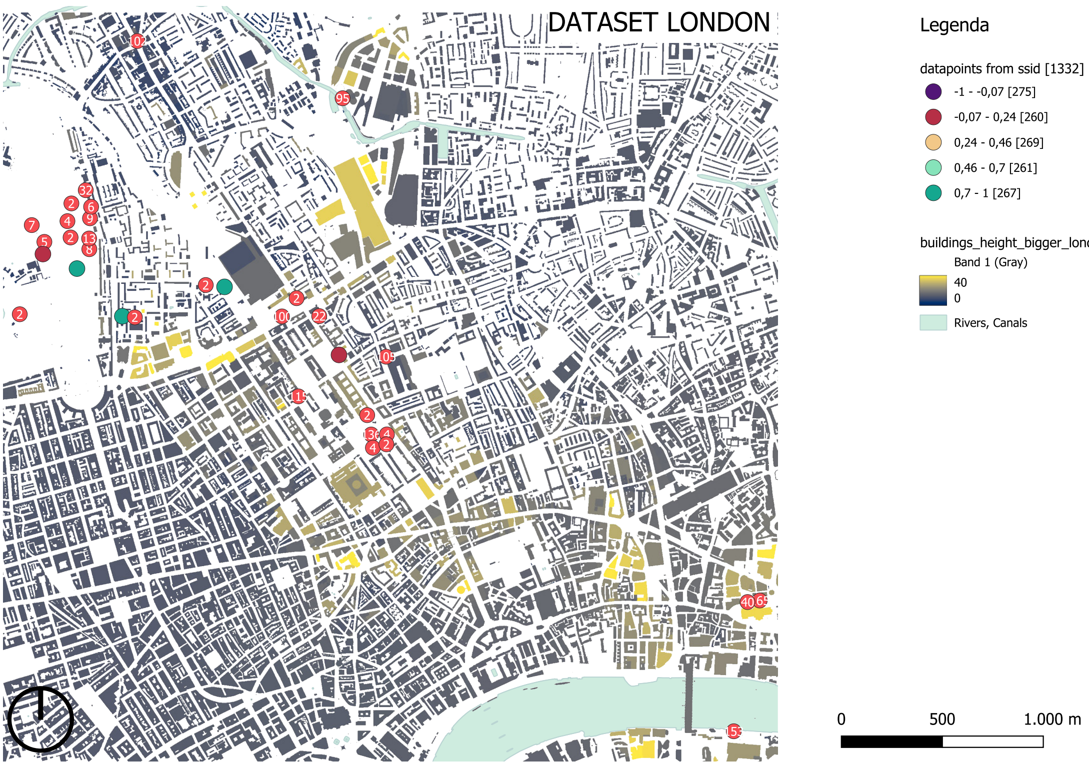


Figure 59 Building heights data, created by author

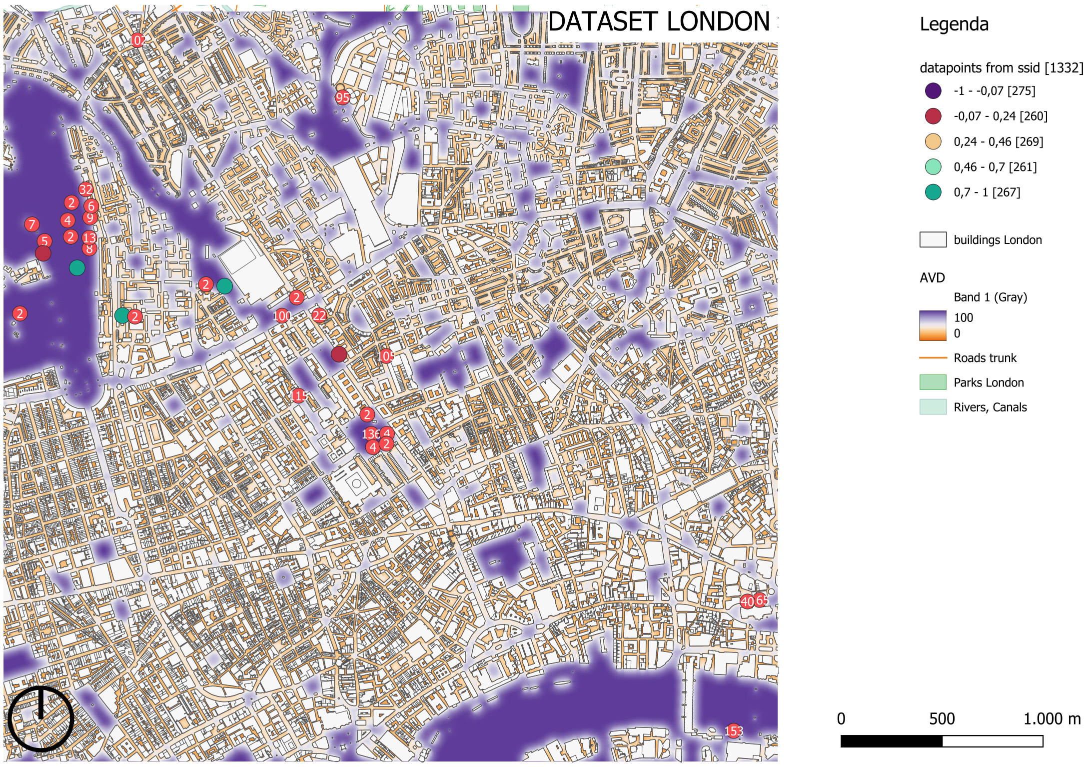


Figure 60 Average View Distance Map, by author

This is the unobstructed hemisphere given as percentage. Lastly it creates an Average View Distance (AVD) map. The values calculated here represent the average distance to the horizon. The map that is created is shown in figure 60, together with the buildings and the datapoints in the dataset.

Correlations building maps

The SVF, Visible Sky, and AVD all show moderate positive correlations with pleasantness: rs[1327]= 0.32 ($p<0.001$), rs[1327]= 0.34 ($p<0.001$), and rs[1327]= 0.36 ($p<0.001$), respectively. Similarly, they exhibit moderate positive correlations with natural sounds: rs[1327]= 0.40 ($p<0.001$), rs[1327]= 0.43 ($p<0.001$), and rs[1327]= 0.44 ($p<0.001$), respectively.

In contrast, they have a moderate to weak negative correlation with Traffic Noise: rs[1327]= -0.19 $p<0.001$, rs[1327]= -0.20 $p<0.001$ and rs[1327]= -0.22 $p<0.001$, respectively.

The AVD map seems to have the strongest correlation with pleasantness in the dataset compared to the Visible Sky and SVF factor map. The explanation for this could be because the receiver and the noise source are on the same plane, Therefore building height might not be a very important factor.

The correlation between the AVD map and the SVF map is notably high at rs[1327]= 0.98 ($p<0.001$). The similarity in calculation methods could explain the notably high correlation. Consequently, the SVF map, which exhibits the lowest correlations, is excluded as input for the machine learning model, as well as the Visible Sky map. In summary, the Average View Distance map seem to be promising inputs for the machine learning model.

Roads

During the statistical analysis, it was determined that L_{den} exhibits the strongest correlation with the perceived pleasantness reported by respondents. Consequently, a map depicting L_{den} levels was generated for the roads. Road data was sourced from OpenStreetMap (OSM) as well. The L_{den} map was created with the plugin Noise Modelling.

Noise Modelling

Noise Modelling was used to create L_{den} noise maps from the surroundings. The application is an open-source noise mapping tool integrated into a Geographic Information System (Bocher et al., 2019). The Noise Modelling plugin assigns certain weights of traffic density to different roads based on their categorization in the highway column. This is very similar to the ways that actual L_{den} maps are calculated. The created map is shown in figure 63.

Correlation of Noise Modelling data and actual measured L_{den}

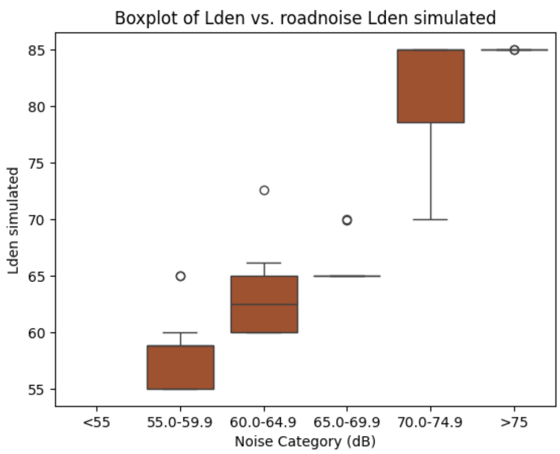


Figure 61 Boxplot of L_{den} from GLA versus the L_{den} map created by the Noise Modelling plugin

The Noise Modeling plugin provides an estimate of what the L_{den} could be, based on information about road hierarchy and sound propagation between buildings. To check the validity of this method the correlation between the simulated.

A spearman correlation is used because both models don't give exact numbers but a range where the noise level can fall in. The Spearman correlation between the L_{den} from Noise Modeling and the Lden from the municipality of London is rs[534]= -0.97, p-value: p<0.001. This distribution is shown in the boxplot in figure 61. This is excluding the datapoints where in the original dataset the L_{den} is lower than 55dB. With including those points the rs[1327]=-0.54, p-value <0.001. The correlation probably has a lower R value because this is the furthest away from the noise source, and there most inaccuracies could occur regarding the simulation. Therefore It is assumed that this model is an accurate way to represent the L_{den} for the machine learning model.

Perceived presence of Traffic noise & pleasantness in the dataset and the L_{den} map

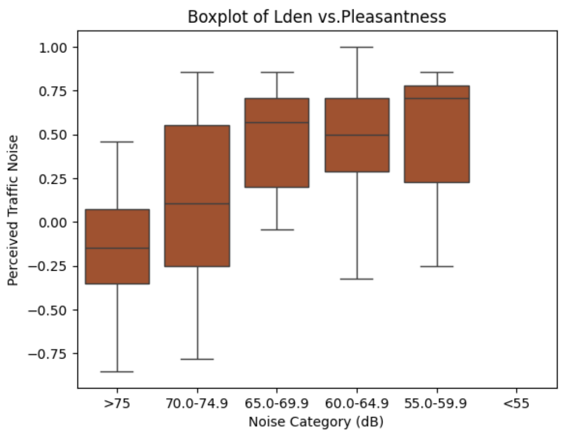


Figure 62 Boxplot of L_{den} from GLA vs the percevied pleasantness from the questionnaire

The relationship between perceived traffic noise and pleasantness in the dataset compared to the L_{den} map shows significant correlations. The correlation coefficient between perceived traffic noise and the L_{den} map is rs[1327]=0.29 ($p < 0.001$), indicating a moderate positive correlation. Conversely, the correlation coefficients between perceived pleasantness and the perceived presence of Natural sound and the Lden map

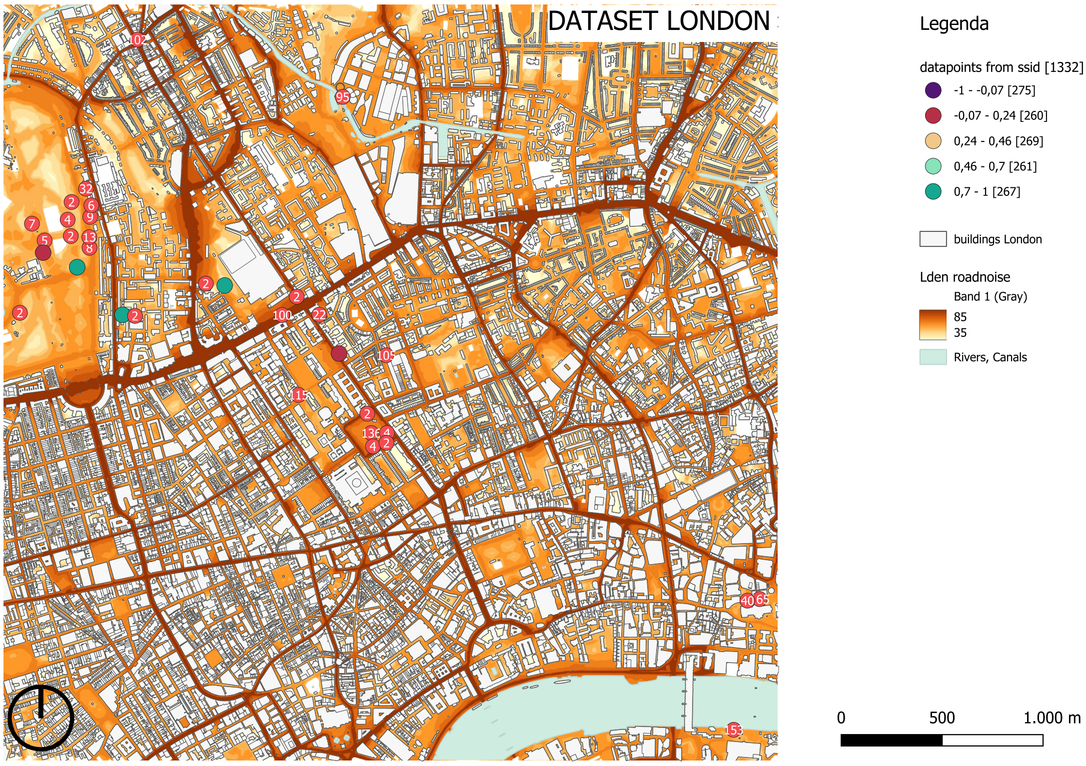


Figure 63 L_{den} map created in Noise Modelling, by author

are rs[1327]=-0.27 ($p < 0.001$), rs[1327]=-0.16 ($p < 0.001$), respectively. This are moderate to weak negative correlations.

When removing the points in the dataset where the original L_{den} values are below 55dB the correlations increase a lot. The correlation coefficient between perceived traffic noise and the L_{den} map is rs[534]=0.50 ($p < 0.001$), indicating a moderate positive correlation. Conversely, the correlation coefficients between perceived pleasantness and the perceived presence of Natural sound and the L_{den} map are rs[534]=-0.57 ($p < 0.001$), rs[534]=-0.43 ($p < 0.001$), respectively. This are moderate negative correlations.

Parks

Similar to trees parks can have both a visual and acoustical impact on the perceived pleasantness of the soundscape. Inspired by the maps created by (Lavandier et al., 2016), for the parks a raster was created where inside parks the weight was higher. This map represents the significant presence of birds on the map. This is because it is assumed by Lavandier (2016) that the bird sounds are better perceived in the center of the parks than at their periphery. The map is created with the proximity plugin available in QGIs. The result is shown in figure 65.

Proximity to parks and the perceived presence of natural sounds and Traffic Noise

The relationships between proximity to parks and perceived presence of natural sounds and the pleasantness is notable. Between the perceived presence of Natural sounds and the created map for the parks there is a correlation of rs[1327]= 0.55, p-value < 0.001. In contrast, the correlation between perceived traffic noise and the park map is rs[1327]= -0.34 (p < 0.001). The integration of Likert scale responses with data from the parks map is presented in Figure 64. The correlations for both natural sounds and traffic noise are evident, with positive and negative relationships, respectively. The negative correlation with traffic noise appears more pronounced, although it exhibits more outliers at Likert scale values of 3 and 4.

A very low perceived presence of natural sounds is not associated with a distance of 200 meters or more from a park but is observed within the range of 0-100 meters outside a park. This indicates that the perception of natural sounds is significantly reduced even at short distances from parks.

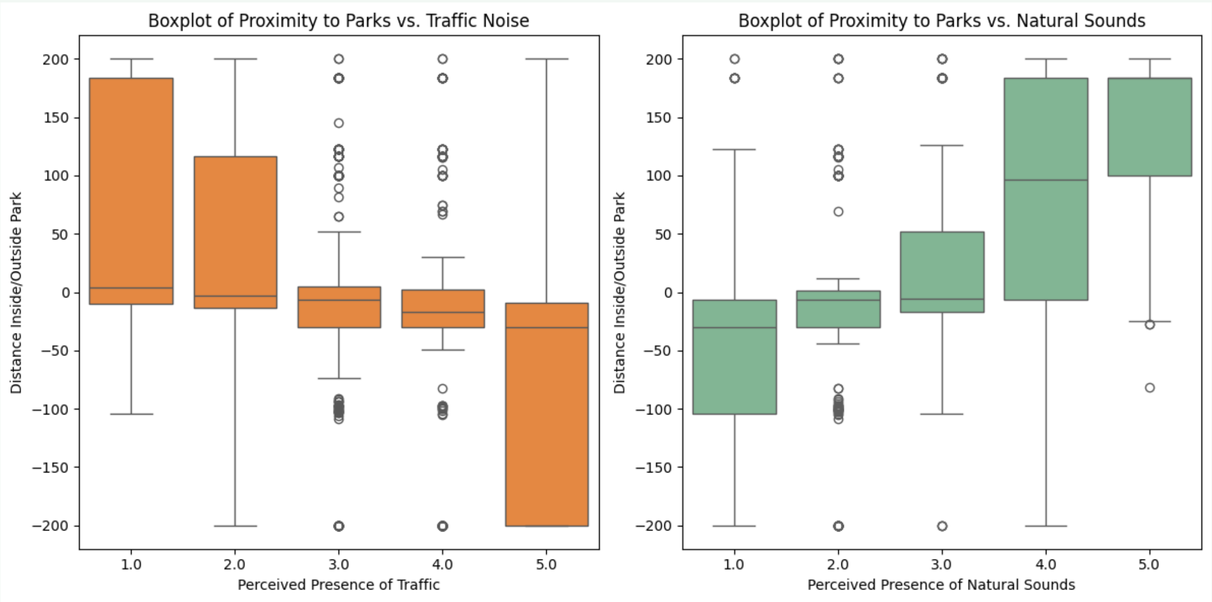


Figure 64 Boxplot proximity to parks and presence of Traffic Noise and Natural sounds, by author

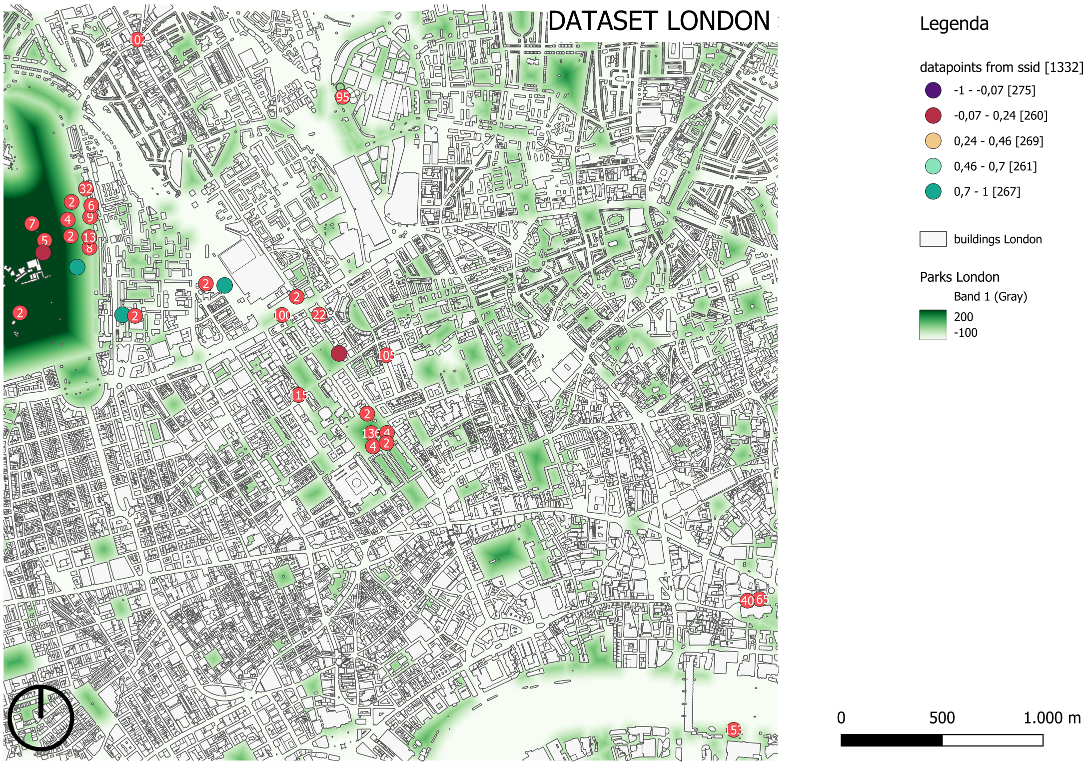


Figure 65 Parks proximity from QGIS, by author

Specifically, people within 0-100 meters outside the boundary of a park report a very low presence of natural sounds, suggesting that the influence of park environments on auditory experiences diminishes rapidly as one moves away from the park, even within a relatively short distance.

Proximity to parks and the perceived Pleasantness

Additionally, there is a correlation of rs[1327]= 0.48 ($p < 0.001$) between perceived pleasantness and the proximity to parks map. This is a moderately strong correlation.

Trees

The literature review revealed a positive correlation between the presence of trees and the enhancement of perceived pleasantness in the acoustic environment (Lugten et al., 2017). Therefore a map depicting the visibility of trees within the urban landscape was generated.

Trees were sourced from OpenStreetMap (OSM), with the option to also incorporate data from the London tree database. Utilizing the visibility analysis tool in QGIS, a map was produced to illustrate the number of trees visible from various points across the area of interest.

visibility of trees and the presence of Natural sounds & pleasantness

The relationship between perceived presence of natural sounds and the visibility of trees on the map exhibits a correlation coefficient of rs[534]= 0.38, p-value < 0.001, indicating a moderate positive correlation. Conversely, the correlation between perceived traffic noise and the visibility of trees on the map is rs[534]= -0.31, p-value < 0.001, indicating a moderate negative correlation. Between the perceived pleasantness and the visible trees map there is a correlation of rs[534]= 0.37, p-value < 0.001. This is a moderate positive correlation, that is similar to the correlation between the visibility of trees map and the perceived presence of Natural sounds.

This is only with leaving out the data when the measured Lden level is below 55dB. If these datapoints are added all correlations are very weak (rs<0.1)and not statistically significant. Therefor this map is not a great fit as predictor for the perceived pleasantness.

Overall the map created for the parks seems to be a better indication of the perceived pleasantness and the perceived presence of natural sounds and Traffic noise than the map created for the visibility of trees. It has higher correlation coefficients.

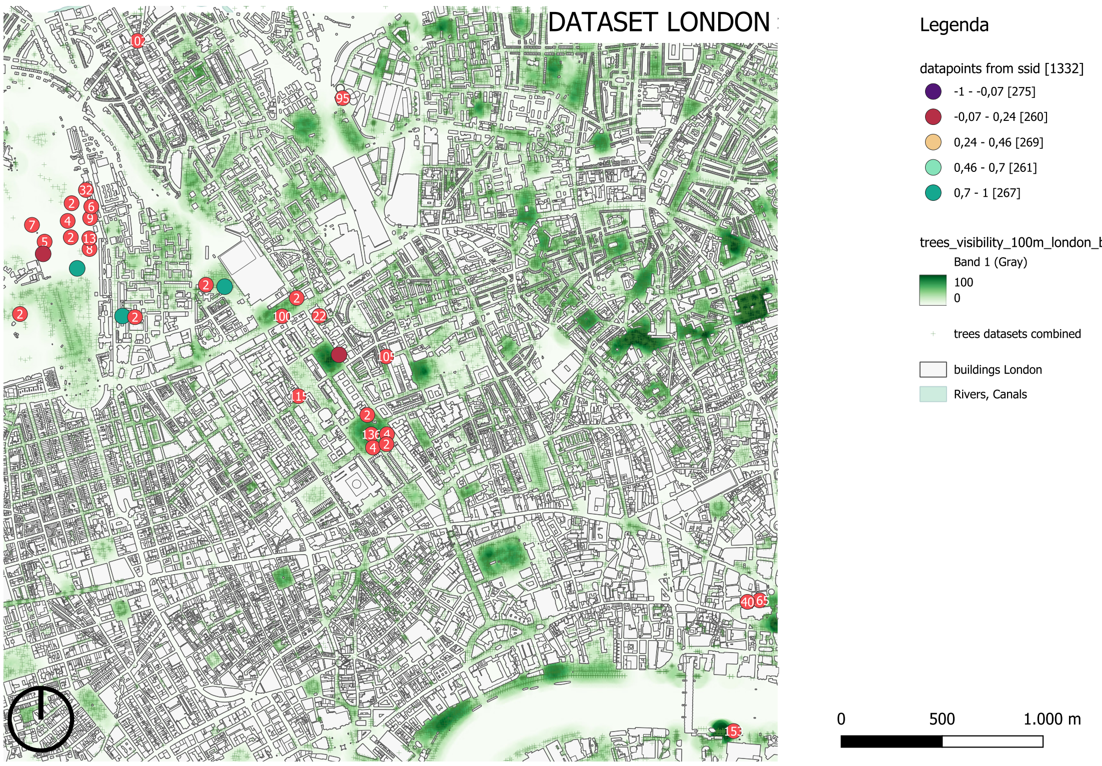


Figure 66 Visibility of Trees with Visibility plugin from QGIS, by author

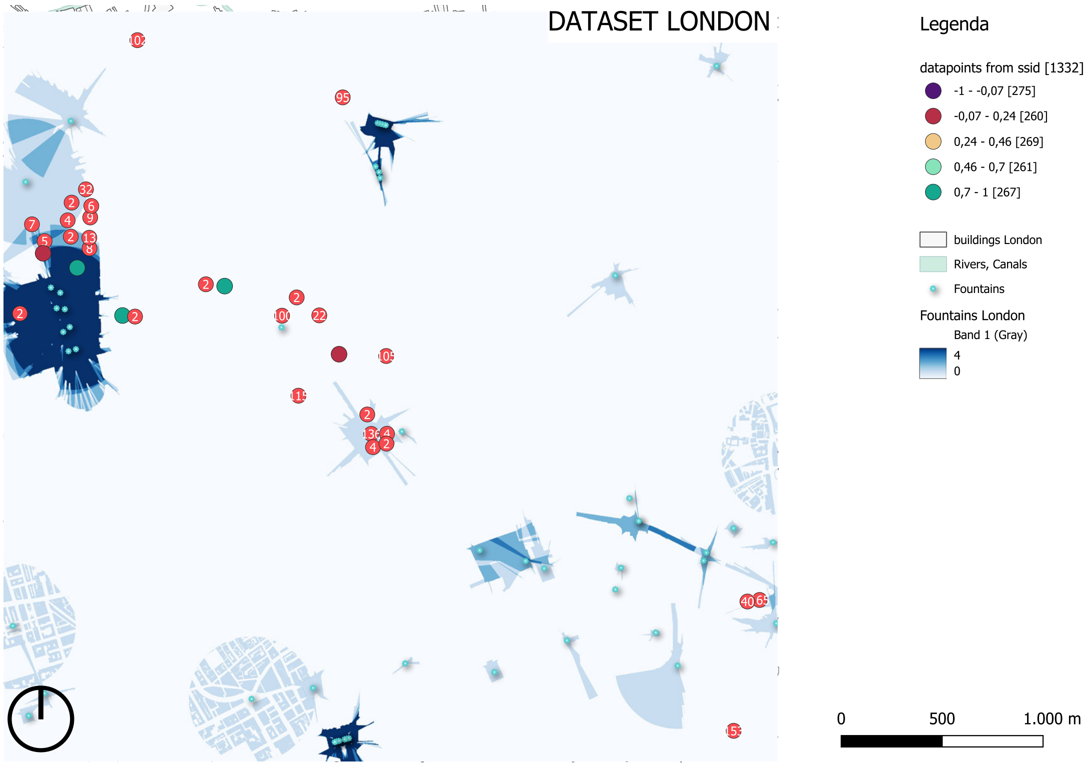


Figure 67 Visibility of Trees with Visibility plugin from QGIS, by author

Fountains

From the literature it is found that fountains can have a positive effect on the perceived pleasantness, and are percevied as calming. Additionally the sound that foutains produce can mask noise such as traffic noise. A map was created showing how far the sound could travel. The created map is shown in figure 67.

correlations of fountains map and presence of Natural sounds and Traffic Noise.

Between the perceived presence of Natural sounds and the fountains map there is a correlation of rs[1327]= 0.43, p-value < 0.001. Between the perceived presence of Traffic noise and the fountains map there is a correlation of rs[1327]= -0.23, p-value < 0.001. Despite expectations from existing literature suggesting a stronger correlation, it's likely hindered by the dataset's lack of fountain data.

correlations of fountains and pleasantness

Regarding the perceived pleasantness there is a correlation of rs[1327]= 0.42, p-value < 0.001, with the fountains map. This is a moderately strong postive correlation. Overall, fountains serve as a moderate to good indicator of both natural sounds and pleasantness.

Compilation of data

During the compilation process, data extracted from raster files is merged with corresponding points that match in location. This is used as input for the machine learning model. The construction of additional maps for different features and the integration of this data has been streamlined using the model builder plugin within QGIS. The model created is shown in figure 69. The Model Builder plugin facilitates the integration of various algorithms available in QGIS, akin to the functionality of Grasshopper in Rhinoceros. The model in model builder is shown below. To simplify the compilations some steps are built in smaller models that are plugged in this bigger model. Here the vector files of the different layers like the buildings, trees, parks and fountains are used as input. The previously discussed layers are calculated. And added to a point layer. This workflow is part of the framework for the design tool where urban designers do not have to do all the calculations one by one by themselves but it forms a streamlined process where they only have to deliver the data that is already in their design.

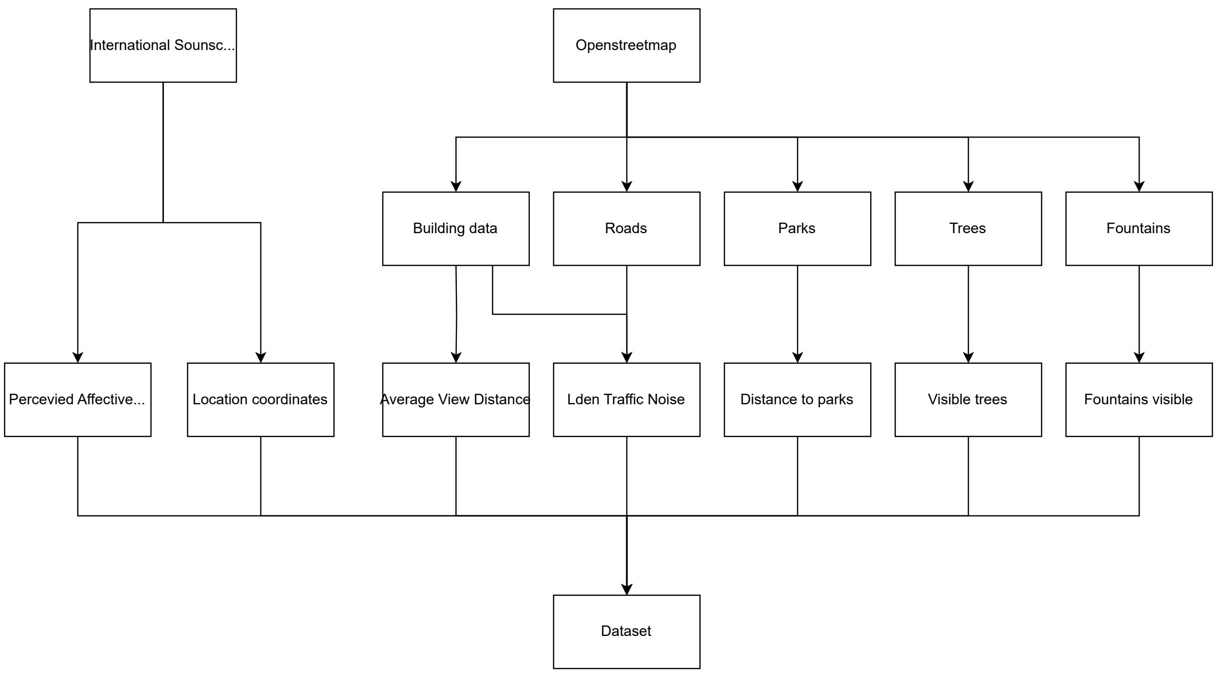


Figure 68 Overview of all the data acculmulated in the dataset, by author

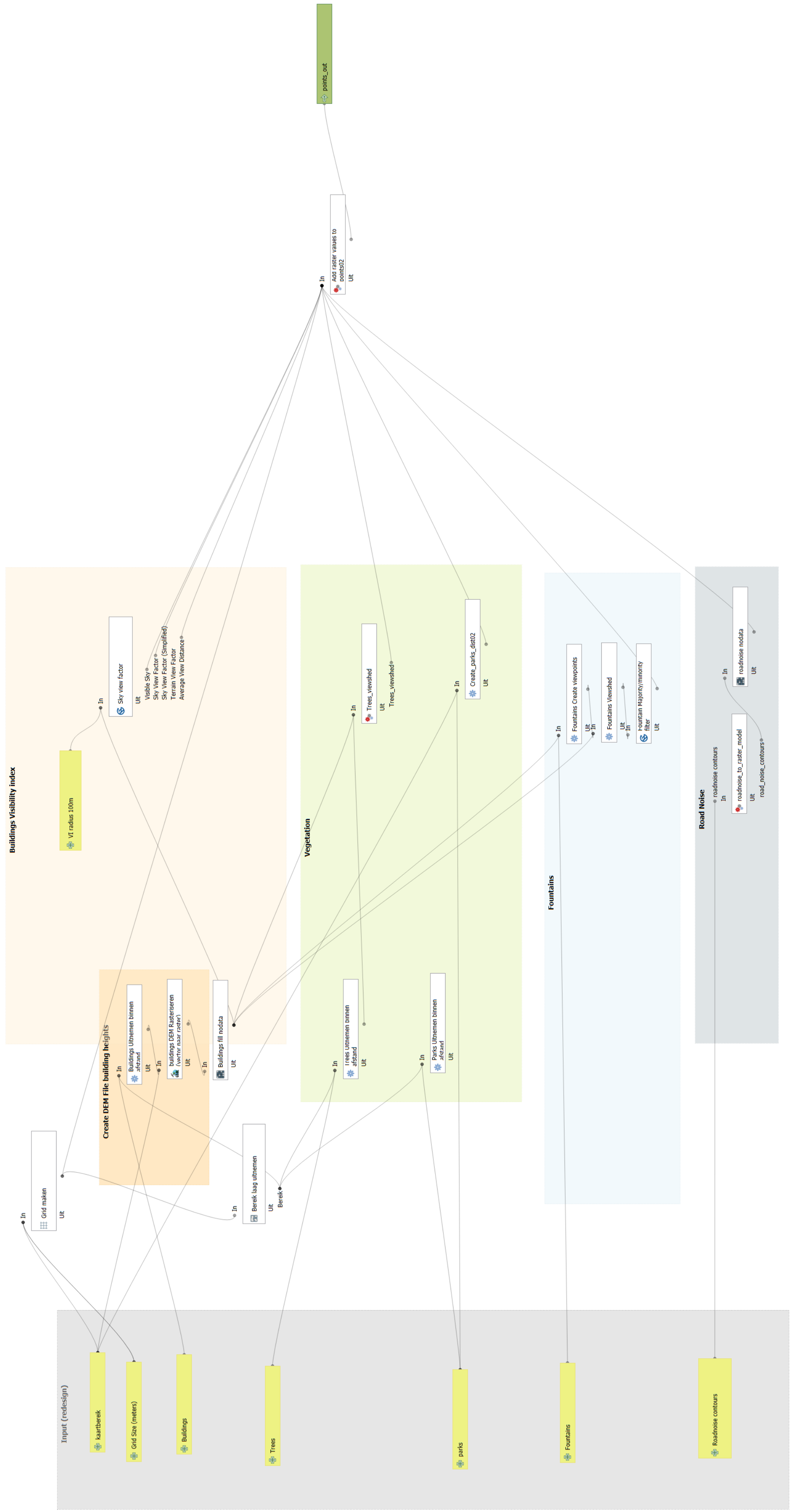


Figure 69 Model Builder model from QGIS for preprocessing data, by author

Discussion & Conclusion

The maps created for the buildings are Visible Sky maps, and Average view distance maps. These maps are created using OSM building data and building height data from GLA by using the SAGA Sky View Factor plugin.. They have a correlation with the pleasantness of the soundscape of 0.34, and 0.36 respectively. Limitations concerning buildings include the absence of precise building height data, because for a part of the buildings height is missing, missing building height were interpolated heights from close by datapoints. Something else that is not included in the building data is the façade materials, which could impact noise propagation, and can have an impact visually.

For the roads, the L_{den} map is an approximation based on the road types in the road data from OSM. This could differ from the actual L_{den}. However in this case the L_{den} from the Noise Modeling Plugin correlates strongly with the existing Lden maps. The L_{den} map correlates strongly with the perceived pleasantness, making it a compatible input for the machine learning model. This aligns with previous literature linking high L_{den} levels with annoyance and disturbance (WHO, 2011)

The correlation between the trees visibility map and the pleasantness in the dataset was very weak. Therefore this dataset is not a good predictor for the pleasantness. Several limitations are evident in the datasets for trees. Firstly, there are gaps in tree coverage within the OSM dataset, indicating incomplete representation. Secondly, due to the absence of height information for trees, a uniform height assumption of 20 meters is applied across the dataset, potentially introducing inaccuracies. Additionally, the discrepancy between trees identified in OSM and those documented in the London database suggests a lack of alignment between the two datasets, raising concerns about their overall validity and reliability for comprehensive analysis and decision-making. This difference is illustrated in figure 70, showing both datasets in different colors. The previous literature suggests a stronger correlation between the visibility of trees and the perceived pleasantness (Lugten et al, 2017). The absence of the correlation in this dataset could be explained by the quality of the available data.

The proximity to parks maps are a good indicator of pleasantness. This map is created using OSM park data. The limitations of using OSM data for parks include the absence of information regarding the quality or attributes of the parks themselves. The map is created using the proximity plugin in QGIS, created a higher value inside the parks further away from the periphery and a lower negative value further away from the border of the parks. The correlation for the perceived presence of Natural sounds and the perceived pleasantness, with the created proximity map for the parks is a strong positive correlation. Lavandier (2016) used a similar methodology to predict the presence of bird sounds. Their linear regression model based on georeferenced data could explain 67% of the variance in the perceived time ratio of birds (how much of the time bird sounds were present). This is slightly higher than the values found from the spearman correlation, but their prediction also included using predicted values of traffic noise.

The fountain maps also used OSM data and were created using the viewshed plugin. The dataset exhibits a notable scarcity of fountains, and crucially lacks information regarding the quality or characteristics of these fountains as sourced from OSM. The correlation with the fountains map and the

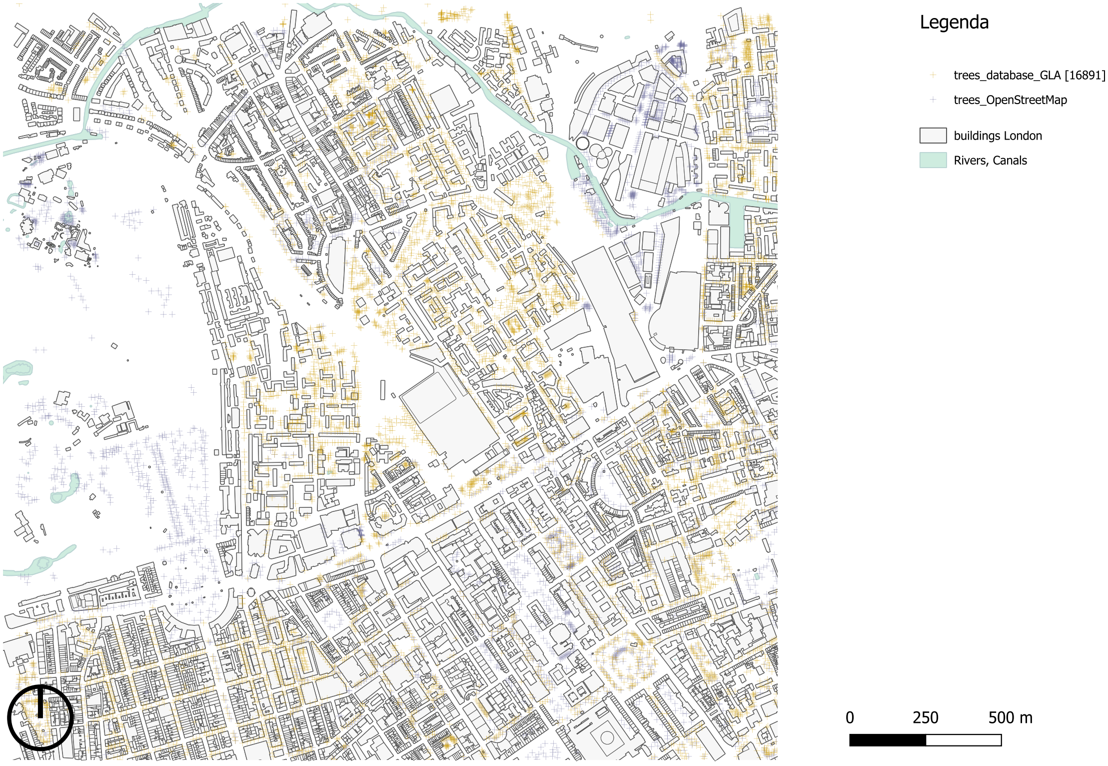


Figure 70 Trees dataset combined. Purple from OSM, and yellow from GLA, by author

pleasantness is high. Overall this is a good to moderate indication for pleasantness. However the strength of this correlation could also be caused by the placement of these fountains. The fountains are all placed inside parks. Consequently, the apparent connection between fountains and pleasant environments could potentially be misleading.

To summarize the created maps have been analyzed statistically and a selection of these maps has been made to be used in the next stage of this research. This is choosing and training the machine learning model.

Chapter 7 Choosing the ML model

After compiling the data into a csv file it was uploaded to a python file and run through the PyCaret plugin, for model selection. Once the model was selected, the model was recreated in the python console of QGIS.

Regression models

For this research the regression model was chosen over a classification model. The soundscape pleasantness is measured as a continuous variable, on a scale from -1 to 1, where different levels of pleasantness can be quantified precisely. Regression models are designed to predict continuous outcomes and can provide insights into the relationship between predictors (e.g., Lden levels, visual presence of natural elements) and the level of pleasantness.

Classification models are used when the target variable is categorical, allowing for the prediction of the class to which each observation belongs based on the input features. If soundscape pleasantness needs to be categorized into discrete classes (e.g., “pleasant,” “neutral,” “unpleasant”), then a classification model could be utilized. However because a regression model shows more nuances a regression model apprach was chosen.

Comparing different regression models

Using PyCaret allows for running multiple ML models and compare the ability of these models to create accurate predictions of the dataset based on different metrics. The metrics that were used to determine

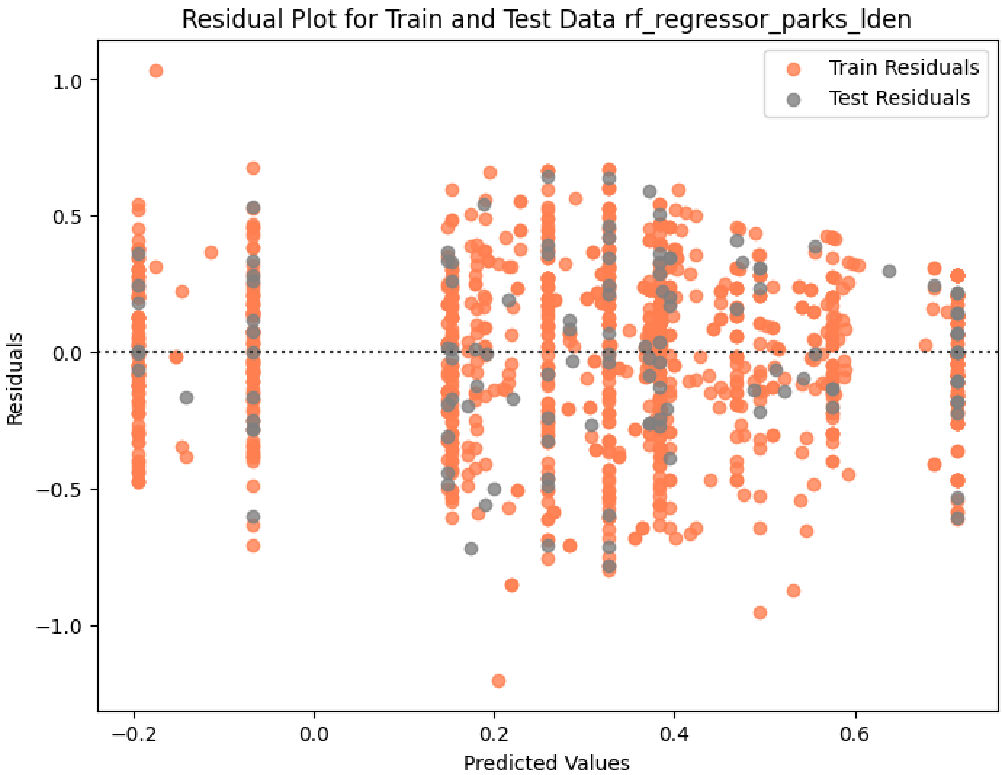


Figure 71 Residuals Plot Random Forest Regressor for input Parks and L_{den}, by author

the accuracy are The Mean Absolute Error (MAE), The Mean Squared Error (MSE), The Root Mean Squared Error (RMSE) and the Coefficient of Determination (R2). For this dataset and its purpose the random forest regressor seems to result in a model with highest accuracy.

Light Gradient Boosting Machine

The initial results with the LightGBM seemed promising. However this method is prone to overfitting, especially with small and noisy datasets. With these things considered, this model has been deemed to not be a good model for creating the prediction model in this research

Linear regression

A linear regression model is a parametric model, and the importance of the variables can be expressed in a function.

Random Forest regressor

The Random Forest (RF) regressor has giving the best results, with an R2 of 0.43.

In this residuals plot, shown in figure 71, the locations with many respondents can be seen very clearly, forming vertical lines. On average, the predicted score also was lower than the actual score.

The RF regressor cannot be expressed in a linear function because it is a non-parametric model, which makes the predction based on an ensemble of decision trees.

RF regressor benefits

non linear relationships

Urban factors influencing the perceived pleasantness of a soundscape are likely to interact in complex, non-linear ways. For instance, the impact of green spaces might be different in noisy vs. quiet areas. Random Forest Regressor can capture these intricate, non-linear relationships without needing explicit specification, unlike linear models that assume linearity

Reduction of Overfitting:

Overfitting is a common problem in predictive modeling, where the model learns noise and details specific to the training set. Random forests mitigate overfitting through ensemble learning, averaging the predictions of multiple trees to generalize better to unseen data. This is still important to look out for.

Feature Importance Insight:

Understanding which factors most influence soundscape pleasantness is valuable for urban planning and policy-making. Random Forest provides feature importance scores, helping to identify and prioritize key variables, such as the presence of green spaces, traffic density, and building heights.

Robustness to Outliers and Noise:

Urban data often contains outliers and noise, such as sudden changes in traffic volume or unexpected construction work. Random forests are inherently somewhat robust to outliers and noise due to the aggregation of multiple decision trees, each trained on different subsets of the data. The outliers in the dataset are already using the z-score method.

High Predictive Accuracy:

Random forests are known for their high predictive accuracy compared to many other algorithms, particularly in datasets with complex interactions between variables. This makes it a strong candidate for delivering reliable predictions of soundscape pleasantness

Flexibility and Versatility:

Random forests can handle various types of predictor variables, including continuous, categorical, and ordinal data, often present in urban datasets.

Model with Parks and L_{den}

Initial attempts involved using various inputs to predict the pleasantness from the dataset. Based on these predictions and statistical analysis, some inputs were removed. The presence of trees was excluded as it was not reliable in predicting ISO pleasantness, both statistically and in the regression model. Similarly, the visibility of fountains was also removed. By retaining only the distance from parks and the Lden map created via NoiseModelling, a prediction of similar accuracy was achieved. This simplified model has an R^2 of 0.41, compared to the R^2 of 0.44 for the model with all features (discussed later in this chapter), indicating only a slight improvement. The model with only two features is less complex and therefore more efficient.

Feature importance

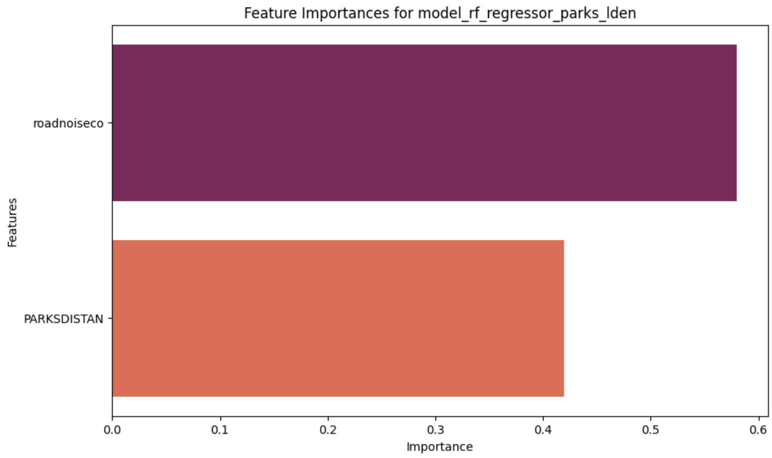
The L_{den} map, which includes the road noise contours, has the greatest impact on the model with an importance value of 0.58. The Parks map follows closely with a feature importance of 0.42. Both maps exhibit a comparable level of influence on the input.

Optimizing the random forest regressor

to improve the accuracy of the model these parameters were adjusted: the maximum depth of the trees & the minimum number of samples required to be considered a leaf node. Specifically, the maximum depth of the trees was set to 6, controlling the maximum number of levels within each decision tree. Additionally, the minimum number of samples required to be considered a leaf node was set to 3, refining the granularity of the tree's decision boundaries. These parameter modifications aimed to optimize the model's performance by balancing complexity and generalization, ultimately leading to improved predictive accuracy.

The prediction model was tested on the locations where the surveys were taken, to be albe to reflect on the performance of the prediction model. The Russels square location was investigated, it has all the

Figure 72 Residuals Plot Random Forest Regressor created with PyCaret library, by author



Metric	Value
Mean Absolute Error	0.26
Mean Squared Error	0.1
Root Mean Squared Error	0.32
R-squared	0.41

Figure 73 Feature importance graph, by author

elements present in the prediction model: variety in buildings (openness), trees, parks and a fountain.

Behaviour of variables

As seen in Figure 74 the L_{den} has the most influence on the rnadom forest regressor. This aligns with the exsiting data. One interesting thing to note is that the relationship between the pleasantness and the L_{den} does not seem exactly linear.

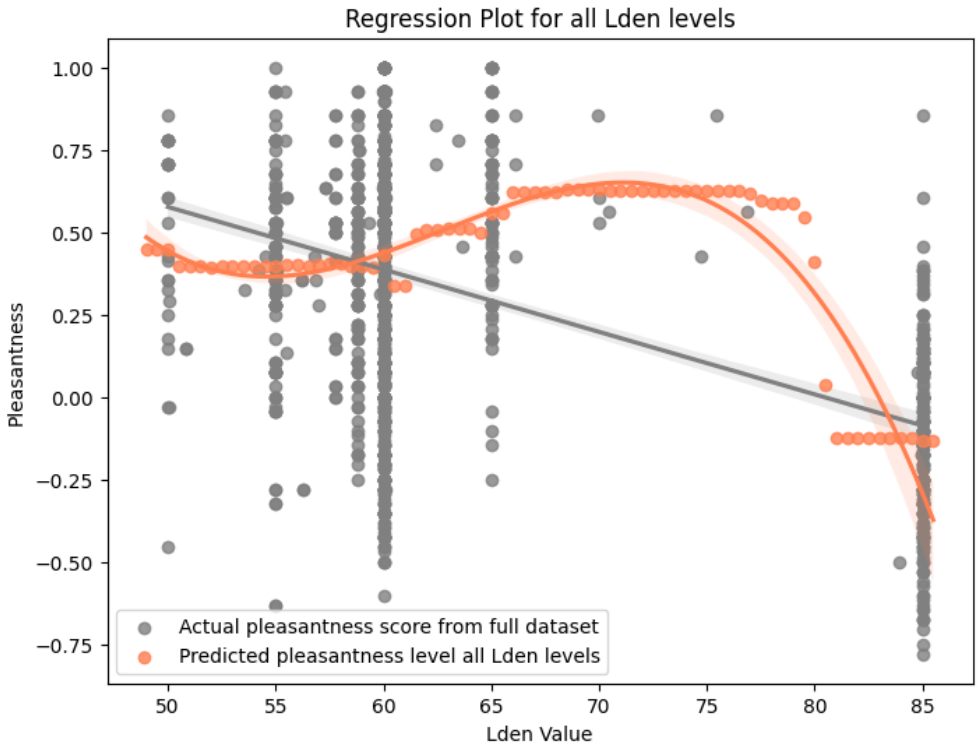


Figure74 Regressor Plot for link between L_{den} and pleasantness, by author

Testing models, with different inputs

For the prediction models a variety of inputs was tested to see their results. The features were tested on their own to see how well they can predict the pleasantness from the dataset. The amount of estimators was 2000. It was found that for multiple combinations of features increasing the amount of estimators did not increase the preformance of the prediction model in terms of

Key Findings

The graph shows feature combinations and their respective importance values as determined by the Random Forest Regressor. The R-squared shows how much of the variance in the model can be explained by the model. Here, PARKSDISTAN (distance to parks) appears prominently in many feature combinations with high importance values.

High Importance of proximity to parks:

PARKSDISTAN appears in the top four features with the highest importance value (0.42), both individually and in combination with other features. This suggests that proximity to parks is a crucial factor influencing pleasantness.

Synergistic Interactions:

Combinations like proximity to parks & Average View Distance (AVD) or Visible Sky (VS) also have high importance values (0.42). This indicates that the interaction between those varaibles enhances the model's predictive power.

Complex Interactions:

More complex combinations, such as Parks, L_{den} & AVD (0.42) and Parks, L_{den} & VS (0.40), still maintain high importance. These suggest that noise levels and visibility, when considered along with proximity to park, play a significant role in influencing the target.

Notable Single Features:

treesvisibi (visibility of trees) has a substantial importance value of 0.40, highlighting its individual impact. This is remarkable, because it contrast with the statistical analysis.

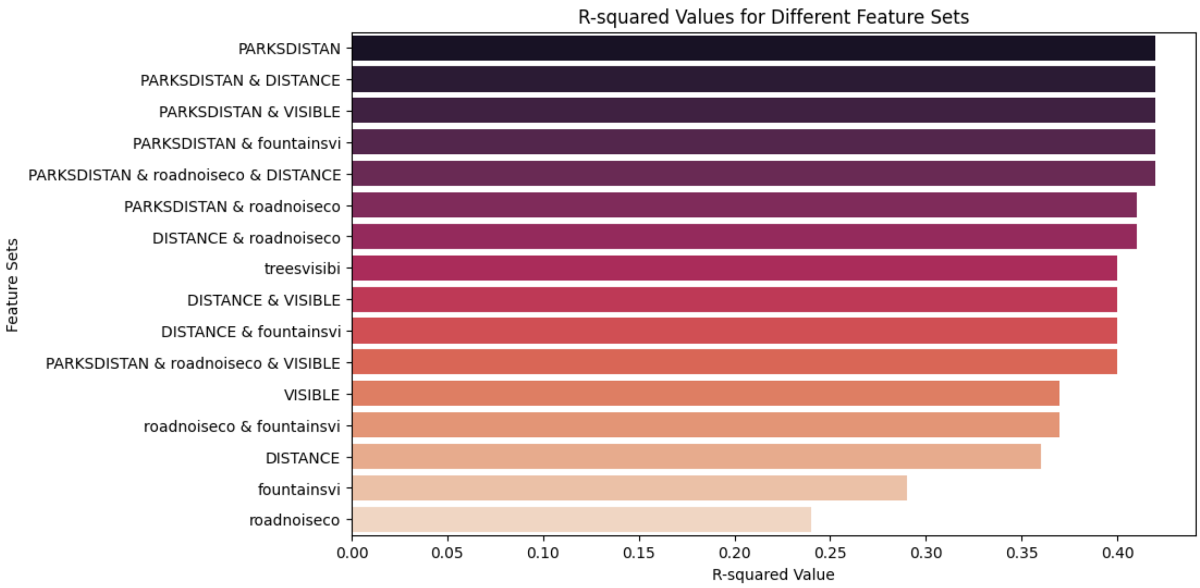


Figure75 Residuals Plot Random Forest Regressor created with PyCaret library, by author

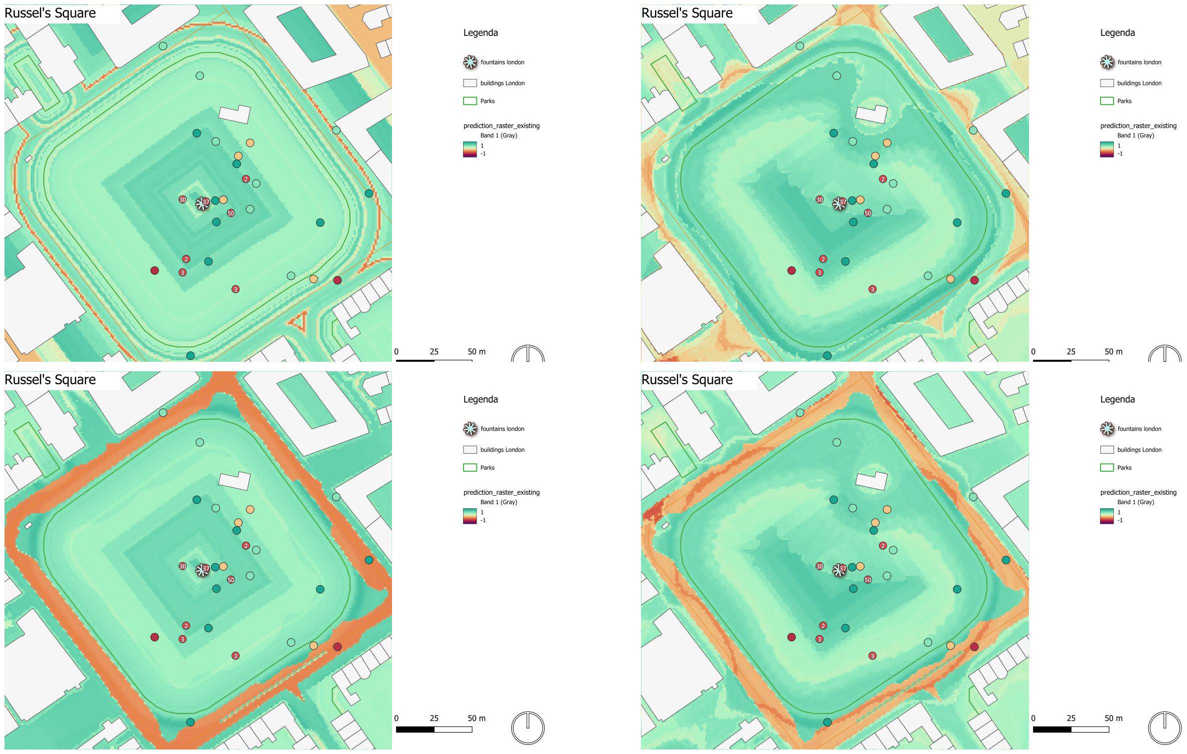


Figure 76 Maps created using prediction models. Top righ: Parks (R^2 = 0.42), Top leftt: Parks & AVD (R^2 = 0.42), bottom right Parks and L_{den} (R^2= 0.41,discussed in previous section), Bottom left: Parks, AVD and L_{den} (R^2 = 0.42)

Single features like visible sky (0.37) and AVD (0.36) are also noteworthy but less critical compared to their interactions with PARKSDISTAN. In this urban context higher amount of open spaces often are parks, so that could explain why this overlap is there.

Impact of Road Noise:

The L_{den} map shows lower importance individually (0.24) but is significant when combined with other features. This implies that while L_{den} alone might not be a strong predictor, its interaction with other factors, such as distance and visibility, is significant.

Less Important Features:

fountainsvi (visibility of fountains) has a lower importance value (0.29) and its combinations with other features have moderate importance. This suggests that fountains' visibility is a less critical factor in comparison to park distance, L_{den}, and tree visibility.

Conclusion

The analysis highlights that PARKSDISTAN is a pivotal feature, both individually and in combination with other features, in predicting the target variable in the Random Forest Regressor model. The interactions between PARKSDISTAN, visibility, AVD, and L_{den} significantly enhance the model's predictive capabilities, demonstrating the complexity and interdependence of these environmental factors.

Generated maps

Figure 76 displays several maps produced using the machine learning models, on the location of Russel's square in the dataset. The process of this visualization step will be elaborated upon in the next chapter. The map generated using only the proximity to parks as an input feature shows signs of overfitting, evident from the very localized changes in the raster. However, incorporating additional features appears to mitigate this overfitting. Comprehensive maps for all prediction models are provided in the appendix.

Prediction model

This is the Random Forest Regressor that has been used in the prediction maps in further chapters of this project. This prediction models includes the process features of the buildings, roads, parks, trees, and fountains.

Feature importance

Feature importance analysis helps identify which features (or variables) in a dataset have the most influence on the target variable (in this case, soundscape pleasantness).

In terms of feature importance for the RF regressor figure 77 shows the result. The L_{den} map that is created to simulate the road noise has the highest variable importance. After that the distance to parks becomes more important. The third feature in importance is the average view distance. This could be related to the sound propagation in narrow vs free field situations. The model has an R2 of 0.43, sothe model can explain 43% of the variance in pleasantness

Metric	Value
Mean Absolute Error	0.25
Mean Squared Error	0.10
Root Mean Squared Error	0.31
R-squared	0.43

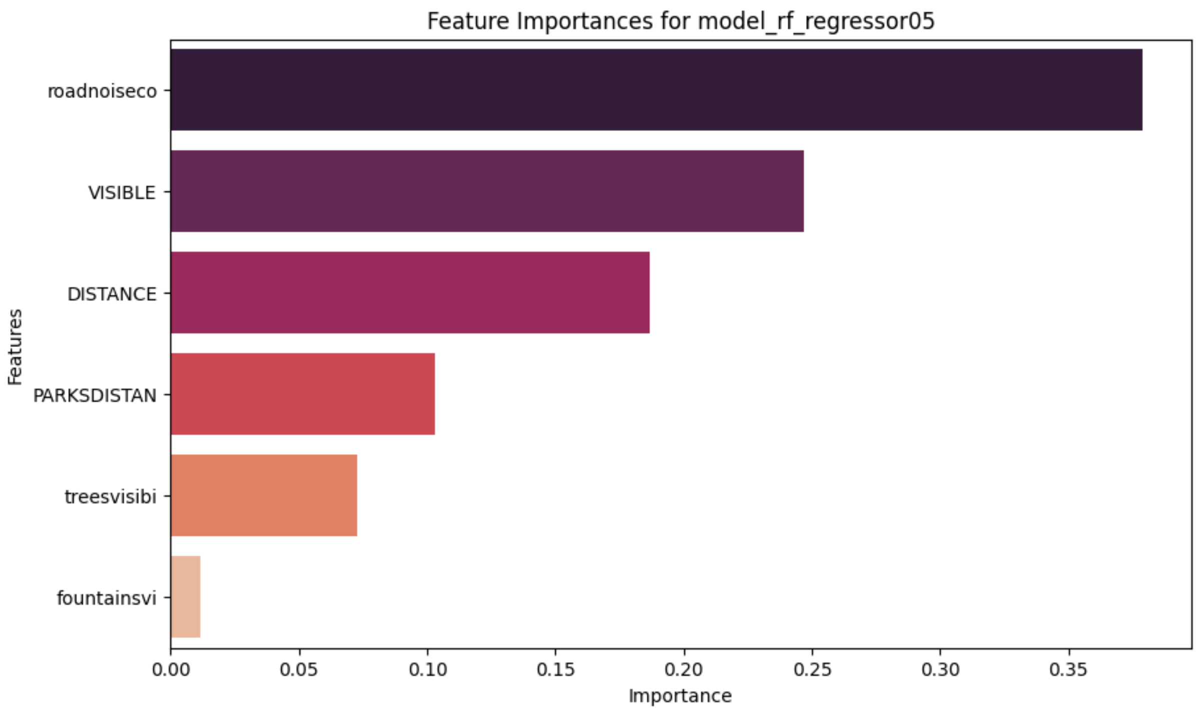


Figure 77 Feature importance Random Forest Regressor created with PyCaret plugin, by author

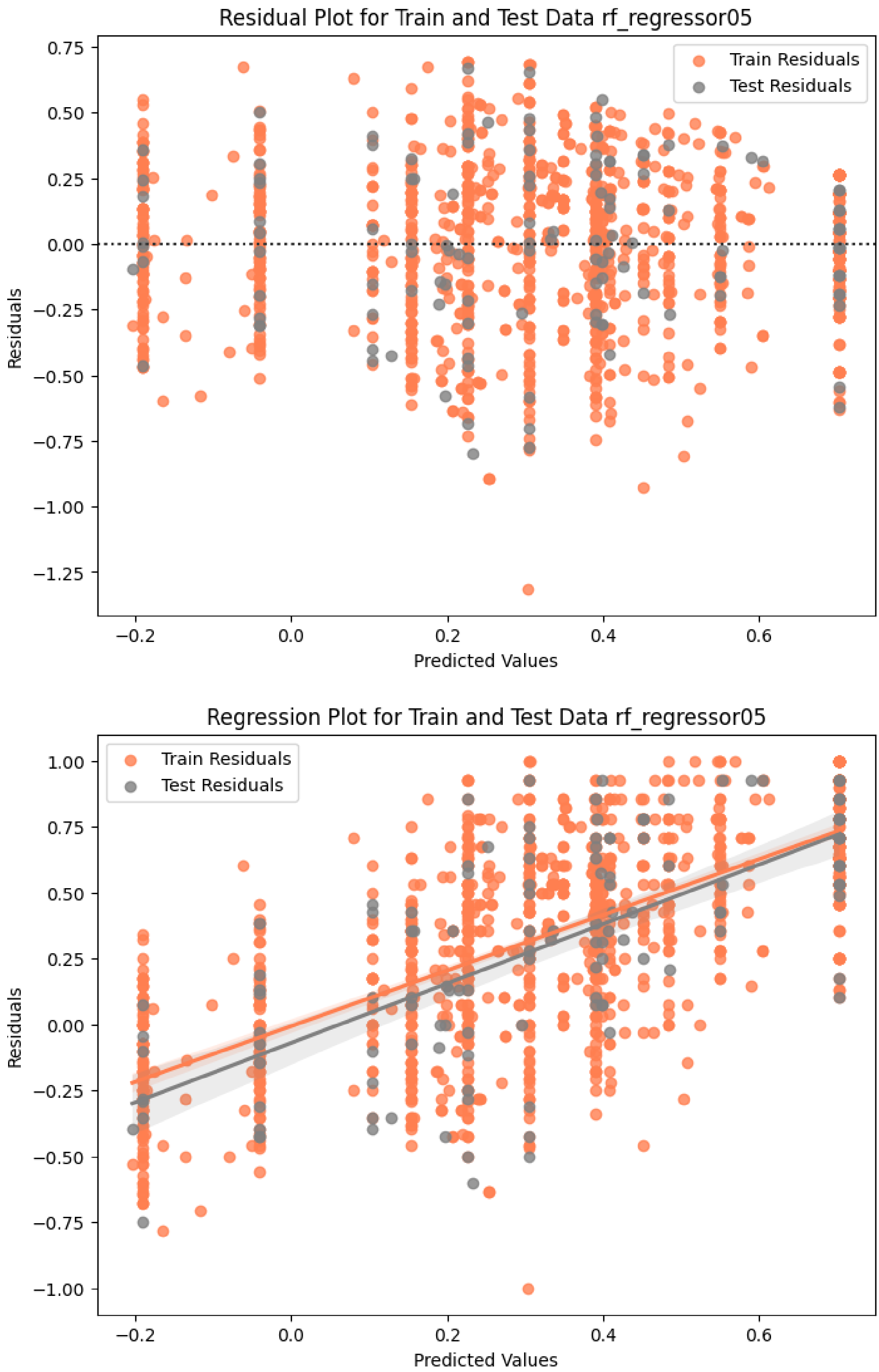


Figure 78 The residual plot (top) and the regression plot (bottom) of the Random Forest Regressor, by author

Discussion

Not a lot of research is done where the soundscape pleasantness is predicted using urban design elements. This chapter looked at different models and ways to predict the soundscape pleasantness and made a choice for the best performing model.

Through analysis from the python library PyCaret, implementing the best working models in QGIS, and using ML model optimization strategies, the Random Forest Regressor gave the best results for this dataset. The ML model achieves an R2 value of 0.4, indicating that 40% of the dataset's variance can be explained by the inclusion of objects in the physical environment.

Roads and visible sky percentage

The model struggles to accurately predict areas with both low visible sky percentages and high L_{den} levels, contrary to expectations set by literature. Typically, lower pleasantness is expected in locations with high traffic noise and limited visible sky according to Silva et al. (2017). One possible reason for this mismatch could lie in the dataset itself. The majority of locations in the dataset are places, where the visible sky percentage tends to be notably high.

Upon examining locations with the highest L_{den} levels, this trend becomes clearer. Take, for example, "Camden Town", situated at a bustling intersection of five roads. Camden Town is after the Euston Tap location the worst ranked location in terms of pleasantness with an average of -0.10. This location is the only location that is more than 200 meters away from a public park, and other greenery is barely present.

The location has high L_{den} levels, and a high average view distance. This can be attributed to the broad roads designed to facilitate traffic flow, enhancing the view distance for observers at the crossroad. In the prediction

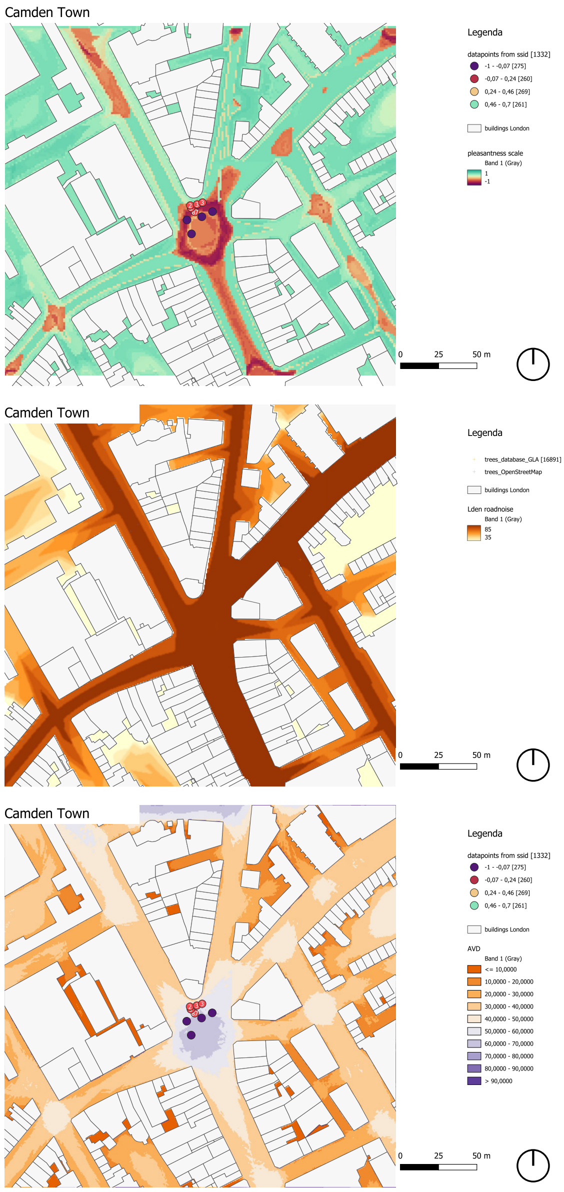
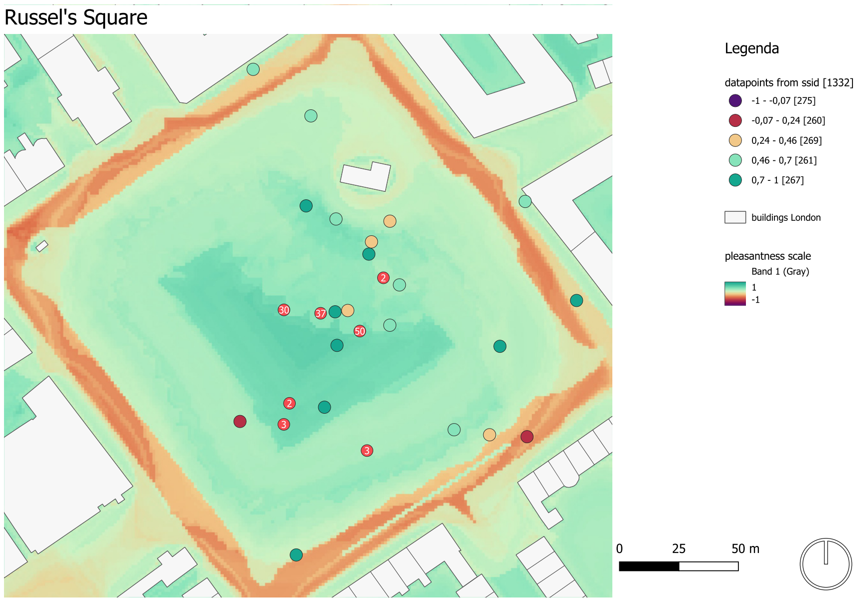
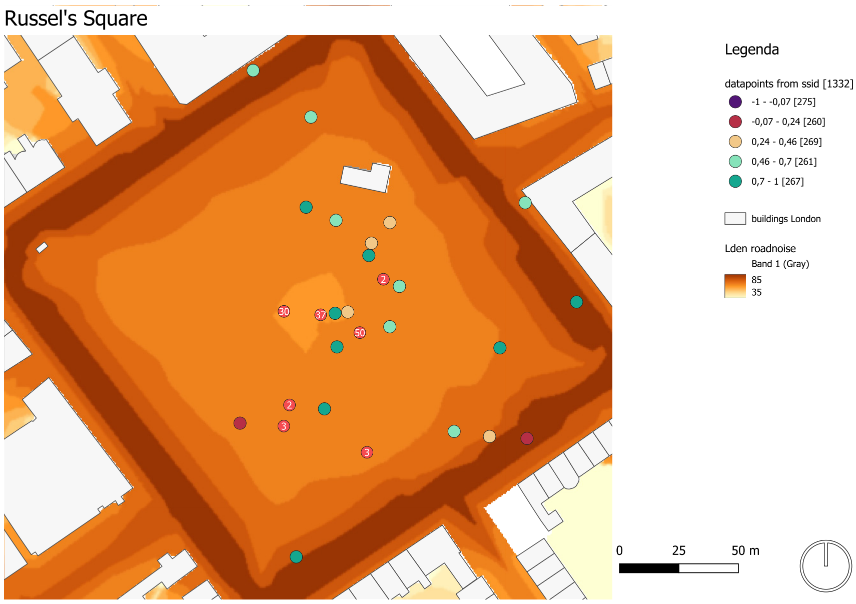


Figure 79 Prediction model used on location CamdenTown (top) and corresponding Lden map (middle) and Average View Distance (AVD) map (bottom), by author

map you can see that at the crossroad where the datapoints are situated the color of the prediction grid aligns with the colors of the predictions. This is the location in the dataset which had to most negative review. The prediction model had a bit more extreme negative prediction in this place. It is interesting to see what happens right outside of the junction. There the predicted soundscape becomes suddenly very





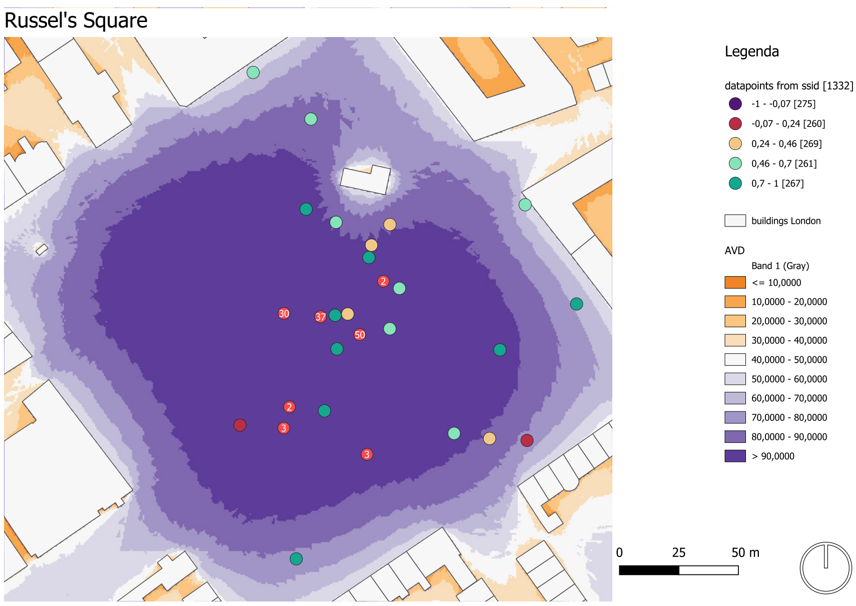


Figure 80 Prediction map for Russel's square (top), and Lden map (middle), and Average View distance (bottom) by author

positive. Even when the L_{den} is still very high. This is likely a result of overfitting, because these types of situations are not available in the dataset.

Figure 81 Created prediction map for location Euston Tap (top), corresponding Lden map (middle) and Average View Distance (AVD) map (bottom), by author

Similarly, "Euston Tap," another heavily trafficked spot with elevated L_{den} levels, also has a high average view distance. In contrast with the Camden Town location there is some greenery in the form of a park nearby.

Figure 62 shows how the high L_{den}, leads to a lower pleasantness score. The other strong outline here is the average view distance map. Once the L_{den} steps down from the most extreme value, The AVD has a positive effect where the AVD is the lowest, and has a negative effect when the AVD has a more average value.

In contrast, "Russell Square," though experiencing moderately high L_{den} levels, garners a better pleasantness score. This is likely due to its central fountain and surrounding greenery, which provide visual and acoustic buffers against traffic noise.

The predictions in this location seem more logical. Except from the busy street in the right lower corner, which is a street with a high L_{den}, but the predicted pleasantness becomes very high.

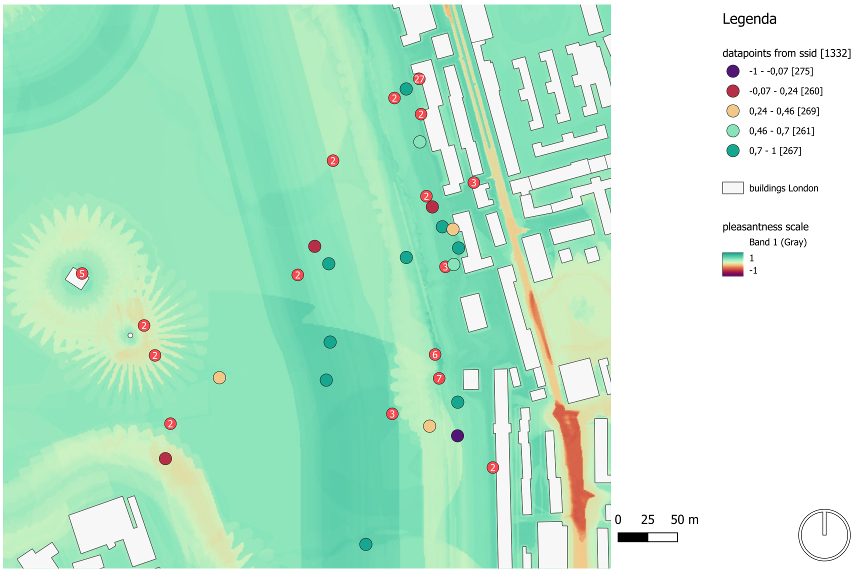
Significantly, the dataset lacks instances of locations with low visible sky values, often found in narrow streets, which also have high L_{den} levels. This gap may contribute to inaccuracies in the model's predictions for such areas. To enhance the model's accuracy, future research and data collection efforts should encompass locations with different urban characteristics.

The Regents park fields location is one of the most positively rated places in the dataset with a mean pleasantness rating for this location of 0.50. Here the pleasantness score seems more aligned with the statistical analysis as well. One this to note is that trees may have a negative impact., when there is a small amount of them.

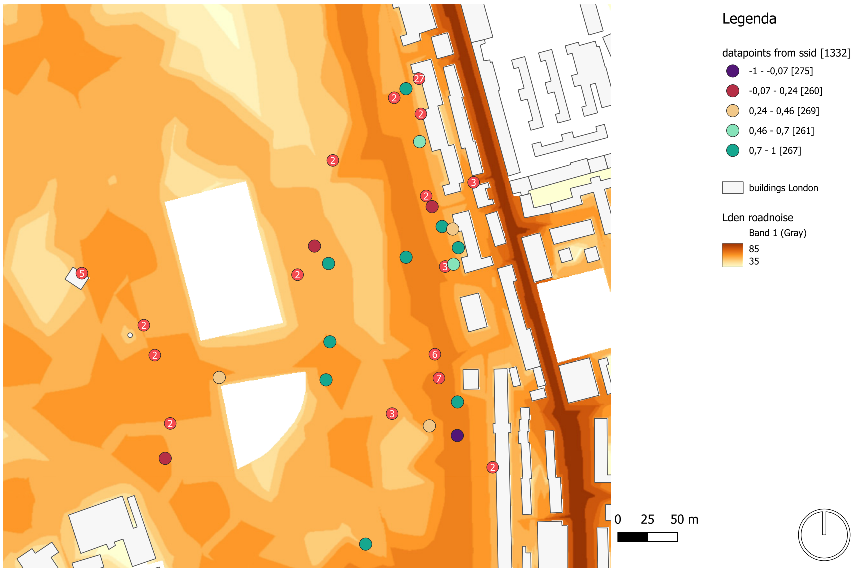
To what extent does the prediction actually reflect reality?

In places similar to the dataset, at a similar time and for a similar demographic, these predictions could be quite accurate.

Regents Park Fields



Regents Park Fields



Regents Park Fields

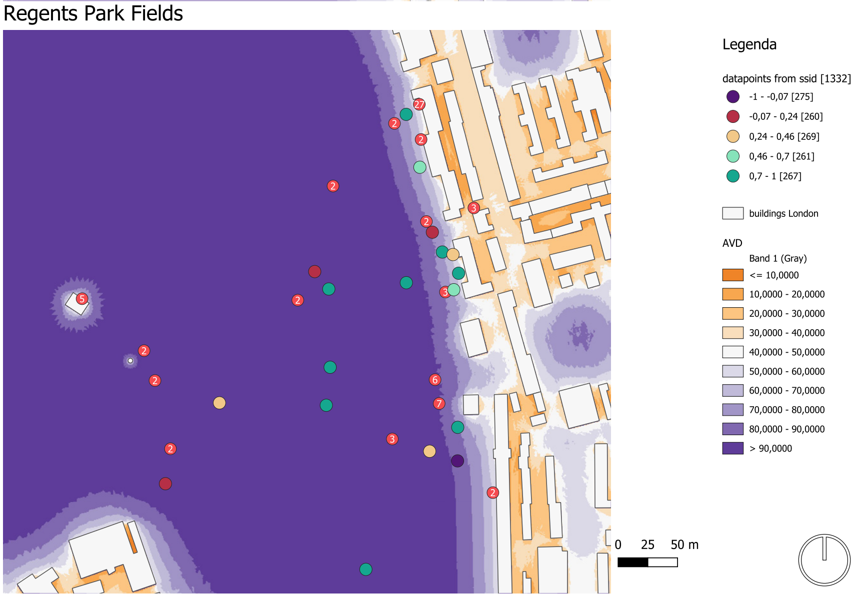


Figure 82 Prediction map for Regents Parks Fields (top), and Lden map (middle), and Average View distance (bottom) by author

Other, less successful attempts

Several methods were tested for the prediction model, including spatial regression methods.

Taking averages per location

Lavandier et al. (2016) saw in the Cart_ASUR project an improvement from r^2=0.58 to r^2=0.89, when reducing the dataset to the averages per geographical location, for the prediction model. This method appeared promising. However, in our context, it did not yield the expected results. This discrepancy may be due to the uneven distribution of respondents across locations, with some sites having over 100 respondents and others only one. When averaged, these locations are given equal weight in the machine learning model, which is problematic. Locations with more respondents provide more reliable predictions because averaging across a larger sample size mitigates individual differences. Conversely, locations with fewer respondents are less reliable. Averaging each location reduced the dataset from 880 to 111 datapoints, with only half of the locations having two or more datapoints. This did not create an accurate machine learning model.

Regressions in QGIS

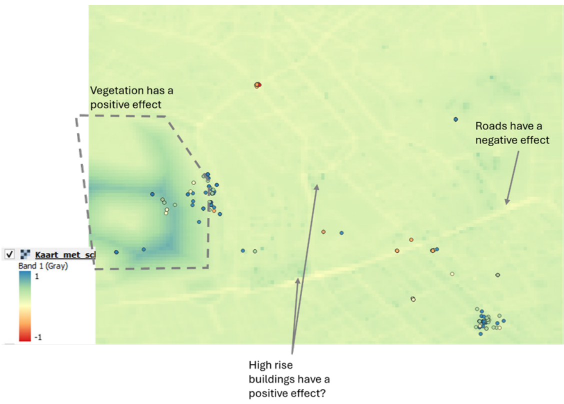
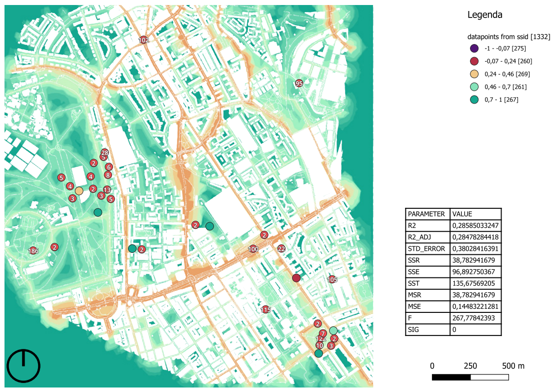


Figure 83 First attempt in multiple linear Regression in QGIS, by author

Multiple linear regression combines the effects of multiple linear regressions. This was not used because of high prediction errors.

Regression Kriging in QGIS



PARAMETER	VALUE
R2	0,28585033247
R2_ADJ	0,28478284418
STD_ERROR	0,38028416391
SSR	38,782941679
SSE	96,892750367
SST	135,67569205
MSR	38,782941679
MSE	0,14483221281
F	267,77842393
SIG	0

Figure 84 Regression Kriging map created using the SAGA plugin prediction pleasantness from the L_{den} map , by author

The Kriging regression was tested but not chosen due to its limitation of accepting only one input variable, which in this example was the L_{den} map. The regression was implemented on a smaller subset comprising 671 samples, predicting pleasantness. The resulting R-squared value was 0.29, indicating a moderate level of explanatory power. However, the standard error was relatively high at 0.38, suggesting considerable variability in the model's predictions. Moreover, the sum of squares values (SSR = 38.7, SSE = 96.7, SST = 135.7) and mean squared error (MSE = 0.14) highlighted the model's limitations in effectively capturing the variation in the data. The high F-statistic value of 267.8 indicated that the model was statistically significant. One of the reasons for this could be that the data points are in groups that are not evenly spaced throughout the map. It can be useful when there is a spatial autocorrelation in the residuals of the regression model, so nearby locations have similar errors. These errors could be due to omitted variables, here the variables for the average view distance and the proximity to parks are not used as input, because the software limits this. These could explained those spatial errors. It could also be the case that this model mis-specifies the relationship between the predictors and the target variable. The performance of the model demonstrates effectiveness; however, a notable limitation arises in its inability to retain the regression for application to new designs. Although the built-in functionalities in QGIS facilitate the creation and immediate visualization of spatial regressions, they lack the options for predictive applications. This constraint underscores the need for a framework that not only generates spatial regressions but also enables their storage and reapplication to novel designs, thereby enhancing the model's utility and scalability beyond initial visualization.

SVM in QGIS smart maps

The Smart Maps plugin for QGIS, employs a support vector machine and ordinary kriging, Despite achieving an R-squared value of 0.37 and an RMSE of 0.343, its utilization was deemed impractical due to similar constraints as the regression kriging model, in applying it to new designs. However the way the interface works could be an inspiration for developping the design tool in this research.

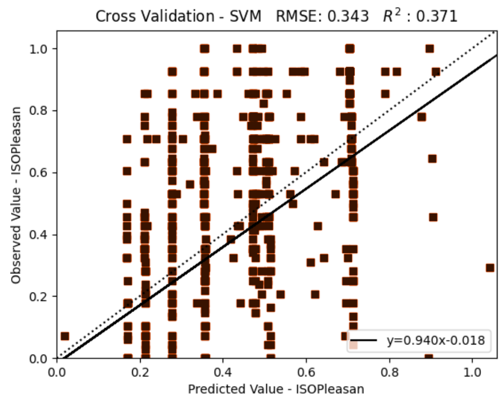


Figure 85 Table for the SVM pleasantness predictions vs real values from Smar tMaps plugin, by author

Multiple linear regression (MLR) model

The MLR model based on the perceived presence of sound source types, with this formula. Knowing from the dataset which sound sources are perceived to be present, the pleasantness can be calculated, with an R^2 = 0.35. This cannot be recreated for new designs.

Pleasantness = 0.477 + 0.115 * Natural - 0.09 * Traffic - 0.08 * Other Noise - 0.03 * Human

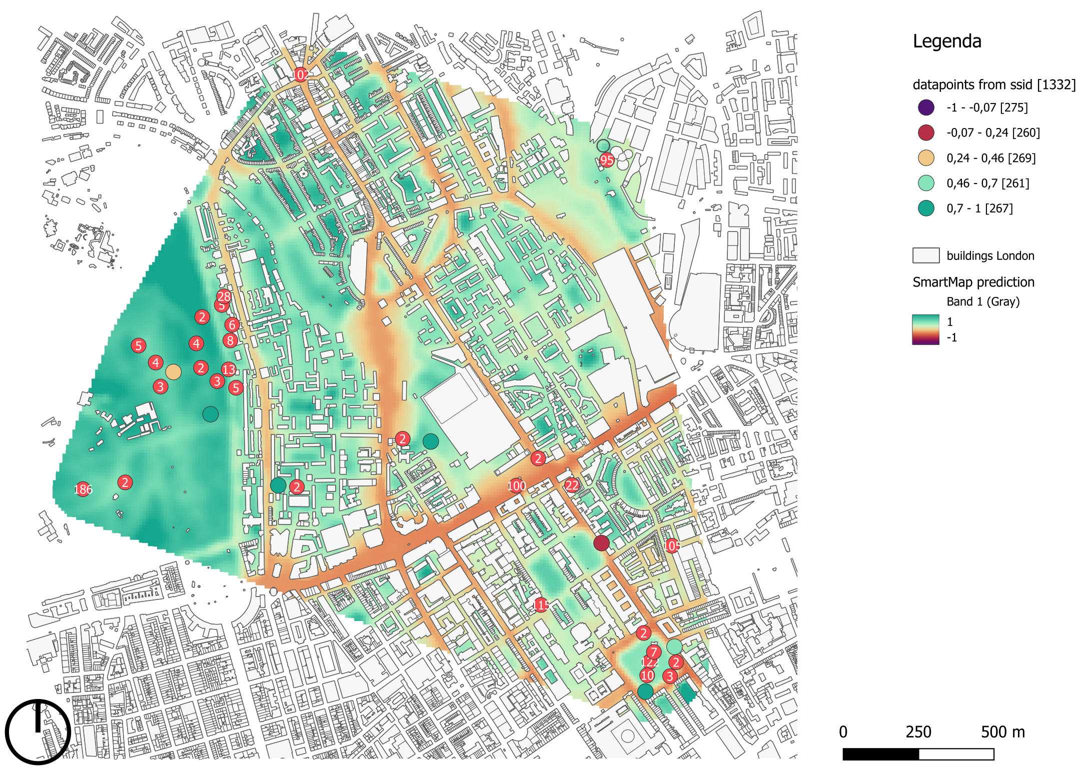


Figure 86 Prediction map created using the Smart Maps machine learning prediction in QGIS, by Author

Maps with Single Feature Input

These maps are generated from Random Forest regressor models using only one feature as input. All maps can be found in the appendix. The models for parks, trees, sky visibility, and average view distance were relatively successful in prediction, with R^2 values of 0.42, 0.40, 0.37, and 0.36, respectively. However, these models appear to be prone to overfitting, as indicated by the rapid, non-linear changes in prediction values. The models for fountains and the L_{den} map for traffic noise performed worse, with R^2 values of 0.29 and 0.26. This could be attributed to the lower number of input values for these features, making them less prone to overfitting but consequently less accurate.

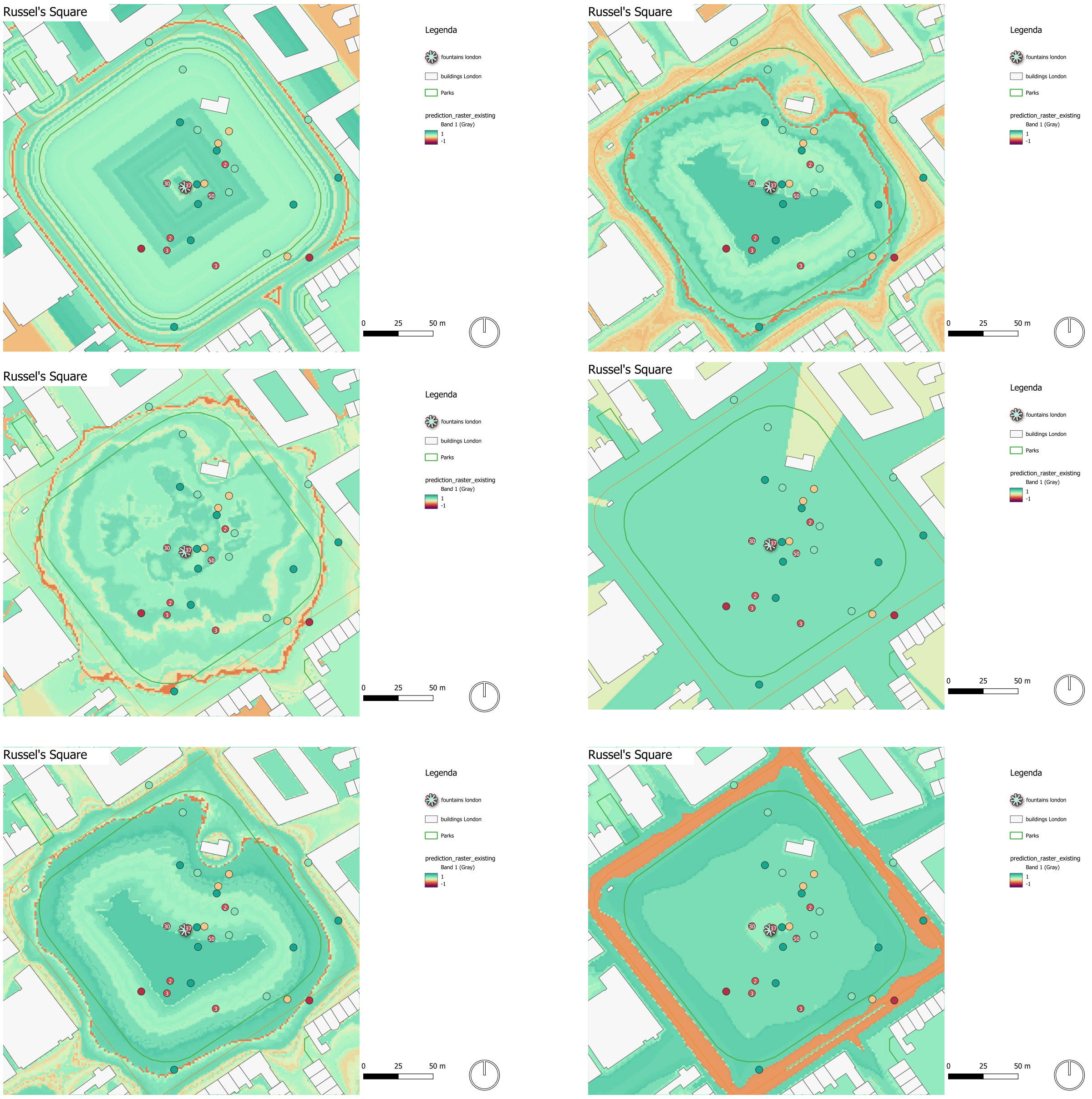


Figure 87 Prediction maps created for Parks, Trees, AVD, Sky visiblity, fountains, and $L_{den,}$ by Author

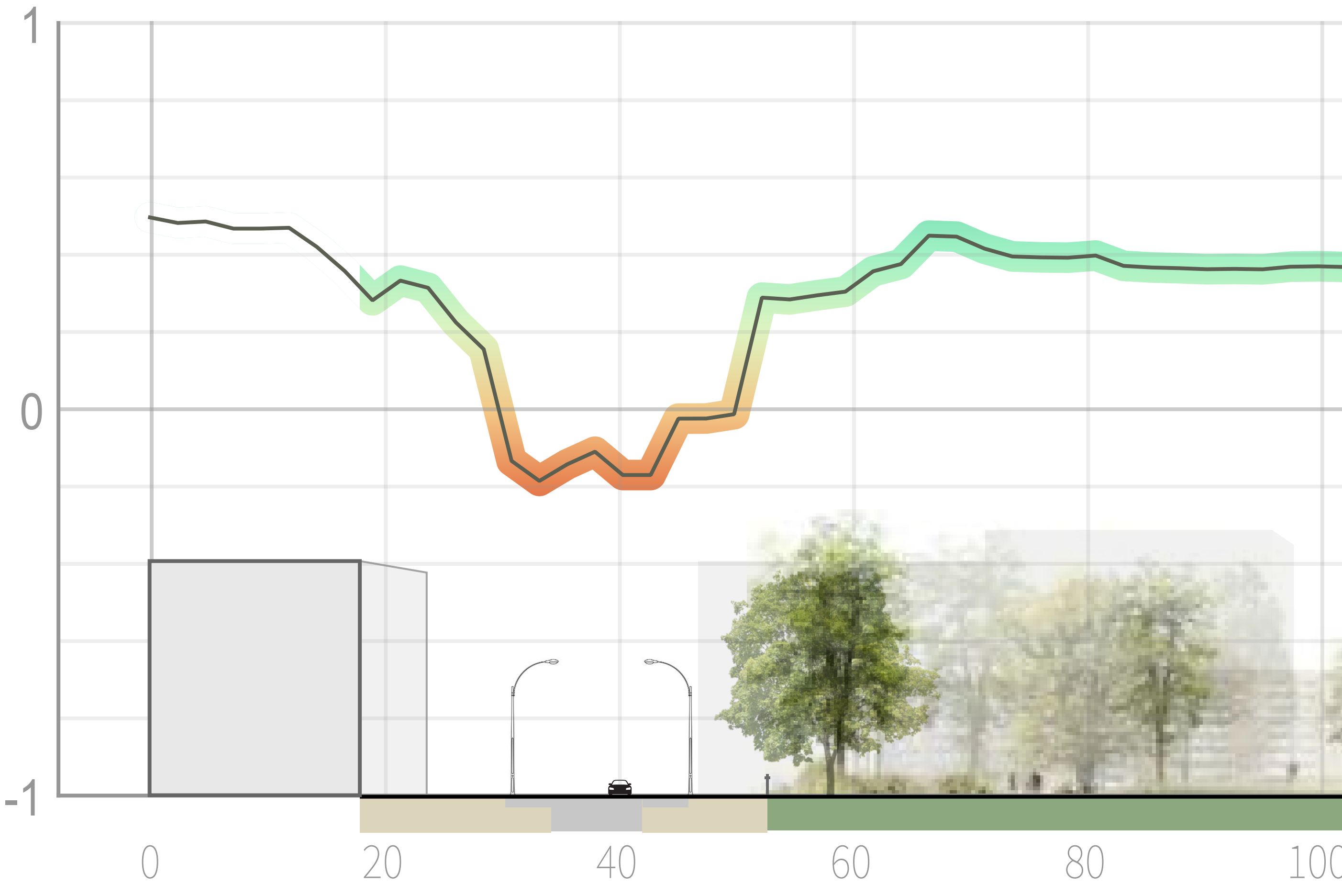
Conclusion

The machine learning model achieves an R^2 value of 0.43, indicating that 43% of the dataset's variance can be explained by the inclusion of architectural objects in the physical environment.

The features that are the most important for the ML model are the L_{den} map created for the roads and the map for the proximity to parks. This aligns with the findings of Chapter 5 where these two factors also have a strong correlation with the perceived pleasantness.

However, the model remains susceptible to overfitting and exhibits inaccuracies, particularly in areas where the dataset lacks representation. To address this, additional data could be incorporated, or alternative modeling approaches could be explored to enhance performance, like linear regressions, which are less prone to overfitting, but have a lower R^2.

The chosen and testing prediction models are available at Github.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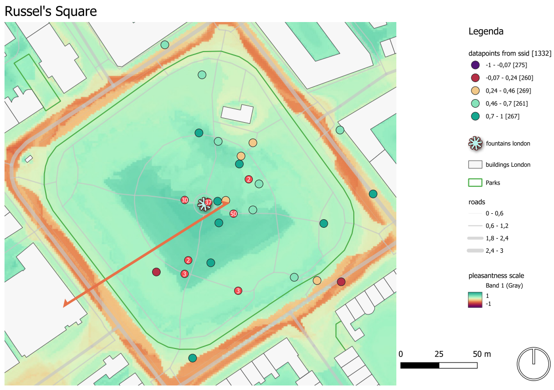
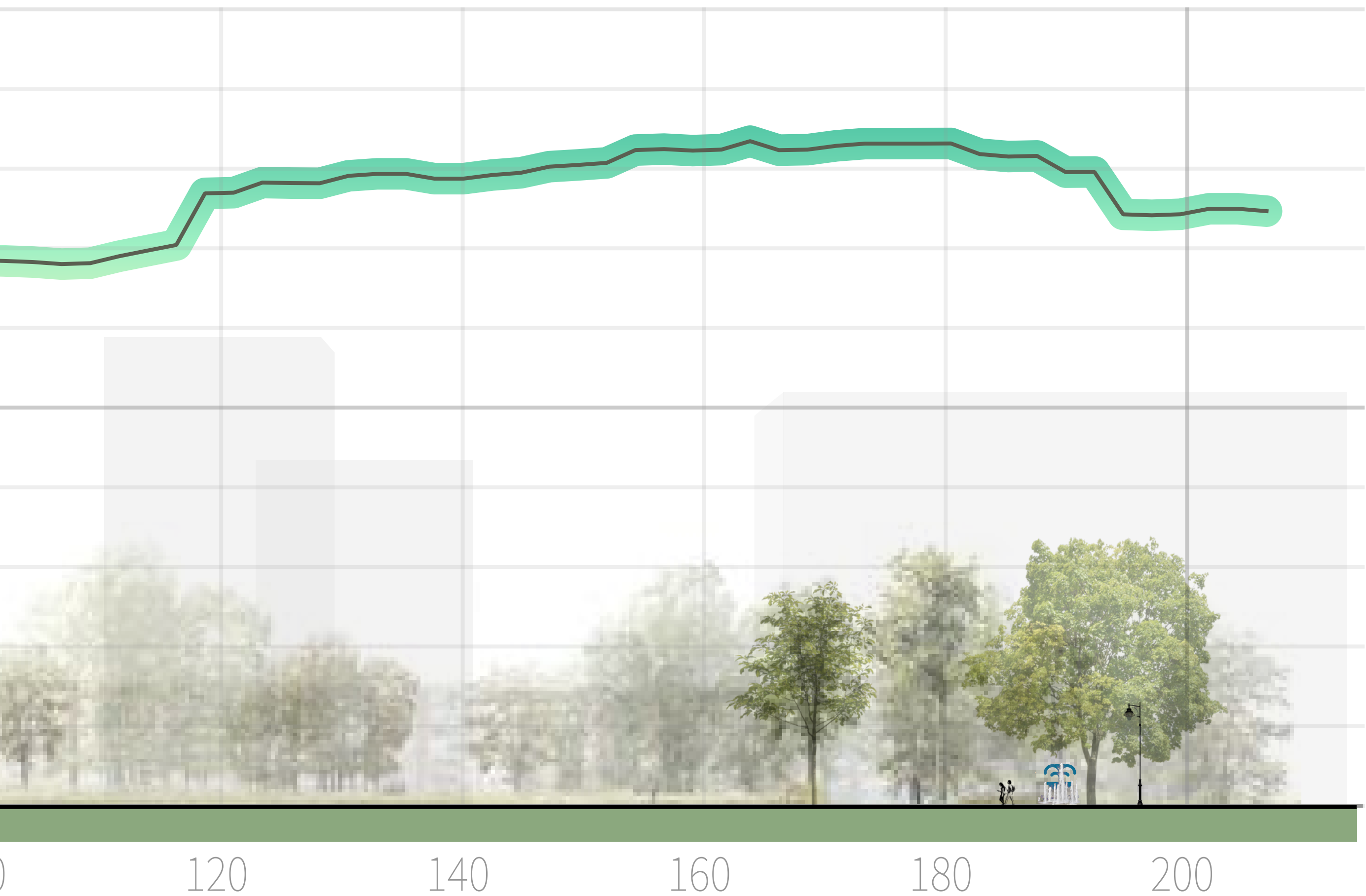




Figre 88 Section from prediction map, by author

Chapter 8 Visualization and Application

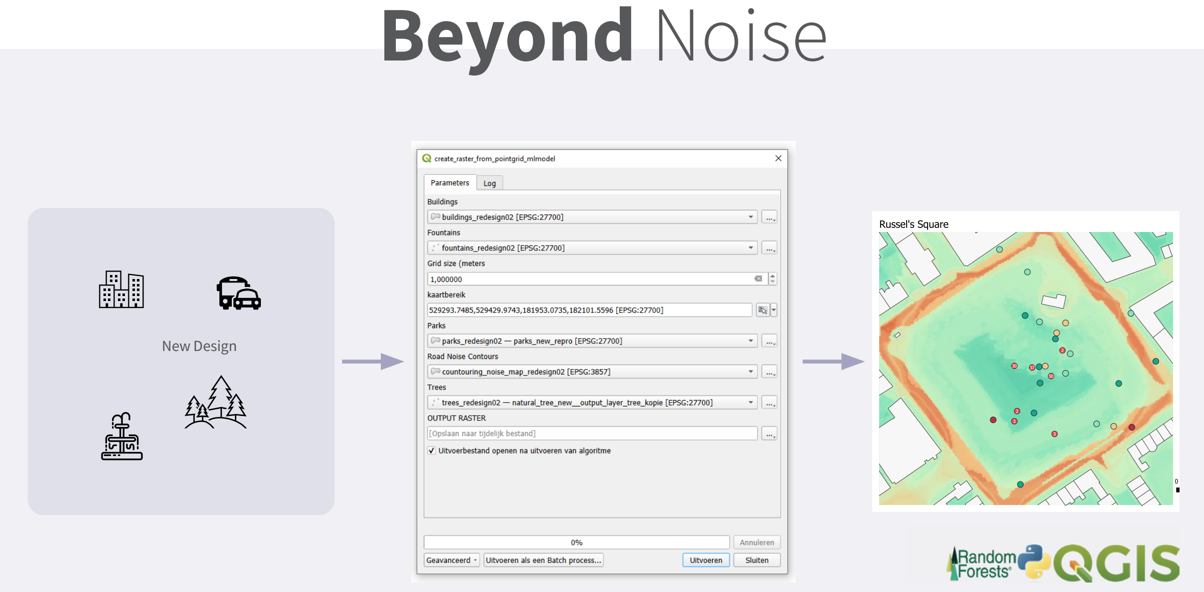


Figure 89 Beyond Noise Plugin, by author

Implementation in QGIS

A QGIS function / plugin, the Beyond Noise function, was created to incorporate the gathered data, does the ML predictions and creates a visualization of this data through a soundscape map. The Model Builder layout of the function is shown in Figure 90.

The prediction model was implemented by writing the python script for the model in the python editor for QGIS. For the first implementation the LGBM model was selected, but upon further research the Random Forest Regressor was chosen. It was implemented using the points from the SSID. The outliers were removed (z=2). The model has an R^2: 0.43. The input features are the buildings, roads, parks, trees and fountains.

Visualization

A grid is created and for each of the points in the grid the data on the parks, road, buildings and fountains is collected to predict the pleasantness with the ML model.

Once every grid point has a prediction, it is visualized by creating a grid. In this chapter the locations in the dataset are visualized, to verify the prediction model with the data from the database.

Colors

The maps use a color scale which goes from dark red to green-blue. The color palette draws inspiration from Lavandier et al.'s (2016) work, which identified these colors as both accurate representations and easily interpretable within the color scheme.

Choice of grid size

When choosing the grid size, the scale paradox (De Jong, 2008) was used as a guiding measure. Grid size plays a crucial role in the calculation of the soundscape pleasantness index, with smaller scales, such as 1-5m grids, being recommended for comprehensive analysis.

Utilizing larger grid sizes, such as neighborhood-level scales (e.g., 500m or

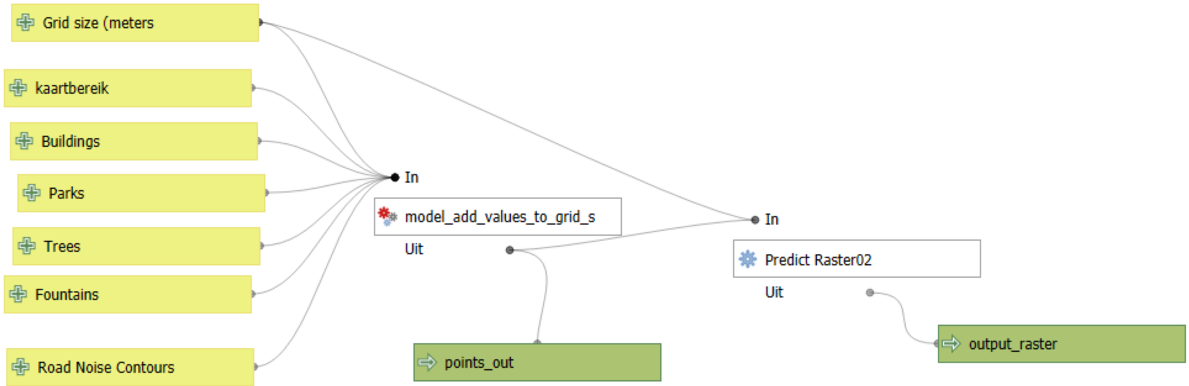


Figure 90 QGIS model builder model for preprocessing data (shown in figure 58) and the prediction and creation of the raster, by author

1km squares), yields limited insights into the nuanced variations experienced across different locations. The perceived quality can change every few meters from streetcorner to streetcorner, depending on the presence of different sound sources and other elements in the context. The precision or granularity of the prediction will be removed when trying to predict 1 soundscape rating for bigger areas at a whole.

Target audience

the target audience is urban designers involved in the urban redevelopment process. The tool is meant to be helpful in the preliminary stages of the design process.

How to use this tool

The Beyond Noise plugin can predict the soundscape pleasantness using the following spatial data. A polygon layer containing the buildings in the area, optionally including the height of the buildings. Parks must also be represented as a polygon layer. For the roads an L_{den} map created with the Noise Modelling plugin should be incorporated. Additionally, create a point layer featuring the fountains. Lastly, a point layer containing the locations of the trees is optional, with the tree height ideally included, but the default is set to 20m if not specified. Since the tool is trained with data in urban environments, it is advised to use this tool in similar applications.

Sections

Sections can be a valuable tool in design, providing a 2D representation of the surrounding environment. A vertical cut, combined with the depiction of people, helps to identify scale and proportion (Chatel, 2019).

Sections are created using Adobe Illustrator. The line indicating pleasantness is derived from map data using the profile section tool. Building heights are taken from the building map to outline structures in the section. Materialization is illustrated through a combination of Illustrator and Photoshop drawings, adhering to the style of landscape sections.

Urban scales for soundscapes

There are 3 scales/ scale types where this tool can be applied. Based on the literature by de Jong (2008), three major design scales are identified that are crucial for soundscapes. These scales are not rigidly distinct, and effective urban design integrates and navigates through these various scales.

Human experience

This scale is about the human perception of an environment, on one specific place, for example people sitting somewhere on a bench. On this scale changes in design can have a lot of impact on how people perceive their environment. Design changes on this scale are vegetation or adding fountains, which mask the effect of unwanted sounds, by introducing wanted sounds. A model is created where the value can be predicted for one single point

Building block / Neighborhood scale

The impact here lies in the layout of the building blocks and how movement and contrast is created through them. People can understand the difference between different spaces and different times of the day. Routing can be an important aspect.

Although this research has mentioned the importance of urban morphology, this field has been explored more by other researches. Buildings shape, height, and façade materials can impact how people perceive their soundscape. The effects of design choices in these two scales can be easily informed by the design tool that is created for this framework. On this scale differences with the buildingblock are clearly expressed.

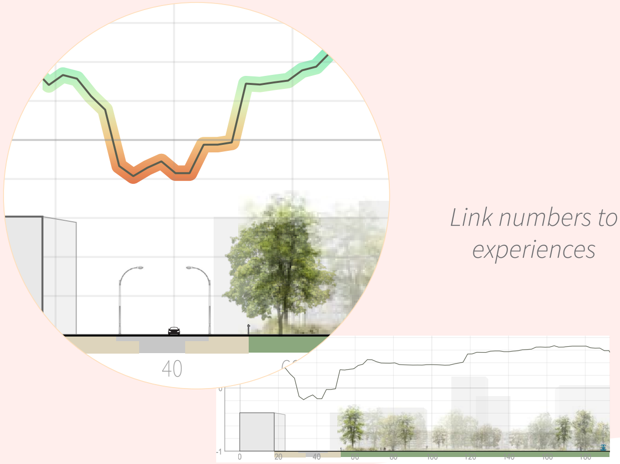
District scale

Creating Soundscape maps for areas larger than a 300 m^2 is discouraged, because the granularity will be removed when trying to predict 1 soundscape rating for large areas as a whole. However the prediction model can still be used to inform design decisions in this scale when used accordingly. By taking small samples in different areas with the prediction model, their different qualities can be determined, and the scale paradox can be avoided. Different improvement strategies per location can be drafted. With this method it can be decided to place certain urban functions in certain places with the most fitting sonic environment. Improvements, such as alternating the route of a busy road, can be motivated, by doing small scale tests with this tool. This method can also be used for creating policies. With using a prediction model soft criteria can be quantified and goals with these number can be formulated.

Figure 91 Different applications in urban design with a section(top), prediction map (middle) and map with multiple predictions (bottom), by author

Human Experience

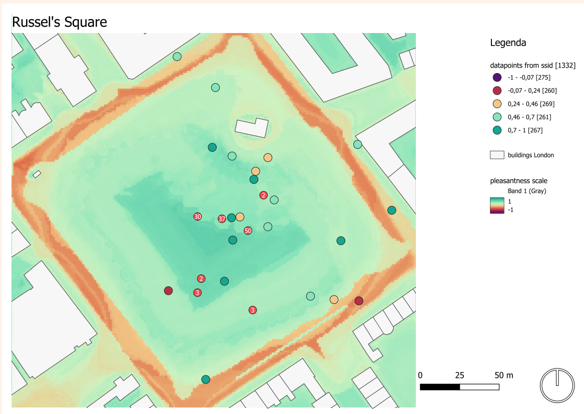
(3-30m)



Link numbers to experiences

Building Block

(30-300m)



District

(300+m)

Take samples in multiple places, for comparison

Discussion

Soundscape predictions are not widely used outside of academia, this part of the research tries to bridge the gap between soundscape research and application to soundscape design. In this chapter of the research a plugin is created which preprocesses the data needed for the prediction model, and then creates the predictions using the random forest regressor. These predictions are then visualized using a grid in QGIS. This is an accessible way to interpret this data.

User-friendliness

Creating L_{den} maps

One aspect of the process that isn't automated is the creation of the Lden map. Currently, this task is carried out using the WPS builder within the Noise Modeling plugin. However, since this tool operates in JavaScript, I have encountered difficulty in converting it into a Python script that can be integrated directly into the QGIS application. These maps had a strong correlation with pleasantness in the dataset, so leaving this step out seemed unlikely

In further expansion of this topic this could be elaborated upon.

Computation time

Currently creating each map costs a few minutes, which may become a bottleneck when iteratively designing multiple scenarios. While the machine learning model's prediction phase is relatively fast, the slowest aspect lies in preparing the input data. Creating the input data for the average view distance is one of the most time-consuming parts. This could be sped up by using less directions, in which the model looks. However this reduces the accuracy of the model. Currently, the model examines 32 directions, but to enhance accuracy, doubling this to 64 directions is ideal. However, this enhancement was deferred due to concerns over increased computation time. Creating the tree map also is time consuming. Since this map is not an important data feature for the machine learning model, it could be left out entirely. Creating the Lden maps also costs some calculation time, however this is the most important feature in the ML model, therefore this should be kept.

Leaving out layers

Currently all the urban design elements have to be present in the selected area to run the prediction, otherwise it will give an error. So leaving object types out, such as fountains, is not currently an option.

Conclusion

Overall a framework is created which uses computational tools to improve soundscape design A QGIS function is created with basic geometrical inputs that uses a machine learning model to predict the pleasantness of the soundscape. All though there is room for some improvement, the created function works the way that was aimed for this framework

This predictions are easy to interpret, by the color labels, and can be used to iterate through design options and for making design decisions.

The created tool is available as python code at Github: https://github.com/niroda01/BeyondNoise To implement in QGIS. THe modelbuilder files should be placed in the modelbuilder folder of QGIS. The python scripts should be placed in the python scripts folder. Make sure that the trained model is loaded through the correct file path.

Figure 91 Usage of tool on multiple scales

Chapter 9 Design proposals

Figure 92 Outlined location from GFrom QGIS, by author

This chapter introduces innovative design concepts aimed at transforming existing spaces. The initial focus lies in identifying areas with the potential for enhancing their sonic environment.

Site choice

The chosen site for redevelopment lies within the city of London, selected due to its notable threats and opportunities. The existing situation is an empty lot in between different buildings. Positioned next to a road with high levels of road traffic noise and situated at a considerable distance from urban greenery, this location emerged as one that has room for growth. Identified as one of the areas on the Camden Town plan map exceeding a 280-meter radius from publicly accessible green spaces, it holds promise as a potential site for creating new urban green public spaces (figure 19).

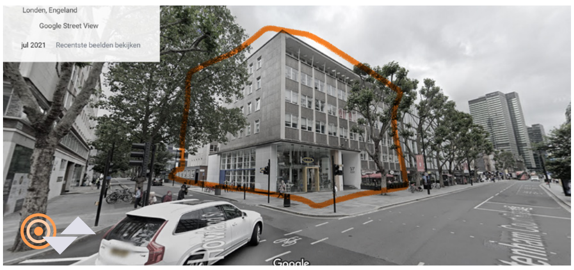


Figure 93 Outlined location from Google Street View Images, by Google

Project requirements

The objective entails revitalizing an undeveloped parcel of land nestled within a busy urban city center. The design involves increasing density, by adding building square meters while concurrently fostering the creation of communal areas. These spaces are envisioned to serve as inviting retreats, encouraging social interaction and leisure activities. Right now the soundscape pleasantness score is around 0. The goal is

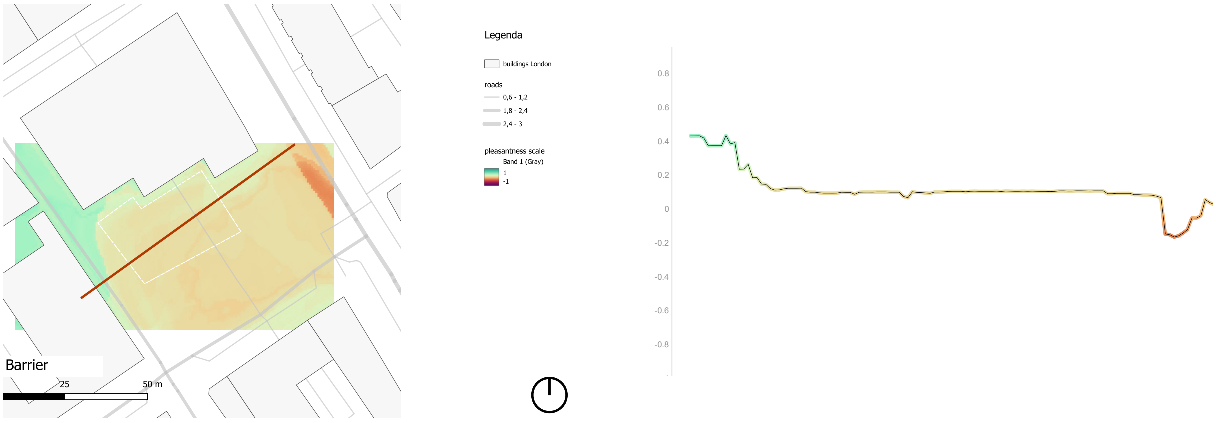


Figure 94 Baseline (b0p0f0), prediction of soundscape pleasantness score using the prediction model (left) and section taken (right), by author

to increase this as much as possible, with the tools available.

Analysis of the predicted values.

Analyzing the data was simplified using the zonal statistics method to calculate various metrics such as mean, minimum, maximum, median, range, and standard deviation for each prediction. This method utilized a vector polygon delineating the open space, chosen consistently across designs as the focal area for analysis. The area is shown in figure75.

Baseline, existing situation (b0p0f0)

The prediction in the existing situation is presented in figure 75. The ratings in the middle of the square are around 0.12 soundscape rating. The first action strategy in soundscape design is the localization of functions. From this viewpoint it could be argued that this is not a suitable site to create a public space, because of the lack of a positive soundscape. However with the soundscape pleasantness evaluation being above and around 0, It could be unwise to write the place off entirely . Rather, it presents an opportunity for potential improvement through targeted design modifications, suggesting the potential for a moderately positive soundscape with appropriate alterations.

Design Variations

Using this soundscape prediction model there are three main ways to alter the design. The first one is to change the building shapes. The second one is to add water features. The third one is add greenery.

Baseline: Illustrates the existing environment devoid of any alterations.

Integration of Sound-Blocking Structures: Introduces the incorporation of a building block strategically positioned to mitigate noise pollution.

Introduction of Water Features: Envisions the installation of fountains to serve as tranquil auditory elements, effectively masking the din of nearby traffic.

Integration of Green Spaces: Explores the addition of parks and verdant landscapes to enhance aesthetic appeal and promote environmental sustainability.

Roadway Transformation: Considers the possibility of reconfiguring the busy thoroughfare to minimize its auditory impact and improve traffic flow.

These design permutations represent a comprehensive approach to urban redevelopment, prioritizing both acoustic harmony and public well-being.

Because the sound levels are so high, it is important to lower these limits first as this is the most impactful for creating a better soundscape environment. Using building volumes for this purpose proves efficient, as these structures are already planned, and the resultant spaces will be publicly accessible.

The first design iterations shown are varaition where only 1 urban design element is altered (Figure 85-88). Next a combination of design strategies is shown.

Courtyard (b1p0f0)

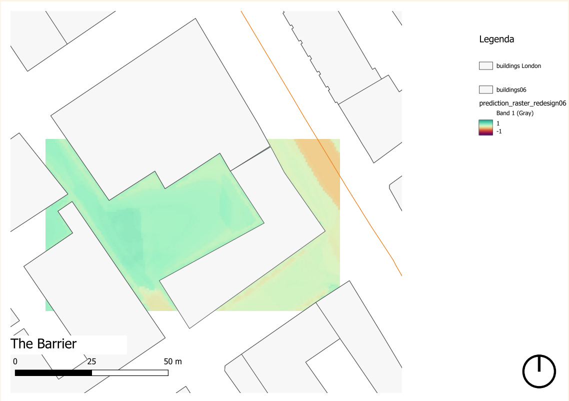


Figure 85 Courtyard (b1p0f0) predicted pleasantness, by author

Creating a u or o-shaped open space with buildings as shields significantly enhances the predicted quality of the area. Only using this strategy increases the pleasantness in the public space by 0.25 to 0.37, showing its effectiveness.

However, it's worth noting that areas closer to the street exhibit higher scores, possibly due to inaccuracies akin to those observed in Camden Town.

Half Open (b2p0f0)

Figure 86 Half Open (b2p0f0) predicted pleasantness, by author

In this design, the building shields against the adjacent busy road, albeit leaving the possibility for noise infiltration from other directions. The improvement is noticeable behind the building's "shadow" from the road, other areas are less improved, with the pleasantness score increasing by 0.14 to 0.26. This approach proves less effective compared to the previous one.

Drops of sound (b0p0f1)

Figure 87 Drops of Sound (b0p0f1) predicted pleasantness, by author

The adding water features only marginally improve the predicted pleasantness to 0.14 with 0.02,. Given the Lden of 65 to 70dB, relying solely on fountains to mask the sound may not suffice

Parkour (b0p1f0)

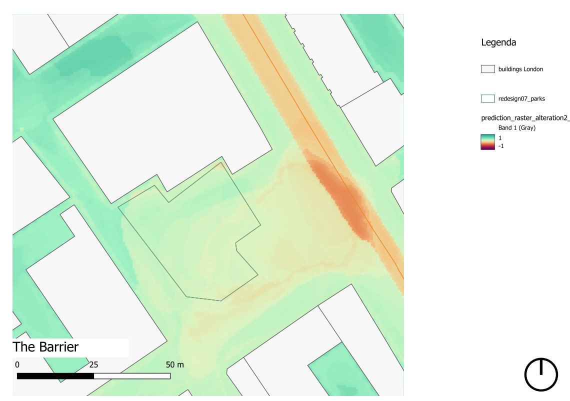


Figure 88 Parkour (b0p1f0) predicted pleasantness, by author

Adding greenery also seems to have a very strong effect. Incorporating greenery to the existing scenario, had an overwhelmingly positive effect. The soundscape pleasantness increases to 0.27 on average, an increase of 0.15.

Combinations of strategies

Now we have seen the individual effects of the three steps. Building shape and adding greenery seemed to have a positive effect when applied well. Fountains did not seem to have a very strong effect.

Buildings Variation 1 - The Green Courtyard (b1p1f0)

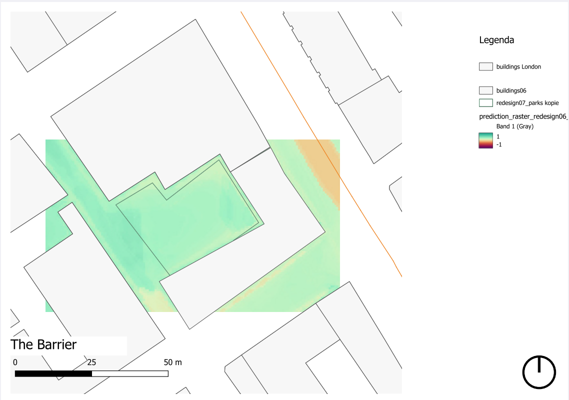


Figure 89 The Green Courtyard (b1p1f0) predicted pleasantness, by author

This variation had the highest score in terms of pleasantness. Incorporating greenery into the courtyard design, did not improve the models outcomes. The mean score remained 0.37, as in the 'Courtyard' design. Adding fountains lowered this number to 0.35 (not shown in the figure). The section below shows the average increase of 0.25 quite clearly.

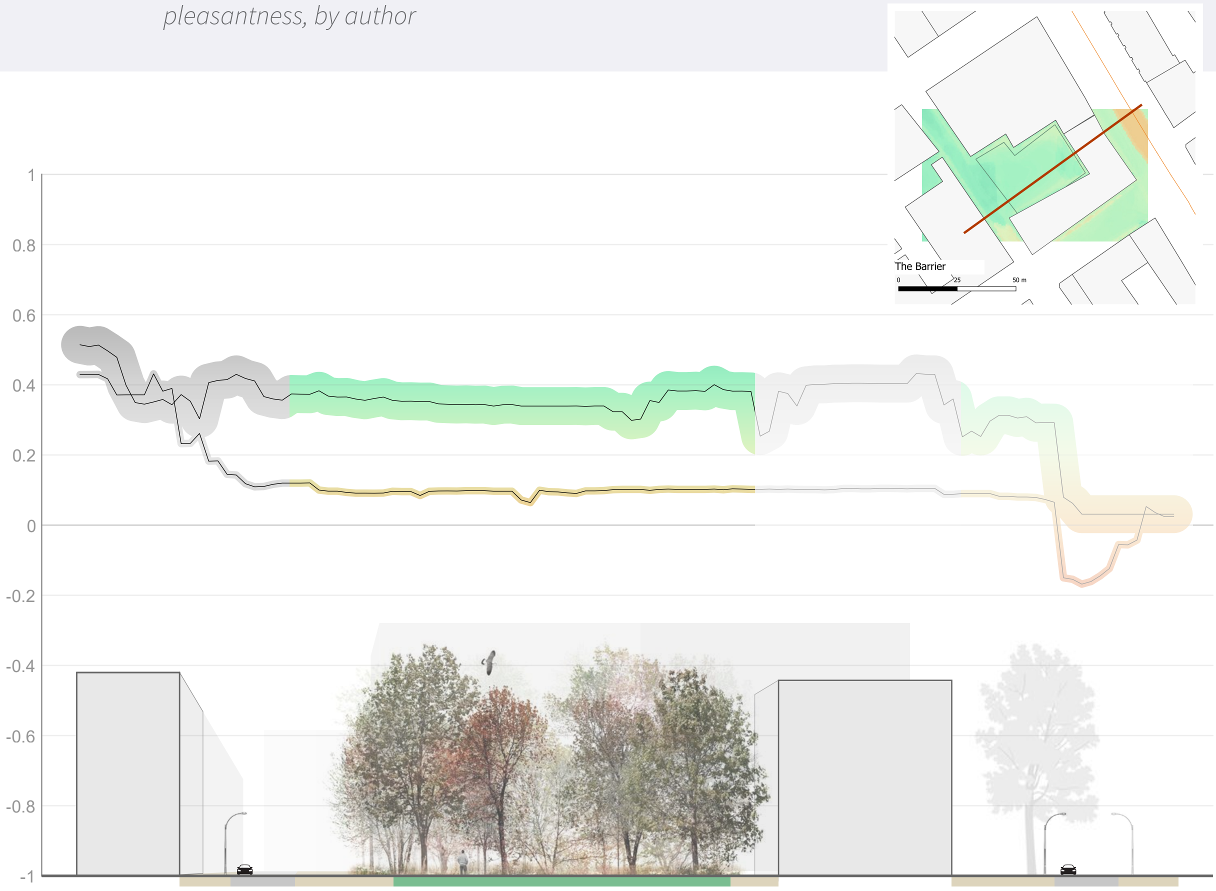


Figure 90 Section of final design, by author

Drops of Green Blue (b0p1f1)

Figure 91 Drops of green blue (b0p1f1) predicted pleasantness, by author

Incorporating fountains alongside greenery in this scenario did not enhance the overall pleasantness, as might be expected. The average score decreased to 0.26, lower than the previous 0.27 in design 'Parkour', suggesting a potential negative effect. This might be an issue with the prediction model itself.

Buildings Variation 2 - Masked (b2p0f1)

Figure 92 Masked (b2p0f1) predicted pleasantness, by author

In this variation adding fountains to the Half open design concept, had a small positive effect. The score is 0.27, 0.01 more than in the 'Half-Open' design concept. This could be because the Lden is measured to be around 5-10dB lower than in the 'Drops of sound design'.

Enclosed green (b2p1f0)

Figure 93 Enclosed Green (b2p1f0) predicted pleasantness, by author

Combining the two strategies of shielding from the road, and adding greenery resulted in a slightly reduced increase compared to their individual effects. Their combined score is 0.32. This represents only a 0.06 increase from the 'Half Open' design (0.26), indicating the effect of adding greenery. Similarly it shows only a 0.05 increase from design 'Parkour' (0.27) which should be the effect from using the buildings as a shield.

The Barrier: Sound centered (b2p1f1).

Figure 94 The Barrier: Sound centered (b2p1f1) predicted pleasantness, by author

Again the effect of adding fountains seem to have little to no effect. Combining the three strategies did have a good impact on the overall soundscape pleasantness score, reaching a score of 0.31. It is slightly lower than the 'Enclosed green' design with 0.3, so the fountains had a slightly negative effect.

Discussion

This part of the research shows a practical application of the function that is created, and shows how new designs can be predicted with this tool as well.

The building shape seems to have a big impact as well as the addition of greenery. The buildings shape is used as a sound shield to decrease the presence of traffic noise in the public area.

Adding fountains has very little effect in this design program. This could be because of the lack of fountains in the dataset.

Changing road traffic intensity is an important tool for urban designers to control traffic noise. Right now practically changing the road type in the program is challenging. This takes extra time to change, and also extra computing time. In a better version this could be integrated into the program.

The maximum increase in average pleasantness core is 0.25, from 0.12 to 0.37. While seemingly modest, this increase represents an eighth of the entire range of pleasantness. However, replicating the very high pleasantness scores observed in park settings far away from the periphery of the park, within the dataset proved unfeasible due to space limitations. This amount of greenery could not be recreated on this scale. The highest average score in the dataset is 0.66, which is Regents Park Japan, in the middle of a very big park, away from city life in London. It has a similar score to the Tate Modern, and St Paul's Cross locations, with 0.38 and 0.36 respectively.

Furthermore, even in the optimal design, traffic noise remains around 50 dB. To enhance comfort, reducing this noise level is imperative. Yet, achieving this balance requires careful consideration. In this design the choice was not made to make it more closed off, as it might not be perceived as publicly accessible, and possibly be perceived as unsafe. Removing the service road traversing the area could potentially alter the dB levels and improve overall comfort. The mean value is used to give an overall impression of the soundscape evaluation.

Using this in urban design

This design is shown on a building block scale. To interpret the data effectively, a new function is created which calculates the mean values per design. Other values from the grid were also calculated, such as the minimum and maximum values in he grid, the range and the standard deviation. however these values did not change significantly throughout the design steps so they are not mentioned in the steps. The total evaluation can be found in the appendix.

Setting targets

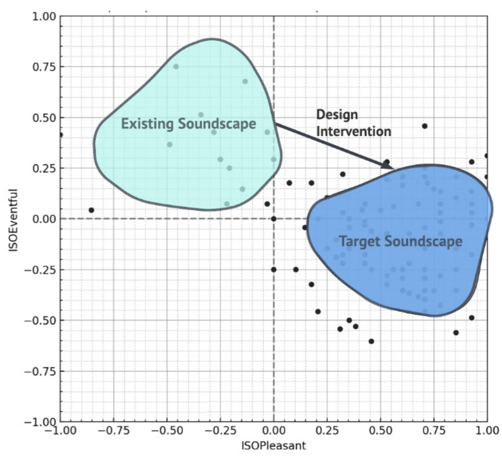


Figure 95 Setting targets taken from Mitchell (2022)

Mitchell (2022) talks in their research about how the pleasantness can be used to set targets in urban design. So improving it from an xx number to another. This model also takes into account the Eventfulness. In this research this dimension of soundscape experience has not been taken into account, but it could be important in communicating designs.

One other thing that this prediction model does not take into account is the distribution of responses. It predicts the average pleasantness as perceived by the general public. However in the statistical analysis it is shown that some places have a higher variability in responses than others. Mitchell (2022), proposes that design goals could be formulated such as 'the soundscape should be likely to be perceived as pleasant by at least 75% of users'. This is something that the current prediction model is not able to show. And even though this can lead to new insights, showing the mean of a location makes comparisons easily to investigate.

The impact of design strategies

It is unclear whether urban designers with no background information would apply the model according to the strategy described here. The designs drawn here we done by myself, having background knowledge on soundscapes. Therefore a short information piece should be included on the effects of each urban design element.

Conclusion

In conclusion, the tool successfully generated multiple predictions for soundscape pleasantness across different design variations. These predictions provide a basis for analysis and evaluation, guiding the subsequent steps in the design process.

There are some areas where there is room for improvement, for example the computation time or ease of use.

Soundscape Design Tool Guide

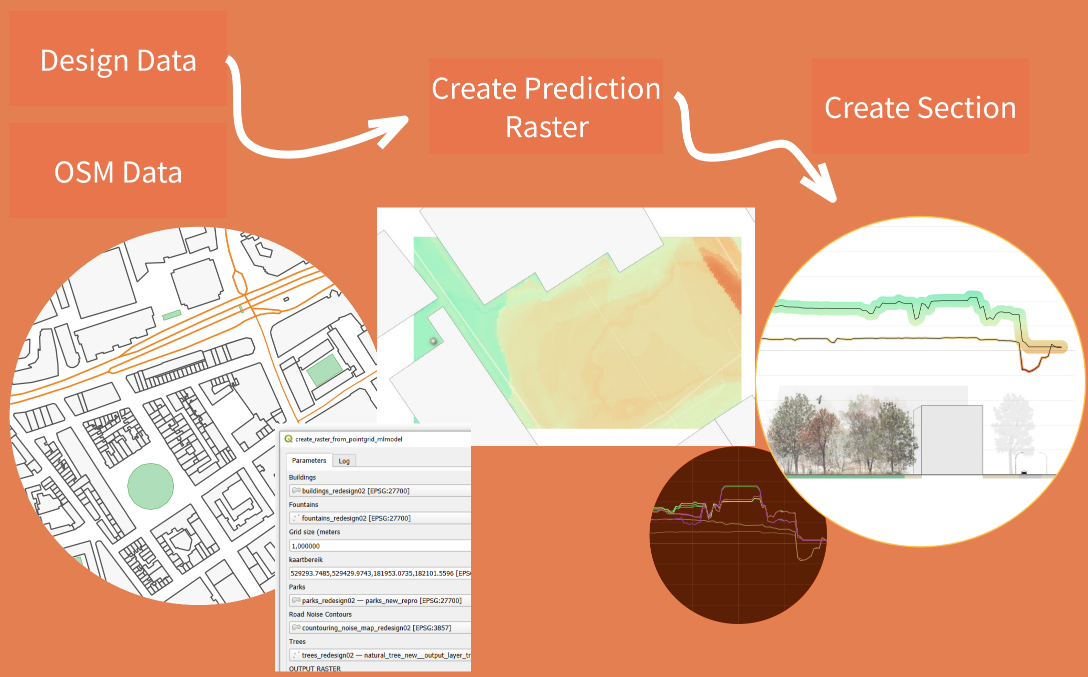


Figure 96 Outlined location from GFrom QGIS, by author

The created tool is available as python code at Github: https://github.com/niroda01/BeyondNoise.

To implement in QGIS. THe modelbuilder files should be placed in the modelbuilder folder of QGIS. The python scripts should be placed in the python scripts folder. Make sure that the trained model is loaded through the correct file path.

Choose the right projection!
The projection should be the same for all files in QGIS to avoid misplacement. The projection type should be in meters not degrees. The default crs from QGIS (4326) should be avoided. This is in degrees. For London the projection 3857 was used.

Load & process all layers
The layers Buildings, Parks, Trees, fountains and Roads can all be loaded from the OSM plugin QuickOSM. These are in the CRS: 4326. Make sure to reproject them within QGIS. These layers can then be altered to fit the new design. For the design all the objects of the same sort have to be in the same layer. For example: if a park is added make sure to combine this object with a file with all the existing objects.

Create the L_{den} map with the NoiseModelling plugin.Follow the steps available at here. Create the Parks map using the parks modelbuilder script.

Create and Train ML model (optional).
Use the ML_script_05.py as a guide, Available at Github. Load in the datapoints from the survey. Make sure the added information of the layers is there. The trained model can be saved to the device. The prediction models uploaded to the github can be used as well. If you want to create your own prediction model, statistical analyis and testing is advised to validate the results of

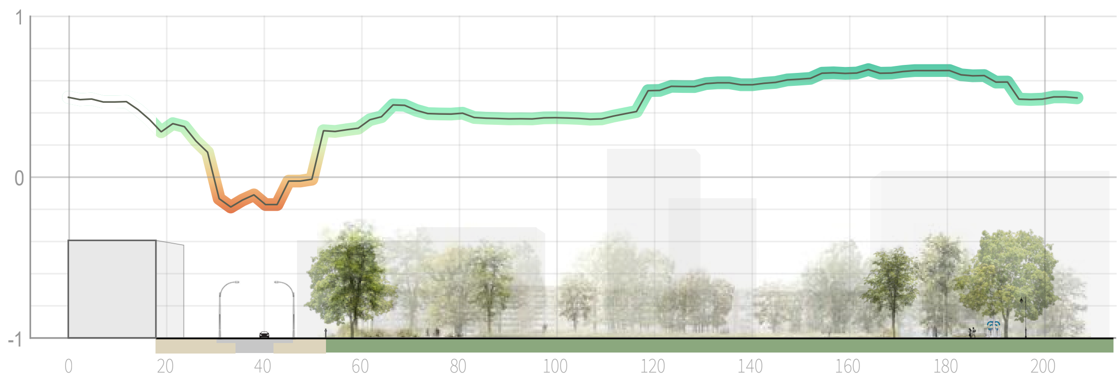


Figure 97 Section of russelsquare, created by Author

the predictions.

Create prediction raster

With the created script in modelbuilder the prediction raster can be created. Make sure that the modelbuilder file is in the right folder. Use the vector files you have as input. If you created your own prediction model, make sure the data is preprocessed in the same way as the training data. Creating your own modelbuilder file for the preprossecing is helpfull for this.

Creating the sections

The sections were created with the help of the section profile plugin in QGIS, and by adding visuals in Illustrator. The profile of the prediction raster is taken as well as the building height.

The building height is use to create the building outlines. Add the roads and parks as line below the section to show materialization. Adding trees also gives a better sense of materiality. Adding people and cars help with giving a sense of the human scale.

The color scale is added to the pleasantness line to communicate the values better. Use the color scale as image in the background and use the line as a mask.

Design iterations

For new designs new layers should be created. With the raster and section tool the differences in the predicted pleasantness can be shown.

For the design iterations the three design action stratigies should be taken into account: Localization of functions, reduction of unwanted sounds and introduction of wanted sounds.

Reducing unwanted sounds can be done using shielding from noise sources. Introducing natural elements such as greenery and fountians can have a positive effect. Fountains can be great for masking traffic noise as well.

Chapter 10 Discussion

Despite its importance, in urban design the incorporation of sound is often overlooked. One cause of this is a lack of availability of information about soundscapes. This research aims to address this oversight by proposing a framework for a computational design tool which assesses the impact of design choices on the soundscape.

While environmental noise, such as traffic noise, poses significant public health risks in urban settings, including noise annoyance and sleep disturbances, focusing solely on its negative aspects disregards the potential positive effects of sound. The concept of the soundscape broadens this perspective by considering the perception of all sounds and their influence on individuals and their surroundings.

This research created the framework for a design tool for soundscape design. The tool consists of a prediction model that can predict the perceived pleasantness of the environment, based on urban design elements. The tool is user-friendly, with simple inputs, and therefore accessible for designers with no background in soundscape design. Some additional information on soundscape design can be provided.

A Random Forest regressor was employed to develop the prediction model capable of assessing soundscape quality at specific locations. Utilizing data from the International soundscape database alongside additional georeferenced information sourced from OpenStreetMap and other databases, the research analyzed the impact of various urban design elements, including roads, buildings, and parks, on perceived acoustic pleasantness. Subsequently, the prediction tool was developed for potential application in future urban design projects.

The random forest regressor achieves R^2 = 0.43, indicating that 43% of the dataset's variance can be explained by combined effect of the urban design elements in the physical environment.

The Smart Maps plugin (Pereira et al., 2022) is an open source plugin which uses machine learning techniques and ordinary kriging for digital mapping. It was developed for mapping soil attributes. This tool worked quite well in the prediction and interpolation on the dataset in the existing situation (R^2 = 0.37). However this prediction model could not be applied to new designs.

Other studies have tried to predict the soundscape quality from different predictors. Lavandier et al. (2016) tried predicting soundscape pleasantness from georeferenced data. About 68% of the variance in pleasantness could be attributed to this georeferenced data. In this study linear regressions were used. This study had a bigger data set of 1800+- rows, which averaged out to 89 locations. An increase in quality of the data could improve the results of this research as well.

The most important feature in the prediction model, created from the random forest regressor is the L_{den} map created from OSM data. The second most important feature is the proximity map for the parks. Lavandier et al. (2016) found that Traffic noise has the biggest impact, with gardens coming second, aligning with the findings in this research.

The dataset in this research, when averaged per location has a very strong positive correlation between the presence of natural sounds and pleasantness and a very strong negative correlation between Traffic noise and pleasantness. Hong and Jeon (2017) used a geographically weighted regression to predict Soundscape Quality. The data is taken from 125 sites. They collected data on the perceived presence of Human, Traffic, Water and Bird sounds, with R^2 = 0.70. This correlation is similar to the correlations done in the statistical analysis. The dataset of Hong and Jeon (2017) is bigger and has a more diverse set of places, compared to the dataset used in this research. The locations in this study are also evenly placed on a grid, unlike thedataset used in this thesis. This correlation found in the study of Hong and Jeon (2017) is high, but does not take into account urban design elements or georeferenced data.

Hong and Jeon (2017) also did some research on the morphological characteristics of spaces with different functions. Respondents in these places can have different expectations which can lead to different ratings for the soundscape design. This is something that is not taken into account in this thesis. Since 11/13 of the locations are an urban park, this was not possible to research with the current dataset. With other data this could be a potential next step, to improve soundscape design, also in relation to one of the three action categories from the soundscape design strategy: the localization of functions.

Cerwén's (2017) soundscape design strategy, has three different types of actions. This strategy was developed also to be used as a design tool in urban design, and fits very well into the design tool framework created in this thesis. The abstraction to the three categories was very helpful on deciding which features to include in the machine learning model. With the urban design elements of the roads and parks, the presence of unwanted and wanted sounds are modeled. As expected also from previous literature these were the two most important features for the prediction model.

The action category of the localization of functions, was not directly related to the input of the machine learning model, namely the strategy action of creating contrast and variety. There was no part of the machine learning modeling that takes into account the effect that the surrounding soundscapes have relating to the current soundscape. However it could be argued that the responses given in the dataset consciously or subconsciously already have taken this into account when filling in the survey. Despite the fact that it was not explicitly modeled in the prediction model, this is discussed in the section on how to apply the design tool. Adding contract or variety is something to take into account in the biggest (and second biggest) of the three urban scales discussed in De Jong (2008).

Limitations

Dataset and Design

The dataset recorded various factors, including pleasantness, at different locations. However, it does not account for changes in public spaces that can influence the soundscape. Incorporating this aspect would be an intriguing approach for design applications, and further validate the created framework.

COVID-19 Lockdown data

Data collection for the International soundscape database was repeated during the COVID-19 lockdown in the spring of 2020. This thesis excludes this data because only acoustic data is available and no information on the pleasantness, and it is not considered an accurate representation of the current urban environment. However, the impact of the lockdown on soundscape within this dataset has been studied by Mitchell (2022). They developed a ML model based on pyscho-acoustic factors that can predict the pleasantness R^2=0.85, and eventfullnes R^2=-.72. These coefficients represent the model's ability to predict the overall response at a given location, averaged across all responses for that location. The model that is created is not generalisable, and only works on the LocationIDs in the dataset. The study found that Sound level reduction does not always lead to increased pleasantness. What is most important are the sound source composition and the sonic character.

Quality of the dataset

These are limitations of the dataset that is used in this research. Even though the dataset is very extensive and contains most of the information that is needed for the experiment in this master thesis, there are some limitations to the dataset that require to be mentioned. The size of the dataset, in regards to dataset to train an machine learning model, is on the smaller side with only 1300 respondents. The locations in the dataset are limited to 13 locations in 2 cities, which are not very diverse in character, where 11/13 are located in parks in an urban environment, and 2/13 are located near a busy road. As a result in 11/13 of the locations the average response was positive. The accuracy of the coordinates of a selection of the datapoints was deemed inaccurate, because of their positioning in water, or inside buildings. These points were taken out of the dataset.

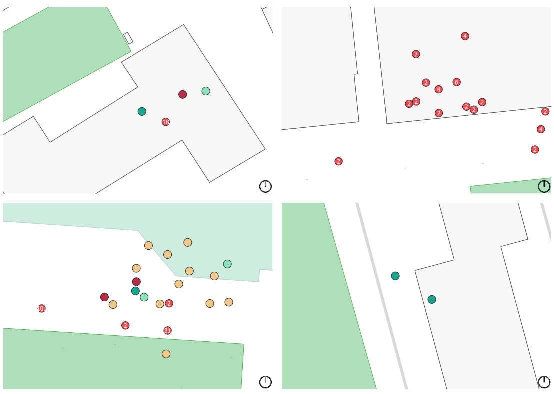


Figure 98 Datapoints that are taken out because of faulty placing, Made in QGIS with OpenStreetMap background, by author

The data mostly represents young people, without hearing impairments, having their lunchbreak in a park that is located in London. The collection of survey responses was mostly done between 11 am and 2 pm. This might not reflect the temporal varieties during the day. The age of respondents in the dataset is on average mostly young adults. This might not be representative of the population as a whole. In terms of inclusivity and accessibility, it would be better to question a broader age group. Because for example elderly people, can experience soundscape differently from their younger peers. To truly characterize the soundscape, long-term monitoring would be needed.

With a small dataset, like the one used in this research, there are things to consider to ensure the validity and accuracy of the predictions of the machine learning model. Firstly removing outliers is very important in small datasets. Otherwise they weigh too heavy in the predictions. Secondly with small datasets models are prone to overfitting.

In the dataset there is a lot of variation on the perceived pleasantness of the acoustic environment even when respondents are in the same environment physically. The statistical analysis shows that on average per location there is a strong correlation with the types of sound sources and how pleasant the environment is perceived to be. However within the same exact location variation of the perceived pleasantness can be very large. Human perception inherently will vary from person to person Therefore errors in the machine learning model will be inevitable.

Quality of the added data

Figure 99 the trees datasets combined, by author

Within the dataset, with its modifications, there are also some limitations, that could impact the accuracy of the model. Materiality is not included in this dataset becaus of a lack of information available. Limitations concerning building data include the absence of precise building height data. From the building data, also information is missing, that could provide insights, such as the façade materials. For the road data, the L_{den} map is an approximation based on the road types in the road data from OSM. However in this case the L_{den} from the Noise Modeling Plugin correlates strongly with the existing L_{den} maps, which are also simulated. Several limitations are evident in the datasets for trees. Firstly, there are gaps in tree coverage within the OSM dataset, indicating incomplete representation. Secondly, due to the absence of height information for trees, a uniform height assumption of 20 meters is applied across the dataset, potentially introducing inaccuracies. Additionally, the discrepancy between trees identified in OSM and those documented in the London database suggests a lack of alignment between the two datasets, raising minor concerns about their overall validity and reliability for comprehensive analysis and decision-making. The limitations of using OSM data for parks include the absence of information regarding the quality or attributes of the parks themselves. The dataset exhibits a notable scarcity of fountains, and lacks information regarding the quality or characteristics of these fountains as sourced from OSM.

Machine learning model inaccuracies

The machine learning model that was developed was a random forest regressor. The model works quite well (R2= 0.40). However in some places the predictions seemed inaccurate. From the literature it was expected in places with a high L_{den}, a lower SVF, and subsequently a lower average view distance (AVD), would create a more negative prediction. However in some places, where green seems to be absent, it seemingly has the opposite effect. However this relation between the AVD and the L_{den} is assumed in the literature and not reinforced by examples in the dataset. Having a dataset including these kinds of instances could improve training the model.

Figure 100 Prediction model used on location CamdenTown (top) and corresponding L_{den} map (bottom), by author

Application as a design tool

The user-friendliness of the tool was an important factor in this research. The creation of the Lden maps however is not integrated into the tool, but has to be done separately. The computation time is also something that should be balanced. The predictions themselves are not taking a lot of computation time. However the preprocessing of the urban design data takes a few minutes. To improve this, the trees visibility layer could be left out, because currently the processing time of this data is relatively high and the feature importance of this input is very low.

The prediction model predicts the average perceived pleasantness of a location's soundscape. However, it overlooks the variability in responses across different places, as highlighted by Mitchell (2022). Mitchell suggests formulating design goals to ensure that a significant majority, such as 75% of users, find the soundscape pleasant. The prediction model lacks the capability to illustrate such variations.

Extending this framework to other datasets can make the framework usable in broader applications and more diverse urban environments. When applying this framework to other datasets, it's important to pay attention to a few factors. The steps taken in this research are firstly statistical analysis, within the dataset, and also with the modified dataset. This way patterns in the data, and lack there off can emerge. OpenStreetMap (OSM) data for the urban design elements is publicly available worldwide, however it's good to check the validity of this data. In this research the data layer with trees from OSM seemed inaccurate. This should be checked for every layer. Removing outliers per location did improve the prediction model in this process, and checking the validity of datapoints.

Currently all the urban design elements have to be present in the selected area to run the prediction, otherwise it will give an error. So leaving object types out, such as fountains, is not currently an option. This decreases the transferability to other designs. The work around this was to put in these places where the calculated value would not count towards the average, so behind or 'inside' buildings, for fountains. For parks it is advised to do a similar thing. When the building height is not in the column the model expects it to be the height will be set to 0, In further research this should be optimized to increase the robustness of the design tool.

Further research steps

Future directions of this research could include looking at other regression models, like regression kriging, to see if there are any improvements there. Another interesting approach is image segmentation. Research could be done to see if this will yield better results.

Collecting Additional Data

To ensure the model minimizes overfitting and achieves high accuracy and predictive power, robust data collection practices are crucial. This includes gathering a large and diverse dataset across various urban settings and conditions. Implementing cross-validation techniques during model training can further mitigate overfitting. Ensuring the dataset is balanced and representative of different scenarios will also enhance the model's generalizability. Additionally, using feature selection methods to identify the most relevant variables can improve the model's performance.

To validate the framework, a new dataset could focus on locations where design changes have been implemented. Examples of such changes include adding a fountain or planting trees. Ideally, only one change should be made at a time to ensure that any differences in the results can be attributed to these specific changes.

Including various urban settings, such as narrow streets with high traffic density or tranquil public spaces shielded from traffic noise with low sky view factors, could improve the accuracy of predicting soundscape quality.

A point to further explore in soundscape design is the materialisation of the urban environment. Due to a lack of data, this aspect could not be included in the current regression model. However, materialisation is crucial for urban designers as different materials affect sound propagation and absorption. Future data collection should include detailed information about the materials used in urban environments, focusing on their acoustic properties, surface textures, and spatial distribution. This level of detail would enable more accurate soundscape models, helping designers create environments that better manage noise and enhance auditory comfort.

In terms of accessibility and inclusivity further data collection could focus more including different ages groups, such as elderly.

Further research could also look into the impact of trees on the perceived acoustical pleasantness, even though in this research this did not give promising results.

Exploring virtual reality (VR) as a research tool holds promise for refining the design tool framework. VR technology enables users to immerse themselves in modified environments, facilitating controlled experimentation with subtle alterations. Leveraging the dataset's 360 images and sound recordings, VR-based data collection can be conducted to evaluate the impact of environmental modifications on perceived pleasantness.

Integrating other sensory experiences into an urban design tool could also be a next step in further research. This holistic approach could offer urban designers valuable insights into the overall sensory experience of their designs.Currently the machine learning model does not take into account that human experience can be relative, this could be interesting to study as well.

Another interesting next step is using this tool in a parametric design workflow. This could be in a design optimization part of the design process.

Other next steps which are important for this research are increasing the user-friendliness of this tool by reducing the computation time and decreasing the complexity in using the tool. In considering further research, it would be interesting to explore adjustments to the input values utilized in generating the maps. Currently, these values strike a balance between maximizing prediction accuracy and minimizing computational time. However, for the tool to be practical for urban designers and planners, it's essential to streamline the map creation process for new designs. If, for instance, analyzing a design iteration takes half an hour, the utility of the tool may be limited for its intended users. Finding ways to optimize this process without sacrificing prediction accuracy would be a valuable path for future investigation.

This research only included people perceived pleasantness of the acoustic environment, but not the eventfulness, even though this dimension is also widely discussed in soundscape research. A next step in to include this dimension as well. Other information to include in the data, would be of human sounds. This was not including in this research, because there was no correlation between the presence of Human sounds and the pleasantness. However it could correlate with the eventfulness.

The main takeaway from this study underscores the critical role of sound in urban design and its often overlooked significance. By developing a predictive model to assess soundscape quality in urban environments, this research highlights the potential for integrating sound considerations into future design processes. The study's primary contribution lies in providing urban planners and designers with a practical tool for evaluating the impact of design choices on the acoustic environment, ultimately enhancing the overall quality of urban spaces and improving the well-being of inhabitants.

Chapter 11 Conclusion

Problem statement

The importance of soundscapes in urban design is often overlooked. One reason for this is the lack of expertise from urban designers in the field of soundscapes. The framework that is created for the design tool for predicting urban soundscapes can help bridge this knowledge gap.

To date, no research has focused on the applicability of soundscape prediction on new urban design. Focusing on this practical application could bridge the gap between academic findings and the applicability in the design world, which would be an important next step for the field of soundscapes.

Research and process

The following conclusions have been made after completing the research for this thesis.

How can soundscape design, and urban acoustical comfort, be integrated in the early stages of the design process of urban (re) development, in an accessible and intuitive way, without relying on the need of experts?

The biggest impact on the design can be made early in the design process. The earlier in the design process, the more flexible the design is and the bigger the impact of design choices will be later on in the process.

Though developing a preliminary prediction model, the model was able to predict the pleasantness perceived by the respondents in the given dataset. This model used architectural elements in the physical environment of the respondents as input.

A Random Forest regressor was employed to develop the prediction model capable of assessing soundscape quality at specific locations. Utilizing data from the International Soundscape database alongside additional georeferenced information sourced from OSM and other databases, the research analyzed the impact of various urban design elements, including roads, buildings, and parks, on perceived acoustic pleasantness. Lastly the prediction data is visualized in maps and sections, to communicate this data to designers and other stakeholders involved in the design process. Subsequently, the prediction tool was developed for potential application in future urban design projects.

What is 'good' soundscape design?

Good urban design, and therefore good soundscape design has the aim of creating urban areas consisting of a high quality of life. Good soundscape design involves creating environments where the acoustic qualities contribute positively to the well-being, comfort, and intended activities of individuals. It considers context-specific qualities, embraces positive auditory features, minimizes unwanted noise, and aligns with the preferences and needs of the community or users. Ultimately, a well-designed soundscape enhances the overall experience and character of a space.

Reduction of unwanted sounds, such as road noise are important. From the data analysis it is found that from a L_{den} level of 60dB, the pleasantness is severely impacted. Reduction of unwanted sounds can be most effectively done by using buildings as a sound barrier. Van den Berg (2022) also analyzed building block shapes in regards to soundscapes and found that creating urban pockets created the most optimal soundscapes, while also creating a feeling of enclosure. This strategy step is relevant to the urban design scale of the building block or the neighborhood. This could be a urban design project where the building footprint, building lots and functions are developed. The impact here lies in the layout of the building blocks and how movement is created through them. Although this research has mentioned the importance of urban morphology, this field could has been explored more by other researches. Buildings shape, height, and façade materials can impact how people perceive their soundscape.

The introduction of wanted sounds, can mask or distract from the perceived presence of the unwanted sounds. In cases where traffic noise levels persistently high, it is recommended to incorporate a fountain within the urban area, masking the noise. Adding vegetation such as parks can invite natural sounds, such as birdsong, which ultimately people will find more acoustically pleasant, as well as visually. This strategy relates to the human/street scale, where soundscape design is the very important, because soundscapes are perceived through personal experience.

On the bigger scales in urban design from district, to city to regional scale. this localization of functions can be realized. Urban design interventions such as land-use planning, street layout optimization, and the creation of pedestrian-friendly zones can help enhance the overall quality of the urban soundscape, in the places where it is the most meaningful.

Furthermore, it is important to propose methods to integrate these considerations into a broader holistic model that encompasses various sensory experiences to improve the experience of urban design overall. Good sound quality should not reduce other urban design qualities in the area, Instead good soundscape design should enhance other qualities in the area.

What correlations exist between the identified soundscape indicators and descriptors of human perception of comfort or discomfort within urban environments?

The perceived presence of different sound source types seem to have strong correlations to the perceived quality of the acoustic environment. There is a clear negative correlation with perceived traffic noise, and unpleasantness. On the other hand the presence of natural sounds for example birds, or fountains can have a positive effect on the perceived quality, and distract from the presence of unwanted noise sources in the area.

In terms of acoustic parameters, the sound pressure level, for example L_{den} is relevant to take as a boundary measurement level. The WHO recommends an L_{den} lower than 53, to reduce the public health impact. According to the RIVM people find roads with a 50km/h speed limit the most annoying. For vegetation like trees, visibility is an important aspect that affects the perceived pleasantness of a soundscape, and can mask the perceived presence of unwanted sound, and mitigate the negative effects that traffic noise can have on the perceived pleasantness. For parks, the distance from the periphery can play a role, since further away from it more natural sounds, such as bird sounds can be perceived. Fountains can also be used to mask unwanted sounds, like traffic noise.

To what extent can computational design tools, in the shape of machine learning models, incorporate soundscape data to inform and shape urban design elements for improved soundscapes?

For new designs collecting soundscape data is virtually impossible. For existing sites collecting soundscape data still is a laborious task. Through computational design methods, such as machine learning, the soundscape quality can be predicted and optimized with knowledge on soundscape design strategies. This saves time and energy, which can make this type of information more accessible to designers with lesser knowledge on the topic.

The data that is needed from that can be taken from standard urban design features, such as buildings, roads, and parks, and optionally fountains. There are different ways to compute their relationship to their environment, which are briefly discussed in the chapter on data collection.

The chosen prediction model for this research was the random forest regressor, which is an ensemble of decision trees. The accuracy of the prediction model is around R2=-0.43. Which means that 43% the variance of the pleasantness can be explained by extracting architectural features from the surroundings. The feature elements which had the most impact in the model are the L_{den} map which simulates the road noise, and the parks map, which present the presence of greenery and bird songs. The visibility of trees seemed to have very little ability to predict the pleasantness, as well as the presence of fountains.

The predicted data can be represented in a map. Maps can allow for easy interpretation of data, presented in a more visual way related to specific location. Soundscape perception is very location based, so therefore this approach would be suitable to communicate this type of data.

How do design iterations impact the perceived quality of soundscapes within urban environments?

Through various design iterations, the influence of diverse architectural elements can be visualized. As indicated in the literature, the presence of roads and their simulated representation via Lden maps. The soundscape quality correlates negatively with the strength of the L_{den} value. Building design, however, can serve as a means to mitigate this noise in specific locations. Furthermore, the inclusion of natural elements such as parks has been observed to enhance the quality of the soundscape in public spaces. While literature suggests a significant positive impact of fountains on their surroundings, this effect was not corroborated through the training of the machine learning model, possibly due to the absence of fountain data in the model.

In chapter 9 on design proposals, a method is shown on how to improve the soundscape of urban design areas. Once a design area is located, design variations are drafted. To evaluate the soundscape prediction score, a 1m grid is created in the public space for which the pleasantness is predicted. The mean of these values is taken and used to evaluate the soundscape overall.

Chapter 12 Reflection

Graduation process

How is your graduation topic positioned in the studio?

This graduation topic is a combination of acoustics and computational design, set in an urban environments. The MSc. Building Technology track from the Faculty of Architecture and the Built Environment is about applying new and innovative technologies to the design world. In Urban design computational methods such as GIS has been widely used to do analysis already. Regression models are also used to analyze existing urban situations. However the tools are absent to do these analysis in new urban designs.

The topic of acoustics, in the field of health and comfort was explored in the soundscape field. This is more about the sensory experience of acoustics rather then the numerical values that are usually calculated. However looking at acoustics from an experience point of view is very relevant in urban design

How did your research influence your design/recommendations and how did the design/recommendations influence your research?

The literature research conducted for P2 influenced the direction of my framework and recommendations

While the literature provided initial guidance, it was through extensive trial and error that I discovered methods that worked best for me.

The input for the machine learning model was based on findings in the literature and the dataset further validated those approaches.

Entering the field of machine learning as a novice, I analyzed different methods through testing and experimenting with them. Alongside this experimentation I looked up the characteristics of these models, which informed my decisions making process. Reflecting on the project, I realize the importance of conducting more comprehensive research prior to diving into a complex topic such as machine learning. Initially, I underestimated the complexity of the subject matter and assumed I could navigate it as I progressed, but in reality, it demanded more thorough preparation. I also spend a significant amount of time testing models, that are open source and already built in in QGIS. Reflecting on my framework, I realize I should have assessed their applicability to new designs more critically. In hindsight, these pre-existing models fell short in meeting the specific requirements of my project.

How do you assess the value of your way of working (your approach, your used methods, used methodology)?

Reflecting on my approach, I recognize the need for a more structured plan in selecting the machine learning model. Much time was devoted to exploring various approaches, even though many of them ultimately proved incompatible with my project framework. Greater emphasis on optimizing the chosen model could have been beneficial. While I extensively experimented with previous models using different inputs, I did not allocate as much time to this process for later models, overlooking potential improvements in the final outcomes. Evaluating the efficacy of my approach involves considering the benefits

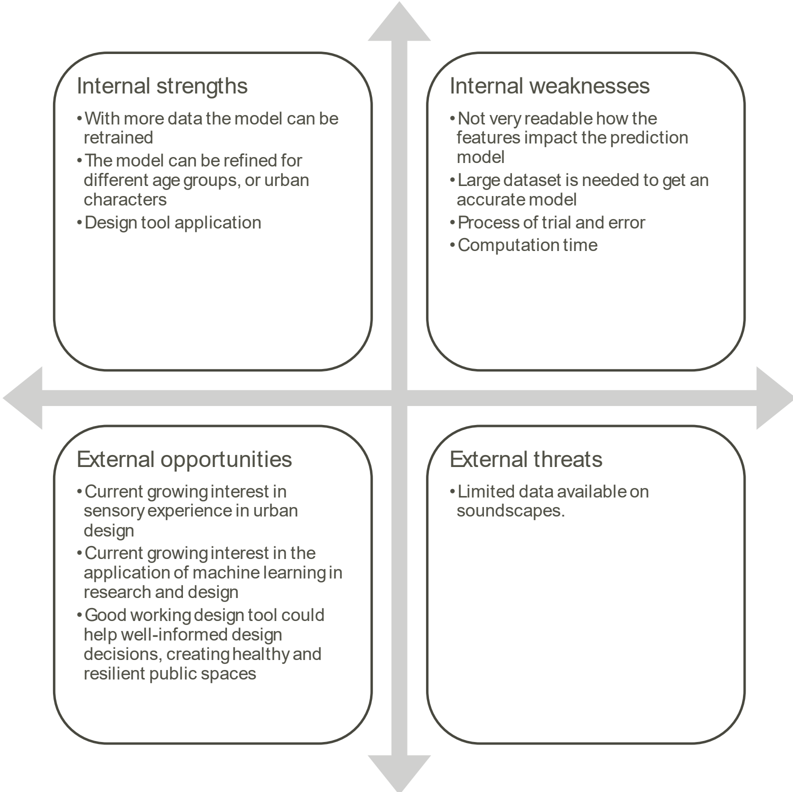


Figure 101 SWOT diagram, by author

of my methods and methodology. While my approach was full of trial and error, A noteworthy aspect in my methodology was the statistical analysis of the additional layers in the dataset. This way it was shown which input would be suited well for the machine learning model input. Emphasizing the importance of data validity, this approach ensured the integrity of the project's findings.

How did the research approach work out (and why or why not)? And did it lead to the results you aimed for? (SWOT of the method)

The methods that were used have some strengths and weaknesses as explained in this section. One weakness of the methodology is that is needs a large dataset to predict the acoustical pleasantness accurately. Soundscape evaluation, like every human experience, varies from person to person. Therefore a lot of data is needed to account for personal preferences.

Because of my personal lack of experience with machine learning, the selection and training of the model has not been the easiest part of this thesis. Other machine learning approaches such as an image segmentation method could also get better results. One problems that the model currently has is a problem of overfitting, and failing to make accurate predictions in areas that very unfamiliar to the model.

The computation time that is needed in this research could be more optimized. Preprocessing the new design data is a weakness in the design tool in this framework. Training a ML model could take time, but the predictions are computed quite fast. Preprocessing the data needs to be done with every design iteration. This takes a lot of time. Additional steps in creating the code could be taken to minimize this time.

The strength of this thesis is the framework that is created. The infrastructure for creating the trained machine learning model and using the prediction model is created in this research. With the right dataset this framework could be transferred to other places, other times of the day, and also other demographics. The prediction model can be retrained with different datasets depending on the requirements. The methodology that is created in this thesis and also the mistakes made can be valuable lessons to reuse in applying this framework in new situations.

There were also external threats in this thesis process. The biggest threat was the availability of datasets that contain the data that is needed to train the machine learning model to make accurate predictions. For this research I compromised on choosing the dataset, because this available dataset was the best option that was widely available. There are some issues regarding the quality of the dataset, which has been explained in section on the limitations of the dataset.

Also the quality of the added data that is acquired poses a threat on the accuracy of the prediction model.

Some great opportunities for this topic are the growing interest in urban comfort and the sensory experience, and also the growing interest in machine learning applications in design.

The framework for the design tool that is created in this thesis, is not a design in itself. However it can be used to inform design decisions. Urban designers and planners currently often do not take into account the effect that the acoustics have on the environment. The design tool that is created bridges this gap.

Did you encounter moral/ethical issues or dilemmas during the process? How did you deal with these?

Using machine learning comes with biases. It is important to be aware of the inherent biases on training a model with a certain dataset. For example this dataset was primarily young people, during their lunch break in an urban park. The prediction model created in this thesis would not be a very good design tool when the design aims to include for example elderly, who can have a very different sensory experience. It might also not be well suited in prediction at other times of the day. These seem like relatively innocent biases, but they can make a huge impact.

Societal relevance

What is the academic and societal value of your graduation project?

The societal relevance of soundscape design is linked to the general societal relevance of urban design. Good urban planning aims to improve the quality of life. This includes auditory quality. Exposure to high levels of noise impacts public health and quality of life. In 2012, an estimation of about 100 million people were to be exposed to road traffic noise (European Environment Agency 2020).

Soundscape design looks beyond noise and look at the urban acoustics as a composition of wanted and unwanted sounds Positive soundscapes are associated with faster stress-recovery processes, and better self-reported health conditions (Alleta et al., 2018). Therefore access to positive soundscapes in environments such as urban areas, which have high amounts of noise pollution, could increase public health and improve quality of life for people living close to and visiting these areas.

to what extent are the results applicable in practice?

Chapter 10 with design proposals shows how applicable the design tool is in practices. Data from the design that is needed is the buildings, building height. Roads and their hierarchy. Parks, trees and fountains.

To what extent has the expected innovation been achieved?

The model works a bit less well than I had expected, which is also based on findings in the literature. However examples from the literature also do a lot of tweaking in the data to find regressions that work (Lavandier et al., 2016). In my opinion, delivering a moderately to good working machine learning prediction model, and building the application for new designs, falls within the scope and planning of a master thesis.

If everything would have gone very well, I would have put more time into optimizing the machine learning model. I would also have put time into created a parametric workflow, that can help optimizing designs. Another step would be integrating it with other senses.

How does your research impact architectural practice?

This prediction model can be used in consultation with new urban designs in the preliminary design phases. By using the tool, a better understanding for the designer is created on what the impact of design choices have on the urban acoustical environment. This makes it more accessible to implement soundscape design into the architectural practice. The soundscape prediction model is a design tool that can put numerical values on soft criteria in design requirements.

How do you assess the value of the transferability of your project results?

This prediction currently is not the most transferable. The dataset contains young people on their lunch break in urban parks. This prediction tool currently is not super ideal for predictions in very different contexts or for a very different demographic. It is also not known if the results can be applied to other times of the day.

The scale is also important to take into account. Predictions made locally, cannot just be interpreted on another scale. Soundscapes are experienced at a specific time and a specific place.

When looking at the framework for the design tool as a whole the transferability can be a strength. The infrastructure for creating the trained machine learning model and using the prediction model is created in this research. With the right dataset this framework could be transferred to other places, other times of the day, and also other demographics. The prediction model can be retrained with different datasets depending on the requirements. The methodology that is created in this thesis and also the mistakes made can be valuable lessons to reuse in applying this framework in new situations.

Appendix

Table 1 Performance Metric for Random Forest regressor with different input layers.

Features	Metric	Value
PARKSDISTAN	Mean Absolute Error	0.26
PARKSDISTAN	Mean Squared Error	0.1
PARKSDISTAN	Root Mean Squared Error	0.32
PARKSDISTAN	**R-squared**	**0.42**
roadnoiseco	Mean Absolute Error	0.29
roadnoiseco	Mean Squared Error	0.13
roadnoiseco	Root Mean Squared Error	0.36
roadnoiseco	**R-squared**	**0.24**
DISTANCE	Mean Absolute Error	0.27
DISTANCE	Mean Squared Error	0.11
DISTANCE	Root Mean Squared Error	0.33
DISTANCE	**R-squared**	**0.36**
VISIBLE	Mean Absolute Error	0.27
VISIBLE	Mean Squared Error	0.11
VISIBLE	Root Mean Squared Error	0.33
VISIBLE	**R-squared**	**0.37**
fountainsvi	Mean Absolute Error	0.29
fountainsvi	Mean Squared Error	0.12
fountainsvi	Root Mean Squared Error	0.35
fountainsvi	**R-squared**	**0.29**
treesvisibi	Mean Absolute Error	0.26
treesvisibi	Mean Squared Error	0.1
treesvisibi	Root Mean Squared Error	0.32
treesvisibi	**R-squared**	**0.4**
PARKSDISTAN & roadnoiseco	Mean Absolute Error	0.26
PARKSDISTAN & roadnoiseco	Mean Squared Error	0.1
PARKSDISTAN & roadnoiseco	Root Mean Squared Error	0.32
PARKSDISTAN & roadnoiseco	**R-squared**	**0.41**
PARKSDISTAN & DISTANCE	Mean Absolute Error	0.26
PARKSDISTAN & DISTANCE	Mean Squared Error	0.1
PARKSDISTAN & DISTANCE	Root Mean Squared Error	0.32
PARKSDISTAN & DISTANCE	**R-squared**	**0.42**

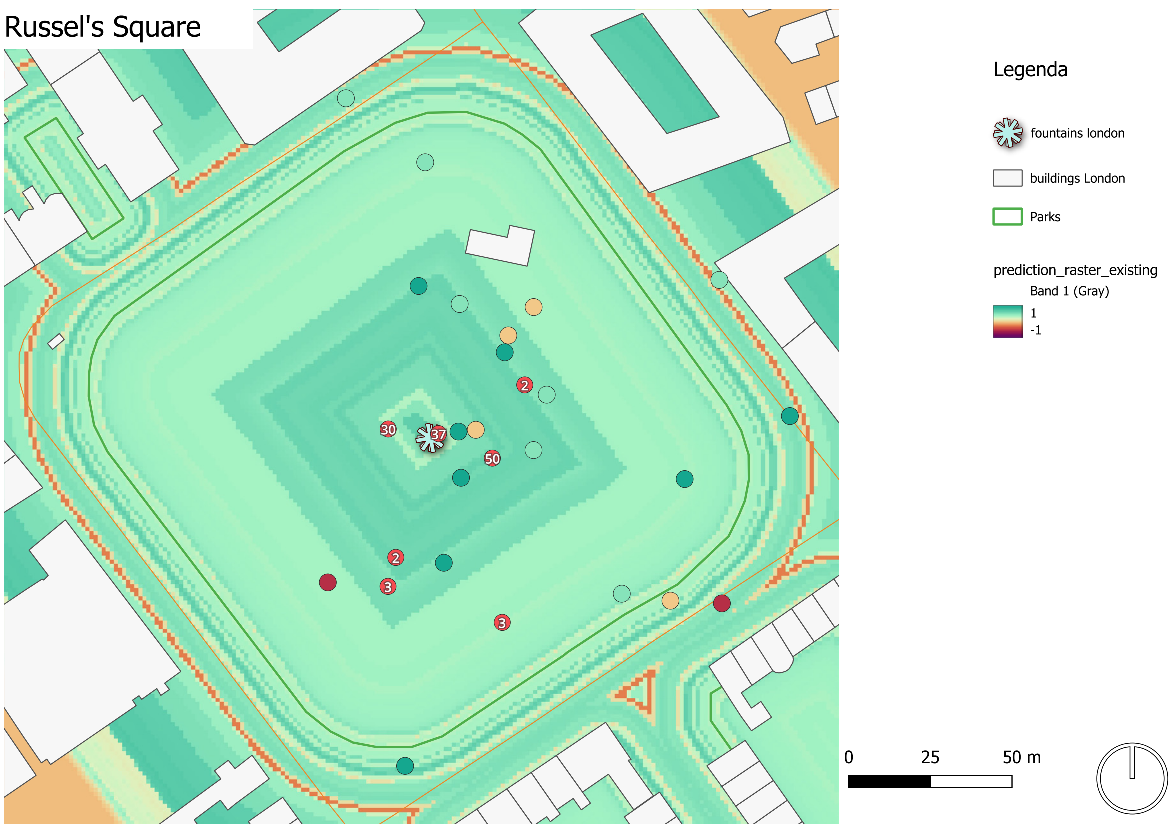
PARKSDISTAN & VISIBLE	Mean Absolute Error	0.26
PARKSDISTAN & VISIBLE	Mean Squared Error	0.1
PARKSDISTAN & VISIBLE	Root Mean Squared Error	0.32
PARKSDISTAN & VISIBLE	**R-squared**	**0.42**
PARKSDISTAN & fountainsvi	Mean Absolute Error	0.26
PARKSDISTAN & fountainsvi	Mean Squared Error	0.1
PARKSDISTAN & fountainsvi	Root Mean Squared Error	0.32
PARKSDISTAN & fountainsvi	**R-squared**	**0.42**
DISTANCE & VISIBLE	Mean Absolute Error	0.26
DISTANCE & VISIBLE	Mean Squared Error	0.1
DISTANCE & VISIBLE	Root Mean Squared Error	0.32
DISTANCE & VISIBLE	**R-squared**	**0.4**
DISTANCE & roadnoiseco	Mean Absolute Error	0.26
DISTANCE & roadnoiseco	Mean Squared Error	0.1
DISTANCE & roadnoiseco	Root Mean Squared Error	0.32
DISTANCE & roadnoiseco	**R-squared**	**0.41**
roadnoiseco & fountainsvi	Mean Absolute Error	0.27
roadnoiseco & fountainsvi	Mean Squared Error	0.11
roadnoiseco & fountainsvi	Root Mean Squared Error	0.33
roadnoiseco & fountainsvi	**R-squared**	**0.37**
DISTANCE & fountainsvi	Mean Absolute Error	0.26
DISTANCE & fountainsvi	Mean Squared Error	0.1
DISTANCE & fountainsvi	Root Mean Squared Error	0.32
DISTANCE & fountainsvi	**R-squared**	**0.4**
PARKSDISTAN & roadnoiseco & DISTANCE	Mean Absolute Error	0.26
PARKSDISTAN & roadnoiseco & DISTANCE	Mean Squared Error	0.1
PARKSDISTAN & roadnoiseco & DISTANCE	Root Mean Squared Error	0.32
PARKSDISTAN & roadnoiseco & DISTANCE	**R-squared**	**0.42**
PARKSDISTAN & roadnoiseco & VISIBLE	Mean Absolute Error	0.26
PARKSDISTAN & roadnoiseco & VISIBLE	Mean Squared Error	0.1
PARKSDISTAN & roadnoiseco & VISIBLE	Root Mean Squared Error	0.32
PARKSDISTAN & roadnoiseco & VISIBLE	**R-squared**	**0.4**

Table 2 R2 for random forest regressor with features as input sorted by highest R2 value.

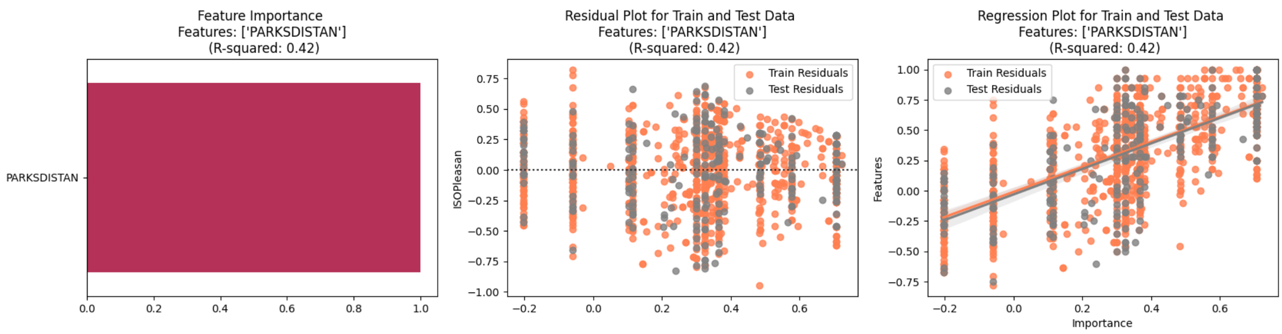
Features	R2 Value
PARKSDISTAN	0.42
PARKSDISTAN & DISTANCE	0.42
PARKSDISTAN & VISIBLE	0.42
PARKSDISTAN & fountainsvi	0.42
PARKSDISTAN & roadnoiseco & DISTANCE	0.42
PARKSDISTAN & roadnoiseco	0.41
DISTANCE & roadnoiseco	0.41
treesvisibi	0.4
DISTANCE & VISIBLE	0.4
DISTANCE & fountainsvi	0.4
PARKSDISTAN & roadnoiseco & VISIBLE	0.4
VISIBLE	0.37
roadnoiseco & fountainsvi	0.37
DISTANCE	0.36
fountainsvi	0.29
roadnoiseco	0.24

Table 3 feature importances per regression model

All features	Feature	Importance
PARKSDISTAN	PARKSDISTAN	1.0
roadnoiseco	roadnoiseco	1.0
DISTANCE	DISTANCE	1.0
VISIBLE	VISIBLE	1.0
fountainsvi	fountainsvi	1.0
treesvisibi	treesvisibi	1.0
PARKSDISTAN & roadnoiseco	roadnoiseco	0.62
PARKSDISTAN & roadnoiseco	PARKSDISTAN	0.38
PARKSDISTAN & DISTANCE	DISTANCE	0.53
PARKSDISTAN & DISTANCE	PARKSDISTAN	0.47
PARKSDISTAN & VISIBLE	VISIBLE	0.53
PARKSDISTAN & VISIBLE	PARKSDISTAN	0.47
PARKSDISTAN & fountainsvi	PARKSDISTAN	0.93
PARKSDISTAN & fountainsvi	fountainsvi	0.07
DISTANCE & VISIBLE	DISTANCE	0.56
DISTANCE & VISIBLE	VISIBLE	0.44
DISTANCE & roadnoiseco	roadnoiseco	0.56
DISTANCE & roadnoiseco	DISTANCE	0.44
roadnoiseco & fountainsvi	roadnoiseco	0.8
roadnoiseco & fountainsvi	fountainsvi	0.2
DISTANCE & fountainsvi	DISTANCE	0.93
DISTANCE & fountainsvi	fountainsvi	0.07
PARKSDISTAN & roadnoiseco & DISTANCE	roadnoiseco	0.53
PARKSDISTAN & roadnoiseco & DISTANCE	DISTANCE	0.26
PARKSDISTAN & roadnoiseco & DISTANCE	PARKSDISTAN	0.21
PARKSDISTAN & roadnoiseco & VISIBLE	roadnoiseco	0.52
PARKSDISTAN & roadnoiseco & VISIBLE	VISIBLE	0.34
PARKSDISTAN & roadnoiseco & VISIBLE	PARKSDISTAN	0.13

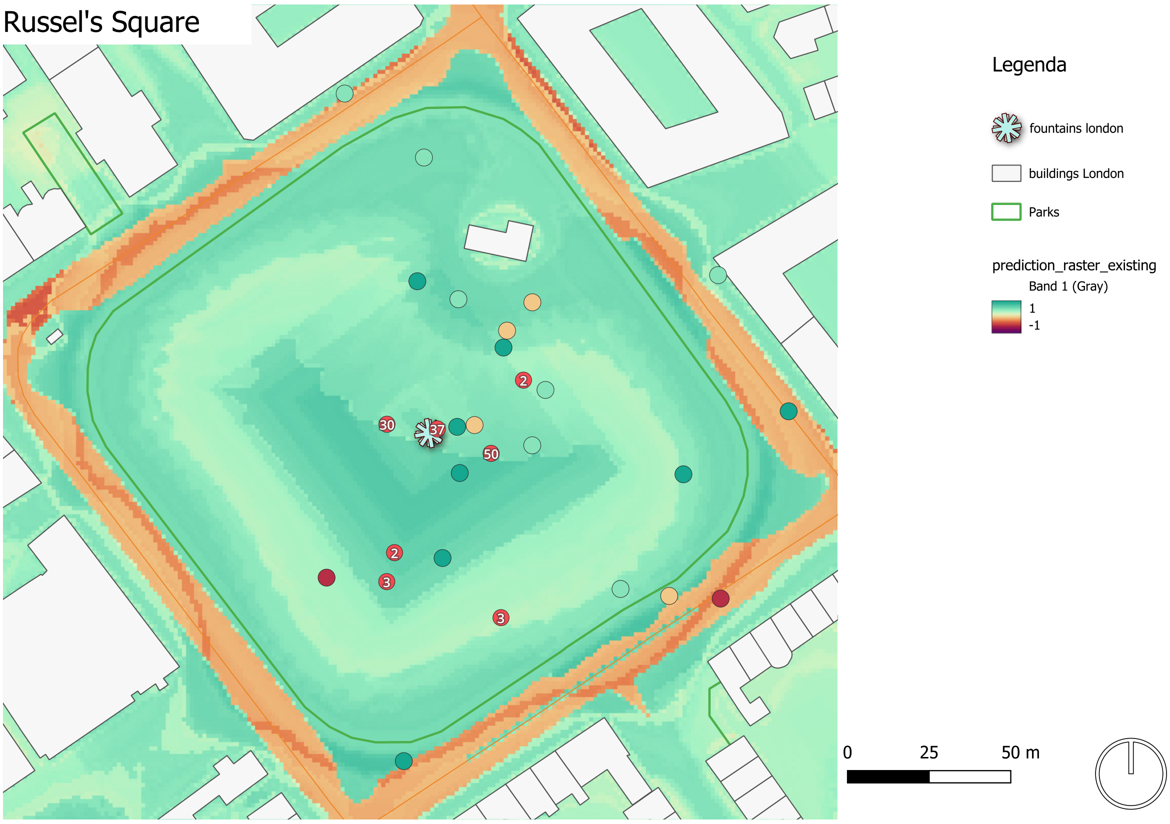


Features	Metric	Value
PARKSDISTAN	Mean Absolute Error	0.26
PARKSDISTAN	Mean Squared Error	0.1
PARKSDISTAN	Root Mean Squared Error	0.32
PARKSDISTAN	**R-squared**	**0.42**

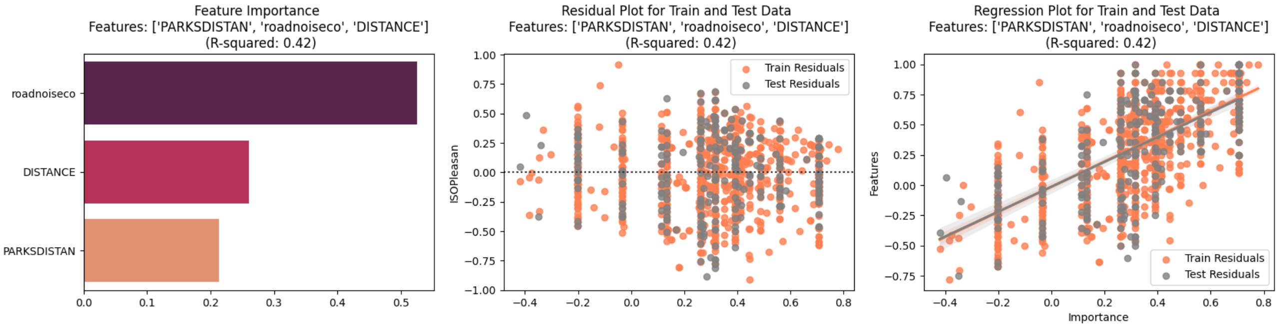


Camden Town

Marchmont Garden

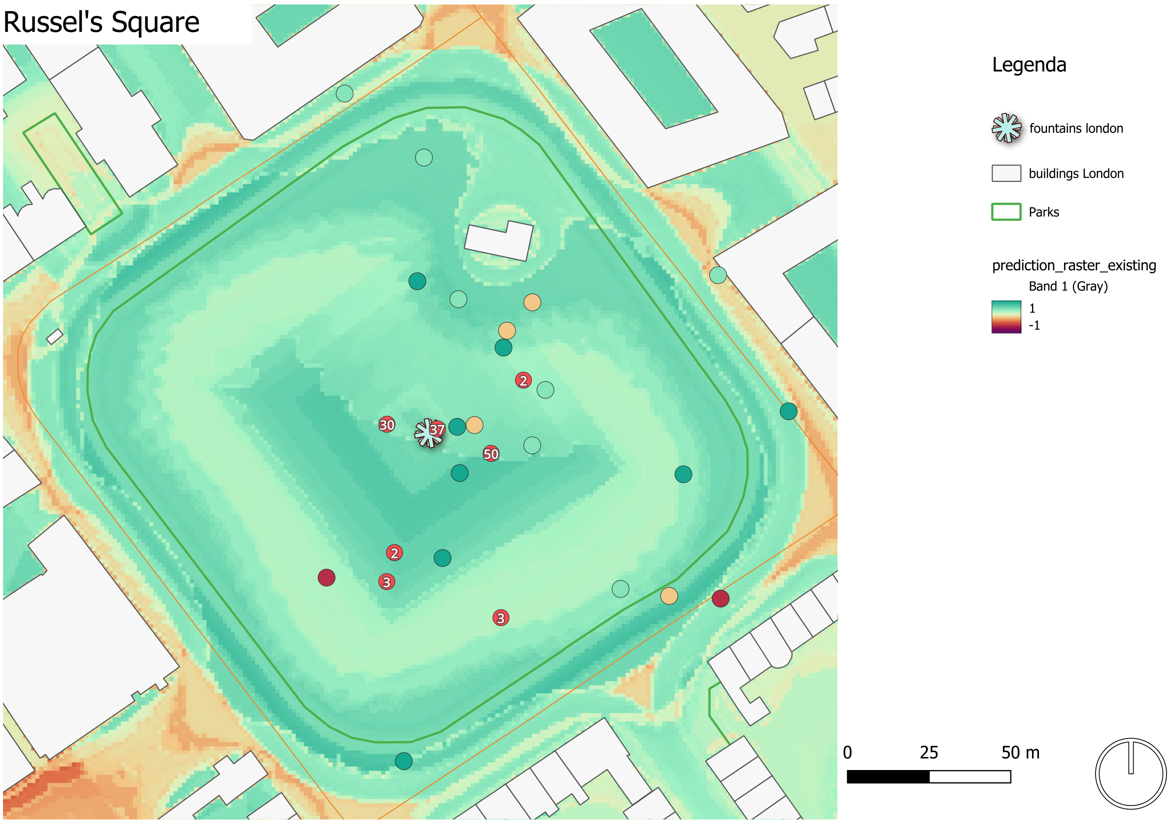


PARKSDISTAN & roadnoiseco & DISTANCE	Mean Absolute Error	0.26
PARKSDISTAN & roadnoiseco & DISTANCE	Mean Squared Error	0.1
PARKSDISTAN & roadnoiseco & DISTANCE	Root Mean Squared Error	0.32
PARKSDISTAN & roadnoiseco & DISTANCE	**R-squared**	**0.42**



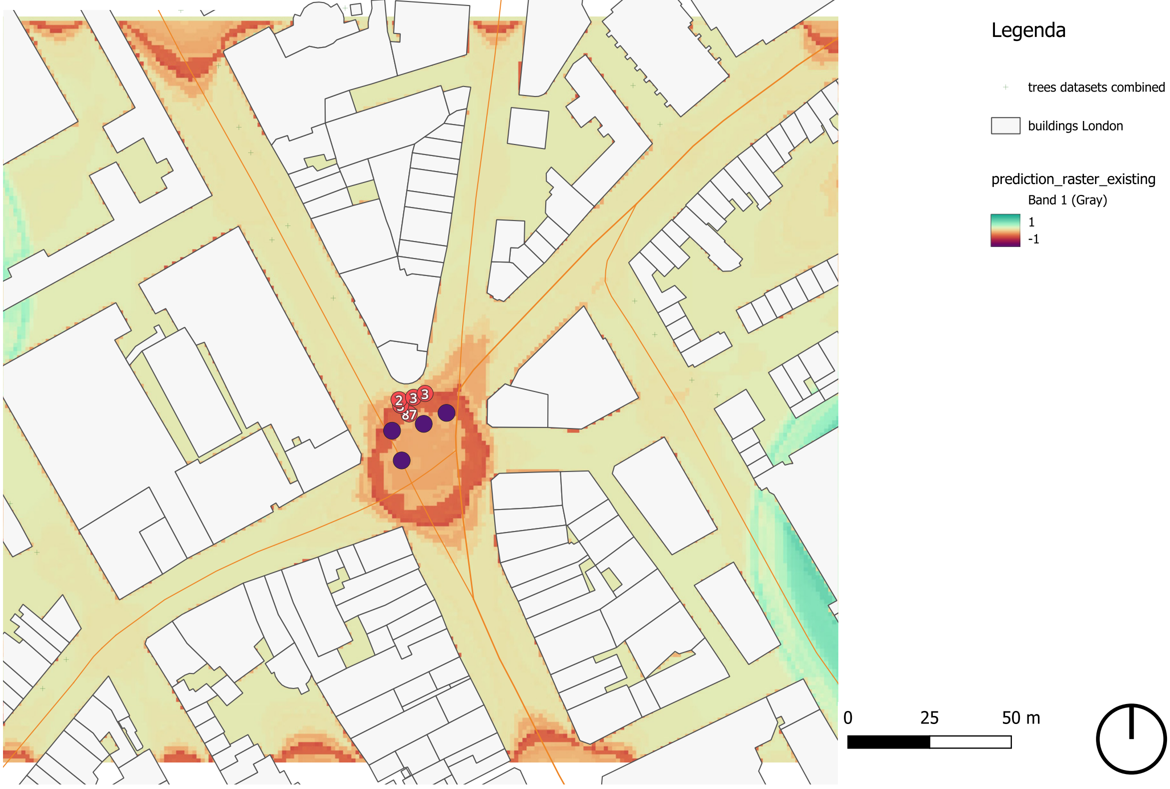
Camden Town

Marchmont Garden

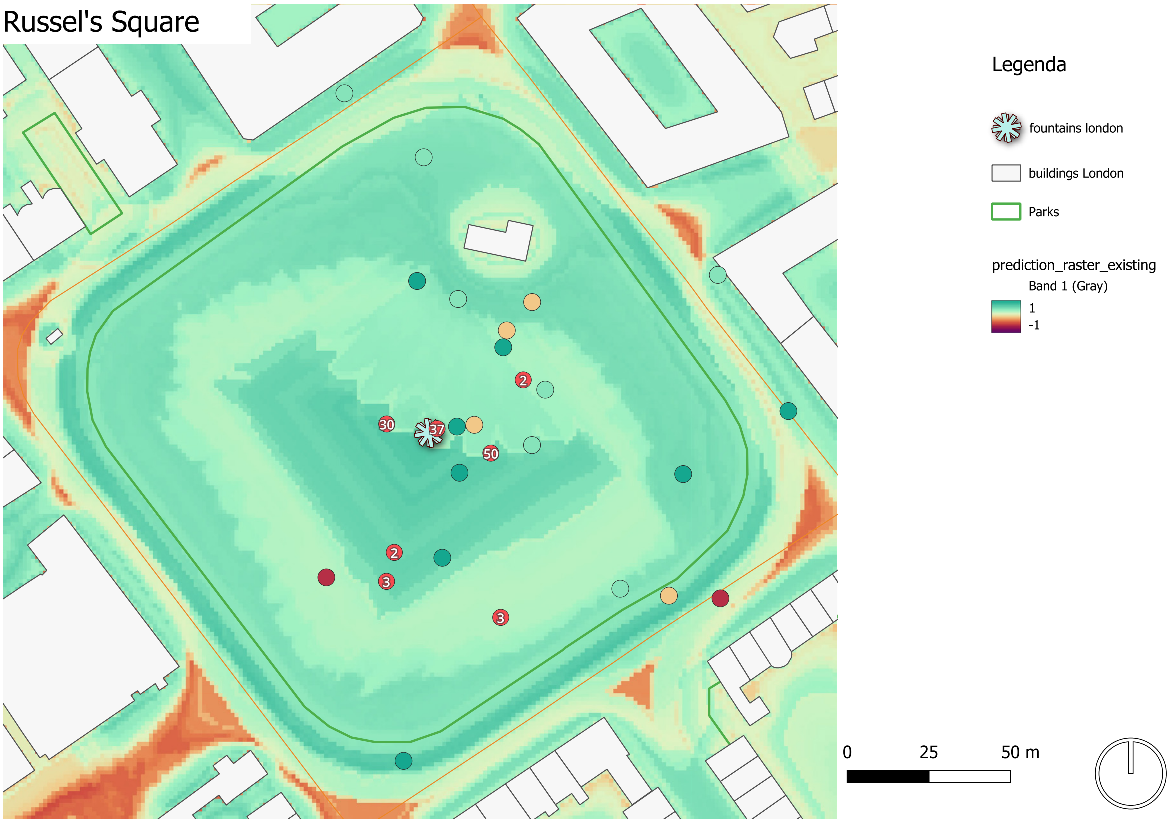


PARKSDISTAN & DISTANCE	Mean Absolute Error	0.26
PARKSDISTAN & DISTANCE	Mean Squared Error	0.1
PARKSDISTAN & DISTANCE	Root Mean Squared Error	0.32
PARKSDISTAN & DISTANCE	**R-squared**	**0.42**

Camden Town

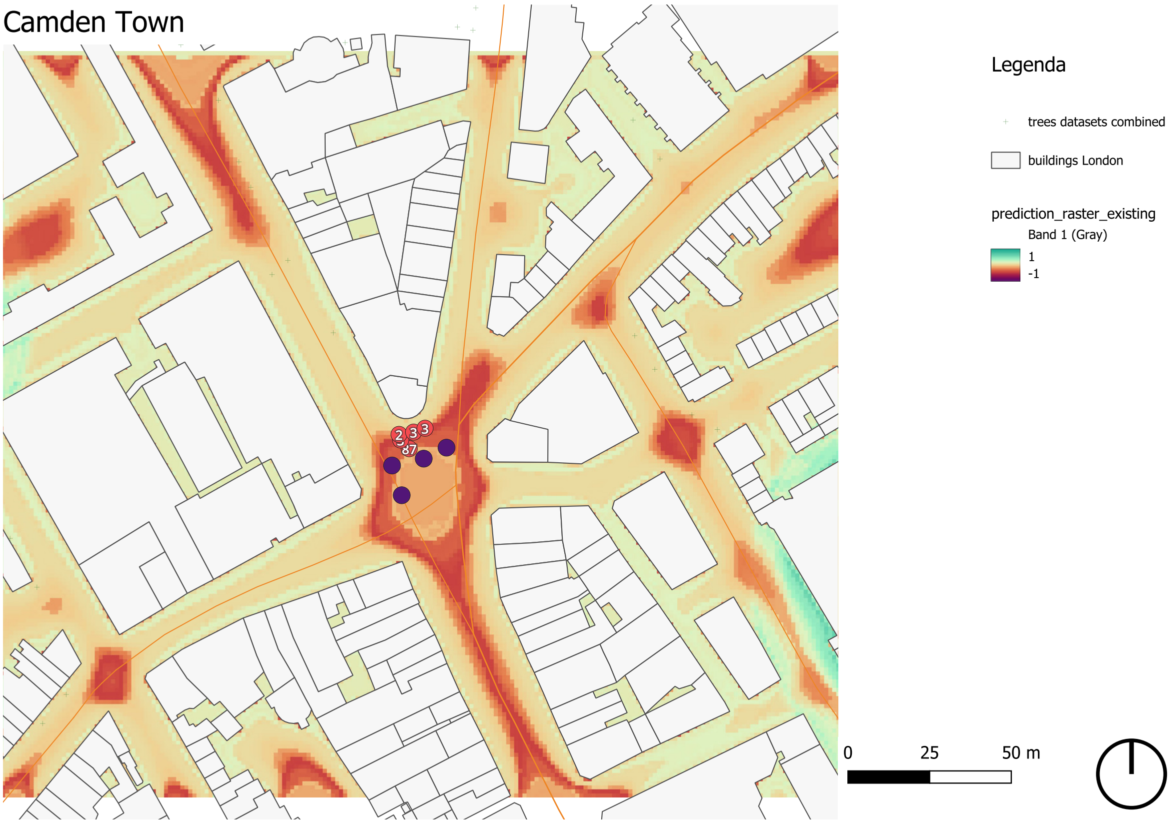


Marchmont Garden

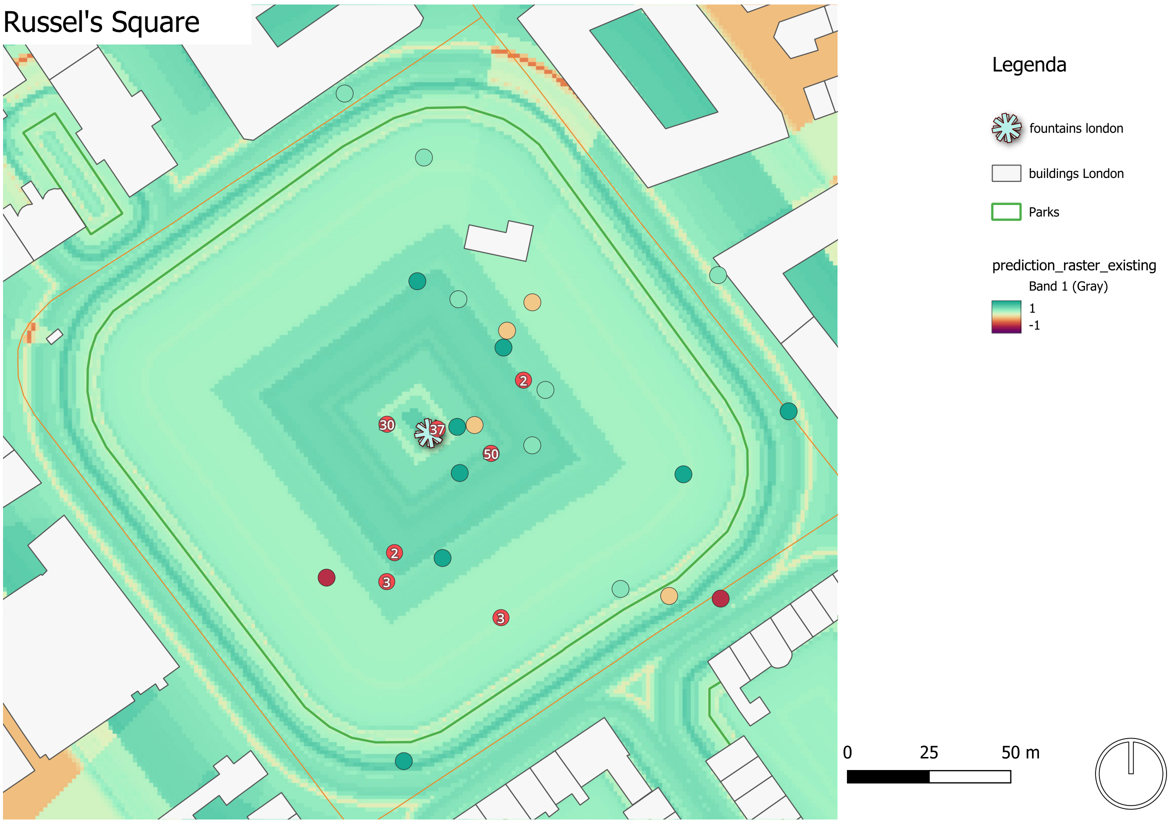


PARKSDISTAN & VISIBLE	Mean Absolute Error	0.26
PARKSDISTAN & VISIBLE	Mean Squared Error	0.1
PARKSDISTAN & VISIBLE	Root Mean Squared Error	0.32
PARKSDISTAN & VISIBLE	**R-squared**	**0.42**

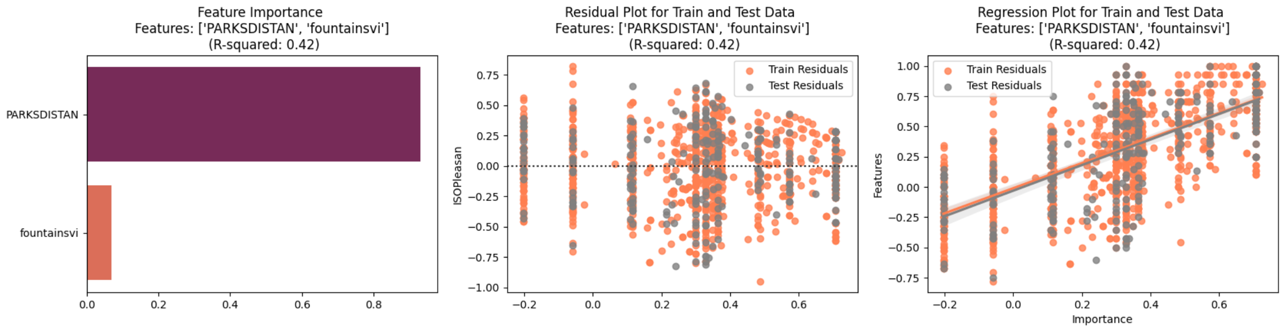
Camden Town



Marchmont Garden



PARKSDISTAN & fountainsvi	Mean Absolute Error	0.26
PARKSDISTAN & fountainsvi	Mean Squared Error	0.1
PARKSDISTAN & fountainsvi	Root Mean Squared Error	0.32
PARKSDISTAN & fountainsvi	**R-squared**	**0.42**



Camden Town

Legenda

trees datasets combined

buildings London

prediction_raster_existing
Band 1 (Gray)
1
-1

Marchmont Garden

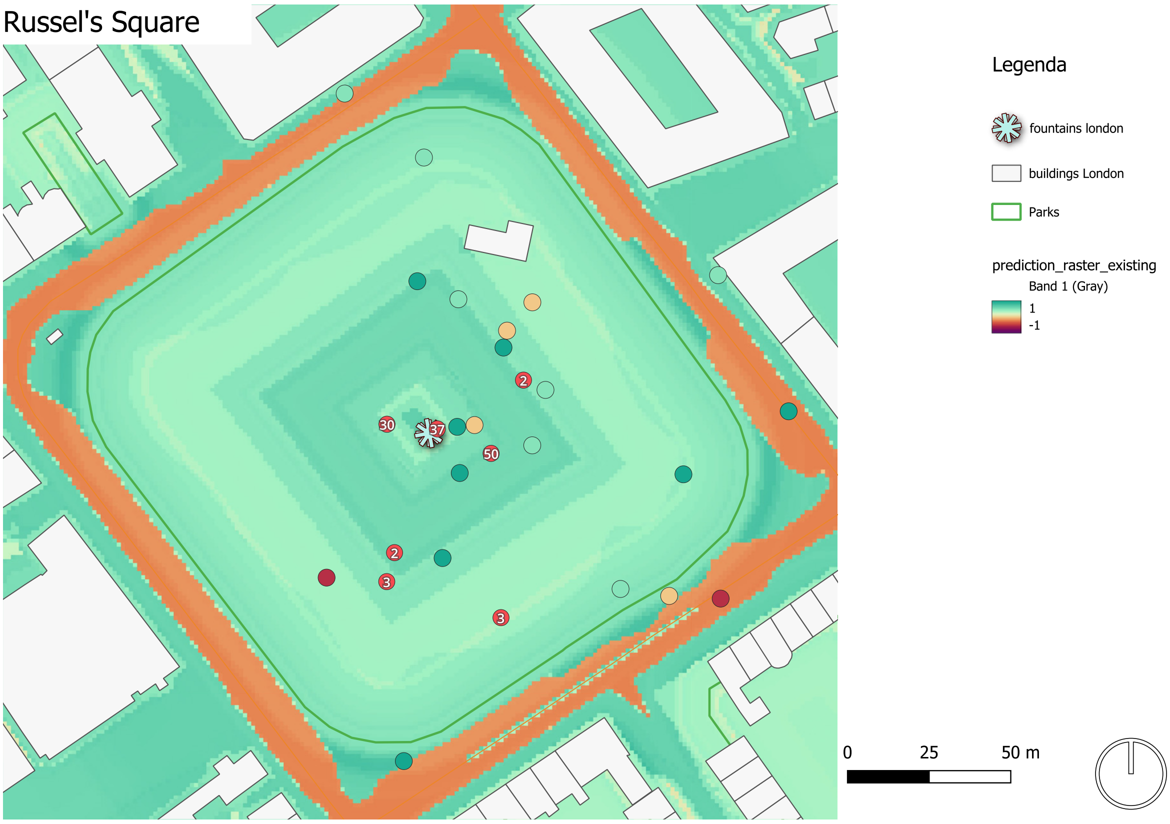
Legenda

trees datasets combined

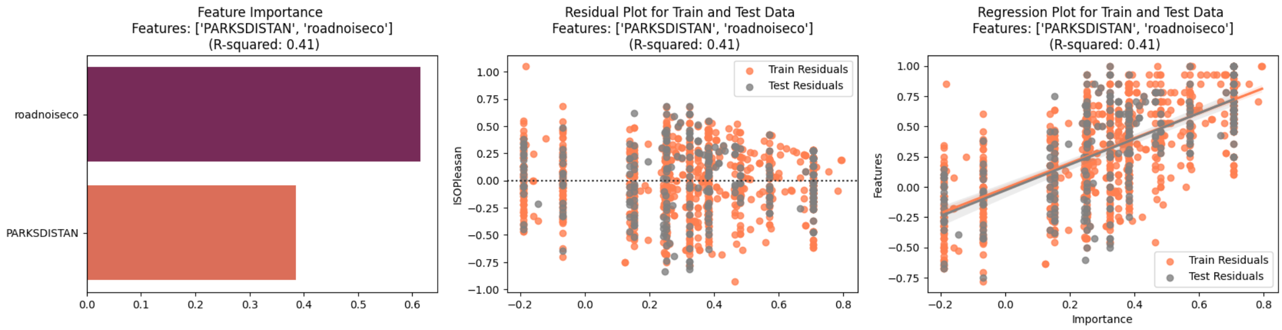
buildings London

Parks

prediction_raster_existing
Band 1 (Gray)
1
-1

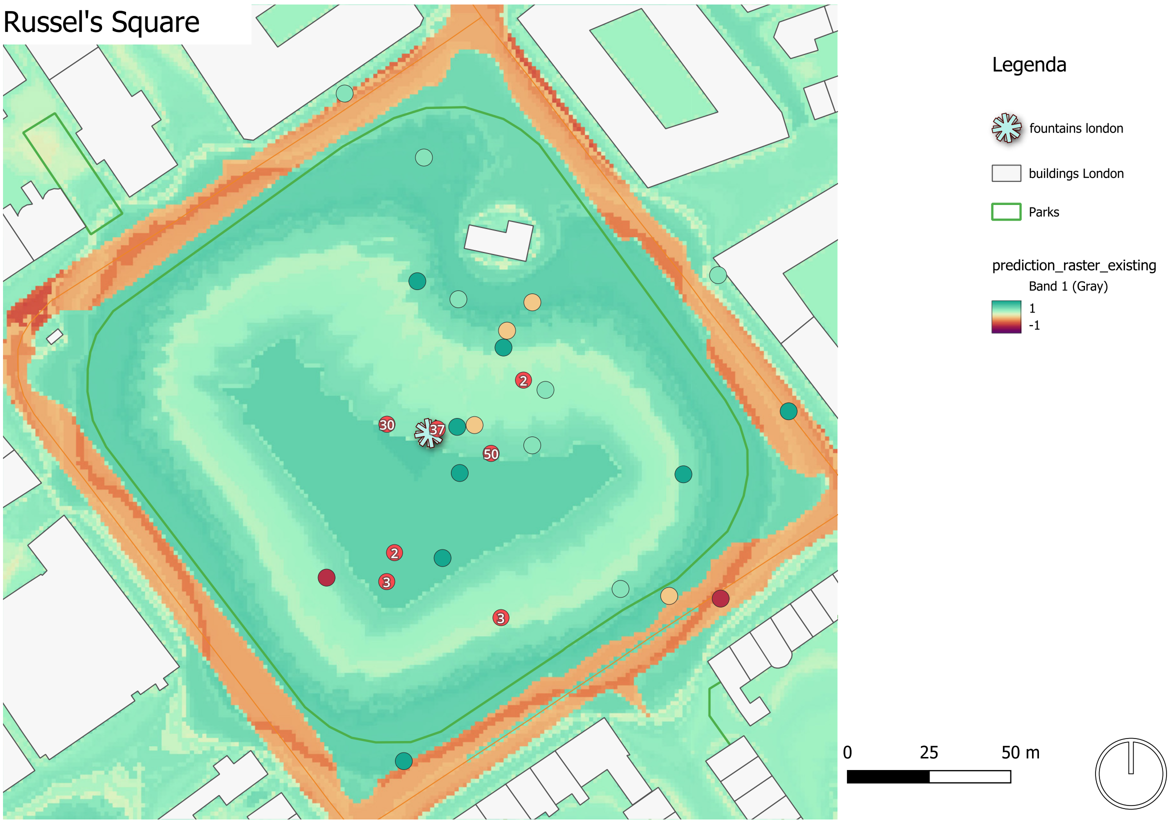


PARKSDISTAN & roadnoiseco	Mean Absolute Error	0.26
PARKSDISTAN & roadnoiseco	Mean Squared Error	0.1
PARKSDISTAN & roadnoiseco	Root Mean Squared Error	0.32
PARKSDISTAN & roadnoiseco	**R-squared**	**0.41**

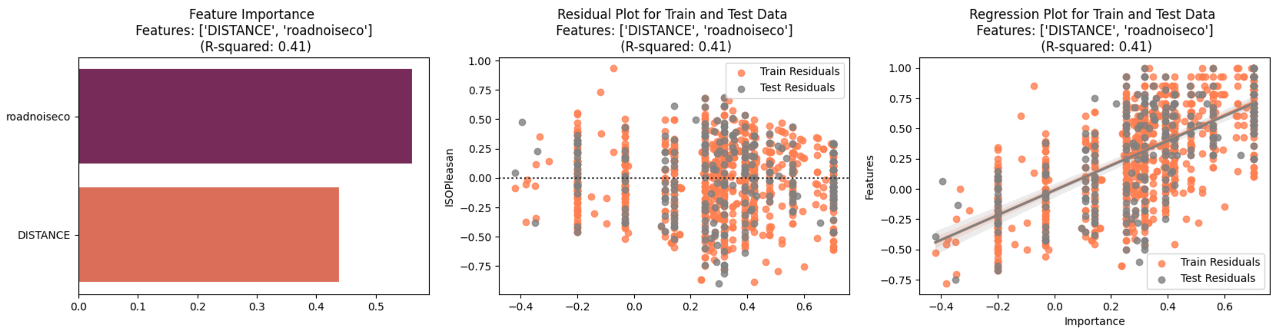


Camden Town

Marchmont Garden

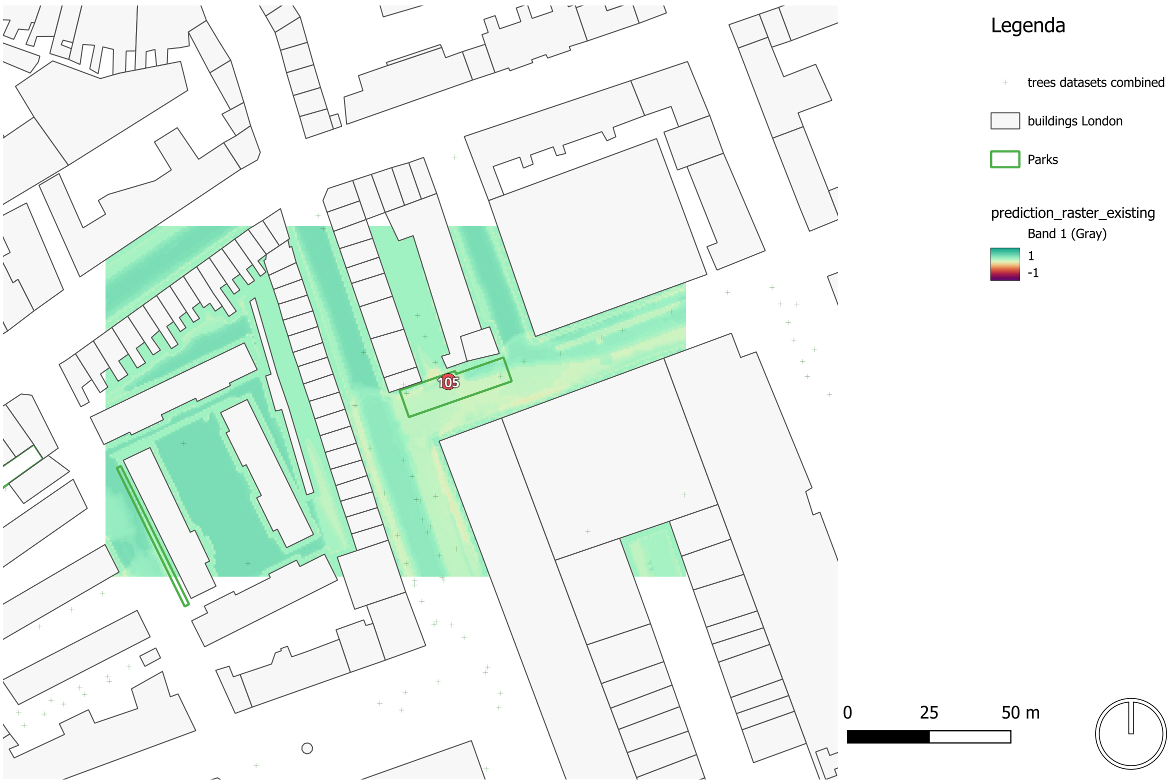


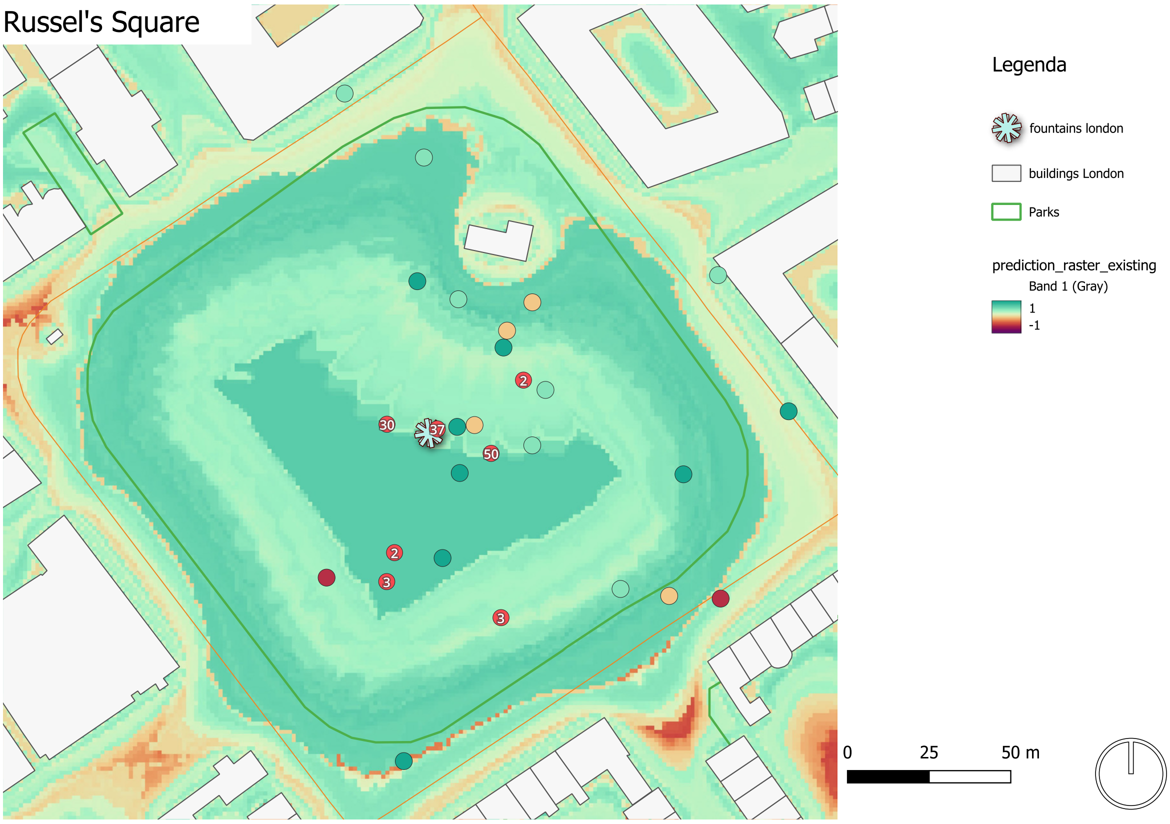
DISTANCE & roadnoiseco	Mean Absolute Error	0.26
DISTANCE & roadnoiseco	Mean Squared Error	0.1
DISTANCE & roadnoiseco	Root Mean Squared Error	0.32
DISTANCE & roadnoiseco	**R-squared**	**0.41**



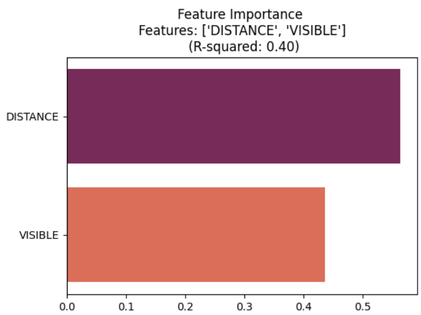
Camden Town

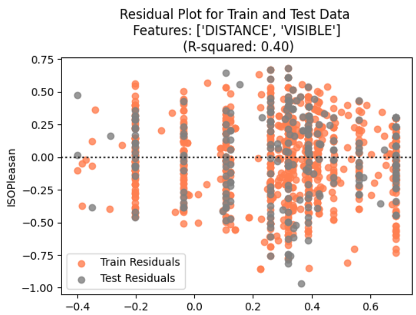
Marchmont Garden



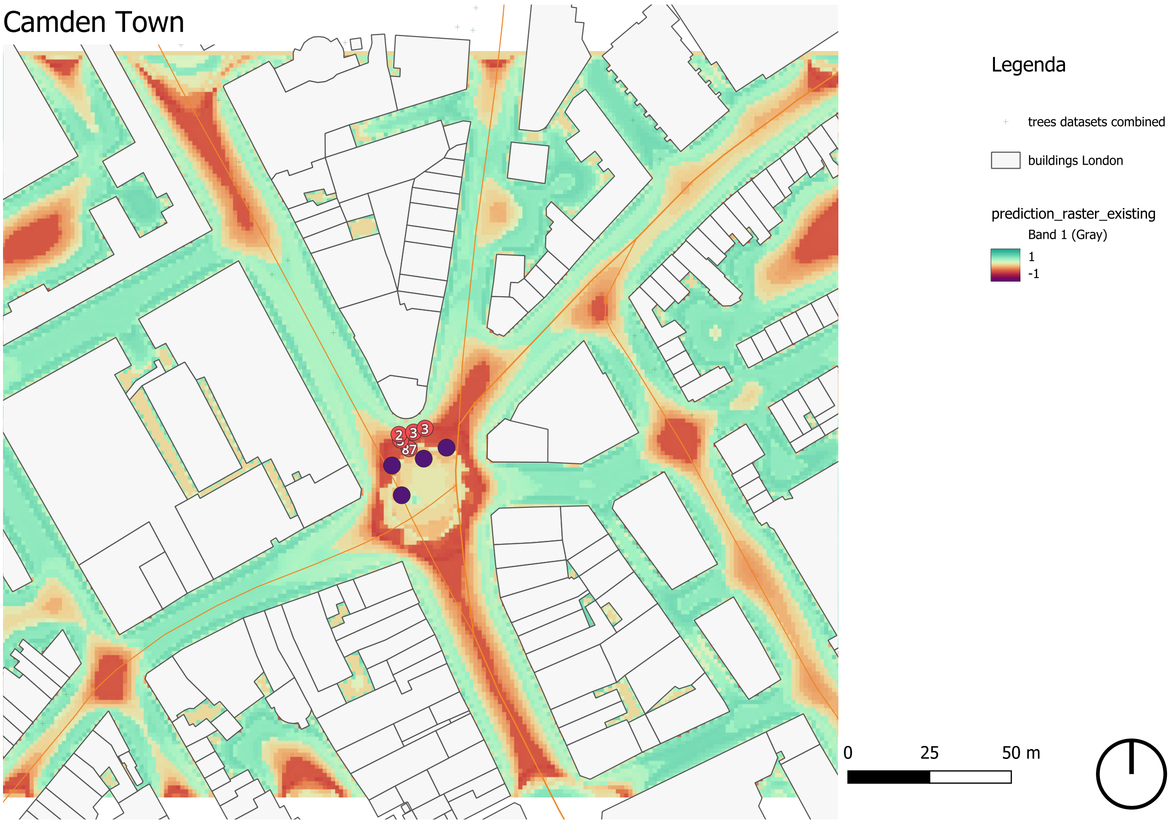


DISTANCE & VISIBLE	Mean Absolute Error	0.26
DISTANCE & VISIBLE	Mean Squared Error	0.1
DISTANCE & VISIBLE	Root Mean Squared Error	0.32
DISTANCE & VISIBLE	**R-squared**	**0.4**

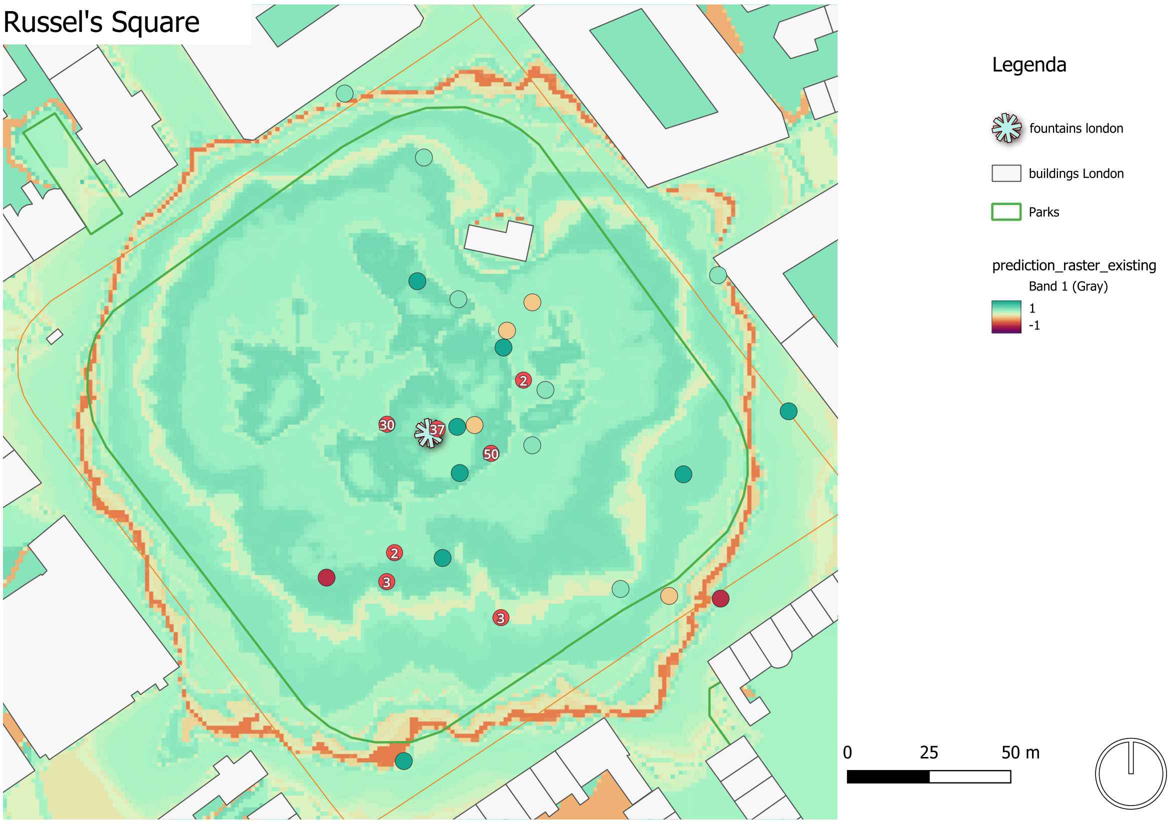




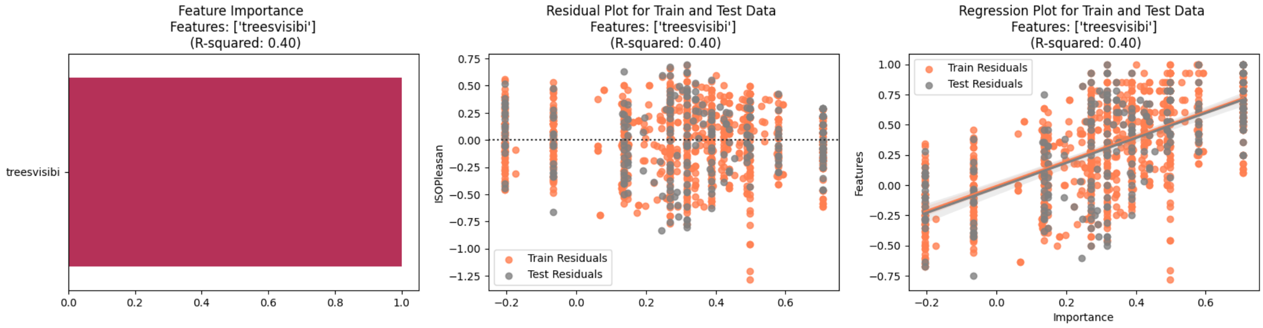
Camden Town



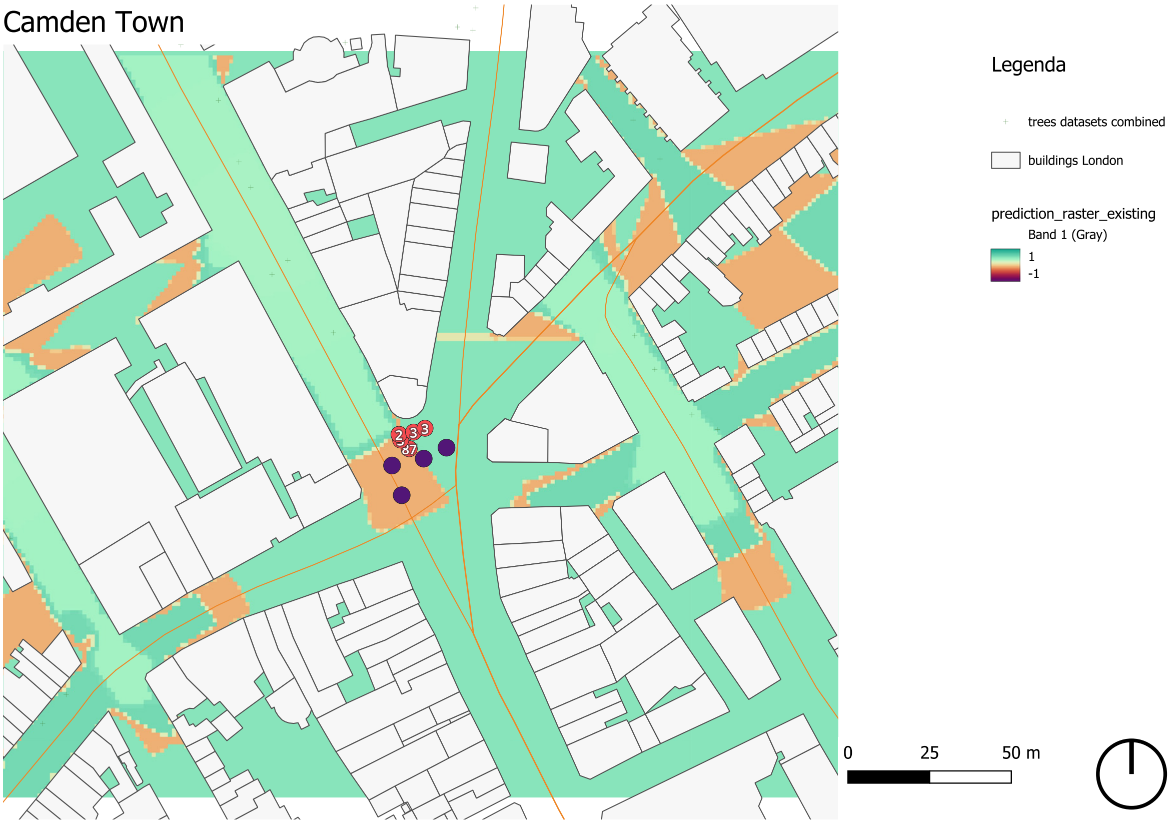
Marchmont Garden



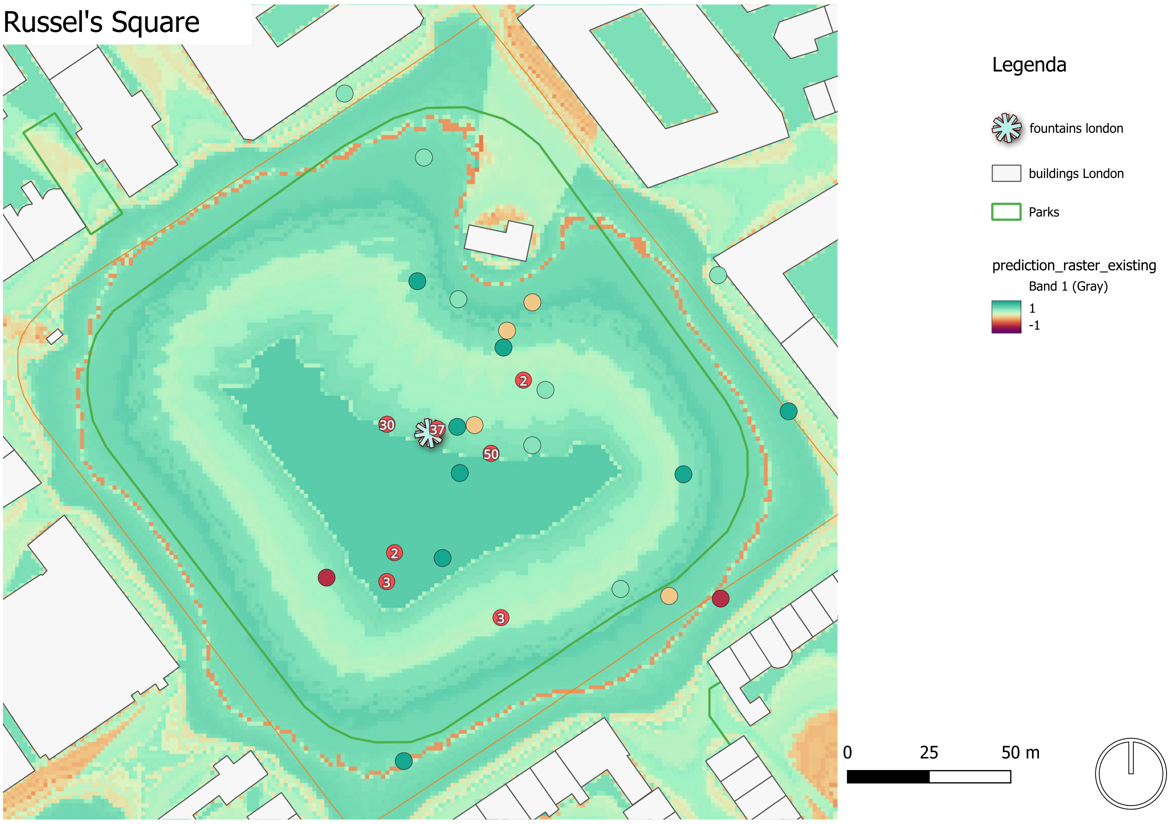
treesvisibi	Mean Absolute Error	0.26
treesvisibi	Mean Squared Error	0.1
treesvisibi	Root Mean Squared Error	0.32
treesvisibi	**R-squared**	**0.4**



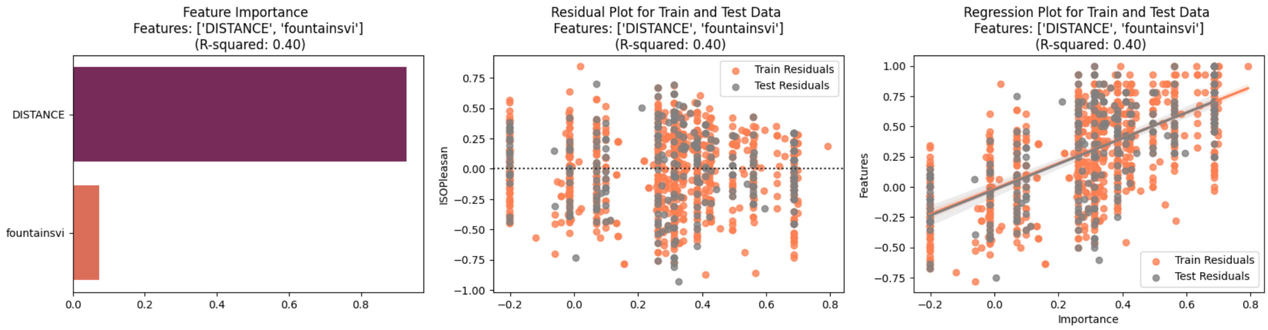
Camden Town



Marchmont Garden

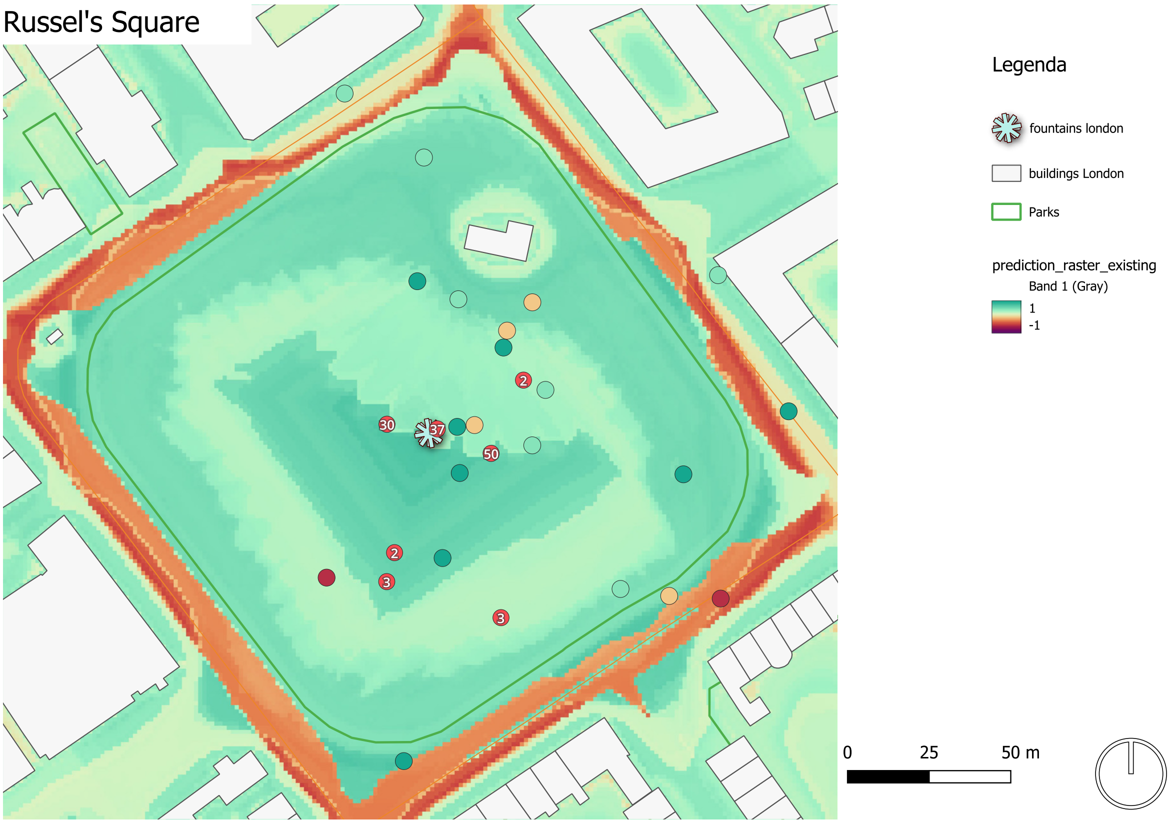


DISTANCE & fountainsvi	Mean Absolute Error	0.26
DISTANCE & fountainsvi	Mean Squared Error	0.1
DISTANCE & fountainsvi	Root Mean Squared Error	0.32
DISTANCE & fountainsvi	**R-squared**	**0.4**

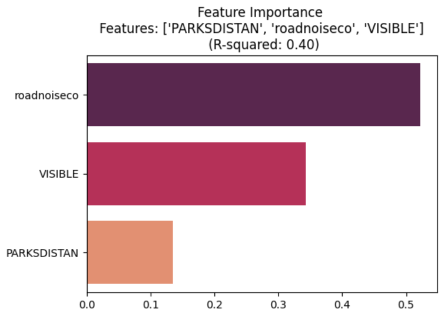


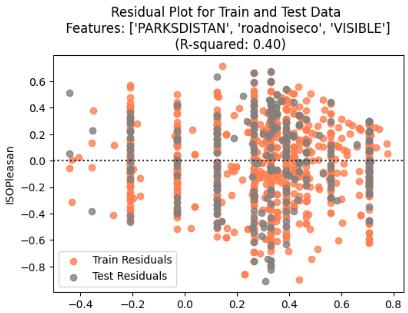
Camden Town

Marchmont Garden

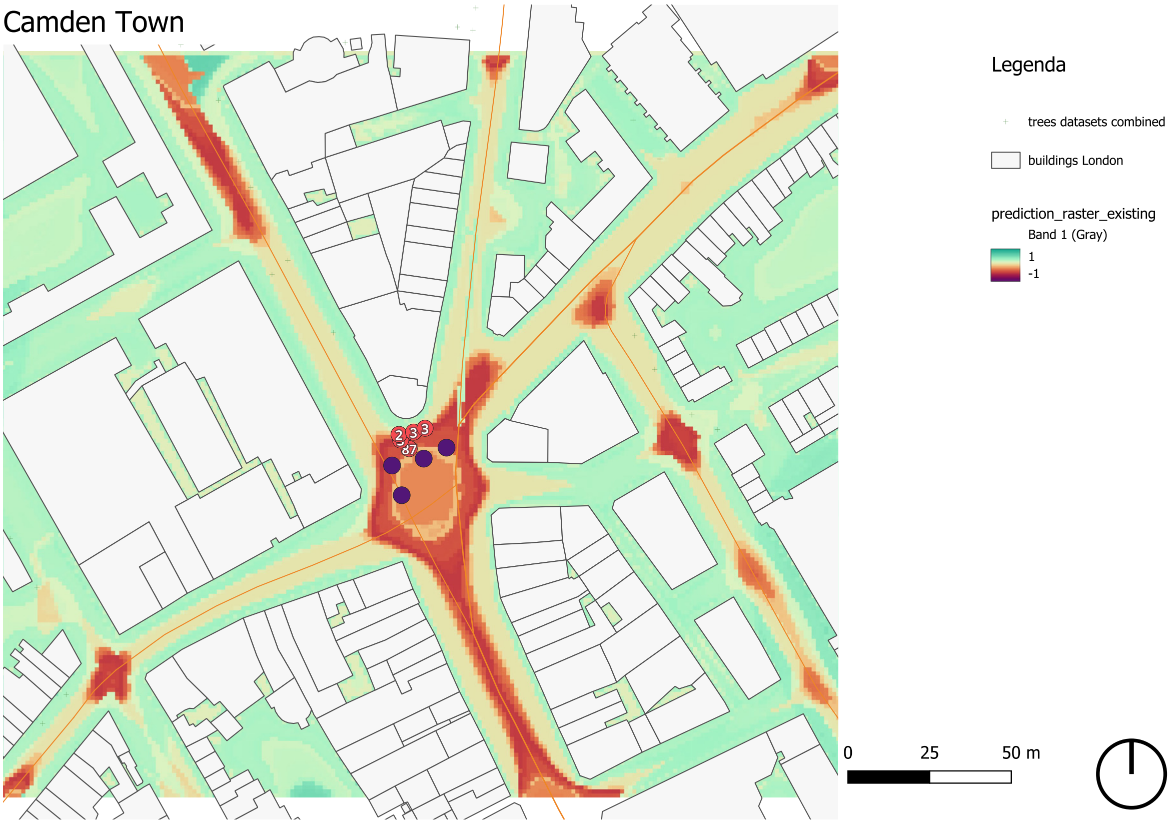


PARKSDISTAN & roadnoiseco & VISIBLE	Mean Absolute Error	0.26
PARKSDISTAN & roadnoiseco & VISIBLE	Mean Squared Error	0.1
PARKSDISTAN & roadnoiseco & VISIBLE	Root Mean Squared Error	0.32
PARKSDISTAN & roadnoiseco & VISIBLE	**R-squared**	**0.4**

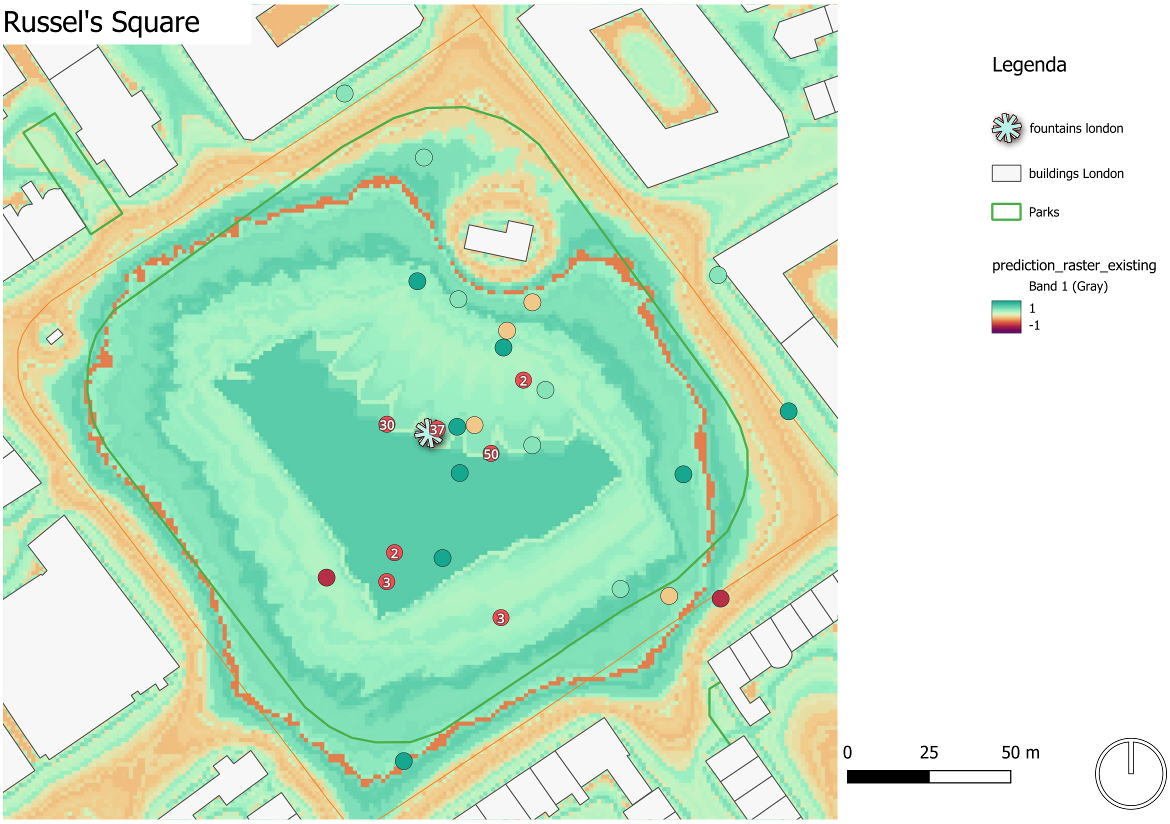




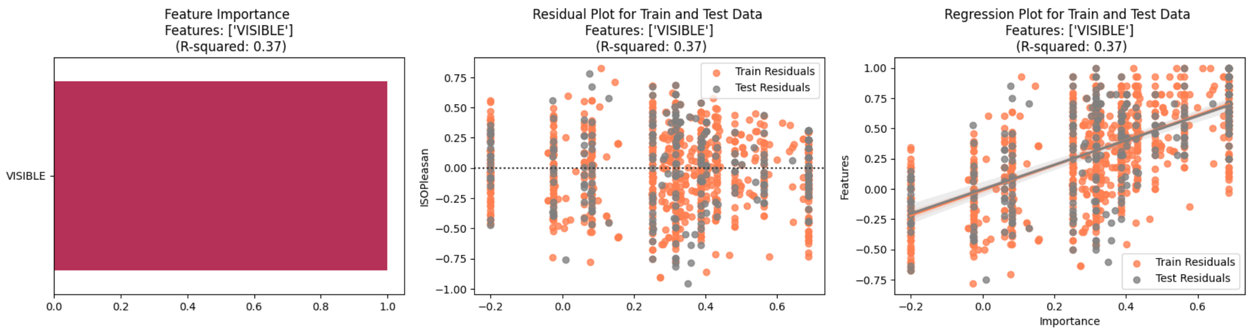
Camden Town



Marchmont Garden

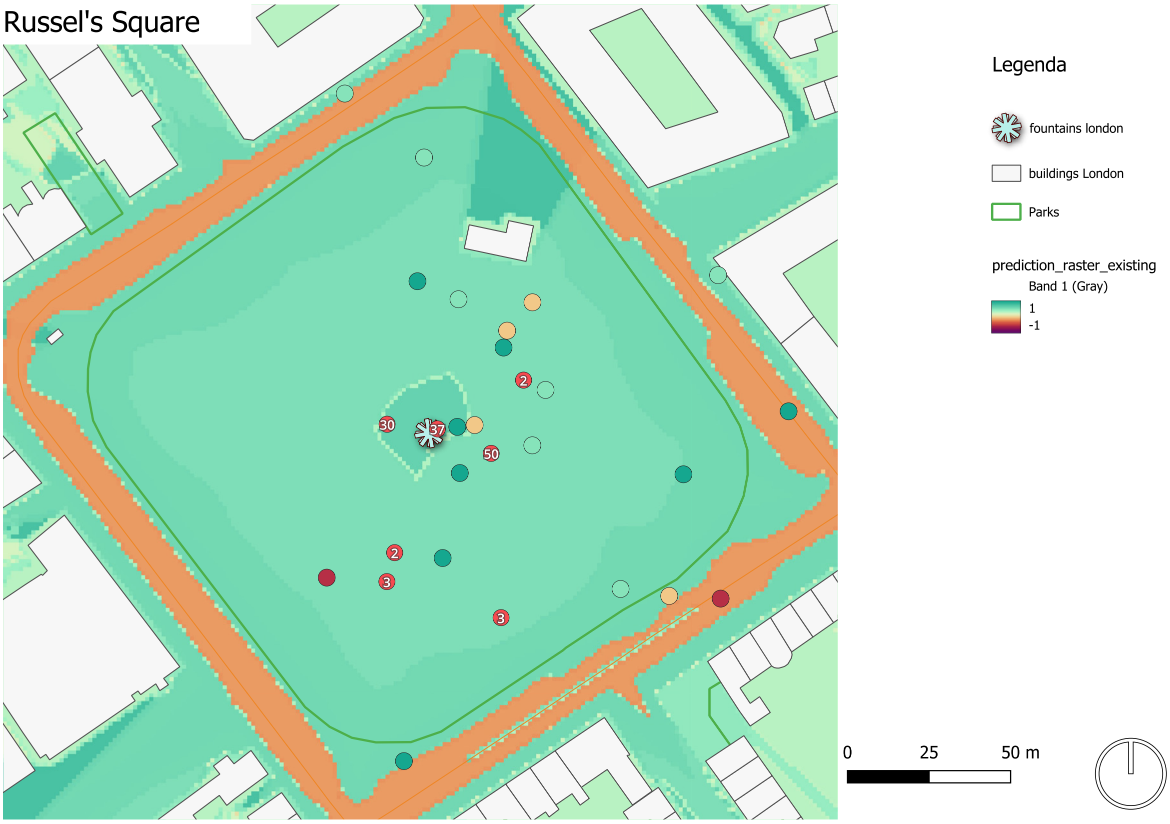


VISIBLE	Mean Absolute Error	0.27
VISIBLE	Mean Squared Error	0.11
VISIBLE	Root Mean Squared Error	0.33
VISIBLE	**R-squared**	**0.37**

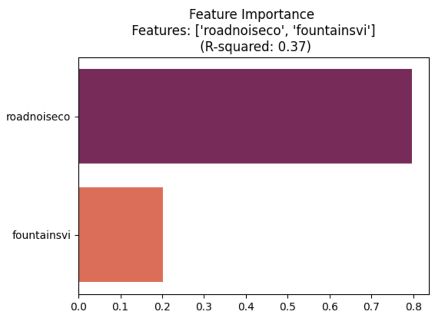


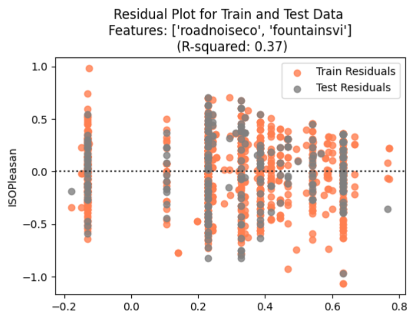
Camden Town

Marchmont Garden



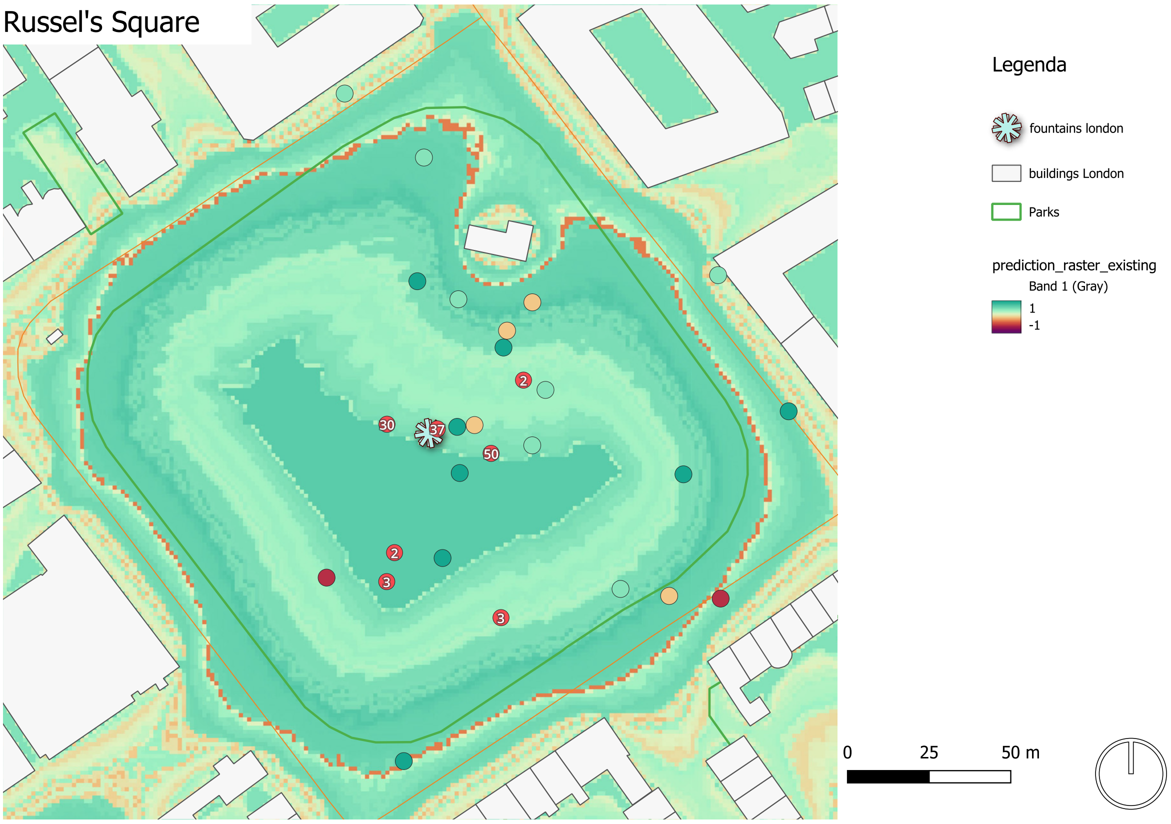
roadnoiseco & fountainsvi	Mean Absolute Error	0.27
roadnoiseco & fountainsvi	Mean Squared Error	0.11
roadnoiseco & fountainsvi	Root Mean Squared Error	0.33
roadnoiseco & fountainsvi	**R-squared**	**0.37**



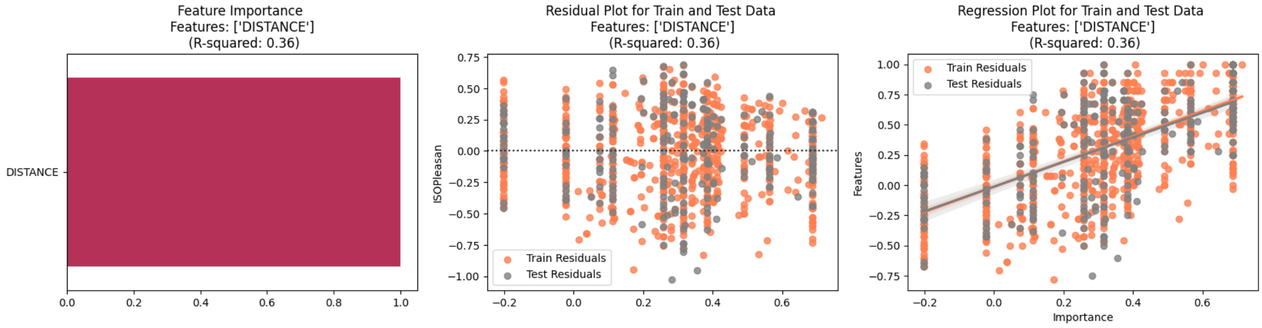


Camden Town

Marchmont Garden

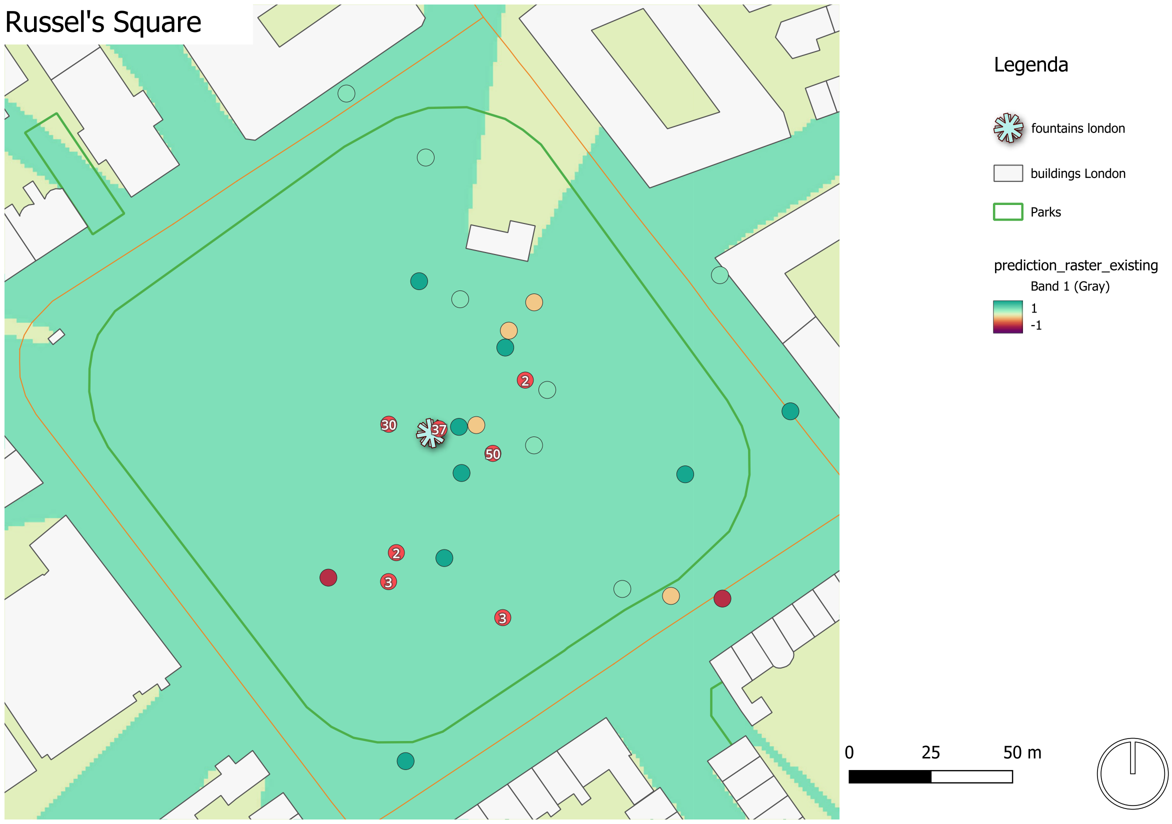


DISTANCE	Mean Absolute Error	0.27
DISTANCE	Mean Squared Error	0.11
DISTANCE	Root Mean Squared Error	0.33
DISTANCE	**R-squared**	**0.36**

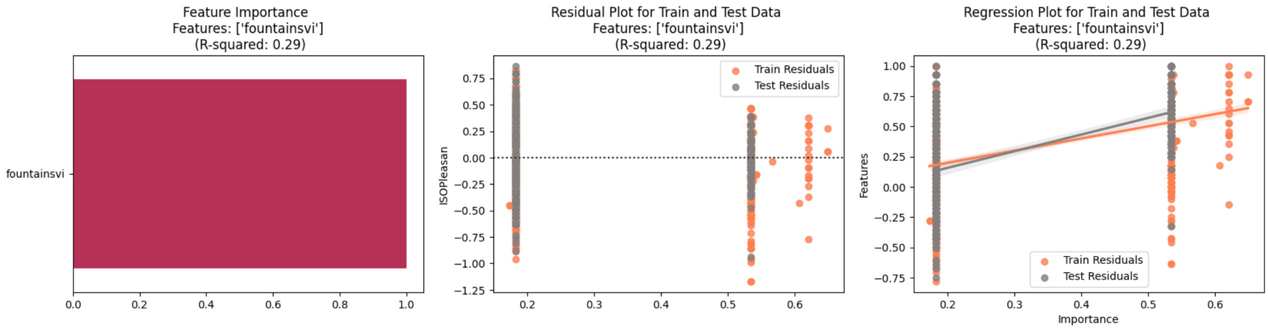


Camden Town

Marchmont Garden

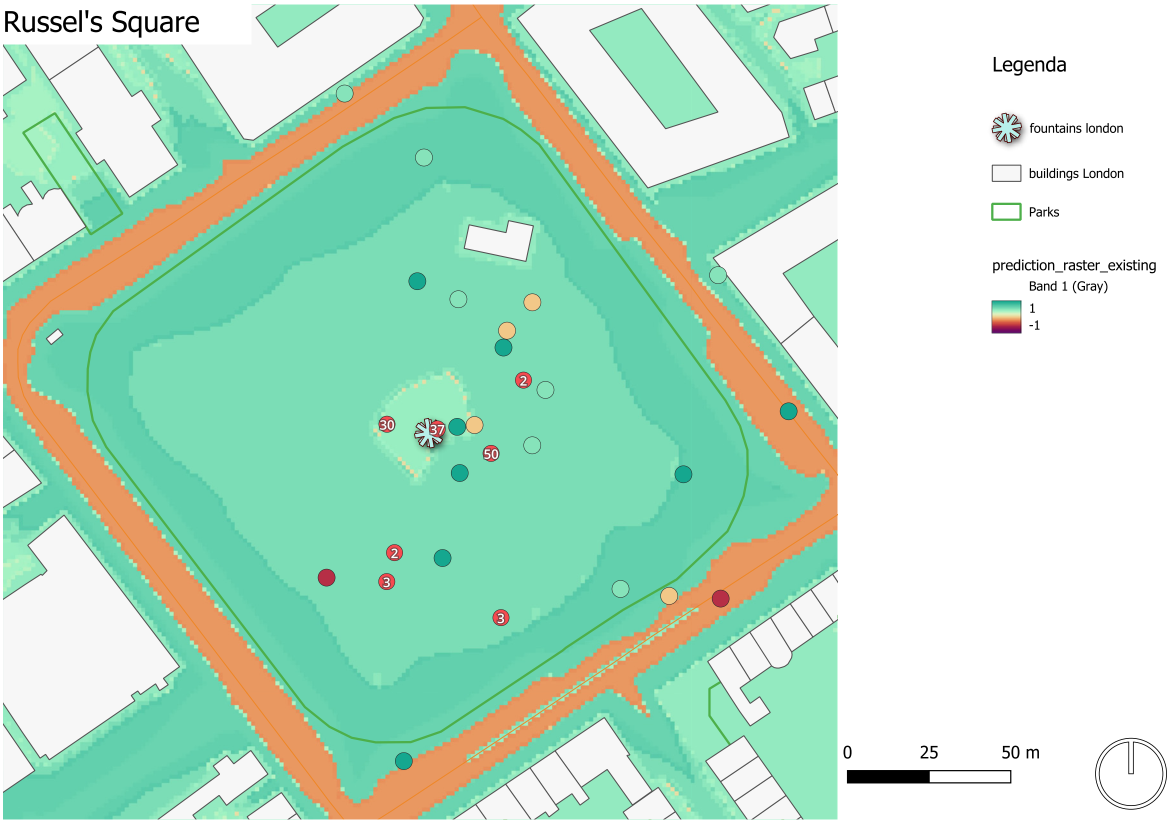


fountainsvi	Mean Absolute Error	0.29
fountainsvi	Mean Squared Error	0.12
fountainsvi	Root Mean Squared Error	0.35
fountainsvi	**R-squared**	**0.29**



Camden Town

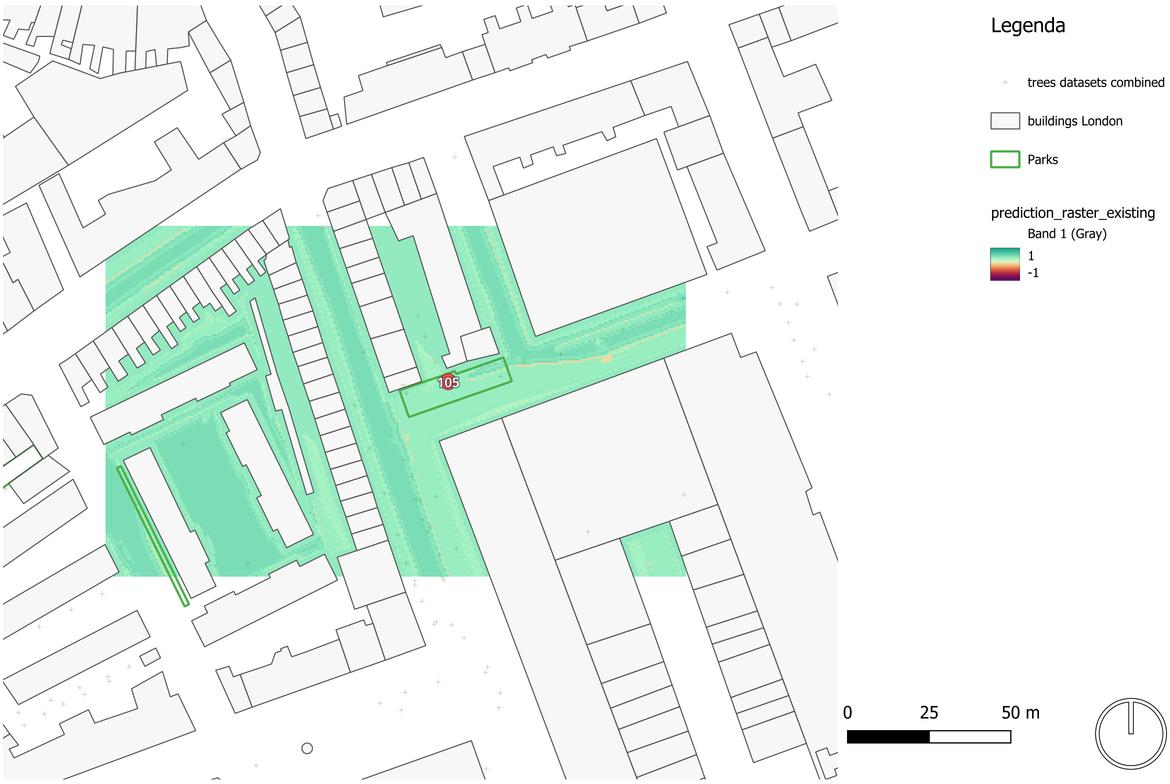
Marchmont Garden



roadnoiseco	Mean Absolute Error	0.29
roadnoiseco	Mean Squared Error	0.13
roadnoiseco	Root Mean Squared Error	0.36
roadnoiseco	**R-squared**	**0.24**

Camden Town

Marchmont Garden



Average ISOPleasant Value per location

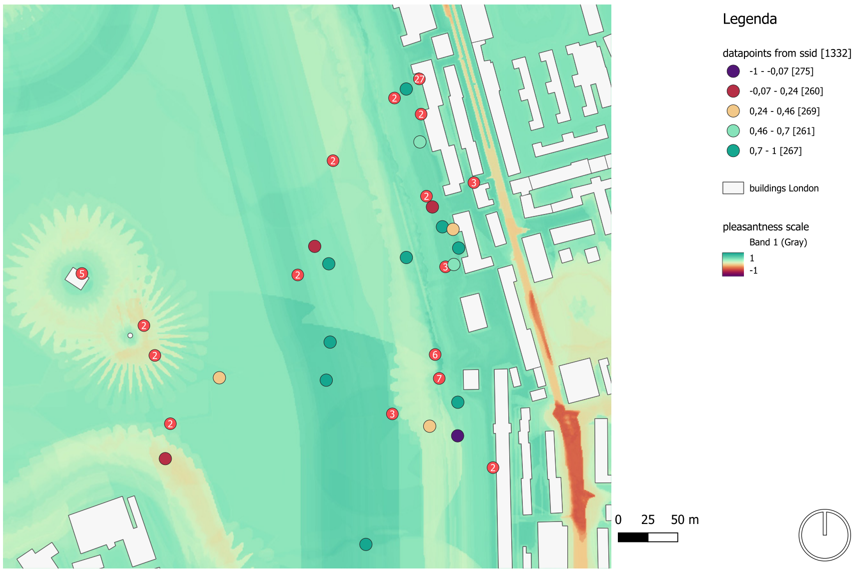
Locations	ISOPleasant
Regents Park Japan	0.70
Regents Park Fields	0.52
Russell Square	0.5
Monumento Garibaldi	0.42
Tate Modern	0.38
St Pauls Cross	0.36
Marchmont Garden	0.31
Pancras Lock	0.28
St Pauls Row	0.23
San Marco	0.22
Torrington Sqaure	0.09
Camden Town	-0.09
Euston Tap	-0.21

The follwing maps are created using the Random Forest Regressor that is used in the thesis chapter with the desing proposals. This was done to check the validity of the model. The input features were buildings, roads, parks, trees and fountains. Next to the maps is the avrage pleasantness from that location

From dataset:

ISO Pleasant = 0.52

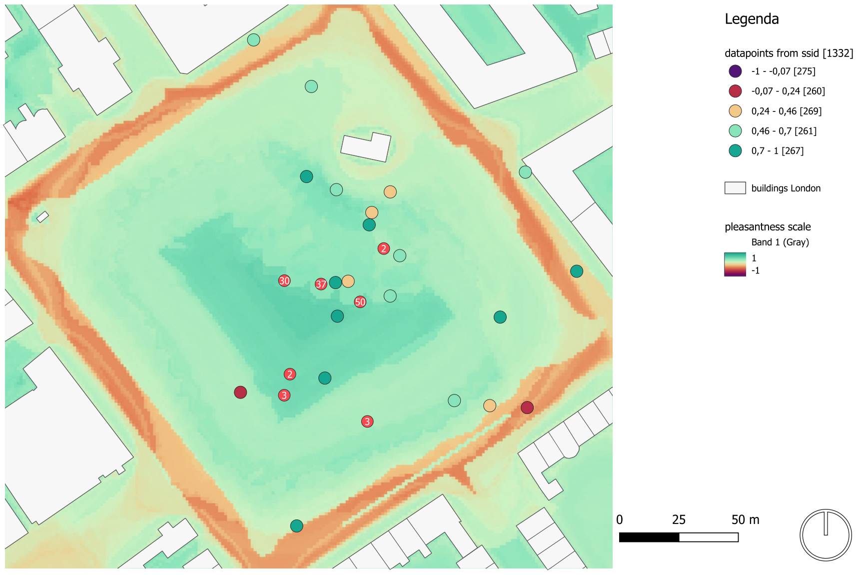
Regents Park Fields



From dataset:

ISO Pleasant = 0.50

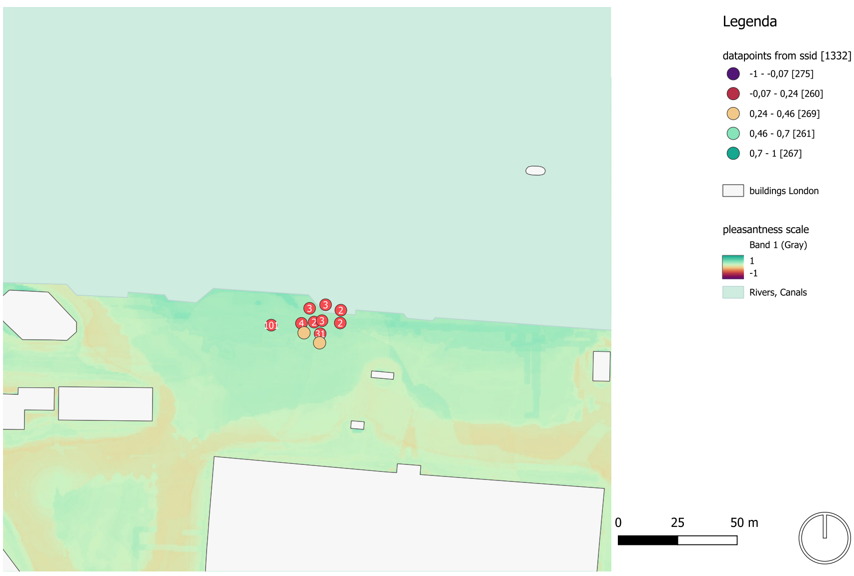
Russel's Square



From dataset:

ISO Pleasant = 0.38

Tate Modern



From dataset:

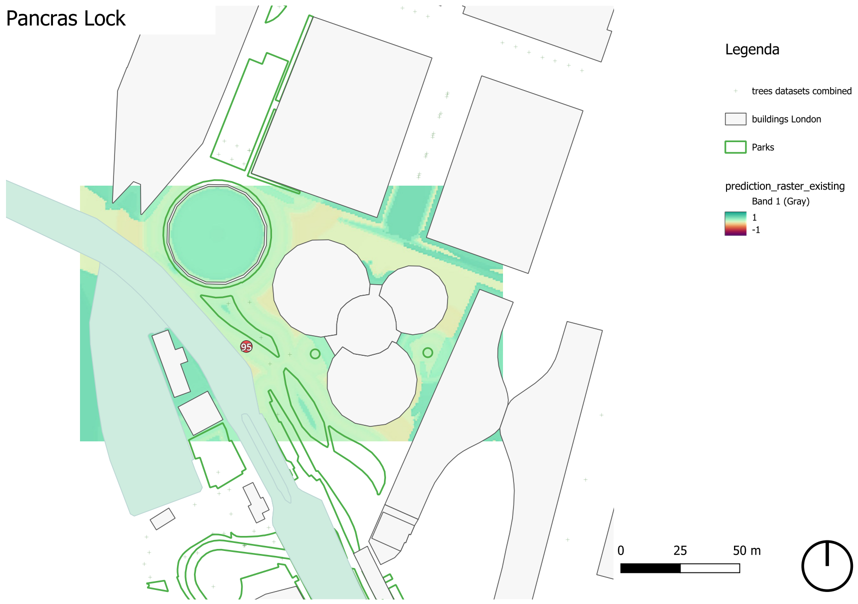
ISO Pleasant = 0.36, 0.23

From dataset:

ISO Pleasant = 0.31

From dataset:

ISO Pleasant = 0.28



From dataset:

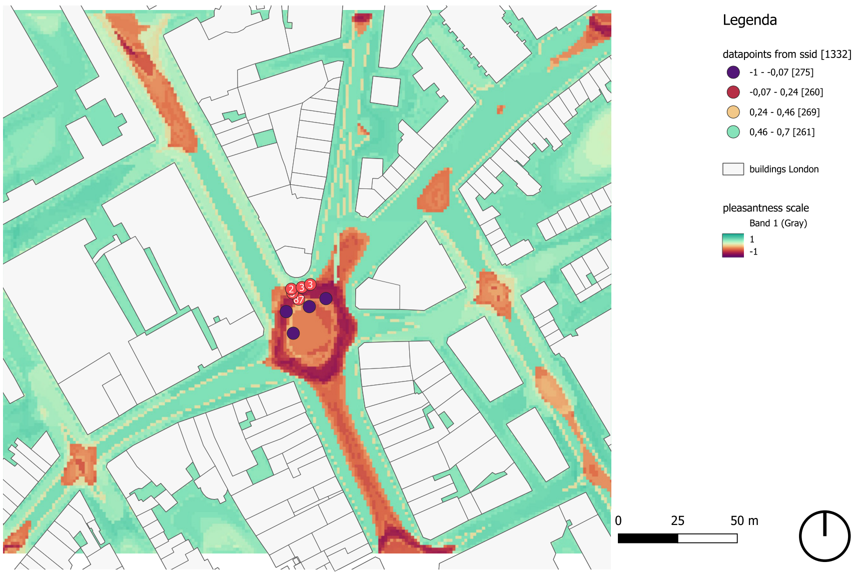
ISO Pleasant = 009

Torrington Square

From dataset:

ISO Pleasant = -0.09

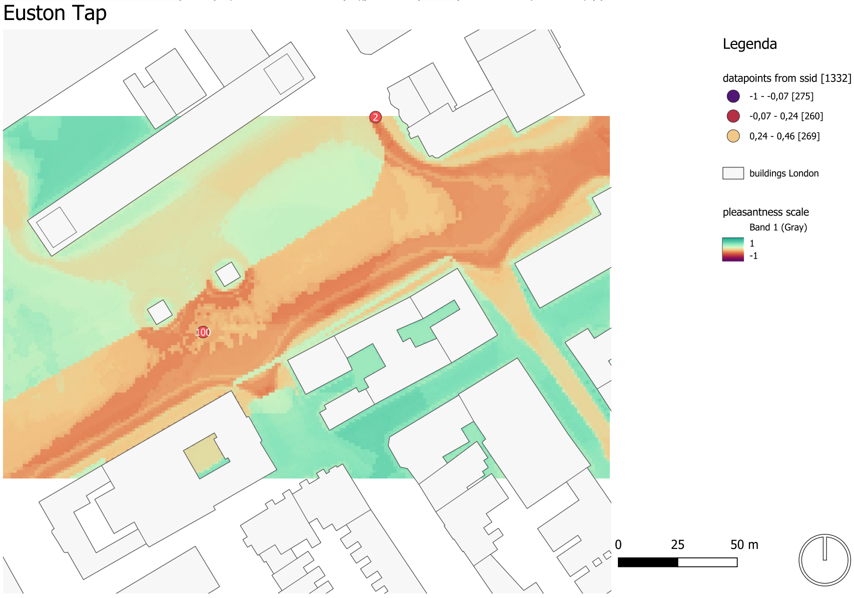
Camden Town



From dataset:

ISO Pleasant = -0.21

Euston Tap



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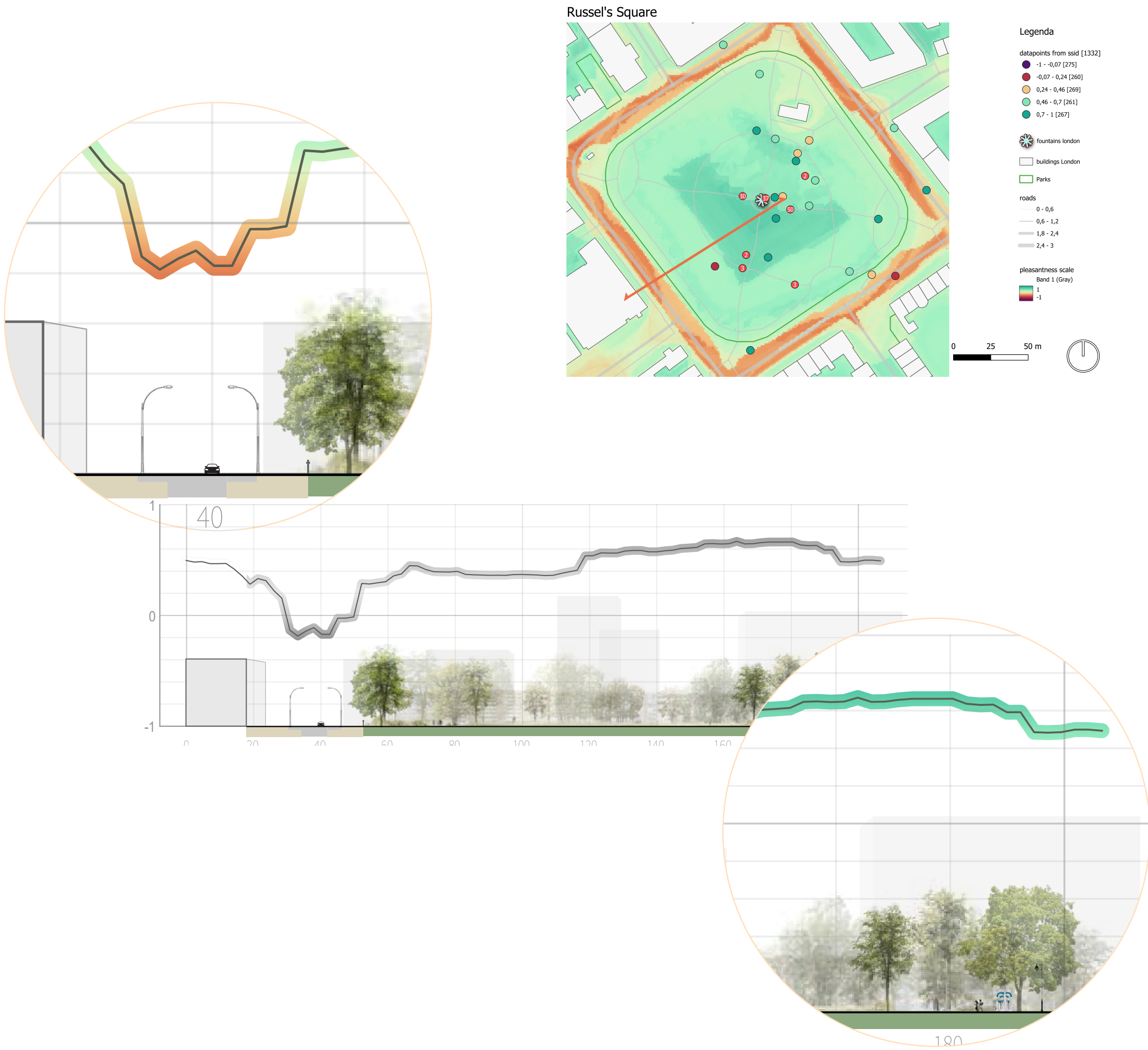

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