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**The environmental quality of the street network and the equity of
access to healthy travel environments in Tallinn**

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Abstract

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The urban street environments have a significant impact on people's health and well-being. Due to the spatial variation of environmental conditions, socio-spatial inequalities may arise in access to healthy street environments. However, our understanding of the exposure to multiple environmental variables in urban street network is limited. This study analysed the spatial distribution of environmental quality in terms of air pollution, noise pollution, and greenery in the street network of Tallinn. For doing so, the study created spatial layers of the environmental quality of the street network by using existing datasets of environmental conditions. This information was then used to study the inequality in access to healthy travel environments by using population registry data. The findings show that: 1) PM_{2.5}, NO₂, and noise levels exceed the health recommendations in 98%, 12%, and 51% of the street network, respectively; 2) high level of greenery is associated with low levels of air and noise pollution; and 3) the Russian-speaking group has better access to healthy street environments than Estonian-speakers or other language speakers overall. The suggested methods aim to increase individuals' and urban planners' awareness about (un)healthy routes in their travel environments and environmental injustice in Tallinn.

Keywords: travel environments, street network, air pollution, noise pollution, greenery, inequality, Tallinn

CERCS code: S230 – Social geography

Abstrakt

Tallinna tänavavõrgustiku keskkonnakvaliteet ja tervisliku liikumiskeskonna kättesaadavus

Linnatänavate keskkonnakvaliteedil on inimeste tervisele ja heaolule suur mõju. Meie teadmised mitme keskkonnatingimuse koosesinemisest, nendega kokkupuute olemusest ja koosmõjust tänavavõrgustikus on aga piiratud. Keskkonnatingimuste ruumilisest varieeruvusest tulenevalt võib tervisliku liikumiskeskonna kättesaadavuses esineda sotsiaalmajanduslik ebavõrdsus. Siinses uurimistöös analüüsiti Tallinna tänavavõrgu keskkonnakvaliteedi ruumilist jaotumist õhusaaste, mürareostuse ja rohealade andmetike põhjal ning seoti need rahvastiku paiknemise andmetikuga Tallinnas. Selleks loodi olemasolevaid keskkonnatingimuste pindalalisi andmetikke kasutades tänavavõrgu keskkonnakvaliteedi ruumikihid ja hinnati keskkonnatingimuste vastavust rahvusvaheliste soovitusetele. Seejärel kasutati saadud informatsiooni tervisliku tänavakeskkonna kättesaadavuse analüüsiks kodulähedases tänavavõrgus, tuginedes rahvastikuregistri andmetele. Tulemused näitavad, et 1) $PM_{2.5}$, NO_2 ja müra tase ületab tervisealaseid soovituslike näitajaid vastavalt 98%, 12% ja 51% ulatuses tänavavõrgustikust; 2) kõrge roheluse tase tänavavõrgustikus on seotud madalama õhu- ja mürasaaste tasemega ning 3) venekeelsel rahvastikurühmal on üldiselt parem juurdepääs tervislikule tänavakeskkonnale kui eesti keele või teiste keelte kõnelejalatel. Uurimistöö aitab suurendada teadlikkust liikumiskeskonna kvaliteedist, (eba)tervislikest marsruutidest linnas ja keskkonnaalasest ebavõrdsusest Tallinnas.

Märksõnad: liikumiskeskond, tänavavõrk, õhusaaste, mürareostus, rohelus, ebavõrdsus, Tallinn

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Introduction

The urban environment is significantly affected by environmental stressors, including ambient air pollution, chemicals, noise, and reduced accessibility to green and blue urban spaces. Environmental health stressors pose major health risks and contribute to 13% of all death cases across the EU (EEA, 2019). Urban streets provide daily activity space for the public while being sites where people are frequently exposed to multiple environmental stressors (Badland & Pearce, 2019; Glazener & Khreis, 2019). Healthy street environments encourage people to walk and improve health outcomes through healthier lifestyles (Sarkar et al., 2015a; Sousa et al., 2019). However, access to high-quality environments may be uneven between social groups (EEA, 2019). Health impact assessment of the urban environment is one of the necessary pathways for improving public health via measures such as reducing air pollution and improving street greenery for healthier and more liveable streets (Nieuwenhuijsen, 2020).

Research on the environmental quality of urban space and environmental exposure is nowadays a studied topic. Recent studies focused on population or individual exposure to air quality, noise, and greenery in the residential neighbourhood or people's activity spaces (Apparicio et al., 2018; Tao et al., 2020; Tonne et al., 2018). Exposure to environmental factors at the residential-level is well studied (Wang et al., 2020; Zhang et al., 2023). Despite not being common, studies addressed environmental exposure during travel covering different transport modes, including cyclists and pedestrians (Apparicio et al., 2018; Hankey et al., 2017; Tran et al., 2020; Willberg et al., 2023). Even though studies included multiple geographic extents, the exposure to multiple environmental stressors is not well covered; most studies focused on exposure to air pollution, while a minority of them covered multiple exposure types (Poom et al., 2021). This indicates a need for further research that addresses the complex interactions of multiple environmental factors.

The importance of environmental variables and the adverse health effects due to exposure are stated well in other studies (Gelb & Apparicio, 2021; Khreis et al., 2016; Vich et al., 2019). In this study, the following factors will be used to characterise the street network environment in Tallinn: air pollution, which is documented to have severe negative health effects (WHO, 2021); noise pollution due to its close relation with traffic and associated health effects, (Dzhambov & Lercher, 2019; Karner et al., 2010); and greenery, due to the multiple benefits of exposure to green spaces and mitigation effects of green space in the street environment (Säumel et al., 2016). Therefore, the novelty of this study is to project multiple environmental

variables to the street-level and use the results to facilitate more comprehensive analyses of the equity of access to healthy street environments and exposure levels during travel.

This study aims to map the environmental quality of the street network of Tallinn and characterise the spatial distribution of the levels of air pollution, noise pollution, and greenery for each street segment using existing environmental datasets. Moreover, this study demonstrates the possibility of using the resulting data in environmental inequality research by assessing the access distribution to healthy travel environments among sociodemographic population groups using population registry data. To reach the aim, the following questions are posed:

1. What is the spatial distribution of environmental quality in terms of air pollution, noise pollution and greenery in Tallinn street network, and how does it correspond to internationally recognised health recommendations?
2. How are the environmental variables of the street network mutually correlated?
3. How does access to healthy travel environments vary among language and gender population groups in residential street network?

1. Theoretical Overview

1.1. Spatial patterns and social inequalities in travel-related exposure

Urban design and addressing air pollution and noise pollution issues are the main pathways to make streets more liveable, promoting public health despite the increasing amount of motorised traffic nowadays (Nieuwenhuijsen, 2020). To determine what constitutes a healthy physical environment, several indicators have been considered according to their health effects and the extent to which people are exposed to these regularly (Pearce et al., 2010). The concentration of air pollution, traffic density, noise pollution, and natural environment affect route choices (Bunds et al., 2019). Poor air quality exposure increases health risk, causing respiratory and cardiovascular diseases, mortality cases and lost years in lifespan (WHO, 2021). Exposure to high levels of noise pollution is linked to annoyance, mental disorders, cardiovascular disease, and mortality cases (Bodin et al., 2015). Although, exposure to greenery promotes physical activity, better mental health, and wellbeing (Tsai et al., 2019; Wang et al., 2020).

Travel exposure studies investigated improving healthy routes while reducing travel time and pollution doses (Wang et al., 2018). The high dependence of environmental variables on the transport mode has been widely studied, finding that public transport users experience higher exposure to noise pollution than others (Apparicio et al., 2018). As for air pollution, due to the inhalation uptakes of cyclists, they represent the most exposed group (Gelb & Apparicio, 2021). The differences in exposure rates among individuals are closely related to individual health characteristics (Apparicio et al., 2018).

Route choice of people and urban design can affect population exposure to multiple environmental variables during their travel (Hankey et al., 2017; King et al., 2009). Spatial exposure patterns differ depending on the type of road, speed limit, network design, temporality, and distance to the high-traffic density areas (Hankey et al., 2017; Sheng & Wa Tang, 2011; Sun et al., 2022). Street width was shown as one of the main factors in increased noise levels, increasing traffic capacity and related noise pollution (Sheng & Wa Tang, 2011). The streets with the highest concentrations of air and noise pollution were found to be situated near areas with high traffic volume, commercial and economic centres, logistics centres, and locations where active travel takes place (Hankey et al., 2017). The lowest levels of greenery were shown in the city centre, new development areas with high levels of pedestrian accessibility (Hua et al., 2022). The balance that greenery can provide to high noise levels is

limited in newly constructed residential neighbourhoods' streets, where less greenery is presented, underlining the significance of including greenery in new development areas (Hankey et al., 2017; Luo et al., 2022).

Minor studies related to travel exposure include broader approaches using population-based analysis (Poom et al., 2021). Sociodemographic inequalities have been found between different ethnic groups regarding traffic-related exposure due to segregation in residential neighbourhoods. This segregation is linked to travel mode choices, as they differ depending on the location of their residence (Park & Kwan, 2020). Lower-income groups and migrants tend to live in areas where housing prices are lower. Consequently, they tend to have less accessibility to greenery due to housing market policies (EEA & Kaźmierczak, 2019). Similarly, exposure to air pollution was correlated to the residential location of different sociodemographic groups finding that in those places where migrants are highly represented less greenery, and higher air pollution exist (Klompaker et al., 2020; Tonne et al., 2018).

Most studies focused on the correlation between air pollution and noise pollution have taken broad scales; however, a smaller fraction of studies looked at this relationship on the street level, indicating how several factors, such as measurement techniques and physical environment characteristics, can influence this correlation (Khan et al., 2018). Depending on the source of the variables, noise pollution, air pollution and greenery were found to be mostly correlated with each other; NO₂ correlated positively with traffic-related noise pollution, whereas traffic-related noise was negatively associated with greenery suggesting the potential of greenery in mitigating noise pollution (Klompaker et al., 2020). The same negative correlation between street greenery and noise was indicated at the street level but too weak to prove a correlation between these variables (Nourmohammadi et al., 2021). Most studies found a strong correlation between the considered types of air pollutants due to their shared source in fuel combustion (Khan et al., 2018). Specifically, PM_{2.5} and PM₁₀ are strongly associated with each other as PM₁₀ carries a significant amount of PM_{2.5}, and both coarse and fine particles mostly show similar spatial patterns (IARC, 2016; Okokon et al., 2017). On the other hand, the correlation between NO₂ and particulate matter was weaker (Okokon et al., 2017; Olstrup et al., 2022; WHO, 2021).

1.2. Exposure to air pollution

Despite the decrease in emissions in urban areas, the majority of the population in Europe is still exposed to air pollutants above the WHO 2021 guidelines (EEA, 2022). The sources of air pollutants were shown to be traffic (Abelsohn & Stieb, 2011; Orru et al., 2011), local heating, industrial areas (IARC, 2016; Orru et al., 2011) and re-emissions from different surfaces (IARC, 2016). Based on the sources, air pollutants can be primary, directly from combustion, or secondary, resulting from chemical, anthropogenic, or natural processes (WHO, 2021). Besides fuel combustion, car brakes and tyres are also sources of emissions (IARC, 2016; Nieuwenhuijsen, 2020). Air pollutants are primarily found in the air in gaseous forms (ammonia (NH₃), carbon monoxide, nitrogen dioxide, sulphur dioxide and ozone) or PM (PM_{2.5}, PM₁₀ and polycyclic aromatic hydrocarbons (PAHs)), which are very small particles (IARC, 2016; WHO, 2021).

The health effects of outdoor air pollution are stated in two ways, short-term exposure is related to cardiovascular and respiratory diseases, as well as increased hospitalisation and emergency cases; meanwhile, long-term exposure is linked to increased mortality, lung cancer, pneumonia, asthma and atherosclerosis (Abelsohn & Stieb, 2011; Brandt et al., 2015). Studies suggest that long-term exposure may be more accurately assessed than short-term exposure regarding health effects and period (Liu et al., 2018; Pope & Dockery, 2006). Long-term effects of air pollution have caused a considerable number of premature deaths, morbidity, and years lived with disability related to diseases in European countries (EEA, 2022b; Wang et al., 2022). Air pollution produced changes in the lung functions of cyclists after long-term exposure to a travel environment (Strak et al., 2010). Apart from direct health effects, the monetary costs caused by the negative effects of air pollution are one of the indirect effects (Orru et al., 2009). Among the air pollutants, PM₁₀, PM_{2.5}, NO₂ and O₃ have shown extensive negative health effects and host the major concerns regarding air pollution in Europe (EEA, 2022a; WHO, 2021). Even though gaseous pollutants are less frequently involved in health assessment studies than PM, gaseous and PM are studied over time (Gelb & Apparicio, 2021; Sun et al., 2022).

Exposure to air pollution during travel is highly dependent on the mode of transport; high exposure happening close to major roads and motorised traffic flow increases the exposure significantly (Cepeda et al., 2017; Okokon et al., 2017). Furthermore, areas characterised by population density and active travel patterns are associated with high concentrations of air

pollutants (Hankey et al., 2017). It has been found that low-income neighbourhoods with high walkability levels have higher levels of traffic-related air pollution (Marshall et al., 2009).

Concentrations of air pollutants show high spatial variability along the street network, while most of the pollutants show considerable increases in concentration around roads, NO₂ and PM_{2.5} can spread over long distances affecting streets nearby main roads (IARC, 2016; Karner et al., 2010). However, spatial variations of PM were demonstrated to be the lowest among all other air pollutants (Hankey et al., 2017; Strak et al., 2010). Traffic volume, noise barriers and other factors affect the differences in observed concentrations of air pollution (Karner et al., 2010). Additionally, speed limit, road configuration and density have been shown to be one of the reasons for the variation of air pollutants in street environments (Sun et al., 2022). As a result, a high concentration was found in street junctions, main streets, and streets close to commercial services (Hankey et al., 2017).

1.3.1. Particulate matter

Particulate matter is a synthesis of microscopic particles or liquid drops created by natural and anthropogenic sources (Anderson et al., 2012). The size of a particulate matter depends on its source and can be above 10 µm, between 2.5 µm and 10 µm (coarse particles), or between 2.5 µm and 0.1 µm (fine particles) (Anderson et al., 2012; IARC, 2016; Orru et al., 2011). Human airways filter out particulate matter whose diameter exceeds 10 µm before reaching the lungs; however, smaller size particles can go into smaller terminal airways and cause harmful effects on people's health (Anderson et al., 2012; Guindi et al., 2018).

PM₁₀ is coarse particulate matter, and its diameter is up to 10 µm (EEA, 2022). PM₁₀ is increased by emissions from fuel combustion during transport, household heating, industrial activities, and street dust (Anderson et al., 2012; EEA, 2022; Orru et al., 2018). The main source of PM₁₀ was identified as energy consumption in different sectors, such as industrial, residential, and commercial, in 2020 (EEA, 2022a). The maximum exposure to PM₁₀ was recorded for bus commuters in Helsinki, indicating strong relation to emissions from road transport (Okokon et al., 2017).

Table 1 shows WHO (2021) AQG and interim targets. The air quality guideline level demonstrates health recommendations for air pollution; above this level, it starts to pose negative health effects. Interim targets refer to air pollution levels above the air quality

guideline level. Interim targets are gradual steps to reduce air pollution in areas with high concentrations (WHO, 2021).

Table 1. WHO recommendation in annual air quality and interim targets for PM₁₀

Recommendations	PM₁₀ (µg/m³)
Interim target 1	70
Interim target 2	50
Interim target 3	30
Interim target 4	20
Air quality guideline	15

The recommendation for long-term exposure level to PM₁₀ is 15 µg/m³, which poses a minimum risk for mortality cases (WHO, 2021). Nevertheless, recent studies have found that there is still a health risk for vulnerable groups in their exposure to PM₁₀ levels below 15 µg/m³ (Olstrup et al., 2022).

PM_{2.5} is a fine particulate matter of a diameter up to 2.5 µm, whose presence in the air has similar to PM₁₀. The concentration of PM_{2.5} is higher in big urban areas and places that host significant amounts of wood and other biomass combustion (WHO, 2006). Due to emissions from multiple sources, PM_{2.5} shows complex spatial and temporal variability over street networks, being affected more by residential and commercial uses rather than traffic during separate times of the day (Zhou & Lin, 2019). Therefore, energy consumption was an important source of PM_{2.5} (EEA, 2022a). High PM_{2.5} concentrations have been found in high-traffic density areas, indicating car breaks and tyres as one of the primary sources (Sun et al., 2022). Nowadays, exposure to PM_{2.5} can be considered the most alarming environmental issue across Europe, with 98% of the population exposed to levels exceeding WHO guidelines (EEA, 2022a).

Table 2 shows interim targets based on WHO (2021) and air quality guideline levels for PM_{2.5}. The air quality guideline level is 5 µg/m³, which is stricter than EEA (2022a). Although lower concentrations of PM_{2.5} below air quality guideline levels were associated with health risk effects not for all population but for children and older people (Olstrup et al., 2022).

Table 2. WHO (2021) air quality guideline level and interim targets for long-term PM_{2.5}.

Recommendation	PM_{2.5} (µg/m³)
Interim target 1	35
Interim target 2	25
Interim target 3	15
Interim target 4	10
Air quality guideline	5

Overall, studies indicate that PM causes a significant reduction in life expectancy among a variety of adverse health effects (Kelly & Fussell, 2015; Orru et al., 2011). For instance, annual exposure to PM_{2.5} of 11.6 µg/m³ caused 296 premature deaths and 0.64 years of life expectancy loss in Tallinn (Orru et al., 2009).

1.3.2. NO₂

Nitrogen dioxide (NO₂) is a gaseous air pollutant that is highly concentrated in urban areas, particularly in big cities with heavy traffic; therefore, the primary source of it remains traffic fleet, and it is found with higher concentrations close to the surface (EEA, 2022b). It is also related to the increasing number of vehicles that are using diesel (IARC, 2016; WHO, 2006). High concentrations of NO₂ are found on major roads while linked to increased fuel combustion, speed limit and traffic fleet (Sun et al., 2022).

Table 3 shows interim targets based on WHO (2021) and air quality guideline levels for NO₂. The maximum safe level of NO₂ is 10 µm/m³, the latest update on health risks associated with air pollution.

Table 3. WHO (2021) air quality guideline level and interim targets for long-term NO₂.

Recommendation	NO₂ (µg/m³)
Interim target 1	40
Interim target 2	30
Interim target 3	20
Air quality guideline	10

Long-term effects of NO₂ are strongly associated with a growing number of mortality cases, respiratory diseases (Wang et al., 2022; WHO, 2021), and bronchitic symptoms (WHO, 2006).

1.3. Exposure to noise pollution

Noise pollution remains an environmental issue in urban areas due to expanding motorised traffic (EEA, 2019; Fink, 2017; WHO, 2018). Traffic noise has contributed to a substantial portion of environmental noise across Europe; however, people are also exposed to aircraft, industry, and rail noise (EEA, 2020). Research has shown that while street noise contributes less to total noise pollution, it significantly exceeds the health recommendations (McAlexander et al., 2015).

Exposure to noise pollution has auditory and nonauditory health effects (Fink, 2017; WHO, 2018). On the one hand, auditory health effects directly cause hearing loss with high noise levels (Fink, 2017). On the other hand, the nonauditory impacts of noise exposure are linked to mental disorders, cardiovascular disease, annoyance, hypertension and ischemic heart disease, mortality cases, and reduction in academic performance (Bodin et al., 2009, 2015; Stansfeld & Clark, 2015). 10 dB increase in noise level is associated with potentially increased anxiety and mental disorders (Dzhambov & Lercher, 2019). Counting all these adverse health effects, noise pollution negatively impacts life quality of people and their travel satisfaction, as their noise exposure is more frequent during their travel (Apparicio et al., 2018; Bunds et al., 2019). Specifically, it strongly affects disadvantaged neighbourhoods, having increased levels of noise pollution (Van Lenthe et al., 2005).

Urban design and traffic may increase exposure to unhealthy noise levels in travel environments (Nourmohammadi et al., 2021; Sheng & Wa Tang, 2011). Speed limit, wider roads and network design were found to impact traffic-related noise pollution significantly (Sheng & Wa Tang, 2011). A peak level of noise pollution was observed in major roads and street intersections where high traffic capacity occurs (Nourmohammadi et al., 2021). This results in higher noise pollution exposure in all travel modes, specifically for bus users (Apparicio et al., 2018).

The level of noise pollution changes over time depending on the intensity of sources; therefore, it has different measurement types (WHO, 2018). L_{den} (day-evening-night noise level) and L_{night} (during the night) measurements presented frequently the noise pollution in environmental exposure studies (Klompaker et al., 2020; WHO, 2018; Willberg et al., 2023).

There are several guidelines for healthy noise levels, depending on the sources. For example, EEA (2020) recommends 55 dB for L_{den} and 50 dB for L_{night} . In contrast, WHO (2018)

guidelines are based on noise sources. Besides these international guidelines, studies have used national guidelines for health assessments and noise mapping, which is higher than these (Geravandi et al., 2015; McAlexander et al., 2015; Sheng & Wa Tang, 2011). However, according to WHO (2018) has the strictest guidelines for healthy noise levels (Table 4). As road noise contributes significantly to total noise pollution, this study considers the healthy noise level to be 53 dB for L_{den} and 50 dB for L_{night} , better adapted to the study case based on the reviewed sources (WHO, 2018).

Table 4. *Noise level guidelines WHO (2018)*

Noise sources	L_{den} (dB)	L_{night} (dB)
Road traffic	53	45
Rail	54	44
Aircraft	45	40

1.4. Exposure to greenery

Surrounding green space has several health benefits, improving mental health and well-being and reducing the risk of cardiovascular diseases (EEA, 2019). Surrounding green can be urban parks and gardens, green urban walls, forests, and street greenery. While residential greenery is well studied, street greenery is a part of the active travel environment (Bunds et al., 2019; Sarkar et al., 2015). Having green space in street environments is associated with increased walking time, encouraging people to perform physical activity (Sarkar et al., 2015; Tsai et al., 2019; Vich et al., 2019). Spending time in natural environments may increase social cohesion and decrease stress levels (Säumel et al., 2016). Not only health impact but urban green infrastructure has also been found to impact the physical environment, mitigating slightly adverse effects of noise and air pollution and ensuring thermal comfort (Nieuwenhuijsen et al., 2017). Evidence has shown that streets without greenery are slightly warmer than surrounding parks (Bowler et al., 2010). With these benefits, greening urban streets is one pathway to reduce climate change effects and provide more liveable streets that support active travel (Nieuwenhuijsen et al., 2017).

Streets with a high level of pedestrian accessibility and commuting were found to have scarce greenery levels (Ye et al., 2019). Specifically, the old city and central part of the new development areas had the lowest street greenery level, followed by private residential areas

and industrial and economic centres (Hua et al., 2022). The spatial variability of greenery levels remains clear between the central and outermost streets of the city, with the highest levels of greenery observed in the outer city and wealthy residential buildings with high tree density (Hua et al., 2022). Accordingly, the lowest greenery class was found in socially disadvantaged neighbourhoods where low-income and the most vulnerable groups live (Luo et al., 2022).

To capture urban greenness, different methods have been used over time. These methods include LIDAR, satellite imagery (NDVI (Normalized Difference Vegetation Index)) and land use data as techniques to observe high-resolution street greenery and represent green spaces (Gascon et al., 2016; Tsai et al., 2019; Vich et al., 2019). New measurement methods have been developed, such as using machine learning and street view images to map eye-level street greenness and measure residential greenery exposure (Li et al., 2015; Song et al., 2022; Wang et al., 2020; Willberg et al., 2023; Wu et al., 2020; Ye et al., 2019; Zhang et al., 2023). Despite new methods being available, satellite images are widely used as a traditional method to assess street greenery (Zhang et al., 2023), residential greenery (Chen et al., 2023; Dadvand et al., 2014; Venter et al., 2023) or accessibility to greenery (Jang et al., 2020).

Scholars claim that human scale measurements of street-level greenery are more accurate than top-down measurements of street-level greenery, as it presents as it reflects better the perceived greenery by pedestrians (Li et al., 2015; Markevych et al., 2017). NDVI compatibility for representing street-level greenery compared to other measurements was proven by showing similar results (Rhew et al., 2011; Tsai et al., 2019). NDVI is sufficient and approachable for any geographical extent to represent the presence of overall greenery, and it can reflect all small-scale urban vegetation with accuracy, whereas it does not provide further information (Fuertes et al., 2016; H. Song et al., 2019).

NDVI is calculated based on the difference between near-infrared and red reflectance to analyse surface vegetation using satellite imagery (Tucker, 1979). As a result, this index can range from -1 to 1 based on the balance of near-infrared and red values (Song et al., 2019). Higher values show dense vegetation, while lower values represent a lack of vegetation. Negative values indicate waterbodies, values around zero correspond to pavements, sidewalks and other concrete surfaces, and positive values correspond to grass, tree, and shrubs (Aryal et al., 2022; Huang et al., 2021; Sonwalkar et al., 2010).

For mapping greenery based on NDVI, negative values, which do not present greenery, were eliminated or classified as zero (Fuertes et al., 2016). That might not be accurate in health

assessment studies, as negative values also show blue urban spaces (Venter et al., 2023). The vegetation cover changes throughout the seasons, making it essential to choose the greenest periods from the available satellite data for more precise analysis (Wang et al., 2020). Another step resides in classifying the positive values since some non-vegetated surfaces may still contain values above 0 (Aryal et al., 2022; Jang et al., 2020). To show greenery levels, universal thresholds have been used to define lower or higher classes; minimum greenery values are 0.3 and 0.2 (Jang et al., 2020) and 0.19 (Aryal et al., 2022). Although, some other methods were developed, for example, showing greenery level as a percentage or taking an equal range for each class. However, these classes are not defined based on health effects (Hua et al., 2022; Venter et al., 2023).

1.5. Projecting environmental variables in street network

Studies mapped air pollution indicators at the street level using portable sensors in selected routes and then interpolated the gathered data using the LUR model to other locations (Sun et al., 2022; Tran et al., 2020). Similarly, portable noise sensors were used to measure noise pollution in urban areas (Alam, 2011; Ma et al., 2021). However, these approaches take time and costs to monitor bigger geographical extents; the need for improving national monitoring systems is emerging (Dias & Tchepel, 2018). For example, Willberg et al. (2023) used the existing available environmental layers to measure exposure to multiple environmental variables.

Finding more accurate spatial variations using road datasets can be done through certain pre-processing of the data, separating road segments, which allows obtaining more precise results in terms of spatial variation of environmental variables in street segments (Sun et al., 2022; Tran et al., 2020). Thus, analysing environmental variable concentrations at the street segment level provides a more refined assessment, enabling the detection of spatial or temporal patterns with higher precision (Nourmohammadi et al., 2021; Sun et al., 2022).

Different scholars have adapted their buffer measures around street networks to determine the street-level exposure environment, considering several peculiarities of each case study (Sun et al., 2022; Tsai et al., 2019; Vich et al., 2019). These include the width of both sidewalks and streets (Tsai et al., 2019; Vich et al., 2019) and the target population and area covered by the study (Burgoine et al., 2015). Depending on the suggested factors, buffers around the street centreline at different distances have been used, such as 10 m as the regular lane width in

Shanghai street (Sun et al., 2022), 20 m as a result of the average street width in Barcelona (Vich et al., 2019) and 25 m in Milwaukee in consonance with the parameters of sidewalks and streetscapes of their network (Tsai et al., 2019). But there are wider buffered routes; for instance, 100 m buffers were taken for paths between school and home locations to measure students' exposure to the environment in the U.S. (Burgoine et al., 2015). All this means that the variance of street design might differ based on local characteristics, so the methods used should be strictly related to the network found in the study area.

1.6. Access to healthy travel environments

Inequalities in access to a healthy environment remain one of the main issues across Europe (EEA, 2019). Several factors have been linked to the rise of inequalities in exposure to air pollution, such as age groups, gender, ethnicity, socioeconomic status, and current health (Pinault et al., 2016; Sacks et al., 2011). The sociodemographic differences in access to a healthy physical environment were examined, with studies indicating that low-income populations are exposed to higher levels of air pollution and have less accessibility to green areas in Oslo (Venter et al., 2023) or inequalities between income and ethnic groups in terms of exposure to noise pollution in London (Tonne et al., 2018). Studies indicated that socioeconomic disparities are stronger than ethnic disparities in access to healthy physical environments (Hankey et al., 2017; Venter et al., 2023).

Incorporating sociodemographic data to address growing social polarisation regarding access to green areas is of great importance, especially in post-socialist countries (Csomós et al., 2020). Considering vulnerable groups individually can also be an effective way to visualise disparities between them, as they may experience different impact rates from environmental pollutants (Stansfeld et al., 2005).

Socioeconomic status and income level of people have affected the people's access to greenery and air pollution (Csomós et al., 2020; Luo et al., 2022; Venter et al., 2023). It has been found that wealthier population groups are exposed to higher levels of greenery and high air quality (Venter et al., 2023). Nevertheless, it can also be the opposite case, as people with high socioeconomic status often live in built-up areas containing lower levels of greenery (Luo et al., 2022). Specifically, the high socioeconomic status is associated with a high level of greenery; educated people live closer to urban greenery in the post-socialist city, Debrecen (Csomós et al., 2020).

To perform population-based analysis, scholars have used mobility data for cycling or walking (Hankey et al., 2017; Willberg et al., 2023). Another method is to use portable sensors to measure differences in exposure levels between individuals, although this method captured only selected routes in the study area (Apparicio et al., 2018). To observe the bigger geographic extent of sociodemographic differences in exposure rate to air pollution and greenery, analyses have been done using survey results, home locations of respondents and environmental layers (Orru et al., 2018; Wang et al., 2020). Other studies were based on population grids, finding a correlation between population density and spatial variability of greenery (Hua et al., 2022). The correlation between sociodemographic peculiarities and environmental variables has been studied using regression models and summary statistics (Tonne et al., 2018; Venter et al., 2023).

The growing importance of the 15-minute city aims to create a sustainable environment that promotes active travel: walking and cycling (Allam et al., 2022). However, it has been found that exposure to air pollution during walking and cycling is higher in residential neighbourhoods (Quiros et al., 2013). For instance, Luo et al. (2022) addressed greenery inequality using the 15-minute city concept at the residential level is the use of buffered zones within a 15-minute distance of the residence location. Thus, promoting healthy street network environments within 15-minute city concept from residential areas represents one of the bigger challenges nowadays.

2. Data and Methodology

2.1. Study area

The study area is Tallinn: the capital and most populated city in Estonia (Figure 1). The population of Tallinn is 450,846 inhabitants. Tallinn has eight administrative districts: Haabersti, Kesklinn, Kristiine, Lasnamäe, Mustamäe, Nõmme, Pirita, and Põhja-Tallinn (Tallinna Linnavalitsus, 2022)

Transport-related emissions remain the highest in Tallinn among other Estonian cities. At the same time, exposure to traffic-related pollutants decreased by $0.4 \mu\text{g}/\text{m}^3$ and $2.2 \mu\text{g}/\text{m}^3$ in terms of $\text{PM}_{2.5}$ and NO_2 in past years, meaning improvements in air quality. Tallinn experiences the lowest greenery among all cities in Estonia. There has been a slight improvement in past years, however it remains low (0,28) (Orru Hans et al., 2022). According to EEA (2020), Tallinn was one of the cities with the highest industrial noise pollution in Europe, and Estonia's traffic-related noise accounts for a high amount of total noise pollution.

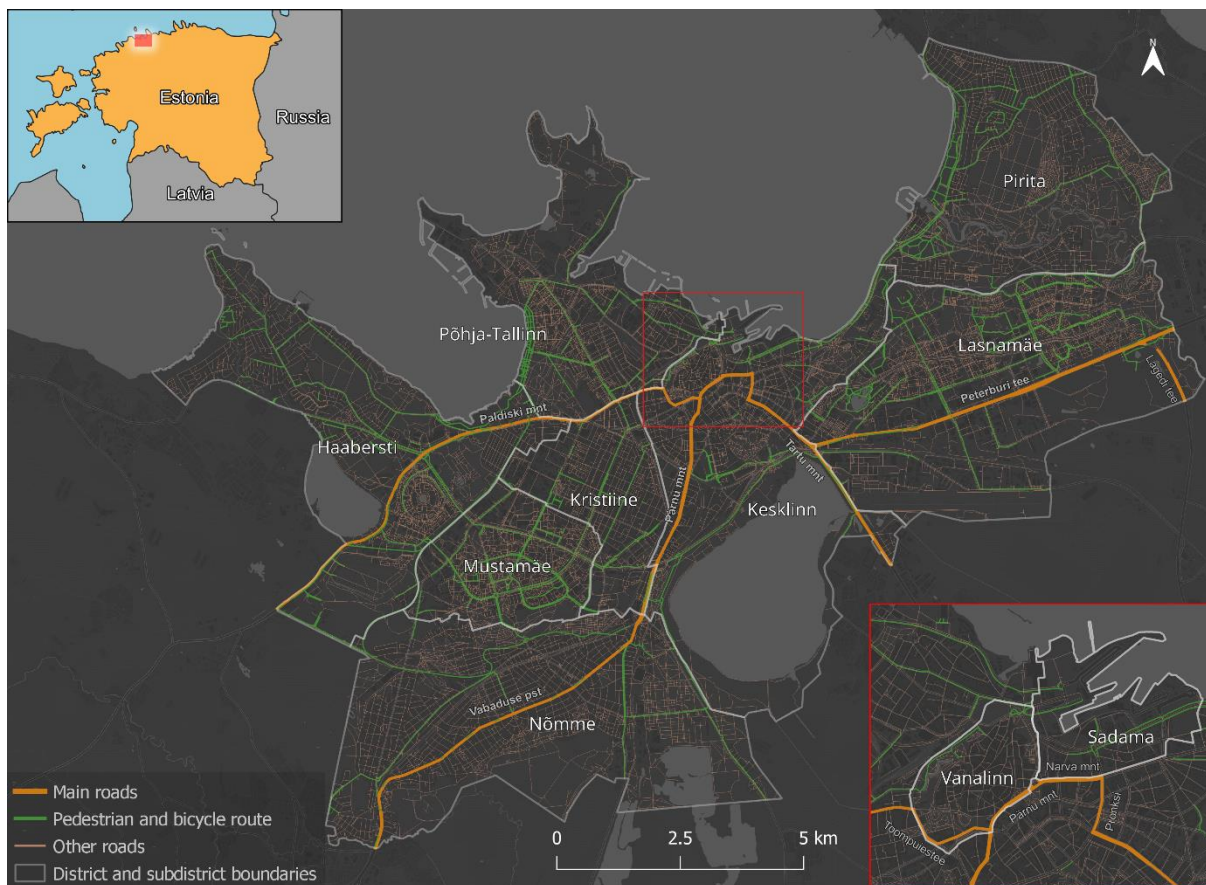


Figure 1. Tallinn city network and districts.

2.2. Data

This study focuses on the environmental quality of the city street and path network of Tallinn. The analysis used street network, NDVI, air pollution, noise pollution, population registry, population grid and Tallinn city borders data as outlined in Table 5.

Table 5. *Input datasets were used in this study.*

Data	Measure	Format	Sources and references
Street network data	n/a	Vector, shapefile	Estonian Land Board
Strategic noise data: L_{den} (day-evening-night)	dB (A)	Vector, shapefile	Tallinn City Government via the Department of Geography, University of Tartu
Annual air pollution: PM ₁₀ PM _{2.5} NO ₂	$\mu\text{m}/\text{m}^3$	Vector, shapefile, grid size 200x200 m, 2020	Institute of Family Medicine and Public Health, University of Tartu (Orru et al., 2022)
NDVI	n/a	Raster, TIFF, resolution 30x30m, June 18, 2021	Sentinel 2, via the Department of Geography, University of Tartu
Tallinn borders	n/a	Vector, shapefile	Tallinn City Government
Population grid	n/a	Vector, shapefile, grid size 500x500 m	University of Tartu Geography Department
Grid-aggregated population data: number of people, language groups, gender	No of people	Excel file, xlsx	Statistics Estonia via the Department of Geography, University of Tartu

Air pollution data contains PM₁₀, PM_{2.5}, and NO₂ vector grid data. The data were modelled from multiple sources using the Airviro system in 2022 and validated with data from national monitoring systems. The data is annual and belongs to 2020. It was calculated by taking the arithmetic mean of the hourly average values for each grid cell (Orru et al., 2022). Original PM₁₀, PM_{2.5}, and NO₂ data were shown in Annex 1.

Strategic noise data contains noise polygons modelled in 2022 for densely populated areas with noise levels exceeding 45 dB. The noise indicator is based on measurements taken 4 m above the ground, considering day, evening, and night times (L_{den}). The data is annual and includes the sum of all source noise levels. Original data can be visualised in Annex 1.

Population data analysis is based on a population grid shapefile and grid-aggregated data representing different population groups in CSV format. Grid-aggregated data was prepared by Statistics Estonia using registry information. Language and gender groups data for 2020 were used in this study. The original data, including the selected groups, were visualised in Annex 2.

2.3. Methodology of spatial distribution analysis

To project environmental variables in the street network, spatial analysis in Figure 2 was done using QGIS software (QGIS Development Team, 2021). Street segments longer than 200 m were divided into smaller segments. Following that, a street environment was created by adding a 25 m buffer zone on both sides of the segments. This approach is similar to the study by Tsai et al. (2019) and considers the width of sidewalks and viewsheds in buffer distance. In the next step, environmental layers were prepared for further analysis. Air pollution vector grids were rasterised, keeping their original resolution. The same tool was implemented for noise polygon data, setting the maximum resolution to capture all network segments. Similar to Song et al. (2019), the current study set the negative NDVI values to zero. This approach aims to eliminate negative values, as they do not represent greenery and reduce the mean greenery level during the calculations.

To project environmental variables in buffered street segments, Zonal Statistics tool was used. This computes the values of raster pixels within zones, which in this analysis, were buffered road segments (see Sonwalkar et al., 2010; Soysal et al., 2012). Buffered road segments were added as an input, and the rasterised datasets were used as a target field in Zonal Statistics. The final data contains street segments with the attributes of environmental variables (access to final data: https://github.com/GeoAyisha/thesis/tree/main/environmental_layers).

Some street segments did not obtain any value after projecting noise data, as the strategic noise map does not cover the street network, and the areas where the noise level is below 45 dB are not mapped. These segments were deleted from the data and shown as below 45 dB in the noise map of the street network.

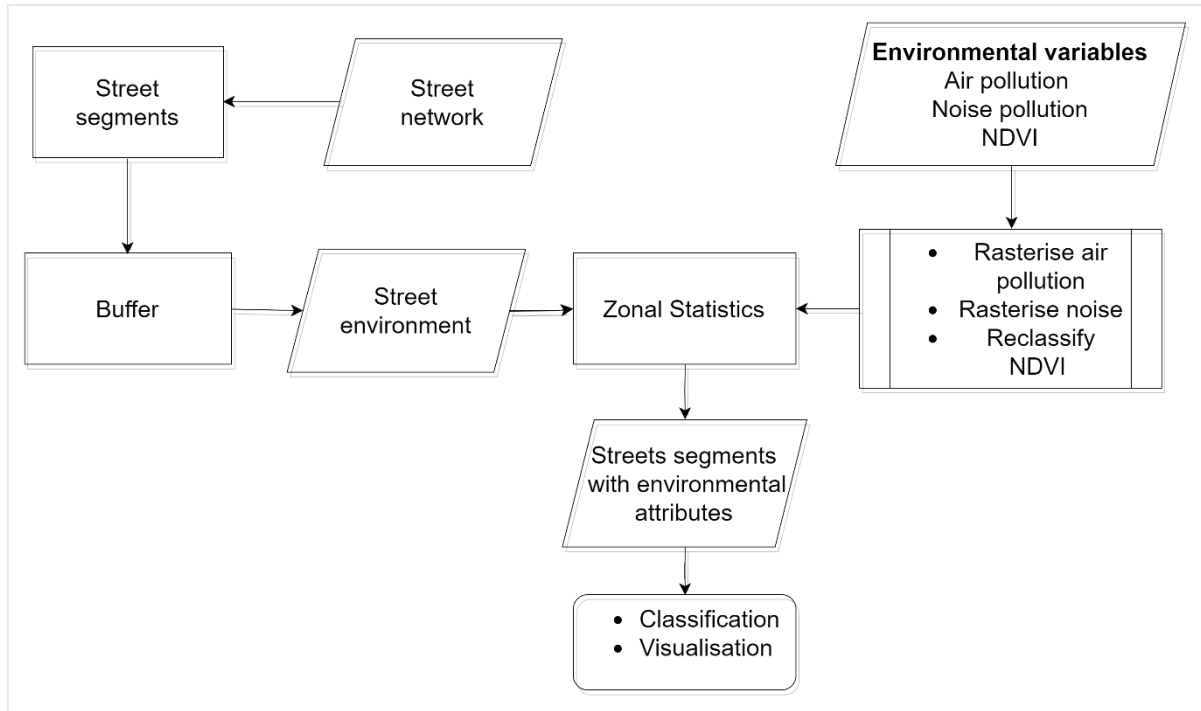


Figure 2. Workflow of the spatial analysis.

To visualise the output, the classification used for the air pollution is based on WHO air quality guideline levels of PM₁₀, PM_{2.5}, and NO₂, as well as interim targets level that needs to be achieved where the values exceed the air quality guideline levels (Table 6). The colour scale was applied according to healthy levels of air pollutants. The blue shades show the values of healthy levels, and the red shades represent the exceedance of health recommendations.

Table 6. The classification of air pollutants is based on interim targets and air quality guidelines defined by WHO (2021).

Classes	PM ₁₀ (µg/m ³)	PM _{2.5} (µg/m ³)	NO ₂ (µg/m ³)
Interim target 1	70	35	40
Interim target 2	50	25	30
Interim target 3	30	15	20
Interim target 4	20	10	-
Air quality guidelines	15	5	10

The healthy noise level is defined by WHO recommendations for traffic noise, which is 53 dB (WHO, 2018). Other class breaks of noise levels are 53dB, 60 dB, 65 dB, and 75 dB. Noise levels above health guidelines were shown in blue shades; noise levels above health guidelines were shown in red shades. There are no guidelines for greenery levels regarding health effects,

and greenery class breaks were defined as 0.2, 0.4 and 0.6. However, the values below 0.2 were shown in red colour to indicate low greenery (Hashim et al., 2019).

2.4. Correlation analysis

The Spearman correlation coefficient was done using R and R Studio (R Core Team, 2022; RStudio Team, 2022) to analyse the correlation between environmental variables. The input environmental values were taken from each road segment using the corresponding segment ID. The method was chosen based on data distribution. The normality of the data was tested by creating histograms for all variables due to large data samples. The data were not normally distributed (see Annex 2). If the data is normally distributed and has outliers, Spearman correlation coefficient can correctly examine the correlation between variables and handle ties (Mukaka, 2012). Firstly, correlation analysis was conducted between PM₁₀, PM_{2.5}, NO₂, and greenery. Correlation between noise and all other variables was performed separately and added to the matrix due to missing segment values in noise data. Spearman's rank correlation test was implemented to test the significance using $p < 0.001$ value represented in the tables as ***. The p-value represents the probability against the null hypothesis, which claims the absence of a relationship between the variables.

2.5. Social inequality analysis in access to healthy travel environment

Social inequality analysis in access to healthy travel environments in residential streets was performed by joining the summarised attributes by location using the intersect relationship between street network and distances from population grids. The work includes the spatial analysis part done in QGIS and the statistical analysis part done in Excel (Microsoft, n.d.). Firstly, the grid-aggregated population data with gender and language group was georeferenced. The residential street network includes all streets in the 1200 m street network distance buffer from the centroids of 500 x 500 m population grid cells. The environmental value of the residential street network represents the mean value of all streets in the buffer. The calculated distance refers to assessing inequality within the 15-minute city, similar to Luo et al. (2022). This approach makes buffer distance around the population grid centroid as creating a network distance was not possible due to the computing power requirements of service areas. Join Attribute by Location (summary) tool with intersect spatial relationship was adopted to calculate the sum of segment length and environmental values multiplied by segment length

for each buffer. These two resulting fields were divided to get weighted average values of environmental variables.

$$x_n \equiv \frac{a_1 d_1 + a_2 d_2 + \dots + a_n d_n}{d_1 + d_2 + \dots + d_n}$$

X is the grid ID, a is the environmental value, and d is the length of each segment.

In the final step, the grid data with language groups, gender groups and environmental attributes for each grid were exported to Excel to find the distribution access to healthy and unhealthy classes of respective environmental variables.

3. Results

3.1. Spatial distribution of environmental variables at the street-level

Table 7 presents the descriptive statistics of the environmental variables of the street network in Tallinn. The minimum PM₁₀ level is 6.77 µm/m³ with a 9.93 µm/m³ range. In contrast, the minimum value of PM_{2.5} is 4.68 µm/m³, with a range of 4.97 µm/m³ indicating the lowest variability. The minimum value of NO₂ is 2.59 µm/m³ with a range of 20.61 µm/m³, indicating the highest variability among air pollutants. The mean PM₁₀, PM_{2.5}, and NO₂ value of Tallinn street network is 8.99 µm/m³, 5.89 µm/m³, and 6.89 µm/m³, respectively. The mean noise value of the Tallinn street network is 54.61 dB and ranges between 45 and 75 dB. The mean greenery level based on NDVI is 0.45.

Table 7. *Descriptive statistics of environmental variables in the street network of Tallinn.*

Environmental variables	Measure	Min	Mean	Median	Max	Range
PM₁₀	µm/m ³	6.77	8.99	8.84	16.70	9.93
PM_{2.5}	µm/m ³	4.68	5.89	5.81	9.66	4.97
NO₂	µm/m ³	2.59	6.89	6.32	23.20	20.61
Noise	dB (A)	45	54.61	53.50	75.00	30.00
Greenery	-	0.03	0.45	0.46	0.84	0.81

Table 8 shows the length of segments regarding different classes of environmental variables. According to the results, 99.96%, 1.95%, and 88.62% of the segments, length-weighted, fall into the best air quality class of PM₁₀, PM_{2.5}, and NO₂, respectively, according to the air quality guidelines. The rest of the segments do not meet the health recommendation levels of PM₁₀ and PM_{2.5}. Additionally, 11.31% and 0.06% of segments need to achieve air quality guideline levels and interim target 3 level for NO₂, respectively. 49.34% of the segment's length falls into healthy level of noise pollution, which is 53 dB. Greenery level is high (between 0.4–0.83) in 67% of street segment length, and 5.83% of the street segment length have a greenery value below 0.2.

Table 8. Descriptive statistics of street segments by length and by the classes of environmental variables.

Classes	Total length		Count	Min	Max	Mean	Median
	km	%					
PM₁₀							
≤15	2,621.09	99.96	42,489	0.01	200.00	61.69	44.1
>15...≤20	1.17	0.04	26	5.11	194.86	44.99	38.65
PM_{2.5}							
≤5	51.21	1.95	470	0.01	200.00	108.98	43.83
>5...≤10	2,571.03	98.05	42,045	0.01	200.00	61.15	102.81
NO₂							
≤10	2,323.82	88.62	37,366	0.01	200.00	62.19	44.63
>10...≤20	296.76	11.32	5,132	0.38	200.00	57.83	40.52
>20...≤30	1.67	0.06	17	9.88	200.00	98.33	41.57
Noise							
<53	1,139.74	49.34	18,354	0.01	200.00	62.10	46.28
≥53...<60	527.11	22.82	8,912	0.01	200.00	59.15	42.71
≥60...<65	359.61	15.57	6,141	0.03	200.00	58.56	37.94
≥65...<75	282.73	12.24	4,479	0.06	200.00	63.12	37.72
≥75	0.89	0.04	7	5.4	200.00	58.55	199.99
Greenery							
≤0.2	152.79	5.83	2,333	0.47	200.00	65.49	45.14
>0.2...≤0.4	715.37	27.28	13,033	0.01	200.00	54.89	36.09
>0.4...≤0.6	1,192.62	45.48	19,584	0.07	200.00	60.90	44.84
>0.6	561.48	21.42	7,565	0.01	200.00	74.22	56.47

Figure 3 shows the spatial distribution of PM₁₀ in the street network of Tallinn. Healthy classes are shown in gradient blue, with darker tones indicating a healthier environment and lighter shades of blue stressing a closeness to air quality guidelines. Most streets represent the healthy level of PM₁₀ below 15 µm/m³. Only 16 segments (0.04%) have higher PM₁₀ levels. These segments are in the city centre, close to the port area. Streets with the lowest PM₁₀ values are in the suburbs of the city.

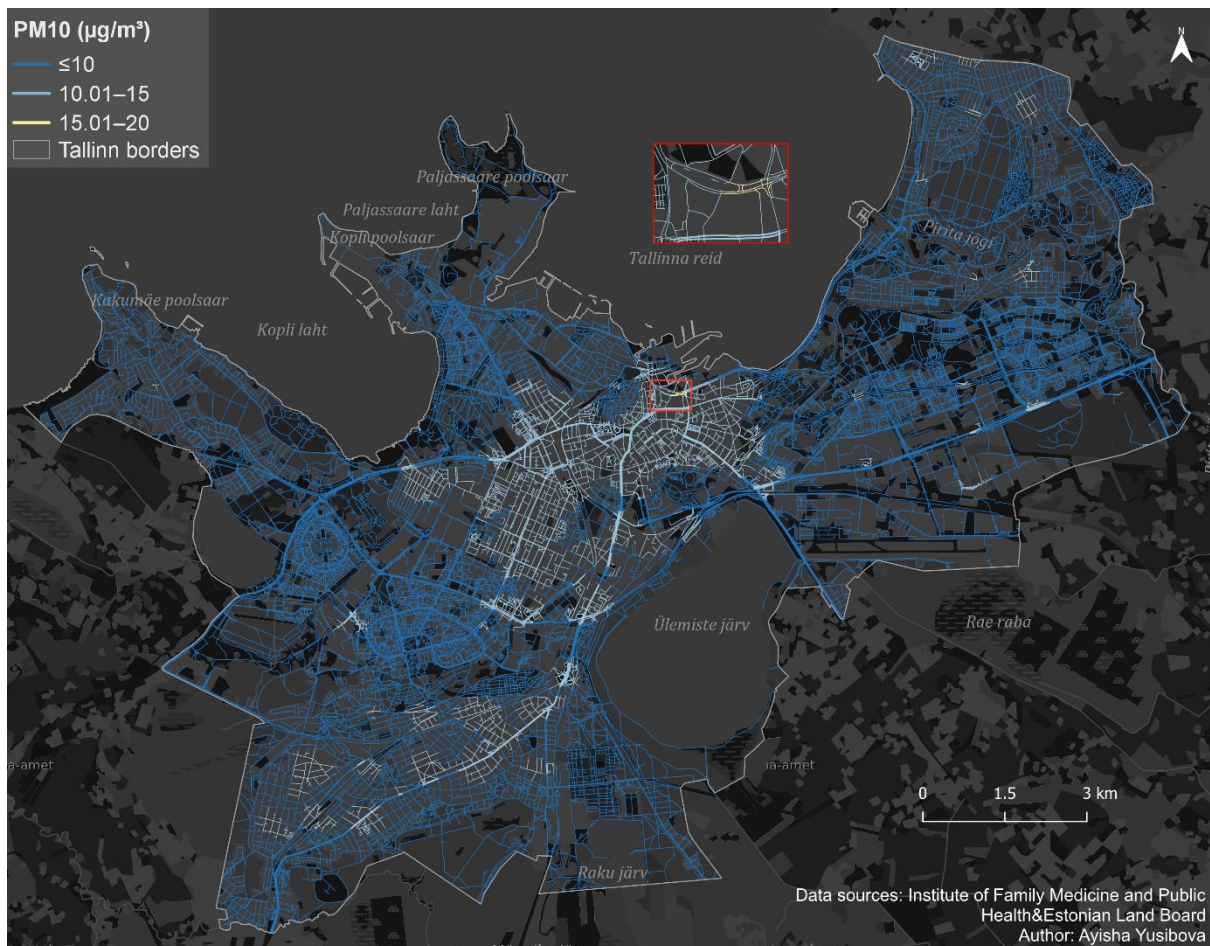


Figure 3. The spatial distribution of PM₁₀ in the street network of Tallinn. 10 µm/m³ is health recommendation and 20 µm/m³ is interim target 4 defined by WHO (2021).

Figure 4 presents the spatial distribution of PM_{2.5} in the street network of Tallinn. 98.05 % of the street segment length in Tallinn had PM_{2.5} pollutant concentrations between 5 µm/m³ and 10 µm/m³, exceeding health recommendations, despite the low spatial variation. Streets close to industrial hubs, in the city centre, particularly the port area, and intersections have higher values (6.5–10 µm/m³) than other streets in the suburbs. Only 1.95 % of street segment length is in the healthy class of PM_{2.5} with concentrations below 5 µm/m³. These streets are on the edges of the city.

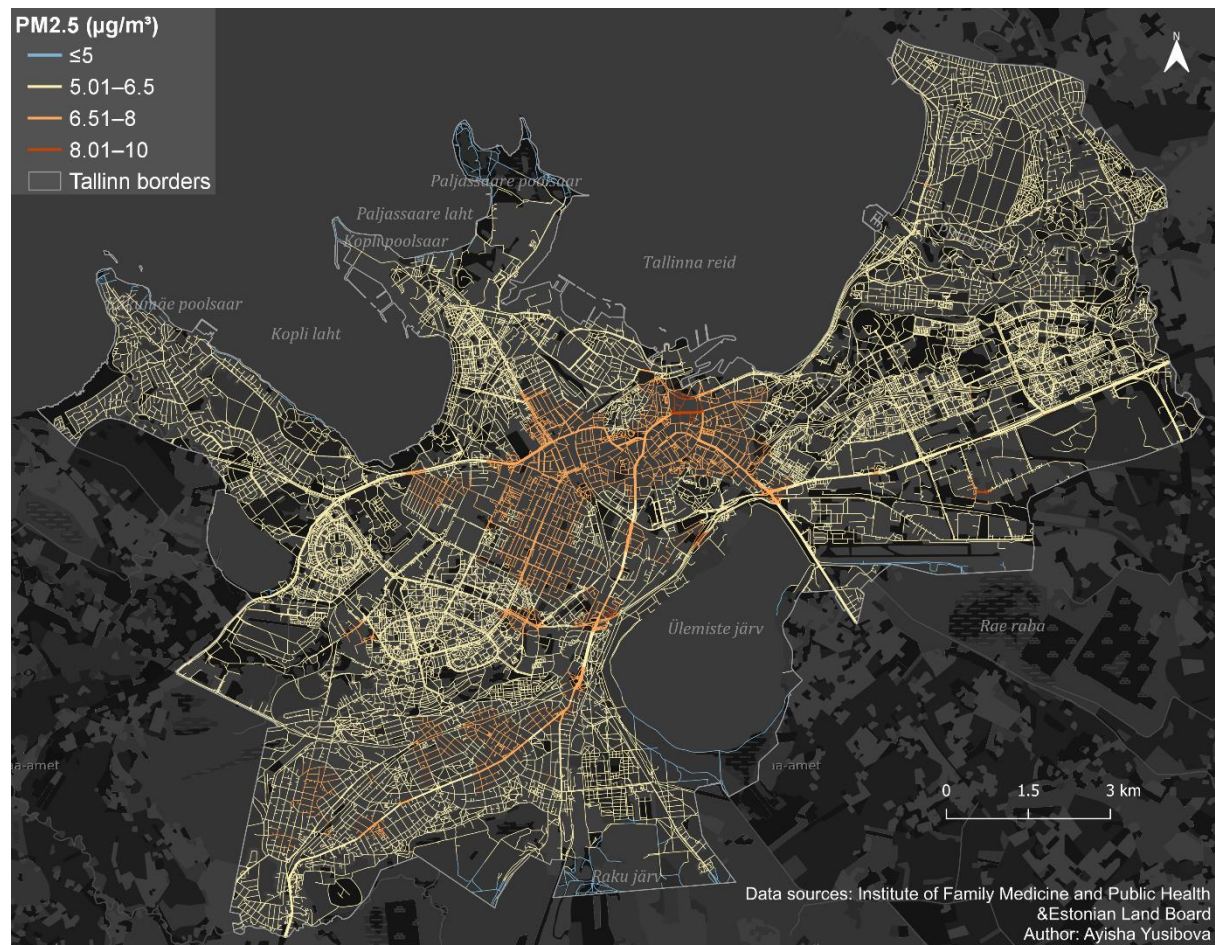


Figure 4. The spatial distribution of PM_{2.5} in the street network of Tallinn. 5 µm/m³ is health recommendation, and 10 µm/m³ is interim target 4 defined by WHO (2021).

Figure 5 indicates the spatial distribution of NO₂ in the Tallinn street network. 88.62 % of the street segments represent healthy levels of NO₂ concentration according to the air quality guidelines, below 10 µm/m³. These streets are located in the suburbs. NO₂ values increase in road intersections, two-lane roads, and roundabouts. Main road intersections get the highest values between 20–23.2 µm/m³, above the level of interim target 3 and contributing 0.06 % of street segment length. Similarly, the concentration of NO₂ exceeds health recommendations in streets located in Kesklinn with values between 10 and 20 µm/m³, i.e., above the air quality guidelines level. Street segment length with values between 10 and 20 µm/m³ accounts for 11.32 % of the total segment length.

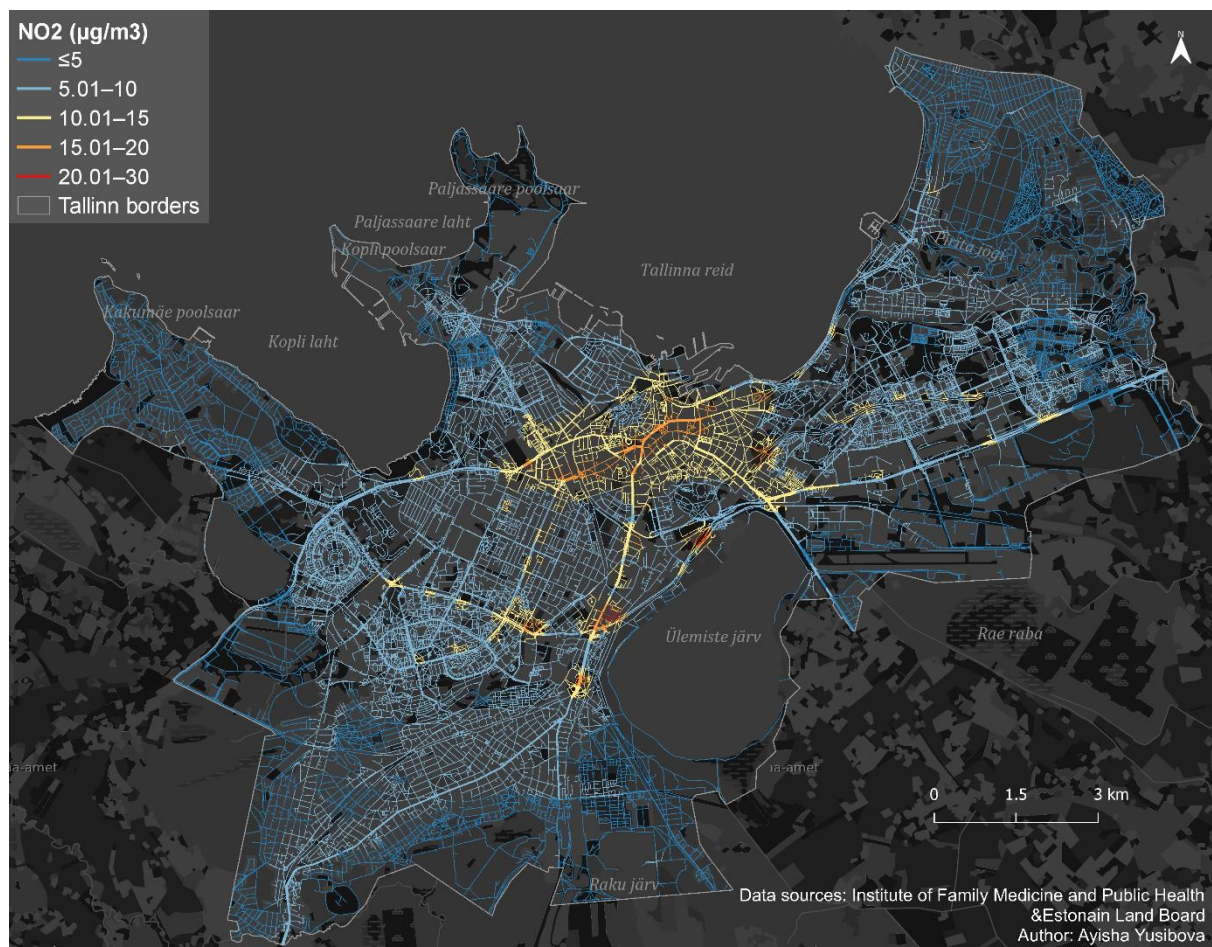


Figure 5. The spatial distribution of NO₂ in the street network of Tallinn. 10 µm/m³ is health recommendation, 20 µm/m³ is interim target 3 and 30 µm/m³ is interim target 2 defined by WHO (2021).

Figure 6 shows the spatial distribution of noise pollution in the street network of Tallinn. 49.34 % of street segments' length met the health recommendations below 53 dB. These streets are in the suburbs, far from the main streets and old town. The noise level in main streets significantly exceeds the healthy level, ranging between 53 and 75 dB. Moreover, noise levels exceed the health recommendations in streets in Kesklinn district, which connects the street centre to other parts and cities. The large parts of streets are straight with two-lanes where the noise level exceeds 65 dB. Apart from this, it is possible to see the effects of airport and railway on the closest streets (60 dB).

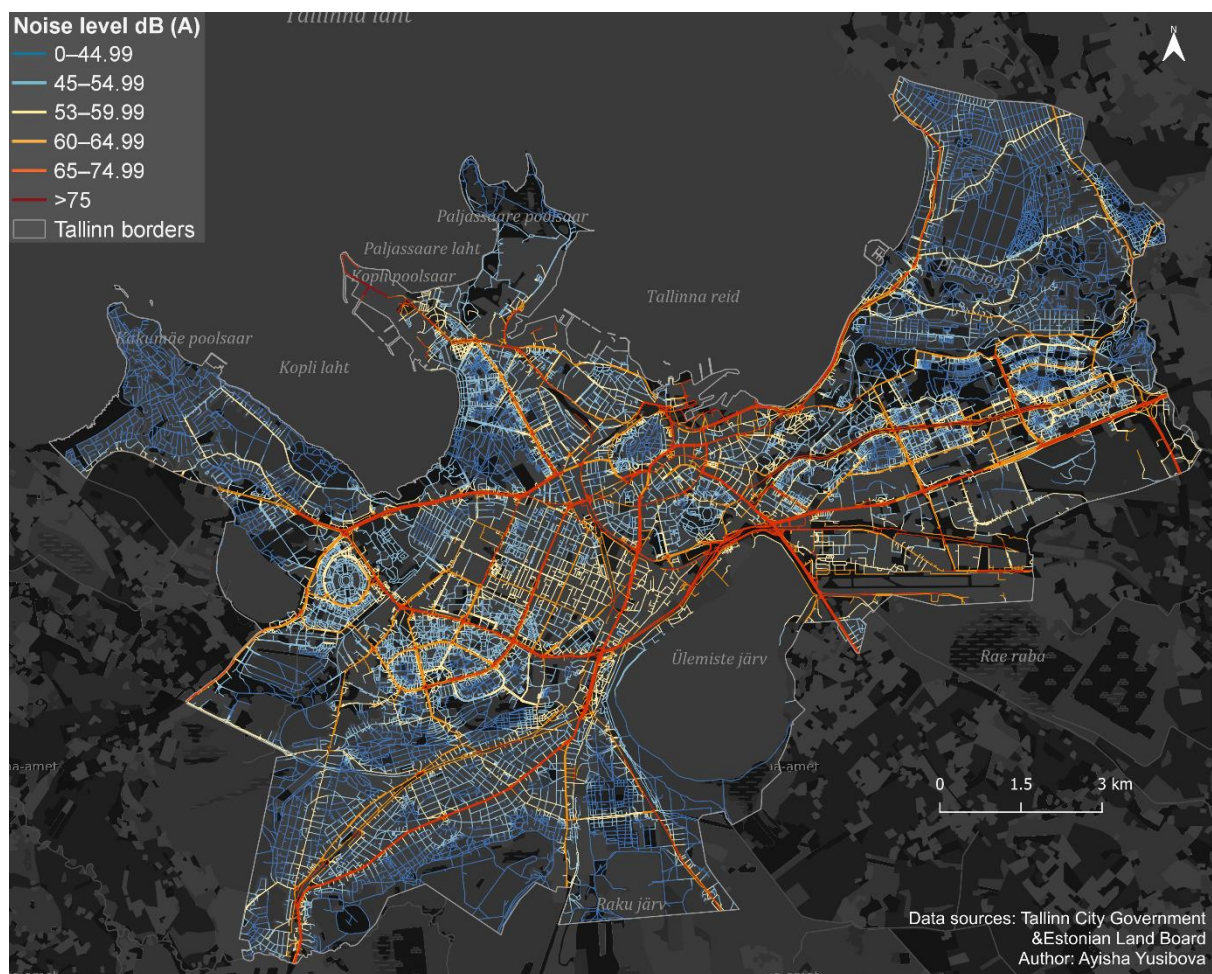


Figure 6. *The spatial distribution of noise in the street network of Tallinn. 53 dB is health recommendation defined by WHO (2018).*

Figure 7 presents street-level greenery based on NDVI layer. The presence of greenery in the streets of Tallinn is high overall. Street segments with the lowest greenery values below 0.2 are located in the city centre, including the old town and port area, along the main roads, and in industrial areas or airport. Streets with greenery values between 0.2 and 0.4 are mostly main streets or residential areas, such as Lasnamäe, Mustamäe or Pelgulinn. Local streets in low-density residential areas, such as Piritä, Kristiine, or Nõmme, have greenery values between 0.4 and 0.6. Streets or paths in recreational areas and urban forests represent greenery values above 0.6.



Figure 7. The spatial distribution of greenery in the street network of Tallinn. There are no guidelines for greenery levels.

3.2. Correlation analysis

The correlation between multiple environmental variables of the street network, i.e., air pollution indicators, noise pollution, and NDVI, was analysed using Spearman correlation coefficient r . The results are shown in Table 9. A very high positive correlation was found between particulate matter, i.e., PM_{10} and $PM_{2.5}$ ($r=0.93$, $p<0.001$). A strong positive correlation was found between NO_2 and PM_{10} ($r=0.78$, $p<0.001$), as well as between NO_2 and $PM_{2.5}$ ($r=0.74$, $p<0.001$). The correlation between noise and air pollutants is positive but low: the correlation coefficient between noise and both $PM_{2.5}$ and PM_{10} is 0.25 ($p<0.001$), and between NO_2 and noise, it is 0.35 ($p<0.001$). NDVI has a moderate to low negative correlation with noise and NO_2 , with correlation coefficients being -0.40 and -0.46, respectively ($p<0.001$).

Table 9. Spearman correlation analysis between noise, air pollution, and greenery.

Variable	PM_{10}	$PM_{2.5}$	NO_2	Noise	NDVI
PM_{10}	1,00***	0,93***	0,78***	0,25***	-0,22***
$PM_{2.5}$	0,93***	1,00***	0,74***	0,25***	-0,24***
NO_2	0,78***	0,76***	1,00***	0,34***	-0,40***
Noise	0,25***	0,25***	0,34***	1,00***	-0,46***
NDVI	-0,25***	-0,24***	-0,41***	-0,46***	1,00***

*** Statistical significance $p < 0.001$

3.3. Social inequality assessment

Table 10 shows the number of people in total and per language and gender groups who have access to streets with healthy or other levels of environmental variables in their residential street network, according to population registry data. The residential street network includes all segments within a 1200 m buffer distance. The environmental value of the residential street network represents the mean value of all streets in the buffer. All people have access to healthy travel environments in terms of PM_{10} (below $10 \mu\text{m}/\text{m}^3$) within the residential street network. None of the population groups has access to healthy travel environments in terms of $PM_{2.5}$. In their residential street network, people are exposed to levels between 5 and $10 \mu\text{m}/\text{m}^3$ above air quality guideline level. 83.66% of the population is exposed to a healthy level of NO_2 , which is below $10 \mu\text{m}/\text{m}^3$. Only 21.05% of the population has access to healthy noise levels, i.e., below 53 dB. There are no population groups for whom the greenery level in the residential street network belongs to the lowest class below 0.2.

Table 10. The number of people having access to the residential street network of a certain environmental quality, according to the population registry data and the mean value of environmental variables in the residential street network.

Variables	Total population		Estonian speakers		Russian speakers		Other language speakers		Female		Male	
	N	%	N	%	N	%	N	%	N	%	N	%
PM₁₀												
≤15	437,586	100	218,965	100	187,753	100	21,894	100	238,553	100	199,033	100
>15...≤20	0	0	0	0	0	0	0	0	0	0	0	0
PM_{2.5}												
≤5	0	0	0	0	0	0	0	0	0	0	0	0
>5...≤10	437,586	100	218,965	100	187,753	100	21,894	100	238,553	100	199,033	100
NO₂												
≤10	366,091	83.66	172,715	78.88	172,310	91.77	15,903	72.64	200,317	83.97	165,774	83.29
>10...≤20	71,495	16.34	46,250	21.12	15,443	8.23	5,991	27.36	38,236	16.03	33,259	16.71
>20...≤30	0	0	0	0	0	0	0	0	0	0	0	0
Noise												
<53	92,086	21.05	53,311	24.35	33,671	17.93	3,811	17.41	49,106	20.59	42,980	21.60
≥53...<60	341,483	78.05	163,338	74.60	153,110	81.55	17,712	80.91	187,506	78.61	153,977	77.37
≥60...<65	3,976	0.91	2,291	1.05	959	0.51	368	1.68	1,922	0.81	2,054	1.03
≥65...<75	0	0	0	0	0	0	0	0	0	0	0	0
≥75	0	0	0	0	0	0	0	0	0	0	0	0
NDVI												
≤0.2	0	0	0	0	0	0	0	0	0	0	0	0
>0.2...≤0.4	112,827	25.78	60,187	27.49	40,019	21.31	8,039	36.72	61,044	25.59	51,783	26.02
>0.4...≤0.6	322,972	73.81	157,537	71.95	147,269	78.44	13,792	62.99	176,580		146,392	73.55
>0.6	1,787	0.41	1,241	0.57	465	0.25	63	0.29	929		858	0.43

Figure 8 shows the proportion of gender and language groups with access to healthy or unhealthy classes of NO₂ within the residential street network. About 90% of residents belonging to the Russian language group, according to the population register data, are exposed to healthy levels of NO₂, i.e., below 10 µm/m³. The second proportion belongs to Estonian language group with 79%, while around 73% of other language group is exposed to the same class of NO₂. The proportion of female and male groups is about the same, with 83% and 84% having access to healthy levels of NO₂ in residential street network, respectively.

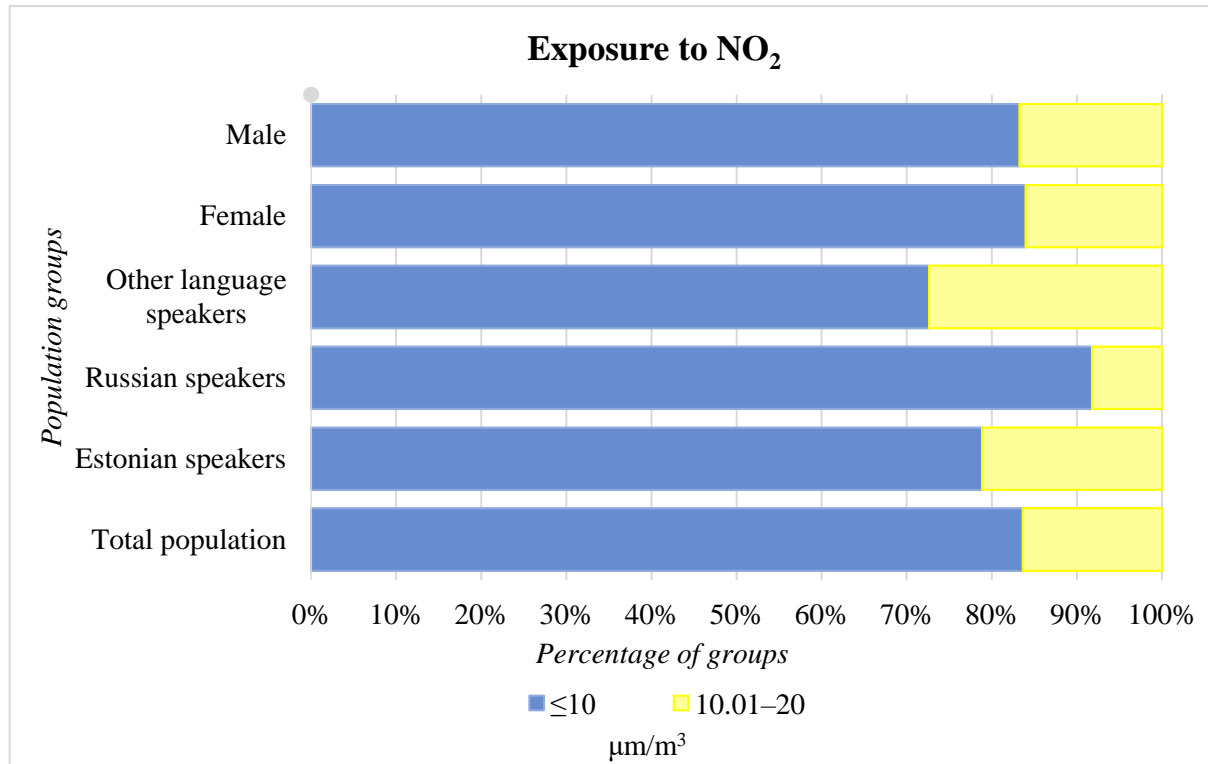


Figure 8. Distribution of access to healthy or unhealthy level of NO₂ in the residential street network among the population of Tallinn. 10 µm/m³ is the health recommendation for NO₂ and 20 µm/m³ is interim target 4 as defined by WHO (2021).

Figure 9 shows the proportion of gender and language groups with access to healthy or unhealthy noise classes within the residential street network. Approximately 24% of Estonian-speaking group has access to residential street network with noise levels below 53 dB, which meets the health recommendations. Approximately 18% of Russian speakers and 17% of other language speakers group have access to healthy noise levels. Additionally, other language speakers' group is slightly more exposed to noise levels ranging between 60 and 65 dB than Estonian- and Russian speakers. The proportion of female and male groups is about the same, with 21% and 22% having access to healthy noise levels in residential street network, respectively.

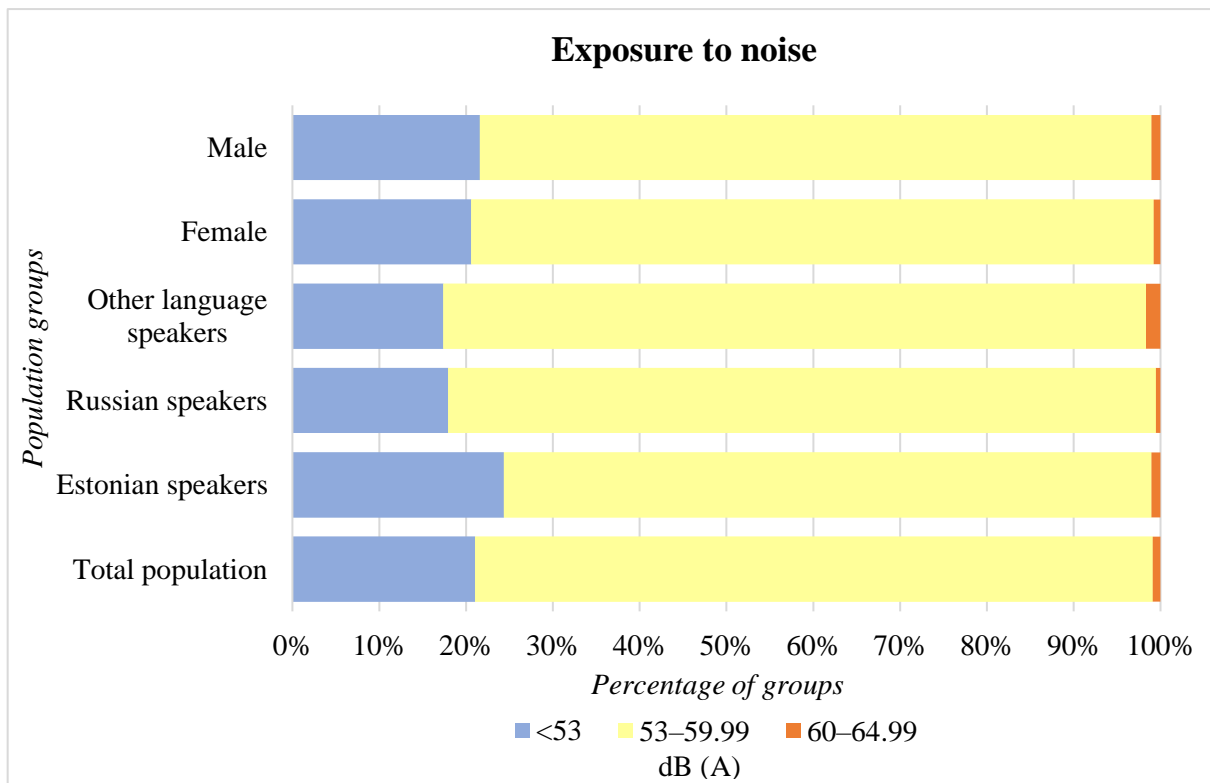


Figure 9. Distribution of access to healthy or unhealthy level of noise in the residential street network among the language and gender groups in Tallinn. 53 dB is the health recommendation for traffic noise pollution as defined by WHO (2018).

Figure 10 indicates the variation of access to greenery levels (defined by NDVI) in residential street network between language and gender groups. Access to residential street network with greenery levels between 0.41 and 0.6 is the highest among the Russian speakers' group (78%), followed by Estonian speakers' group (72%) and other language speakers' group (63%). The rest of the population has access to residential street network with greenery levels between 0.21 and 0.4, besides 0.6% of Estonian speakers and 0.3% of both Russian and other speakers' group having access to greenery levels above 0.6.

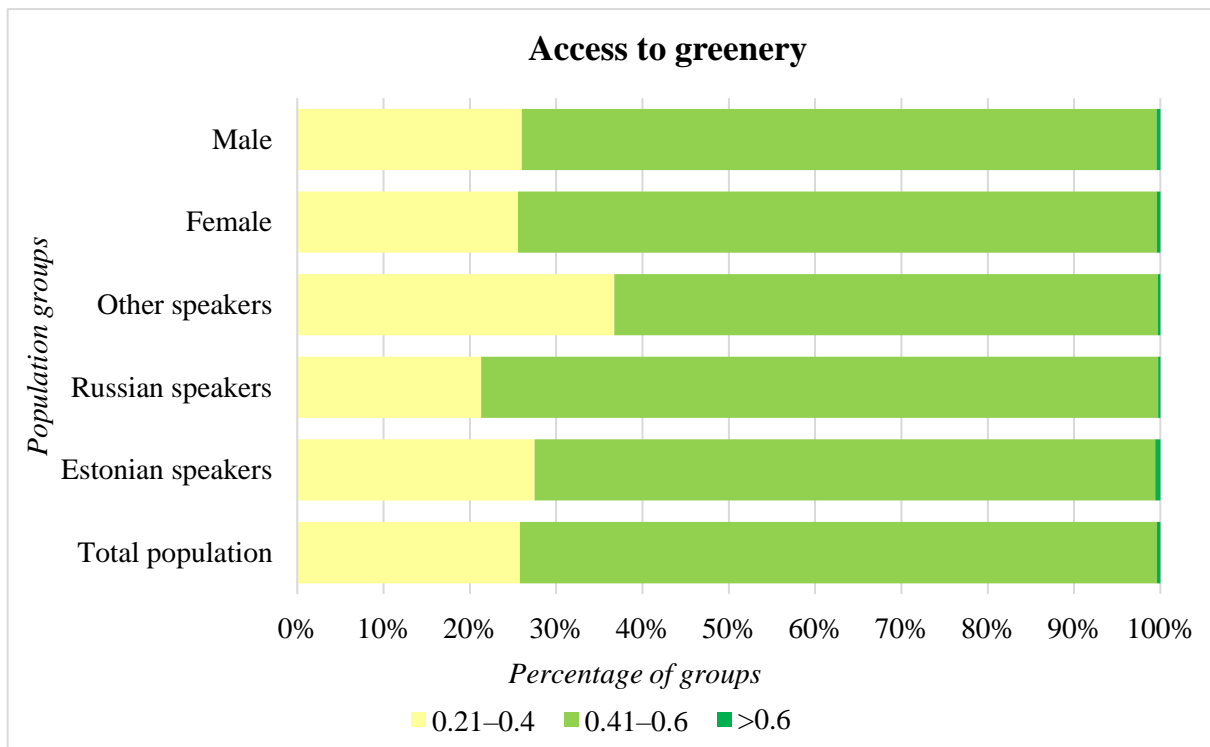


Figure 10. *Distribution of access to greenery among language and gender groups in Tallinn. Greenery levels do not have health recommendations.*

4. Discussion and conclusions

This study created a spatial layer of environmental variables for the street network of Tallinn using existing environmental surface layers. The environmental condition of streets was examined using health recommendations and internationally recognised guidelines in terms of air pollution and noise pollution. This study shows street-level greenery as a pathway to mitigate the adverse effects of air and noise pollution in travel environments. Considering these aspects, correlation analyses were conducted between these variables in street environments. Using spatial layers of street-level environmental variables, this study showed the possibility of performing population-level exposure analysis to investigate the distribution of access to healthy travel environments between language groups and gender groups within the residential street network.

The spatial analysis reveals that 99.96%, 1.95%, and 88.62% of street segments met recommended air quality guideline levels of PM₁₀, PM_{2.5}, and NO₂, respectively (WHO, 2021). However, the rest of the segment length exceeds the health recommendations, indicating the need to improve air quality and achieve the air quality guideline levels. This study found the level of PM₁₀ above health recommendations in 0.04% of street segment length, which is in the city centre close to the port area. This area can be accounted for new development areas and economic centres where there is high traffic capacity. Implications in reducing PM_{2.5} concentrations are emerging, as 98.05% of the street segment's length exceeds the health recommendations. This study found a low spatial variation of PM_{2.5} in Tallinn street network, with concentrations ranging between 4.68 µg/m³ and 9.66 µg/m³. The streets with the highest concentrations are industrial hubs, road intersections, and central streets. These findings suggest that traffic patterns and industrial activities have increased the concentration of PM_{2.5} in Tallinn street network. This study aligns with the results of previous studies that observed consistent spatial variability and linked to the presence of traffic and industrial activities (Hankey et al., 2017). This study found high spatial variability of NO₂ concentrations at the street-level, ranging between 2.59 and 23.2 µg/m³. 11.32% of the street segment's length exceeds health recommendations between 10 and 20 µg/m³. 0.06% of segments need to achieve interim target 3 level and then air quality guideline level. NO₂ levels above air quality guideline levels are in various locations: major roads, major roads intersections, two-lane roads, most central streets, and close to economic centres. These results suggest that high traffic capacity and velocity robustly affect increased NO₂ concentrations. In line with the study results of Sun

et al. (2022) found a higher level of NO₂ concentrations in major roads compared to other local roads with high traffic speeds.

In this study, the analysis of the Tallinn street network revealed that approximately 49.34% of the segment length falls within the healthy level of noise pollution. However, the remaining segments were found to be within the health recommendations. The main streets, characterised by their two-lane configuration, straight design, proximity to the port area, industrial zones, airport, railway tracks, and high traffic capacity, indicated the highest noise levels (above 65 dB). This study's findings align with the results of a study conducted by Sheng & Wa Tang (2011) in Macao Peninsula, China, a port city. Sheng & Wa Tang (2011) observed the highest noise levels in logistics centres and roads with more than two lanes, while lower noise levels were observed in local roads. However, compared to that location, Tallinn's historical centre demonstrates a healthier noise pollution level.

5.83% of street segments length have the lowest greenery below 0.2. The lowest level of greenery is in the city centre, new development areas, and close to the port area. This study's results are consistent with a study by Hua et al. (2022) that indicated greenery in the central city, particularly in new development areas characterised by a mix of economic centres and residential areas in Hong Kong. This study also aligns with the results of Willberg et al. (2023), that found the lowest greenery in the port area highest greenery in the suburbs of Helsinki.

Correlation analysis was performed to address the correlation between environmental variables at the street-level. Results revealed a high positive and statistically significant correlation ($p < 0.001$) between all pairs of air pollutants: PM₁₀, PM_{2.5}, and NO₂. Their common source—road transport, as presented by IARC (2016) results in a high positive correlation between NO₂ and both particulate matter. The correlation between PM_{2.5} and PM₁₀ is the highest among all other pairs. Olstrup et al. (2022) reported a strong positive correlation (0.70) between PM_{2.5} and PM₁₀. Furthermore, their study found a moderate to a low positive correlation between NO₂ and PM_{2.5} (0.4) as well as between NO₂ and PM₁₀ (0.5) using Pearson correlation analysis at the city level in Tallinn. In contrast, this study found a higher correlation between all three pairs (0.93, 0.74 and 0.78, respectively) by measuring them at the street-level and using Spearman correlation while not looking for a linear relationship between pairs. Okokon et al. (2017) state that NO₂ is related to speed limit and traffic, which results in a high correlation with particulate matter. However, studies indicate more common sources for PM_{2.5} and PM₁₀, such as industrial and natural sources, which can explain these two having the highest

correlation at the street network level (IARC, 2016). A negligible negative correlation (-0.22) was observed between particulate matter and greenery, and a slightly stronger correlation (-0.33) between NO₂ and greenery, both correlations being statistically significant ($p < 0.001$). While this is a weak eventual relation, a negative correlation between air pollution and greenery has also been observed elsewhere (e.g., by Klompaker et al., 2020). A moderate to low correlation (-0.46) was found between noise and greenery, being statistically significant ($p < 0.001$). Similarly, Willberg et al. (2023) found evidence for a moderate negative correlation (-0.41) between greenery and noise in cyclists' routes in Helsinki. A study conducted by (Sheng & Wa Tang, 2011) shows that high green cover in urban areas may result in the reduction of noise levels. According to the positive effects of greenery in street environments stated by Säumel et al. (2016), the present study's findings suggest that enhancing greenery initiatives in Tallinn may reduce adverse health effects from air and noise pollution.

To examine the distribution of access to healthy travel environments between gender and language groups, this study analysed the values of environmental variables in the residential street network according to population registry data. The results identified equality between gender groups in access to healthy travel environments in the residential street network. That might be related to their similar spatial distribution in Tallinn. However, this research found inequality between language groups in access to healthy travel environments. All language and gender groups have access to healthy travel environments in terms of PM₁₀. In contrast, none of these groups has access to healthy levels of PM_{2.5}. This result is in line with the report of EEA (2022) that 98% of the total population in Europe expose to PM_{2.5} levels below health recommendations. Russian speakers' group has better access to healthy travel environments regarding NO₂ and greenery than Estonian and other speakers' groups. However, Russian speakers' group has less access to greenery than Estonian speakers' group. Other speakers' group has the lowest accessibility in terms of all environmental variables due to a high proportion living in the city centre, where air and noise pollution have the highest and greenery has the lowest values. The recent study has found no difference between Norwegian native speakers and immigrants in access to healthy residential environments regarding air pollution and greenery, showing more influence of socioeconomic status in Oslo (Venter et al., 2023). However, the proportion of minority language speakers in Tallinn is higher than in Oslo. Another study found inequalities between ethnic groups in exposure to air pollution linked to residential segregation, having minority groups exposed to higher levels of PM₁₀, PM_{2.5}, and NO₂ in the USA (Woo et al., 2019). In contrast, the current study found that Russian speakers'

groups had better access to healthy travel environment in terms of NO₂ and greenery compared to the majority group of Estonian speakers. Nevertheless, other language speakers' group was exposed to the highest levels of NO₂.

This study developed the methodology to create the spatial layers of environmental variables at the street-level and to investigate social inequality in access to healthy travel environments between language and gender groups in the residential street network. Using the same methodology, more work is needed to study other population groups, such as age and socioeconomic, as inequality was often observed between these groups in their exposure to different environmental variables rather than language groups (Luo et al., 2022; Tonne et al., 2018; Venter et al., 2023).

The current study used annual air pollutant indicators and NDVI data from the greenest month. However, these environmental variables showed spatial temporality at the street level over studies (Nourmohammadi et al., 2021; Sun et al., 2022). Having access to models of higher temporal resolution for environmental layers helps researchers to develop dynamic street network environmental attributes that could be used to perform exposure analysis of people's daily mobility. For example, a recent study used GPS tracking to measure exposure to greenery during walking (Vich et al., 2019). In some cases, these measurements might not examine the real perception of environmental quality; studies emphasised that measured environmental quality indeed differs from precepted one, which may affect the level of symptoms caused and wellbeing of people (Orru et al., 2018; Tonne et al., 2018). Further research is also needed better to understand the perceived environmental quality of travel environments.

Several factors, such as road safety, street intersections, traffic density, and land use characteristics, were shown to be the main indicators of pedestrian environment (Sousa et al., 2019). However, air quality, noise, and greenery were found to affect people's route choices (Bunds et al., 2019). Although selecting healthy routes increases travel time, it may decrease the exposure to multiple environmental variables during active travel (Wang et al., 2018). For enhancing environmental exposure during active travel, the information about environmental quality is needed to integrate alongside traditional aspects such as safety, monetary costs, and utility of travel. This study's results would help individuals to optimise their routes in Tallinn. Moreover, the results can be used to create available tools to find optimised routes for air pollution, noise pollution, and greenery in Tallinn. For instance, Green Path software finds

exposure-optimised routes for its users in terms of multiple environmental variables. This application was implemented in Helsinki, Finland (Helle et al., 2021).

This study covered the most alarming air pollutants in Europe. Still, there are other air pollutants found in travel environments and related to road transportation, such as carbon monoxide (CO), black carbon (BC), ozone (O₃), and ultrafine particles (UFP) (Hankey et al., 2017; Sun et al., 2022). Even though CO and BC were less studied than other air pollutants, they were found to have high inhalation doses by pedestrians and cyclists in Barcelona (de Nazelle et al., 2012, 2017). Concentrations of O₃, BC and UFP are linked to several adverse health effects such as mortality, changes in lung functions, inflammation, and allergic diseases in European cities (Olstrup et al., 2022; Stafoggia et al., 2022; WHO, 2021). Enwidening the scope of analysis by adding mentioned air pollutants and other environmental indicators, such as urban heat, would help to get more comprehensive information about the environmental quality of streets.

There are some limitations in this study. This study did not cover all street segments with noise attributes, which may reduce the value of the correlation coefficient. Missing segment data resulted from strategic noise map covering only the areas above 45 dB (Lind et al., 2022). According to the temporality of used datasets, this study only used the NDVI data from one season when greenery has the highest reflectance and greenery and annual air pollution. However, this study aimed to show the overall presence of greenery and its accessibility. Interpretation of healthy and unhealthy classes of greenery level is limited due to a lack of health-related greenery studies and guidelines. Another limitation of the study is using buffered distance instead of network distance to define the 15-minute residential street network. Network distance could be created by adding service areas around building data containing population estimates or population grids. However, this study had to use buffer distance from grid centroids instead due to technical issues related to the high computational power required to create service areas.

This study emphasises the importance of incorporating multiple environmental variables in travel environments. It aims to increase public awareness about the environmental quality of street network and identify healthy and unhealthy routes. By identifying vulnerable groups with limited access to healthy travel environments, urban planners and policymakers can address environmental injustice. Additionally, promoting equal and high street environmental quality

in Tallinn through improvements in green urban infrastructure and reduction of air and noise pollution is one of the pathways to enhance public health and urban liveability.

5. Summary

The objectives of this work were to project environmental variables, such as air pollution indicators, noise pollution, and greenery in Tallinn's street network and use resulting data to address social inequality between language and gender groups in access to healthy travel environments within their residential street network.

The input datasets for mapping environmental variables included vector grids for PM₁₀, PM_{2.5}, and NO₂, raster NDVI data for greenery, and vector polygons for noise. The grid-aggregated population data centroids were considered as the individuals' home locations, and a 15-minute walking distance buffer was used to identify the residential street network. The weighted average environmental data was calculated to indicate environmental quality within these service areas.

Results showed that 98%, 11%, and 51% of street segment length meet health recommendations of PM_{2.5}, NO₂, and noise, respectively. The rest of the street segment's length needs to achieve health recommendations. This study found a significant moderate to weak correlation between greenery and NO₂, as well as greenery and noise. Results suggest improving green urban infrastructure in unhealthy routes. Social inequalities exist between language groups in access to healthy travel environments. Russian speakers' group has better access than Estonian speakers' and other speakers' group regarding NO₂ and greenery. In contrast, Estonian speakers' group has better access than Russian speakers' and other speakers' groups in terms of greenery.

Further research is needed to extend the scope of analysis, adding more environmental quality indicators, such as air pollutants and urban heat, to ensure liveable streets and investigate the inequality between other population groups in access to healthy travel environments.

This study has limitations. This study captured the approximate 15-minute walking distance of the population. The street network noise layer had missing noise attributes. Finally, using guidelines for the greenery level classifications was not possible.

This study aims to increase individuals' and urban planners' awareness about (un)healthy routes in travel environments and social inequality in access to healthy travel environments.

Tallinna tänavavõrgustiku keskkonnakvaliteet ja tervisliku liikumiskeskonna kättesaadavus

Ayisha Yusibova

Kokkuvõte

Tänapäeval mõjutavad linnakeskkonda negatiivselt mitmed keskkonnatingimused nagu õhu- ja müraaaste ning kliimamuutused, sealhulgas linnaruumi soojenemine ning rohealade piiratud kättesaadavus. Nende aspektide ruumiline varieeruvus põhjustab erinevate sotsiaalsete rühmade vahel ebavõrdsust, sest mõned neist rühmadest puutuvad oma asukohast ja liikumisteedadest tulenevalt kahjuliku mõjuga keskkonnamuutujatega rohkem kokku kui teised rühmad (EEA, 2019). Tänavavõrgustik on inimeste liikumiskeskonna ja keskkonnaomaduste peamine kokkupuutepunkt. Seega on tervislikud, vähese liidluse ja rohke haljastusega tänavad üks peamisi viise linnapiirkondades aktiivse liikumise edendamiseks ja sotsiaal-ruumiliste erinevuste vähendamiseks (Badland & Pearce, 2019; Nieuwenhuijsen, 2020). Samas ei ole üheaegset kokkupuudet mitme keskkonnatingimusega tänaval liikumise kontekstis palju uuritud. Varasem erialane kirjandus on valdavalt keskendunud kokkupuutele õhusaastega, samas kui vähesed uuringud on käsitletud mitme keskkonnatingimusega samaaegset kokkupuudet liikumise kontekstis (Poom et al., 2021). Siinse uurimistöö eesmärk on kaardistada tänavavõrgu keskkonnaparametreid, täpsemalt õhusaaste, müraaaste ja roheluse määr olemasolevate pindalaliste ruumiandmete põhjal, ning hinnata tervisliku liikumiskeskonna kättesaadavust kodulähedases tänavavõrgus rahvastikuregistri andmete põhjal, järgides 15-minutilise linna kontseptsiooni.

Uurimistöös püstitati järgnevad uurimisküsimused.

1. Milline on keskkonnakvaliteedi, st õhukvaliteedi, müra- ja roheluse ruumiline jaotus Tallinna tänavavõrgus ning kuidas see vastab rahvusvahelistele tervisealastele soovitudele?
2. Kuidas on tänavavõrgu keskkonnatingimused omavahel seotud?
3. Kuidas erineb tervisliku liikumiskeskonna kättesaadavus kodulähedases tänavavõrgus rahvastiku soo- ja keelerühmade lõikes?

Siinse uurimistöö tugineb õhukvaliteedi puhul 2020. aasta keskmistatud PM_{10} , $PM_{2.5}$ ja NO_2 pinnakihtidele, müraaaste puhul strateegilisele mürakaardile ja roheluse puhul kaugseire andmetele, kasutades normaliseeritud taimkatte erinevuste indeksit (*Normalized Difference*

Vegetation Index – NDVI). Õhukvaliteedi ja mürataseme tervisliku taseme piirmäärad selgitati rahvusvaheliselt tunnustatud suuniste alusel. Maailma Terviseorganisatsiooni WHO (World Health Organization) juhised annavad värskeimad soovitused õhu- ja mürasaaste kahjuliku mõju vähendamiseks (WHO, 2018, 2021). Tervisega seotud künnistest ei tohiks õhusaaste ületada PM₁₀ peenosakeste puhul 15 µg/m³, PM_{2.5} peenosakeste puhul 5 µg/m³ ja NO₂ puhul 10 µg/m³. Lisaks ei tohiks liiklusrüraaaste ületada 53 dB taset. Haljastuse, sh tänavavõrgu roheluse miinimumtaseme kohta puuduvad konkreetsed tervise- ja heaolualased suunised.

Olemasolevad pindalised keskkonnaparameetrite kihid projitseeriti tänavalõikudele, kasutades QGIS tarkvara Zonal Statistics. Korrelatsioonanalüüs viidi läbi tarkvaras R, kasutades Spearmani korrelatsioonikordajat. Tervisliku tänavavõrgu kättesaadavuse sotsiaalset ebavõrdsust hinnati kodulähedase tänavavõrgu keskkonnaandmete ja rahvastikuregistri andmete põhjal, kasutades aadressina rahvastiku ruutvõre keskpunkti ja 15-minutilise jalutuskäigu määramiseks võrgustikanalüüsi. Sotsiaalse ebavõrdsuse hindamiseks kasutati QGISi ruumianalüüsi ja statistilist analüüsi Excelis.

Uurimistöö tulemused näitavad, et PM_{2.5}, NO₂ ja müratase ületavad tänavavõrgustikus tervise seisukohalt soovituslikke näitajaid vastavalt 98%, 11% ja 51% ulatuses tänavavõrgustikust. Õhu- ja mürasaaste kontekstis on kõige ebatervislikumad suure liiklustiheduse, asustustiheduse ja majandustegevusega piirkonnad. Korrelatsioonanalüüs näitas, et kõrge müra- ja õhusaaste tase on seotud madala roheluse tasemega. Tänavalõikude keskmised keskkonnaparameetrid on PM₁₀ peenosakeste puhul 9 µg/m³, PM_{2.5} peenosakeste puhul 5,9 µg/m³, NO₂ puhul 6,9 µg/m³, mürataseme puhul 54,6 dB ja haljastuse puhul on roheindeksi keskmine väärtus 0,45. Tervisliku kodulähedase tänavavõrgu kättesaadavus ei erinenud rahvastikuregistri elukoha asukoha põhjal soorühmade vahel, kuid uuringus selgus, et keelerühmadel on Tallinnas ebavõrdne juurdepääs tervislikele kodulähedastele tänavakeskkondadele. Nii on venekeelt kõneleval rahvastikurühmal parem ligipääs tervisesoovitustele vastavale NO₂ tasemega ja kõrgema roheluse määraga tänavavõrgule kui eestikeelsel või muukeelsete rahvastikurühmal. Samas on eestikeelsel rahvastikurühmal parem ligipääs vaiksemale ja tervisesoovitustele vastavale tänavavõrgule võrreldes venekeelse või muid keeli kõneleva rahvastikurühmaga.

Siinses uurimistöös töötati välja meetodika keskkonnaparameetrite projitseerimiseks tänavalõikudele, kasutades olemasolevaid keskkonnatingimuste pindalalisi andmekogusid. Antud informatsioonile tuginedes analüüsiti uuringus rahvastikuregistri andmeid kasutades soo- ja keelerühmade vahelist ebavõrdsust tervislikule liikumiskeskkonnale Tallinna

tänavavõrgus. Metoodika võimaldab tulevikus viia läbi uuringuid, kus hinnatakse võrdset ligipääsu tervislikule liikumiskeskonnale ka teiste elanikkonnarühmade lõikes, võttes arvesse vanust, haridust ja sotsiaalmajanduslikku staatust. Teine suund tuleviku-uuringuteks on analüüsi ulatuse laiendamine, lisades mudelisse muid keskkonnakvaliteedi näitajaid, nagu näiteks muud õhusaasteained ja temperatuur või soojusmugavus.

Siinne uuring rõhutab, kui oluline on suurendada üldsuse teadlikkust tänavavõrgu ja liikumiskeskonna keskkonnakvaliteedist ning anda soovitusi tervislike marsruutide valikuks inimeste liikumisotsustes. Samuti tuuakse välja linnaplaneerijate ja poliitikakujundajate võimalus tegeleda keskkonnavalase ebavõrdsusega, näidates ära kõige haavatavamad rühmad, kellel on piiratud juurdepääs tervislikule liikumiskeskonnale.

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My thanks,

A handwritten signature in black ink, consisting of several loops and a vertical stroke on the right side.

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Annexes

Annex 1. Spatial distribution of input datasets

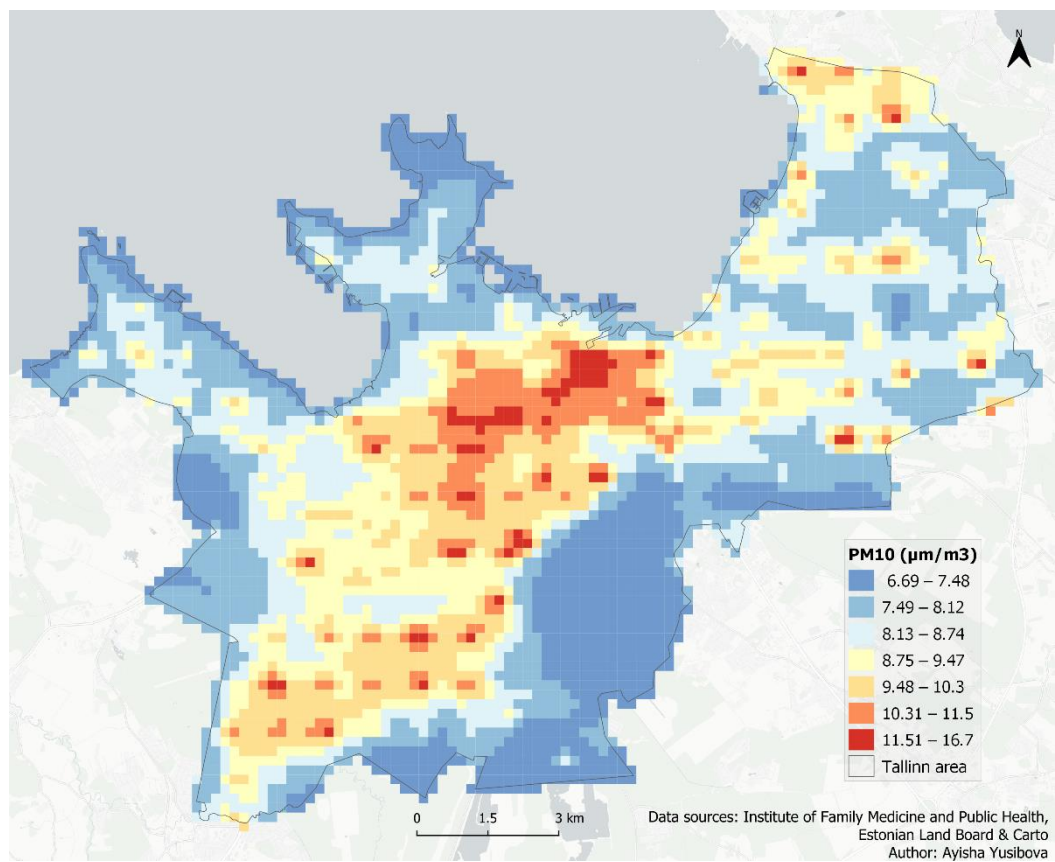


Figure A1. Spatial distribution of PM₁₀ in Tallinn

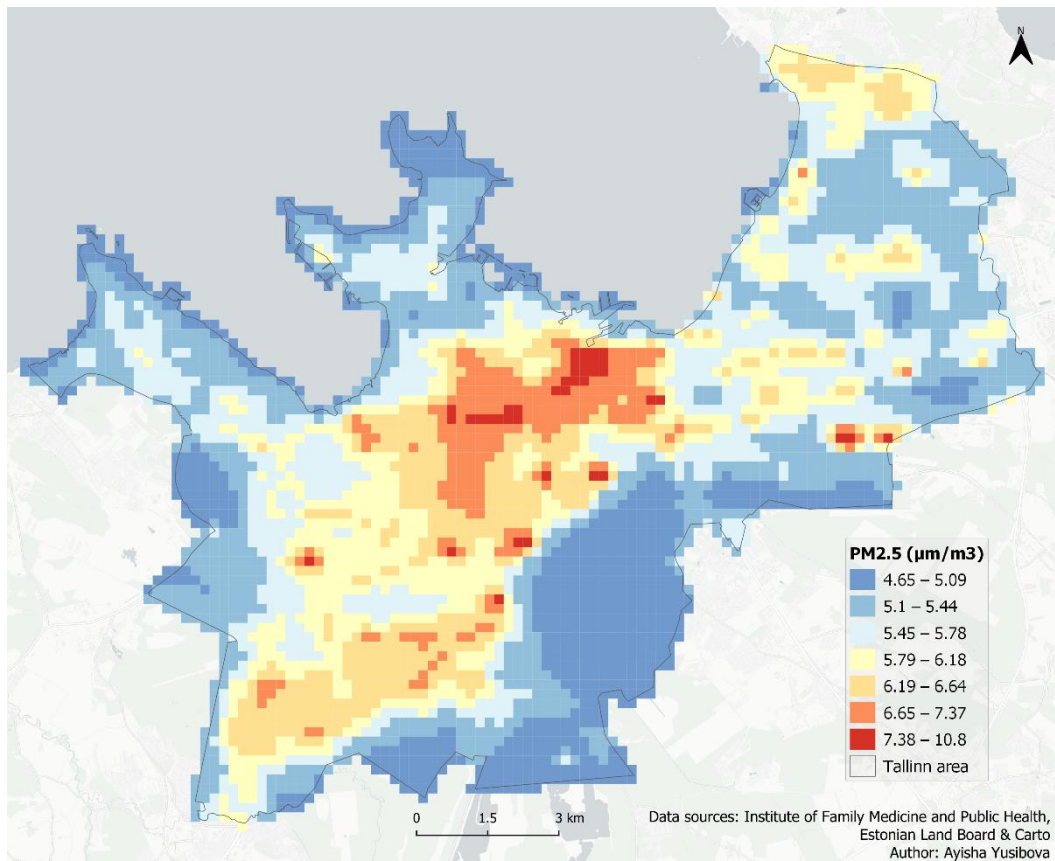


Figure A2. Spatial distribution of PM_{2.5} in Tallinn

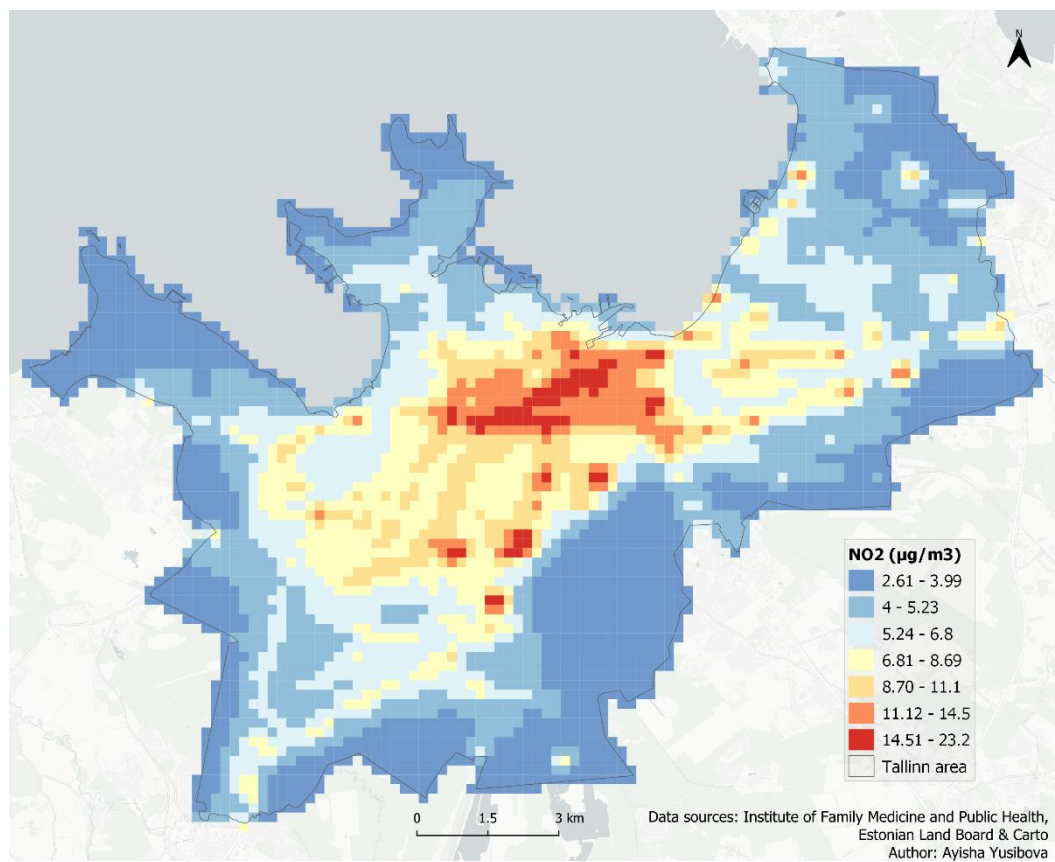


Figure A3. Spatial distribution of NO₂ in Tallinn

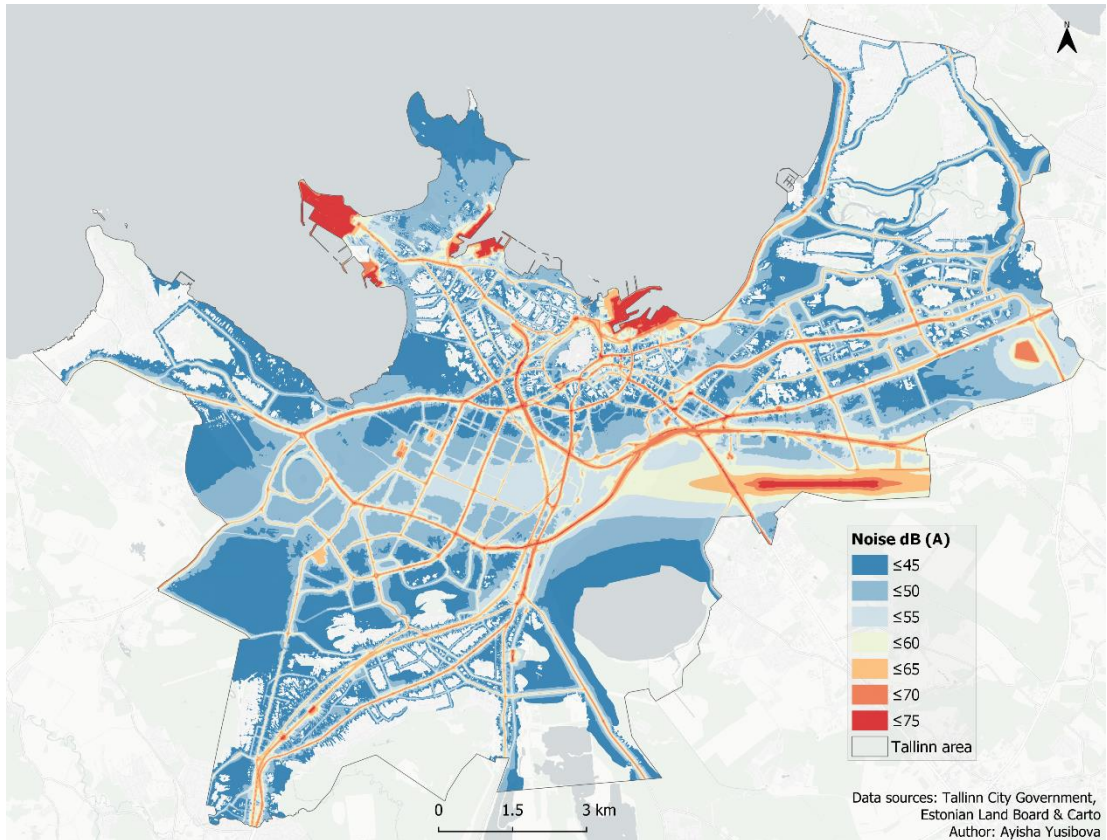


Figure A4. Spatial distribution of noise in Tallinn

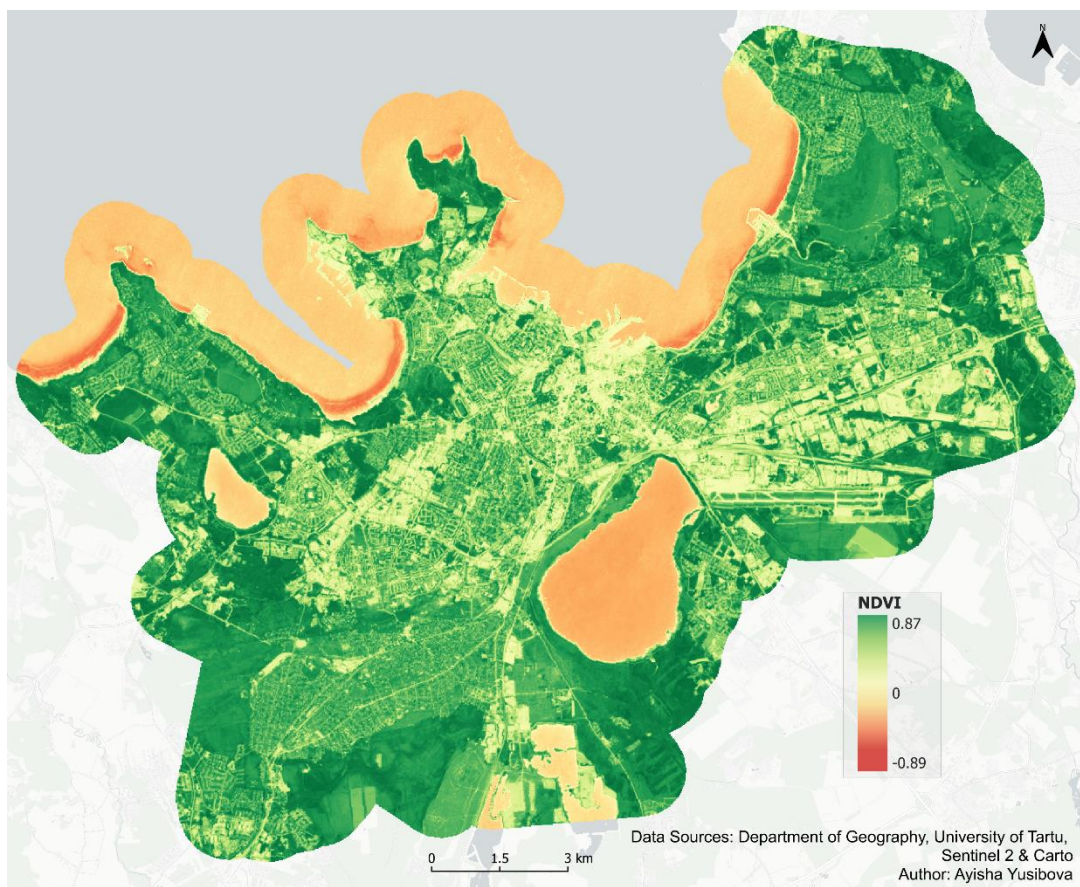


Figure A5. Spatial distribution of NDVI in Tallinn

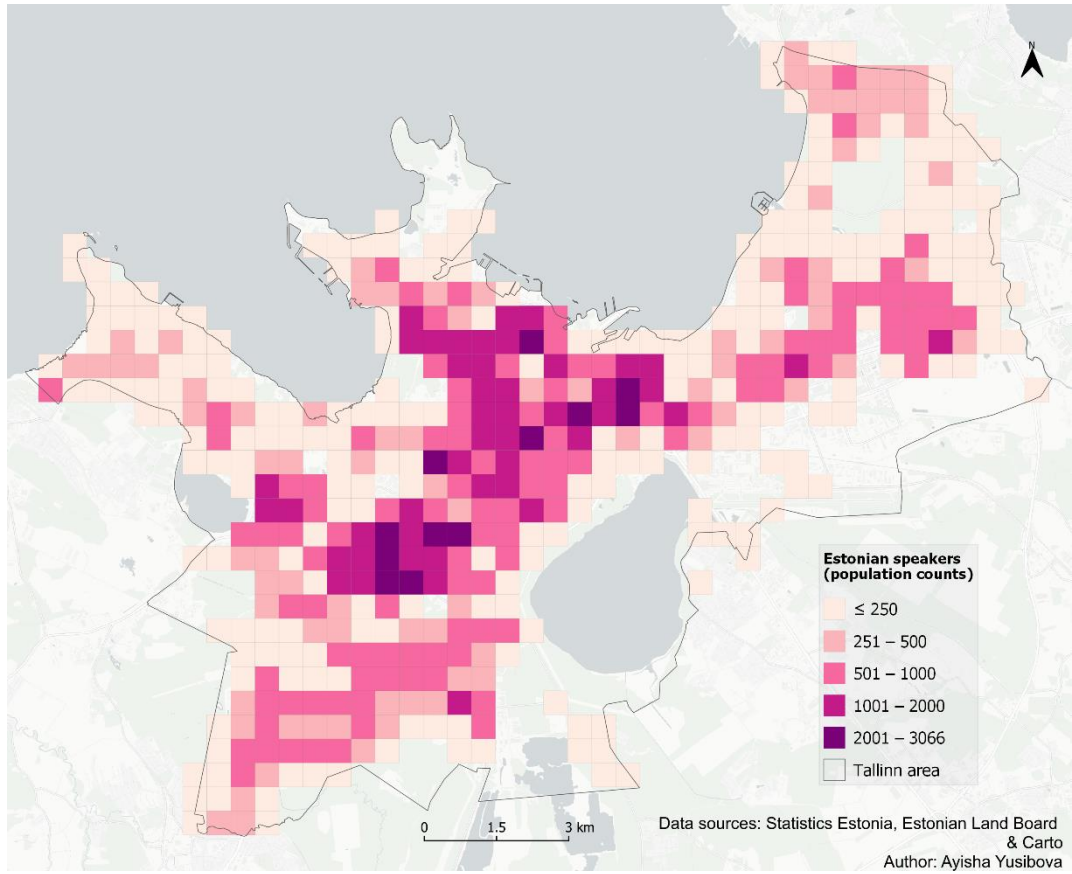


Figure A6. Spatial distribution of Estonian speakers' group in Tallinn

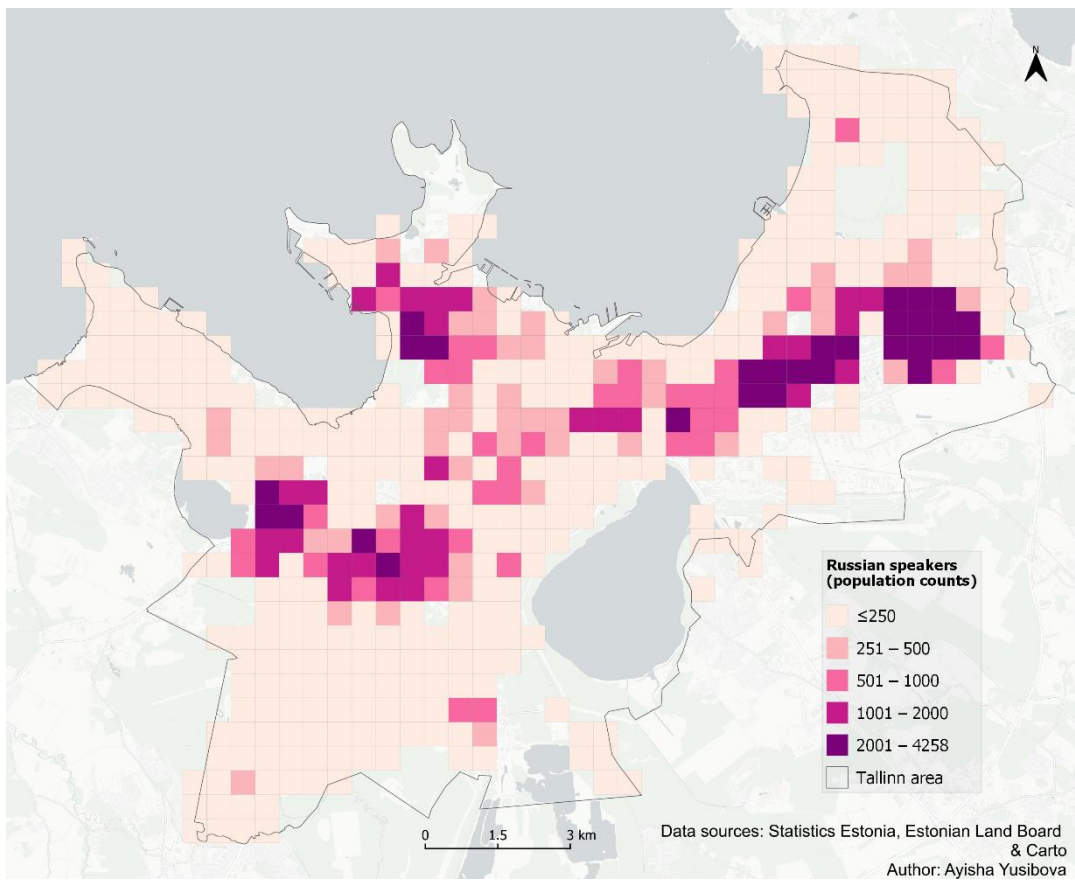


Figure A7. Spatial distribution of Russian speakers' group in Tallinn

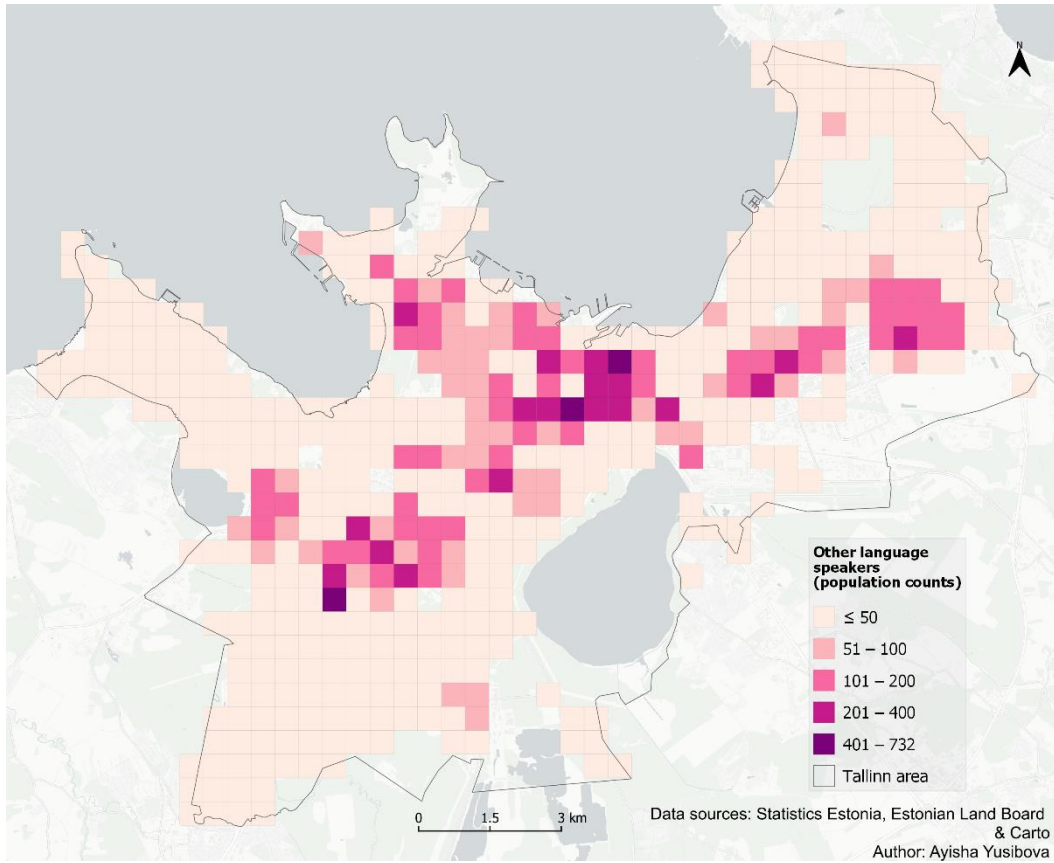


Figure A4. Spatial distribution of other language speakers' in Tallinn

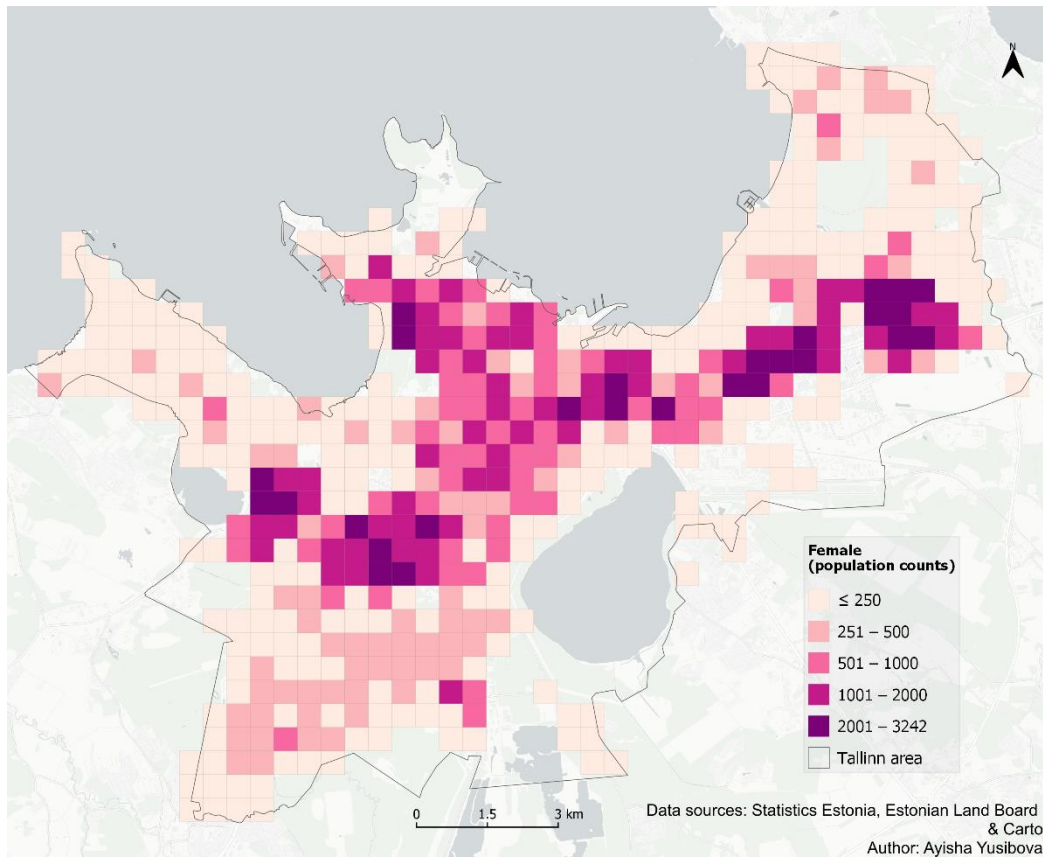


Figure A5. Spatial distribution of female population in Tallinn

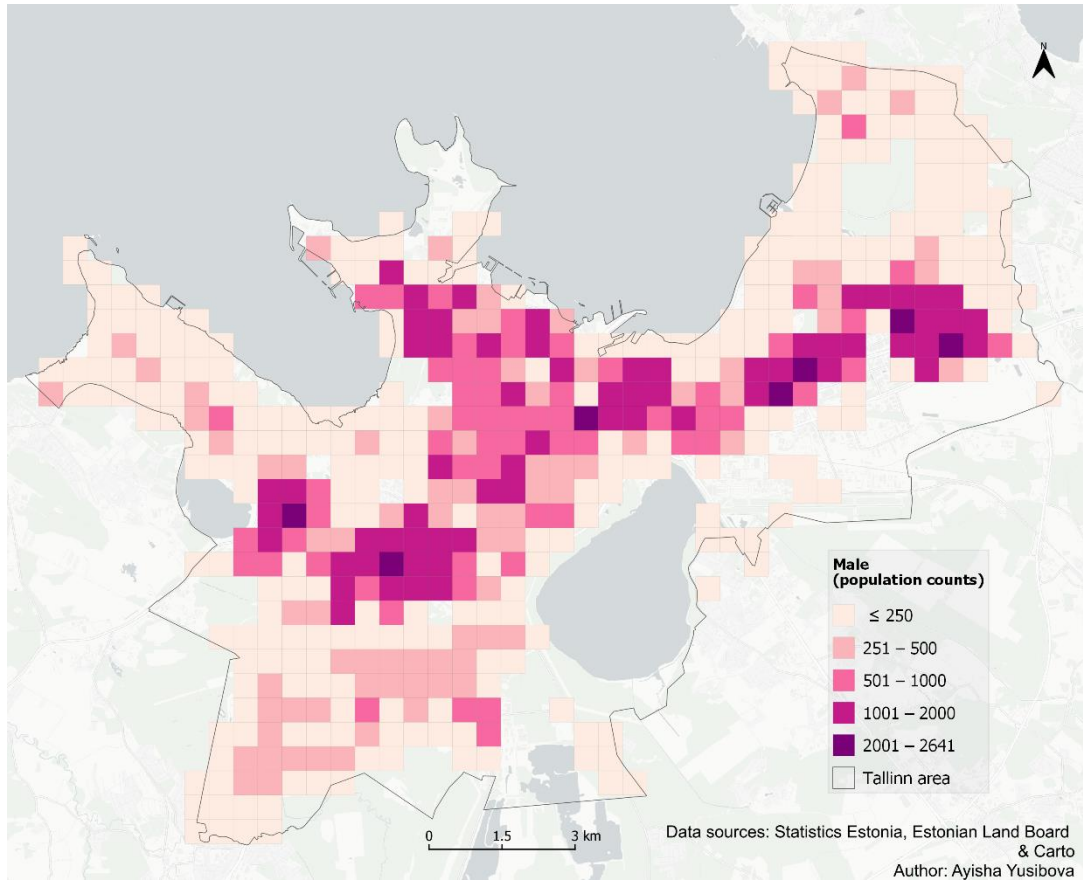


Figure A10. Spatial distribution of male population in Tallinn

Annex 2. Distribution of datasets for road segments

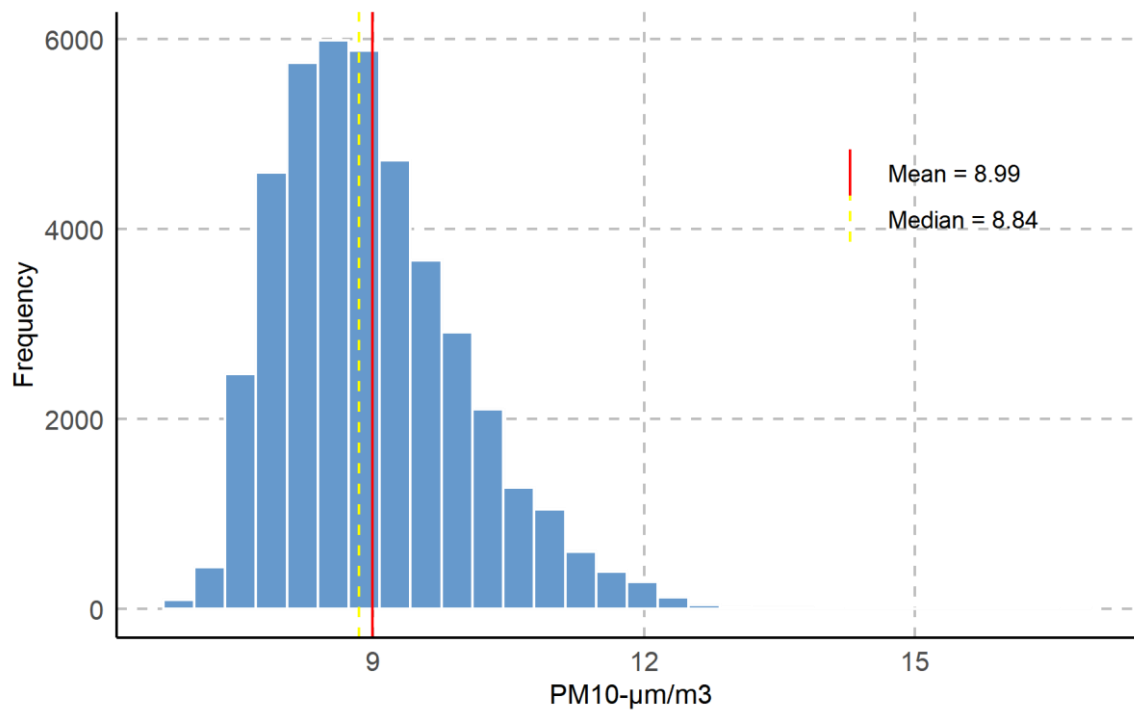


Figure B1. The distribution of PM₁₀ data for street segments

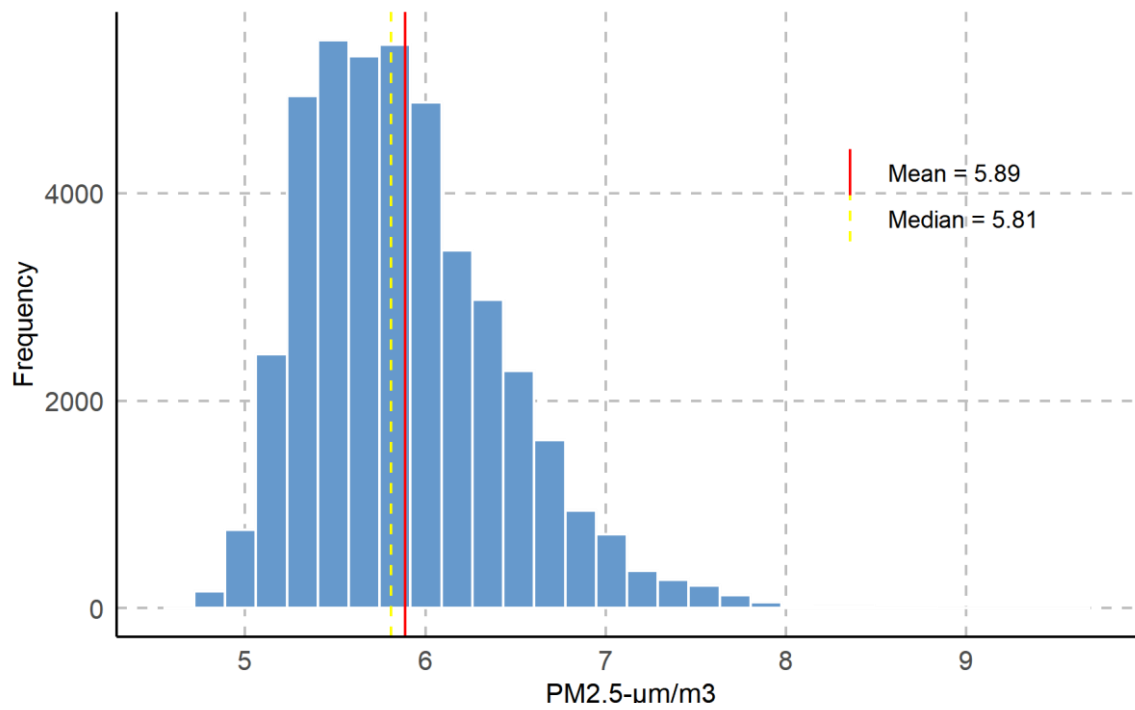


Figure B2. The distribution of PM_{2.5} data for street segments

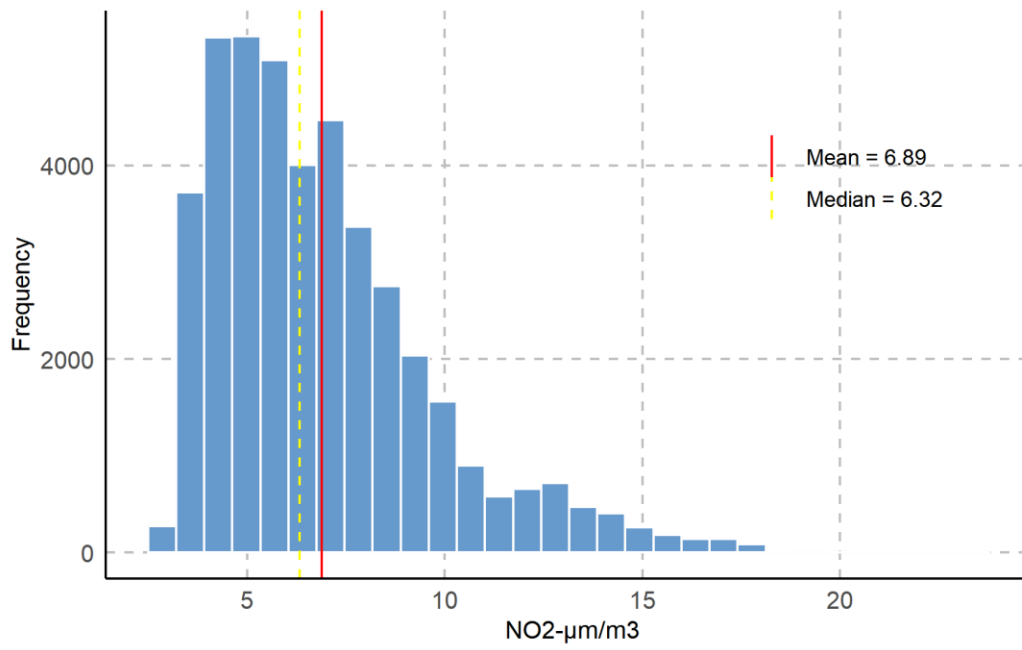


Figure B3. The distribution of NO₂ data for street segments

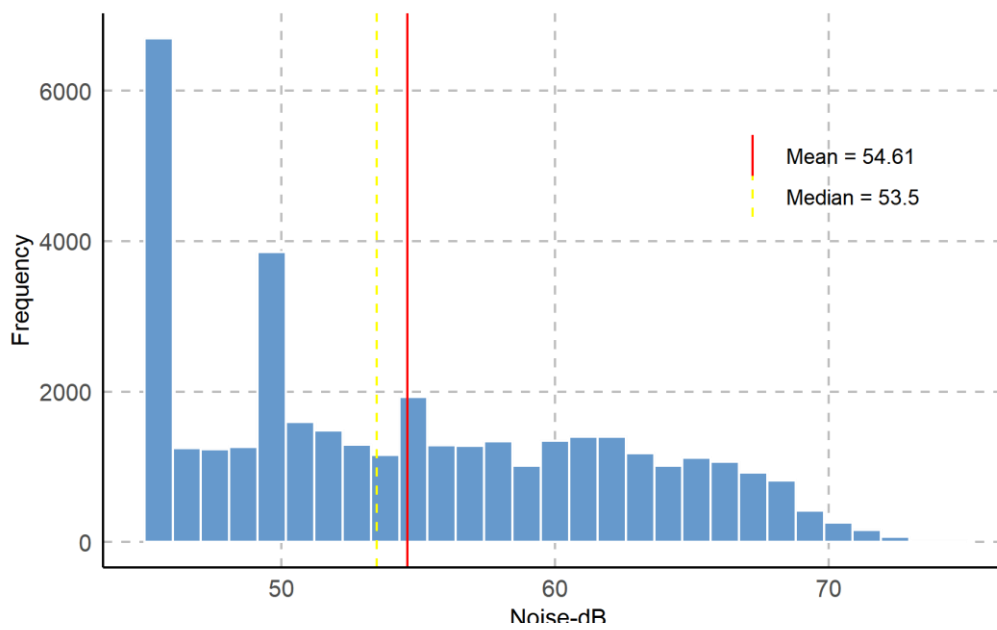


Figure B4. The distribution of noise data for street segments

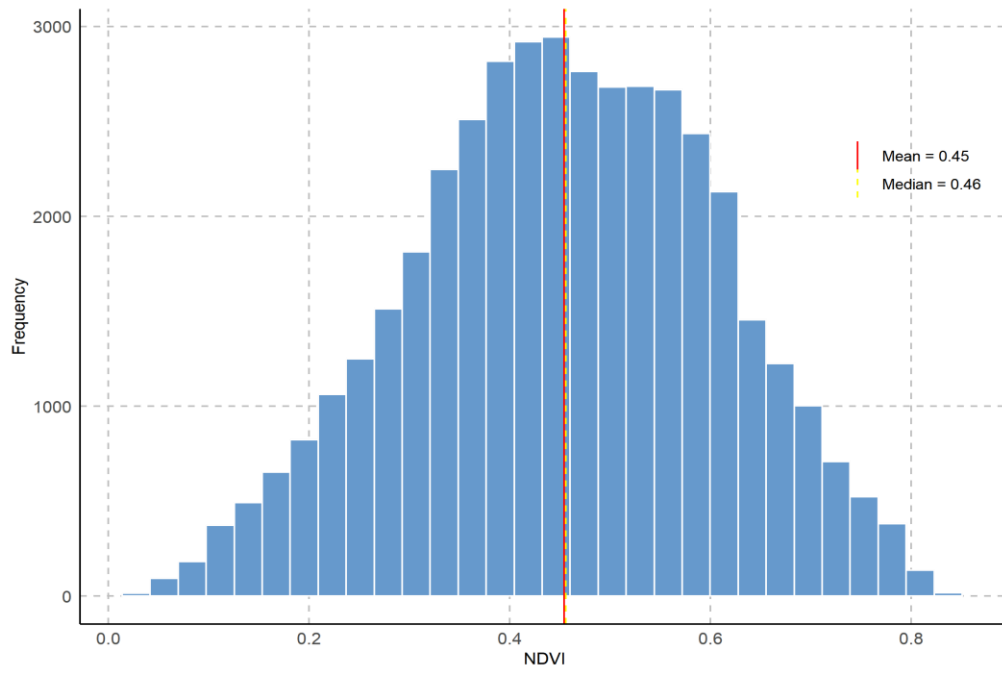


Figure B5. The distribution of greenery data for street segments

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23/05/2023