Amsterdam University College
Excellence and Diversity in a Global City

An Analysis of Dutch Environmental Inequalities in Air Pollution Exposure

Yvonne Plate (ID: 11925965), AUC, yvonne.plate@student.auc.nl

Supervisor: Eric Koomen, VU, e.koomen@vu.nl

Reader: Eduardo Dias, VU, ess580@vu.nl

Tutor: Lara Mazurski, AUC, l.e.mazurski@uva.nl

Date of Submission: 27.05.2020

Major: Social Sciences

Word Count: 7879

Abstract

This project investigates the environmental inequalities in air pollution exposure for groups with different socioeconomic characteristics and migration backgrounds in the Netherlands. This is achieved through GIS and statistical analyses of open-source and otherwise acquired spatially explicit data on air pollution (PM_{10}, $PM_{2.5}$, & NO_2) and social factors (Socioeconomic status indicators & migration background) on a $100 \times 100\,\mathrm{m}$ resolution. It is studied to show the relationship between social and environmental problems and to indicate problems in areas that are highly affected and should be the focus of future policy to reduce health inequalities. This study found that nationally, the Netherlands exhibits urban demographic patterns related to air pollution exposure, where cities show higher income levels and higher ethnic diversity, as well as more air pollution. However, when looking at unhealthy exposure areas, lower-income groups and more ethnically diverse groups are often overrepresented compared to national proportions. This indicates significant environmental inequality. Further findings, comparisons, relevance, strengths and limitations and future research are discussed.

Keywords: Geospatial; Race-Ethnicity; Socioeconomic Status; Environmental Inequality; Air Pollution

Table of contents

1. Introduction

Air pollution is an environmental issue that affects social groups unequally — air pollution exposure is often experienced disproportionately more by people with lower socioeconomic status (SES) and by racial minorities (Fecht et al., 2015; Flanagan et al., 2019; Jerrett et al., 2001; O'Neill et al., 2003; Samoli et al., 2019). This is problematic, as long-term exposure to air pollution can have serious public health risks (Künzli et al., 2000) and can lead to higher mortality rates in affected areas, as is documented, amongst other countries, in the Netherlands (Fischer et al., 2015). The unequal exposure to air pollution for different groups in society shows underlying environmental injustices. Environmental injustice is a growing issue in various environmental problems. Their effects often do not hit the responsible parties, but rather people who are already less well-off and minimally responsible for the issues that affect them (Agyeman et al., 2016). Schlosberg (2004) argues there are three parts of environmental justice: the equitable spread of environmental risk, the recognition of diversity in both participants and experiences in communities that are affected, and inclusive participation in creation and management of environmental policy through political processes. By investigating what characterises the distributional differences, the recognition of social diversity can be improved, and underlying reasons for unjust distribution can become more evident (Schlosberg, 2004). In other words, the examination of ways in which social characteristics differ in groups with varying levels of air pollution exposure can indicate where deeper structural problems give rise to social inequalities that manifest themselves in these environmental issues. This has the potential of showing which problem areas should be addressed by policy actors, as it could help reveal where air pollution measures might be most necessary. While this does not necessarily address the last part of environmental justice as presented by Schlosberg, it might help set the development of more just policy measures into motion.

Since air pollution exposure is an inherently geospatial issue, a Geographic Information System (GIS) analysis is a suitable method for exploring the role of various factors. This inequality issue will be investigated in this study using GIS, to address the question: how do different social factors (income, unemployment, & migration background) characterise high levels of exposure to $PM_{2.5}$, PM_{10} and NO_2 in the Netherlands on a 100×100 m scale? $PM_{2.5}$ is particulate matter with a diameter of 2.5 micrometres or less, PM_{10} is particulate matter with a diameter of 10 micrometres or less, and NO_2 is nitrogen dioxide. This analysis will expand on previous research done on the neighbourhood scale and with older data (Fecht et al., 2015). It can extend discussions on the interconnection of social and environmental issues as well as argue for the need to address both in order to solve current problems and to prevent future problems by creating a more sustainable society.

2. Research context

A variety of studies have addressed air pollution, health impacts and related inequalities in numerous regions across the world — with the focus often being western countries (e.g. United States, Canada, Europe) or China (Beelen et al., 2008; Flanagan et al., 2019; Jerrett et al., 2001; Clark et al., 2017; Liu et al., 2018). These studies explore interrelations and causal relationships between air pollution and health, mortality, socioeconomic status, poverty, ethnicity/race, climatic factors and more, monitoring specific and small sample populations (Flanagan et al., 2019; Jerrett et al., 2001; Marshall, 2008) or analysing large national or European databases (Beelen et al., 2008; Fecht et al., 2015; Samoli et al., 2019). A few studies focus on the geospatial aspect of environmental inequalities as well (Fecht et al., 2015; Jerrett, 2001; Milojevic et al., 2017).

2.1. Dangers of Air Pollution

The dangers of air pollution are well-documented and supported on various scales and in many different regions. Hall (1996) and Mayer (1999) are just two examples claiming it is no longer a question of whether air pollution negatively affects health, but rather how much. The World Health Organization (WHO) has also set out guidelines describing which amounts of each air pollutant can be in the air before it becomes a serious health risk (2006). Air pollution exposure is generally seen as a severe health problem (Mayer, 1999; Künzli et al., 2000; Gehring et al., 2006). Exposure was also explicitly linked to mortality in a broad study of the Dutch public by Fischer et al. (2015). Several studies including Beelen et al. (2008) and Hoek (2002) specifically address traffic-related air pollution by measuring black soot and NO_2 in the Netherlands and found similar adverse effects on health; If not necessarily a high risk on an individual level, it can still prove a significant risk to public health. When looking at more ambient air pollution, the focus usually lies more on particulate matter (e.g. Liu et al., 2018; Mikati et al., 2018), which gives a more general measure of air pollution. The WHO air quality guidelines for particulate matter are a mean of $10 \mu g/m^3$ annually for $PM_{2.5}$ and a mean of $20 \mu g/m^3$ annually for PM_{10} (2006). These are at the low end of exposure that could have severe effects on health, although there is no clear threshold for particulate matter at which point adverse health effects would be expected (WHO, 2006). For NO_2, $40 \mu g/m^3$ is the annual mean. These regulations are going to serve as a guideline for this research to determine which levels are a serious health risk.

2.2. Characteristics of Groups Exposed to Air Pollution

Socioeconomic characteristics and race, have been investigated in relation to people's exposure to air pollution (Clark et al., 2017; Fecht et al., 2015; Flanagan et al., 2019; Goodman et al., 2011; Jerrett et al., 2001; Liu et al., 2018; Marshall, 2008; Mikati et al., 2018; Milojevic et al., 2017; Morello-Frosch et al., 2002; Samoli et al., 2019). SES has been negatively correlated with exposure to air pollution in several studies using different methods, as explored in the following text. SES does not always consist of the same factors, but usually includes some measure of income, as well as different combinations of measures of education, the crime rate in a neighbourhood, age or unemployment. Jerret et al. (2001), Marshall (2008) and Goodman et al. (2011) use statistical analysis in addition to GIS, finding that indicators of lower SES were positively associated with higher exposure to air pollution. Goodman et al. (2011) did find some exceptions, for example, central London. This could point to growing preferences for living centrally, where air pollution is likely to be higher, as it is more urban (Milojevic et al., 2017). Flanagan et al. (2019), Liu et al. (2018) and Samoli et al. (2019) conducted binary logistic regression, stepwise regression models and linear regressions respectively. All three also found that a key characterising factor of exposure to air pollution is SES. While O'Neill et al. (2003) state that the relationships among SES, air pollution and health differ across nations and communities, they do express that groups whose health is most at risk due to air pollution are generally also the recipients of the highest exposure. So, vulnerable groups — often with a lower SES — not only receive more exposure to air pollution but are also more affected by air pollution exposure relative to the average population (O'Neill et al., 2003). This may imply that environmental inequalities are even further exacerbated. Both Flanagan et al. (2019) and Milojevic et al. (2017) also emphasize that improvements in air quality have the potential to reduce environmental injustices and socioeconomic differences in health.

Apart from and in relation to SES, ethnicity and race have also been explored as a factor characterising different levels of exposure to air pollution. Mikati et al. (2018), in a study of the United States of America (USA), found that solely looking at socioeconomic disparities may not be sufficient to achieve equity in air pollution exposure, as racial disparities were a more significant factor in particulate matter burdens than poverty. Marshall (2008), in line with this study, found that not only lower-income and high population density were determining factors in the USA, but also that the non-white population experienced higher exposure to air pollution. Clark, Miller & Marshall (2017) support these findings with their results showing higher NO_2 concentrations for non-whites than for whites. A spatial focus also shows that the burdens of air pollution are disproportionately felt by the non-white population in California, USA in exposure and effects (Morello-Frosch et al., 2002), as well as urban neighbourhoods in the Netherlands and the United Kingdom looking at the same distinction (Fecht et al., 2015). Altogether, there have been some compelling studies suggesting this environmental inequality not solely to be socioeconomic, but also include other factors like race and ethnicity. These are worth exploring to add to a more complete and complex picture of what differentiates groups which are exposed to air pollution to different degrees.

Similarly, population density is a factor often interacting with the previously mentioned social components, as well as air pollution and should be a consideration in studies of this type. Marshall (2008) names population density as a characterising factor of air pollution exposure. Samoli et al. (2019) and Liu et al. (2018) also find population density to be a determining factor in characterising different levels of air pollution. However, the main employment of this factor would be the indication of urbanization. Therefore, the population of a certain area is mainly important in determining how many people are affected in particular areas and what the predominant characteristics of these are. This can be compared in different areas to reveal inequalities. Overall, socioeconomic and ethnic-racial factors seem to be the main focus in determining environmental inequality, taking population density as an interacting urban factor and a part of a method of analysis.

2.3. Spatial Investigations

Spatial considerations are deemed an important aspect to consider in order to determine previously mentioned environmental inequalities and show the unequal distribution of exposure to air pollution (Mayer, 1999; Samoli et al., 2019; O'Neill et al., 2003). Fecht et al. (2015) have investigated these inequalities spatially in the Netherlands, with their focus being on the neighbourhood level. However, as neighbourhoods can be relatively large and air pollution is a more continuous and spatially explicit phenomenon, the analysis of exposure requires more spatial detail. This is especially true for the pollutants that are related to traffic such as NO_2 (Samoli et al., 2019; Fecht et al., 2015). One side of a neighbourhood could have a much higher exposure due to a large road than the other side of the neighbourhood, bordering a park. Therefore, the investigation of a smaller spatial resolution to test these results on a more detailed scale and compare them to the previous study would be beneficial.

3. Methodology

3.1. Study Specification

This study investigates the social characteristics of varying NO_2, $PM_{2.5}$ and PM_{10} concentrations on a 100×100 m resolution in the Netherlands. The Netherlands was chosen as the study area, as additional specifications could add to the existing research. Some interesting findings were also present, such as those by Fecht et al. (2015) regarding the socioeconomic deprivation factor in the Netherlands specifically. The data needed for this research was also accessible in this area.

Following a previous study (Fecht et al., 2015), this research will address yearly mean PM_{10} and NO_2 concentrations, but also add $PM_{2.5}$ concentrations, as it has just as, if not more significant health impacts (Liu et al., 2019; Fischer et al., 2020; Beelen et al., 2008). The pollutants PM_{10} and NO_2 are used to make possible comparisons to the previous research by Fecht et al. (2015) — in the same area but at a larger resolution — easier. $PM_{2.5}$ was added, as the smaller diameter of these particles and the larger distribution of unhealthy concentrations make them detrimental to people’s health (Liu et al., 2019). Using these three pollutants also provides the inclusivity of a large variety of anthropogenic sources, including traffic (NO_2) (Samoli et al., 2019; Fecht et al., 2015), mechanical processes (PM_{10}) (WHO, 2006), and combustion sources ($PM_{2.5}$) (Liu et al., 2019; WHO, 2006).

A 100×100 m resolution of the social characteristics of different groups exposed to air pollution in the Netherlands was used to build on previous research done on the neighbourhood level and is a step towards furthering our understanding of the connection between social and environmental problems. It improves the overgeneralization of neighbourhoods that may lack heterogeneity and compatibility with continuous spatial measures of air pollution. The social characteristics used were those available through this data, including migration backgrounds, income level and unemployment rate. These were the available factors that fit in with previously studied indicators and explanatory factors common in the literature.

The investigation of different scales and pollutants is relevant due to the complex relationship between air pollution concentrations and social factors (Briggs et al., 2008). Additionally, there is no universally consistent system of environmental inequity (Briggs et al., 2008), so a specific investigation of one country can yield results necessary for that area, which are not necessarily transferable from other countries.

3.2 Methods

This study used spatially explicit data of population characteristics and annual mean concentrations for air pollutants, analysing the overlap using GIS and the significances and degrees of correlations and associations using statistical analyses. The statistical analyses include descriptive statistics, Pearson's correlation, and multivariate (linear) regression analysis, following the approach by Fecht et al. (2015). Additionally, independent sample t-tests and comparisons of proportionality are conducted. GIS allows for some visualizations and spatial overlay to create spatially specific data sets to be used in statistical analyses. Statistics then allow an investigation into the degree of association.

The spatially aggregated data from GIS was used in SPSS to investigate statistical correlations and associations. First, descriptive statistics, Pearson's correlations, and linear regression analyses were conducted for the full national data set. Descriptive statistics give a general picture of the data, for the entire nation, metropolitan agglomeration areas and a dataset with only data points that do not contain missing values. These analyses were also conducted for metropolitan agglomeration areas (urban) and a dataset including only data without missing values (no missing data), to investigate the sensitivity of the data and biases introduced through missing data. Pearson's correlations, as well as linear regressions (with the pollutants as the independent variable), were explored next, in order to investigate significance and degree of correlations between variables. A sensitivity analysis repeating the same methods was executed with urban areas, as well as no missing data areas.

To explore not only variable correlation to air pollution levels, but also significant discrepancies in the representation of social characteristics in unhealthy air pollution areas, as determined by WHO guidelines (2006), compared to lower air pollution concentration areas, independent sample t-tests were conducted. These t-tests show if the difference between the mean representation of certain characteristics is significant. Additionally, the proportions of different migration backgrounds and income levels were calculated from the dataset. This was done by calculating the number of people with each characteristic for each data point, taking the sum of this number for each characteristic and then calculating their percentage in relation to each other. This allowed for a weighted result to compare between high concentration areas and national demographics, as well as the official figures as obtained from Central Bureau for Statistics (CBS) (2016a). These calculations made possible the further investigation of indications of environmental inequality, which were then visualized through box-plots.

These research methods were chosen, as they address the crucial spatial aspect of, but also allow specific numbers on, the environmental inequality issue. It is also a feasible method taking into consideration available data and time constraints.

3.3. Data Specifications

NO_2, $PM_{2.5}$, and PM_{10} concentrations were obtained from Atlas Leefomgeving (2016) in $\mu g/m^3$ at a 25×25 resolution. These concentrations were produced by combining larger scale maps based on model calculations and measurements with local traffic data calculations (Atlas Leefomgeving, 2016). The choice of pollutants provides diverse spatial distributions, as can be seen in Figure 1.1, 1.2, & 1.3, where red indicates unhealthy annual levels of pollutant concentrations according to WHO guidelines (2006). This diverse distribution can be attributed to different pollutant sources. The spatial pattern of NO_2 can be linked to the biggest urban agglomerations, notably Amsterdam and its airport and the Rotterdam and the Hague region with its harbour, as can be seen in Figure 1.1. $PM_{2.5}$ is more widely spread (Fig. 1.2) as it mainly originates from combustion sources, also including power generation, manufacturing and industry, transportation, homes and agriculture (National Research Council, 2010). Lastly, PM_{10} concentrations can be seen to be higher in cities (Fig. 1.3), as this pollutant originates from mechanical processes. The general temporal trend for air pollution concentrations of the three pollutants is decreasing according to the European Environmental Agency (2019), which presents concentrations from 2008 to 2017.

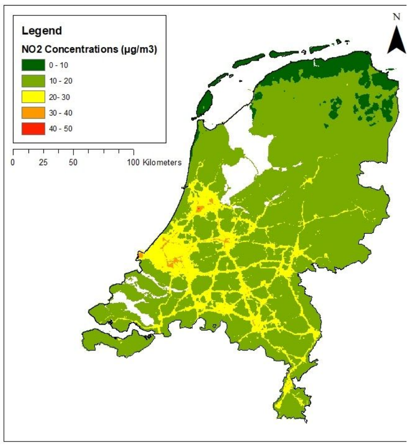


Figure 1.1 *- Dutch NO_2 concentrations 2016*

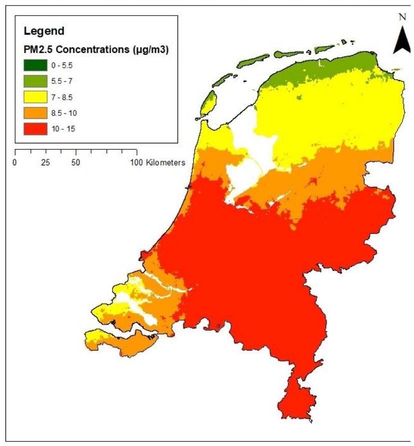


Figure 1.2 *- Dutch $PM_{2.5}$ concentrations 2016*

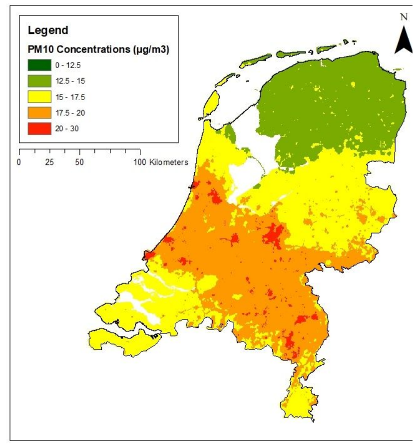


Figure 1.3 *- Dutch PM_{10} concentrations 2016*

Concerning Population characteristics, migration background percentages, amount of unemployment and income level are a part of the 100×100 m squares obtained from CBS (2016b). Migration backgrounds were used to give an indication of race or ethnicity, where a migration background could indicate an ethnic minority and a non-white racial background. The number of people receiving unemployment benefits was taken as an indication of unemployment in the area, but converted to a percentage relative to the total number of residents of an employable age (15-65), as this will give a relative view of unemployment. This was done in SPSS, as it allowed for consideration of missing values (indicated by -99997), which were taken out of the calculation. However, the unemployment variable had a large portion of missing data points due to this removal of those data points from the calculation, some of which also seemed to replace true zero values (as none occurred for this variable). Therefore, unemployment is a slightly less reliable variable, where results should be taken with some scepticism. Income levels are used as the main measure of SES besides unemployment. As they are given in string values, they were reclassified into numerical values for the analysis, where low income level (<16 800€) was reclassified into 1 and high income level (>36 600€) into 5 (exact € differentiations for other levels are presented in Table 5). As 2016 was the most recent year with available data on these income levels, it was chosen as the time specification for this study. The social characteristics data had a fair amount of missing data points, which were left out of the analysis. This is likely due to the difficulty in obtaining such specific data for a whole population.

To prepare the data for the statistical analyses, the projections were homogenised in GIS to ensure spatial accordance. As the pollution data was in raster form, but the population characteristics in vector form, the relevant categories from the population characteristics (population, income level, unemployment rate, Dutch, Western & Non-western backgrounds (%)) were also converted into raster form. After carrying out these steps, all necessary data for every $100 \times 100m$ square in the Netherlands was compiled into a table. In doing so, the fact that pollution data was at a smaller resolution than the population characteristics had to be taken into account. This was accounted for while creating the table, where bilinear interpolation was used to get an accurate number for pollutant concentrations of the correct area analysed. This was done instead of correcting resolution, as the resolutions did not line up when put at the same size. This table was then transferred to SPSS and missing data points were added in to be taken out of the analyses. Metropolitan agglomeration areas (including the cities as listed in Appendix III) which were used to distinguish urban areas, were acquired through a colleague (Jip Claassens).

4. Results

The following are the results of the statistical analysis based on the explicit spatial points obtained through GIS. Supplemental materials are attached in Appendix II.

4.1. Descriptive Statistics

Table 1 *- Descriptive statistics of all variables*

	National					Urban					No Missing Data				
	N	Min.	Max.	Mean	Std. Deviation	N	Min.	Max.	Mean	Std. Deviation	N	Min.	Max.	Mean	Std. Deviation
NO_2 Concentration	375353	0.94	71.76	18.16	4.76	92297	5.62	60.90	22.41	4.46	159270	1.26	57.87	19.45	4.66
$PM_{2.5}$ Concentration	375353	5.58	18.31	10.49	1.56	92297	6.73	17.70	11.39	1.16	159270	5.58	16.88	10.79	1.47
PM_{10} Concentration	375353	13.05	35.40	17.53	1.84	92297	13.23	26.70	18.64	1.53	159270	13.28	29.75	17.91	1.73
Population	373002	5.00	1275.00	43.84	43.74	92547	5.00	1275.00	71.08	59.58	159285	10.00	1195.00	70.96	43.77
Income Level	215055	1.00	5.00	2.80	1.03	43167	1.00	5.00	2.70	1.06	159285	1.00	5.00	2.79	1.02
Unemployment (%)	61682	0.69	120.00	19.72	11.25	14713	-14.73	84.33	18.13	13.21					
Dutch Background (%)	186001	0.00	100.00	81.87	16.99	54933	0.00	100.00	72.52	18.99	159285	0.00	100.00	80.66	17.24
Western Migration Background (%)	86609	0.00	100.00	14.52	8.02	20591	0.00	90.00	16.20	8.08					
Non-Western Migration Background	66776	0.00	100.00	22.00	16.56	18444	0.00	100.00	31.34	20.48					
Valid N (listwise)	36682					7701					159270				

The descriptives statistics for national and urban levels, as well as for no missing data points are presented in Table 1. The percentages are not weighted by population but are rather there to give an indication of the average grid cell. Further weighted analysis is conducted in chapter 4.4. Due to a lot of missing data, especially in the unemployment and non-dutch migration background variables, these variables were taken out of the no missing data dataset completely. As the average population per grid cell - 70.95 - is higher in this dataset than nationally (43.84), it is likely that data is more prevalent and complete in more urban areas. There are instances in all three of unhealthy concentrations of all three pollutants, but only the mean of $PM_{2.5}$ is at an unhealthy level (>10 $\mu g/m^3$) for all datasets. The main differences that can be seen between the datasets is the average population.

4.2. National Analysis

4.2.1. Pearson's Correlation

Table 2 *- Pearson's Correlations Nationally*

	NO_2	$PM_{2.5}$	PM_{10}	Population	Income	Unemployment (%)	Dutch	Western	Non-Western
NO_2	1.00								
$PM_{2.5}$	0.79	1.00							
PM_{10}	0.83	0.92	1.00						
Population	0.42	0.27	0.33	1.00					
Income	0.05	0.08	0.10	-0.13	1.00				
Unemployment (%)	-0.08	-0.09	-0.13	-0.10	-0.62	1.00			
Dutch	-0.43	-0.30	-0.35	-0.47	0.33	-0.32	1.00		
Western	0.06	0.07	0.03	-0.18	-0.02	-0.01	-0.32	1.00	
Non-Western	0.24	0.17	0.19	0.20	-0.38	0.35	-0.88	-0.09	1.00

all correlation are significant ($p<0.05$)

The results for the Pearson's correlation analysis are all at a significant level. Unemployment and percentage with a Dutch background are both negatively correlated with all three pollutants. Income and population, on the other hand, are both positively correlated with the pollutants. Population and Dutch background are most highly correlated to the pollutants, followed by non-western background. Additionally, non-western background is correlated with higher populations, lower incomes and higher unemployment, even though population is negatively correlated to unemployment. Box-plots visualize the patterns nationally (Appendix II, 6).

4.2.2. Regression Analysis

Table 3 *- National linear regression results*

	NO_2		$PM_{2.5}$		PM_{10}	
	Unstandardized Coefficients		Unstandardized Coefficients		Unstandardized Coefficients	
	B	Std. Error	B	Std. Error	B	Std. Error
(Constant)	**28.29**	0.46	**12.37**	0.13	**19.98**	0.16
Income Level	**0.38**	0.03	**0.13**	0.01	**0.28**	0.01
Unemployme	**-0.09**	0.00	**-0.02**	0.00	**-0.03**	0.00
Dutch (%)	**-0.10**	0.01	**-0.02**	0.00	**-0.03**	0.00
Western (%)	**0.05**	0.01	**0.02**	0.00	**0.02**	0.00
Non-Western	**0.01**	0.01	0.00	0.00	**0.01**	0.00

*bold indicates significance ($p<0.05$)

The linear regression analysis on the national level proved the variables to all be significant except for one: non-western for $PM_{2.5}$ ($p>0.05$). The results show a similar pattern to the Pearson's correlations, with negative relationships between pollutants and unemployment and Dutch background, and positive relationships with income level and migration backgrounds. All three pollutants yield very similar results, though the beta values for NO_2 are slightly higher. On the national level, higher air pollution exposure seems to be characterised by higher SES (high income and low unemployment) and higher proportions of people with migration backgrounds. Following the Pearson's correlation analysis, the most impactful characterising factors seem to be the Dutch background, while for the linear regressions analysis, it is the income level. Supplementary results for the full linear regressions on the national level are provided in Appendix II, 1.

4.3. Sensitivity Analysis

Table 4 gives an indication of sensitivity with linear regression analyses of the metropolitan agglomeration dataset (urban column) and the no missing data dataset (complete column). The full linear regressions are provided in Appendix II, 2 (urban) & 3 (complete).

Table 4 *- Linear Regression Sensitivity Analysis*

		Unstandardized Coefficients B		
Pollutants	Variables	National	Urban	Complete
NO2	(Constant)	**28.29**	**28.79**	**27.72**
	Income Level	**0.38**	**0.35**	**1.00**
	Unemployment (%)	**-0.09**	**-0.08**	**-0.14**
	Dutch (%)	**-0.10**	**-0.08**	
	Western (%)	**0.05**	**0.05**	
	Non-Western (%)	**0.01**	**0.01**	
PM2.5	(Constant)	**12.37**	**12.54**	**12.51**
	Income Level	**0.13**	**0.14**	**0.28**
	Unemployment (%)	**-0.02**	**-0.01**	**-0.03**
	Dutch (%)	**-0.02**	**-0.02**	
	Western (%)	**0.02**	**0.02**	
	Non-Western (%)	0.00	0.00	
PM10	(Constant)	**19.98**	**20.26**	**20.26**
	Income Level	**0.28**	**0.30**	**0.41**
	Unemployment (%)	**-0.03**	**-0.02**	**-0.04**
	Dutch (%)	**-0.03**	**-0.03**	
	Western (%)	**0.02**	**0.02**	
	Non-Western (%)	**0.01**	**0.00**	

***bold indicates significance p<0.05**

As can be seen in Table 4, the relationships of the variables to the pollutants stay mostly the same. Therefore, it can be concluded that the national analysis is relatively robust, with a slightly higher income level characterisation for the 'complete' dataset.

The metropolitan agglomeration areas include around 6.6 million residents (of those included in the $100 \times 100\,\text{m}$ squares data). Urban Pearson's correlations (Appendix II, 4) show a less telling relationship between income and pollutants, with reversed (negative) correlation and insignificant correlation to PM_{10}.

Unemployment also shows the reversed correlation with NO_2 and insignificant correlations with $PM_{2.5}$ and PM_{10}. This indicates that income and unemployment (SES indicators) does not hold robustly within urban areas. For Pearson's correlations for full data (Appendix II, 5), the correlations are incredibly similar to those nationally.

The box-plot comparisons between national and urban areas (Appendix II, 6) show that both datasets present pretty similar trends, although urban areas are at a higher average concentration. For income, a slightly down-turned relationship can also be seen compared to the positive national correlation.

4.4. High Risk Area Analysis

Large areas in the Netherlands are affected by air pollution that is above WHO guidelines (2006), as illustrated by the red areas in Figures 1.1, 1.2, & 1.3. These areas are most significant to this study, as addressing specifically these is most crucial to prevent health risks. Therefore, the demographics and the significance of the differences are presented in the following section.

4.4.1. Demographic Proportion Comparison

According to calculations from the dataset, 4815 people are affected by annual mean NO_2 exposures that are above the WHO guidelines (2006) of above 40 $\mu g/m^3$, creating a health risk. As there are very few areas that exceed the WHO limit on NO_2, these results might not be very robust. Conversely, as can be seen in Figure 1.2, the majority of the Netherlands has $PM_{2.5}$ concentrations that are above the WHO guidelines (2006) of 10 $\mu g/m^3$. Therefore, almost 13 million people are exposed to unhealthy levels of $PM_{2.5}$. This also means that this analysis does not differ much from the national analysis. Regarding PM_{10}, almost 2 million people are exposed to unhealthy levels, according to WHO guidelines (2006) which classify concentrations of 20 $\mu g/m^3$ and above as risky to health.

Table 5 *- Demographic Comparison*

Proportions of different migration backgrounds				
	National / %	NO_2 **unhealthy exposure area / %**	$PM_{2.5}$ **unhealthy exposure area / %**	PM_{10} **unhealthy exposure area / %**
Dutch	77.72	48.33	75.25	57.02
Western	9.11	18.82	9.90	15.17
Non-Western	13.17	32.85	14.85	27.81
Proportions of different (median) income levels				
1 - Low (<16 800€)	12.61	34.13	12.17	20.31
2 - Low-medium (16 800€ - 22 200€)	29.50	27.00	28.77	33.53
3 - Medium (22 200€ - 28 400€)	34.98	20.84	34.47	29.09
4 - High-medium (28 400€ - 36 600€)	19.43	15.33	20.61	13.49
5 - High (>36 600€)	3.48	2.70	3.97	3.58

The comparison, as presented in Table 5, indicates the biggest difference in demographics between the national level and unhealthy NO_2 concentration areas. A much smaller portion of people with a Dutch background experience unhealthy exposure levels of NO_2 (48.33% compared to 77.72% nationally), while groups with migration backgrounds double in representation. Additionally, groups with the lowest income level are most prominently represented in high exposure areas (34.13% compared to 12.61% nationally), while all other income level groups are underrepresented.

As for NO_2, although much smaller, there is also a smaller proportion of people with Dutch backgrounds for areas with harmful $PM_{2.5}$ exposure (75.25% compared to 77.72% nationally). However, the income level distribution changes the opposite way of groups with high NO_2 exposure. Here, low to medium income level groups are underrepresented, while high-medium to high income level groups are a larger proportion of the population compared to the national figures. This is likely due to the widespread of unhealthy $PM_{2.5}$ exposure levels showing similar patterns as the national level.

Unhealthy PM_{10} concentration areas show similar differences as for NO_2, but less extreme. The proportion of people with a Dutch background is far lower in unhealthy PM_{10} exposure areas than nationally (57.02% compared to 77.72% nationally), while groups with migration backgrounds are highly overrepresented. For income level groups, it is the low to low-medium income level groups that are highly overrepresented, while medium to high-medium groups are underrepresented. However, notable is that high income level groups are also slightly overrepresented (3.58% compared to 3.48% nationally).

To put the figures into the real-world context, the following statistics are presented to compare to the calculations from the dataset used for statistical analysis. According to CBS (2016a), 3.8 million inhabitants (22.1%) had a migrant background. Of those, 2.1 million (12.21%) had a non-western background and 1.7 million (9.89%) a western migration background. From the dataset, 22.28% have a migration background, but there is only data available for 11 million people, with 9 million Dutch people, 1 million people with a western migration background and 1.5 million people with a non-western migration background. So, while there is data available on only part of the population, there is a similar ratio.

4.4.2. Independent Sample t-tests

To test if the difference between the means is significant between unhealthy concentration areas and low concentration areas, independent sample t-tests were conducted. The blue highlighted lines indicate the relevant row for each variable.

Table 6 *- Independent Sample t-test* NO_2

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Income Level	EV assumed	9.35	0.00	2.33	215053.00	0.02	0.36	0.15	0.06	0.66
	EV not assumed			1.87	44.01	0.07	0.36	0.19	-0.03	0.75
Dutch (%)	EV assumed	6.89	0.01	7.30	185999.00	0.00	21.58	2.96	15.78	27.37
	EV not assumed			5.49	32.01	0.00	21.58	3.93	13.57	29.58
Western (%)	EV assumed	6.95	0.01	-4.27	86607.00	0.00	-6.59	1.54	-9.62	-3.57
	EV not assumed			-3.16	26.01	0.00	-6.59	2.09	-10.89	-2.30
Non-Western (%)	EV assumed	4.96	0.03	-2.74	66774.00	0.01	-9.26	3.38	-15.88	-2.63
	EV not assumed			-2.17	23.01	0.04	-9.26	4.27	-18.09	-0.42
Unemployment (%)	EV assumed	0.02	0.89	0.02	61680.00	0.99	0.04	2.65	-5.16	5.24
	EV not assumed			0.02	17.01	0.99	0.04	2.78	-5.82	5.90

EV = Equal Variance

Table 6 presents outcomes for NO_2 concentrations. The difference between unhealthy concentration and national area means is significant for migration backgrounds but not for unemployment or income level. The mean difference is especially large for migration backgrounds with mean differences of 21.58 (Dutch), -6.59 (western) and -9.26 (non-western).

Table *7 - Independent Sample t-test* $PM_{2.5}$

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Income Level	EV assumed	50.15	0.00	-50.96	215053.00	0.00	-0.27	0.01	-0.28	-0.26
	EV not assumed			-53.22	92327.11	0.00	-0.27	0.01	-0.28	-0.26
Dutch (%)	EV assumed	4319.08	0.00	96.07	185999.00	0.00	8.61	0.09	8.43	8.78
	EV not assumed			114.65	109110.09	0.00	8.61	0.08	8.46	8.75
Western (%)	EV assumed	0.77	0.38	-3.21	86607.00	0.00	-0.25	0.08	-0.40	-0.10
	EV not assumed			-3.05	16262.70	0.00	-0.25	0.08	-0.41	-0.09
Non-Western (%)	EV assumed	1314.32	0.00	-28.33	66774.00	0.00	-5.19	0.18	-5.55	-4.83
	EV not assumed			-37.40	17082.83	0.00	-5.19	0.14	-5.46	-4.92
Unemployment (%)	EV assumed	211.19	0.00	23.64	61680.00	0.00	2.76	0.12	2.54	2.99
	EV not assumed			21.93	15362.89	0.00	2.76	0.13	2.52	3.01

EV = Equal Variance

The results for $PM_{2.5}$, as presented in Table 7, show a lower difference between means, but the difference is significant for all variables. As for NO_2, the largest difference is for Dutch (8.61) and non-western (-5.19) backgrounds. The difference in income level goes in the opposite direction from the other two pollutants, likely due to the similar pattern of high $PM_{2.5}$ concentrations to national patterns.

Table 8 *- Independent Sample t-test* PM_{10}

		Levene's Test for Equality of Variances		t-test for Equality of Means						
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Income Level	EV assumed	533.48	0.00	26.06	215053.00	0.00	0.23	0.01	0.21	0.24
	EV not assumed			24.28	17186.59	0.00	0.23	0.01	0.21	0.25
Dutch (%)	EV assumed	4620.61	0.00	126.74	185999.00	0.00	19.15	0.15	18.85	19.45
	EV not assumed			91.77	13332.66	0.00	19.15	0.21	18.74	19.56
Western (%)	EV assumed	432.39	0.00	-26.90	86607.00	0.00	-2.28	0.09	-2.44	-2.11
	EV not assumed			-24.92	12370.66	0.00	-2.28	0.09	-2.45	-2.10
Non-Western (%)	EV assumed	3530.99	0.00	-41.48	66774.00	0.00	-7.54	0.18	-7.90	-7.18
	EV not assumed			-31.37	10858.74	0.00	-7.54	0.24	-8.01	-7.07
Unemployment (%)	EV assumed	1.92	0.17	11.23	61680.00	0.00	1.53	0.14	1.26	1.79
	EV not assumed			11.31	10252.31	0.00	1.53	0.14	1.26	1.79

EV = Equal Variance

Results for PM_{10} (Table 8) are similar to the other pollutants. All variables are significantly different for unhealthy PM_{10} levels compared to the national level. In line with the other two pollutants, Dutch (19.15) and non-western migration (-7.54) backgrounds present the biggest difference in means.

4.4.3. Correlation Comparison

The following box-plots visualize the previous analysis. The 1 represents high concentration areas and the 0 is non-high concentration areas. Figure 2.1 visualizes the pattern of lower average income in unhealthy concentration areas for NO_2 and PM_{10}, but the opposite is true for $PM_{2.5}$. Figure 2.2 shows the difference in unemployment rates, which was shown to be quite low and occasionally insignificant. The box-plots make this apparent as well.

Figure 2.1 *- Income Level Comparison for High Concentration Areas*

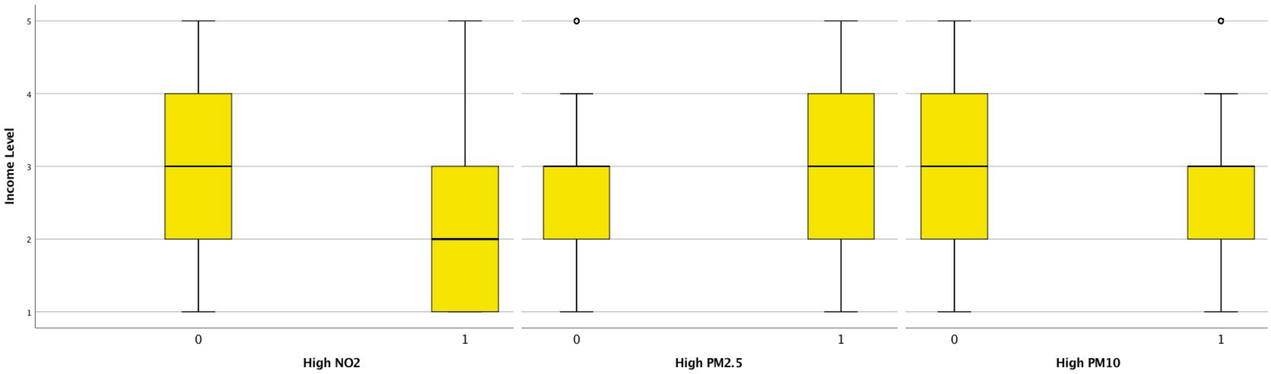
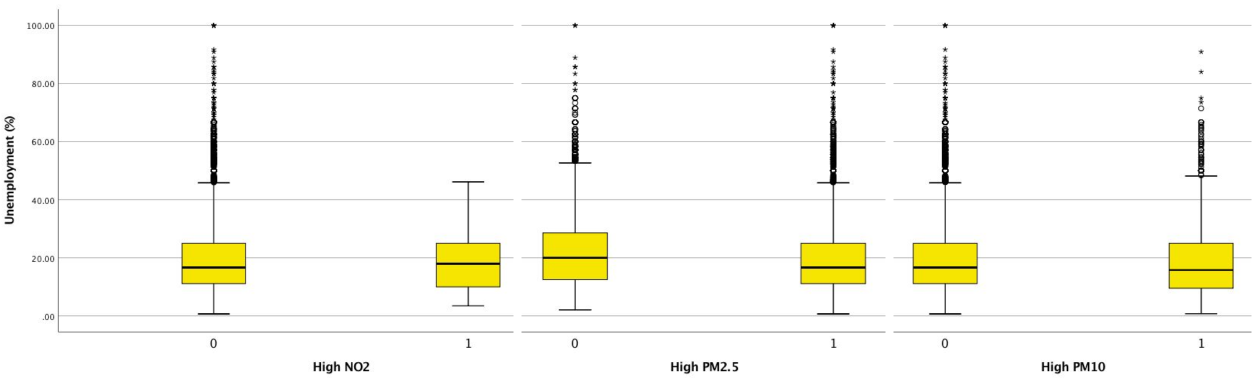


Figure 2.2 *- Unemployment Rate Comparison for High Concentration Areas*



For the difference in proportion of people with a Dutch background (Fig. 2.3), a clear difference can be seen for all pollutants, where they are significantly lower in unhealthy concentration areas. Western background (Fig. 2.4) does not show a very large difference except in NO_2, where the proportion of people with a western migration background is a bit higher in high concentration areas. Lastly, non-western background (Fig. 2.5) shows a large difference between unhealthy and lower concentration areas, where there is a clear overrepresentation of people with a non-western migration background in high concentration areas.

Figure 2.3 - *Dutch Background Proportion Comparison for High Concentration Areas*

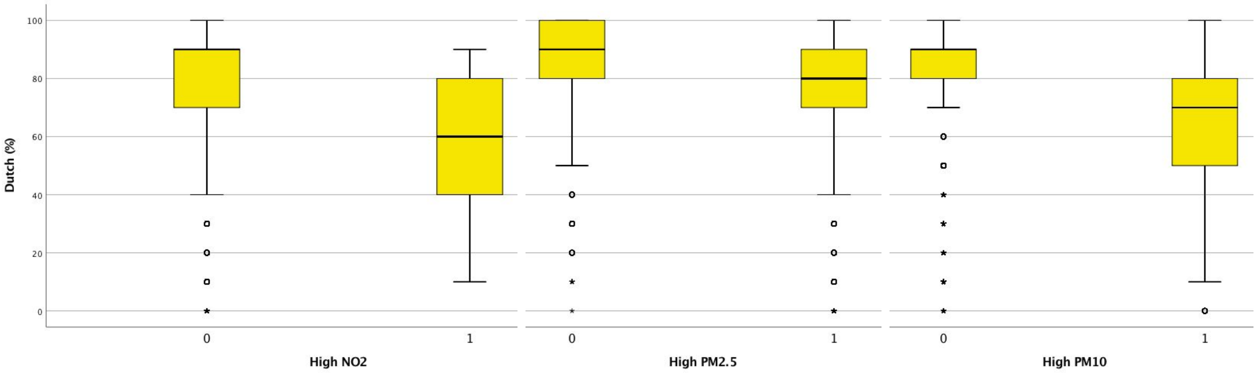


Figure 2.4 - *Western Background Proportion Comparison for High Concentration Areas*

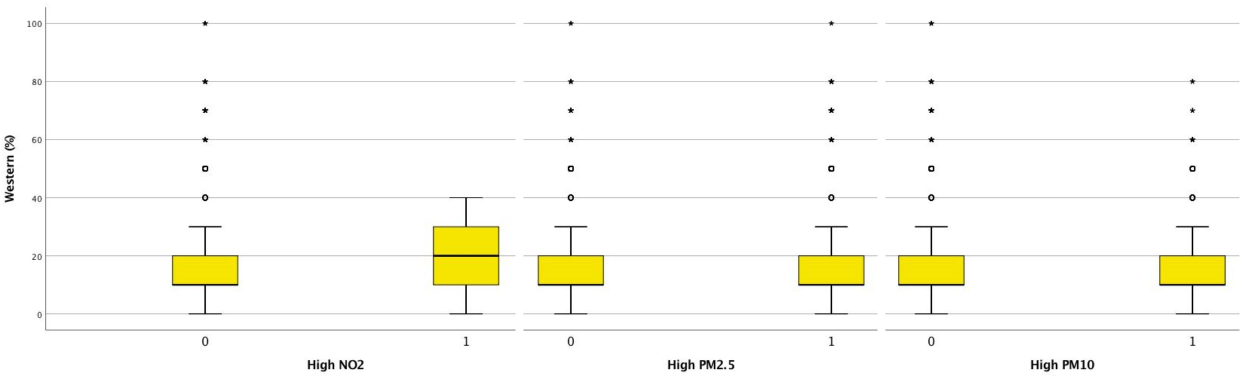
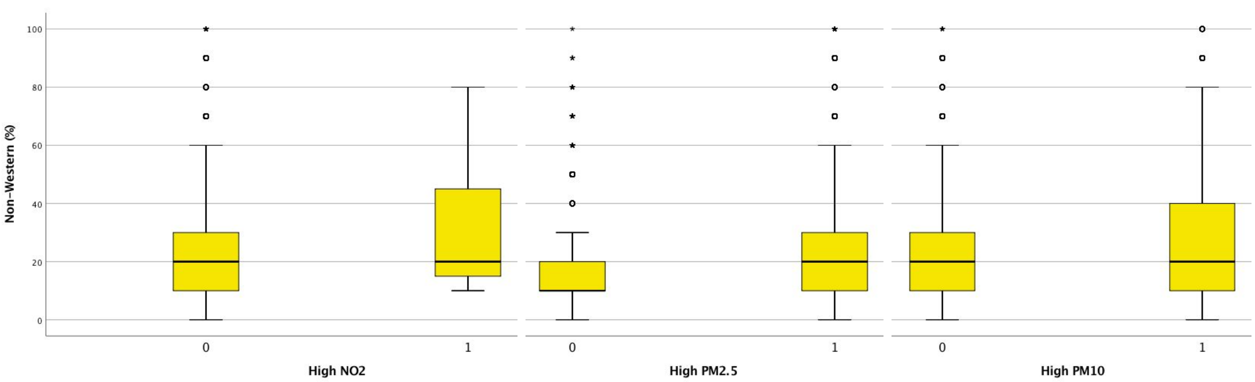


Figure 2.5 - *Non-western Background Proportion Comparison for High Concentration Areas*



4.4.4. Conclusion Health Risk Area Analysis

This analysis of air pollution health risk areas shows a clear, significant difference in demographics in these areas with unhealthy pollution levels compared to national figures. Overall, there is a significantly lower mean of people with a Dutch background and a higher mean population of people with a non-western background. For all three pollutants, the proportion of Dutch people in unhealthy exposure areas is significantly lower than nationally, while the proportions of people with migration backgrounds are higher than nationally in the same areas. Proportions of income level groups are not consistent for all three pollutants. Lower income level groups are overrepresented for NO_2 and PM_{10}, while higher income level groups are overrepresented for $PM_{2.5}$. Results for changes in the average unemployment rate are relatively minor.

5. Discussion

5.1. Findings

The overall findings of this study are in line with previous studies but differ between the national level and the unhealthy concentration areas. The urban factor can explain the divergence between these two and results found in previous studies. The most prominent and consistent finding is that people with a Dutch background are a lot less prevalent in areas with unhealthy air pollution exposure levels according to WHO guidelines, with mean differences of 21.58% (NO_2), 8.61% ($PM_{2.5}$) and 19.15% (PM_{10}). This might be due to people with a Dutch background being more likely to live rurally – with less air pollution – than people with a migration background, who cluster in cities. Mikati et al. (2018) also name the rural-urban divide as a modifier due to the arising patterns from industrialisation, with high non-white representation in city centres. With continuous international migration into the Netherlands, the ethnic population structure is changing – especially in cities (Bontje & Latten, 2005). In the four largest Dutch cities, the incoming migrants have replaced people with a Dutch background in urban centres (Bontje & Latten, 2005). The relationship between non-western migration background and pollutants proved to be minor on the national and urban level. The insignificance of this variable on these levels might suggest this specification is not a defining variable. Although, since Dutch background is a very significant variable, it might be the type of specification that leads to insignificant results. Non-western migration background is a rather vague classification and might not be a good indicator for ethnic minorities. However, with the Dutch variable, conclusions can still be made about foreigners often characterising areas of higher air pollution exposure levels.

On the national level, higher air pollution exposure seems to be characterised by higher SES (high income and low unemployment) and higher proportions of people with migration backgrounds. The sensitivity analysis shows that data without missing values does not make a large difference. In relation to urban areas, the migration background relation holds, but the relationship with income and unemployment seems to be more complicated. This indicates that the positive relationship with income is due to the urban factor. It can be explained by broader urban demographic patterns, as cities are attractive living spaces for high-income groups, but are also likely to have higher levels of air pollution (Milojevic et al., 2017). This pattern has been found in previous studies, as mentioned before, specifically the London example (Goodman et al., 2011). The gentrification of city cores has also been a factor pushing lower-class population groups to the periphery of cities, while higher SES groups move inwards (Musterd et al., 2020).

In areas with unhealthy levels of the studied pollutants, results on migration backgrounds were in line with national and urban analyses. People with Dutch backgrounds were underrepresented by 2.47 ($PM_{2.5}$), 20.70 (PM_{10}) and 29.39% (NO_2), while people with migration backgrounds were overrepresented compared to national proportions. The results for $PM_{2.5}$ were generally very similar to those from the national analysis, as a majority of the country is at an unhealthy annual level of $PM_{2.5}$ concentrations, as illustrated in Figure 1.2. However, PM_{10} and NO_2 show different results regarding income levels (with one exception in the weighted demographic proportions comparison). The proportion of people with a lower income level is significantly larger in PM_{10} unhealthy exposure areas than nationally, showing that a lower SES could indicate a higher likelihood of living in an area with unhealthy mean pollutant exposures. These findings are in line with previous studies (Flanagan et al., 2019; Goodman et al., 2011; Jerret et al., 2001; Liu et al., 2018; Marshall, 2008; Milojevic et al., 2017; Samoli et al., 2019). However, for NO_2 and $PM_{2.5}$, the results for the mean difference between unhealthy and lower exposure levels for income level and unemployment rate were either insignificant or minuscule. While the box-plots (Fig. 2.1) and demographic proportion comparisons (Table 5) seem to show some difference for income level and some small significant results were found for unemployment, this might not be a sufficient enough indicator to draw conclusions about SES. PM_{10} did show some remarkable results where additionally to lower income level groups, the highest income level group was slightly overrepresented as well, if only by 0.1% (Table 5). However, the independent sample t-test analysis showed more significance in the direction of a negative correlation. Still, this could paint a picture of both ends of the spectrum being affected, likely connected by the urban factor and could benefit from further analysis. From this analysis (especially the unhealthy concentration exposure analysis) it seems the Dutch migration background is the most reliable and consistent characteristic defining different levels of air pollution exposure areas.

An investigation of the sources of the different pollutants may also provide an indication of the way in which the results came about. As mentioned before, the main source of NO_2 is vehicular traffic (Samoli et al., 2019; Fecht et al., 2015), supporting the urban-oriented results. As the pollutants are more likely to be found in cities, more diverse ethnic backgrounds and higher overall income levels are a logical pattern. Additionally, when looking at unhealthy exposure levels, they are likely to be found close to roads, where lower income groups might be more likely to live. Similar explanations can be used for PM_{10}, which originates from mechanical processes such as from construction sites (WHO, 2006). These would also likely be found more in cities. For $PM_{2.5}$, the global main anthropogenic sources are combustion-related (Liu et al., 2019; WHO, 2006), but include power generation, manufacturing and industry, transportation, homes and agriculture (National Research Council, 2010), suggesting a wider spread and less urban focus.

5.2. Comparison with Other Studies

As this study follows a similar approach to Fecht et al. (2015) in one of the same study areas, a comparison shows the impact of different spatial resolutions and slightly different approaches. Fecht et al. (2015) concluded that the urban-rural contrast was a main driver of the variables being associated with high pollutant exposure, where the associations did not hold up in rural areas. Similar results were found in this study, where the environmental inequality in varying ethnic diversity was stable throughout different analyses. Exposure inequality for different income level groups varied but was generally affecting low-income groups more in unhealthy (more urban) exposure areas. Looking at the results of their analysis of the Netherlands, associations with deprivation was minimal when taking other factors (like urbanisation) into account. Additionally, possibilities of gentrification inverting income patterns are discussed. These results indicate a Dutch specific pattern of high incomes in urban areas, which are likely to have more exposure. Milojevic et al. (2017) and Goodman et al. (2011) also raise points about high-income groups moving to cities, where air pollution is usually higher, which the current findings reiterate. Fecht et al. (2015) also address previous scepticism about ethnic diversity, where this was often believed to solely be a factor due to its influence on deprivation. From the current research, this does not seem valid, as the Dutch and non-Dutch distinction was a more stable and significant characterising factor of air pollution exposure compared to deprivation (SES) indicators. While the smaller spatial resolution seems to bring up some differing results from Fecht et al. (2015), it also seems to reiterate and specify points made in previous studies including Fecht et al. 's (2015).

5.3. Environmental Justice Angle

From the conclusions drawn through the findings of this study, it is apparent there is some need to address environmental justice in the Netherlands. Even though on the national level, higher air pollution exposure is related to higher levels of income, lower-income groups are overrepresented in most areas with actually unhealthy (over WHO) levels of air pollution. This indicates some deeper structural problems, as more vulnerable groups are hit more even though larger patterns would suggest otherwise. Additionally, groups with migration backgrounds are overrepresented with proportional means being significantly different in unhealthy exposure areas when compared to the national level, which indicates a level of environmental inequality as well. There is an inequitable spread of air pollution, with higher exposures characterised by proportionally more low income and non-Dutch groups. This fact needs to be acknowledged so that interventions can be planned accordingly. Particularly the areas that exceed the WHO guidelines should be addressed to lower these environmental inequalities, with the health effects these high exposures can cause.

5.4. Current Relevance

These findings and conclusions on environmental justice have also proven to be very relevant for the current COVID-19 pandemic. Andrée (2020) found that $PM_{2.5}$ specifically is a very effective predictor of several COVID-19 case indicators. High $PM_{2.5}$ concentrations are correlated with much higher COVID-19 cases in the Netherlands. When concentrations are above the WHO guidelines, the number of cases can double (Andrée, 2020). While further investigations are needed to find if case severity is also impacted, these findings still have a lot of potential. It can provide strong implications for actions in mitigating further spreading of the virus. It also gives further indication of how environmental injustices in the distribution of pollution can have immense impacts.

5.5. Strengths and Limitations of this Study

This study has looked into several aspects of environmental inequality in air pollution exposure in the Netherlands, expanding on previous research and discussions on the interconnection of environmental and social issues. One of the main strengths of this study is the investigation of the entire country on a smaller resolution. This eliminates issues of heterogeneous neighbourhoods and gives more variation in specific regions. This can then give indications of specific policy intervention areas for air pollution. Furthermore, by investigating what characterises the distributional differences of the pollutants, the recognition of social inequality in highly affected areas can be improved, and underlying reasons for unjust distribution can be explored. Specifically, underlying structural issues can be investigated to explain the overrepresentation of people with a migration background and lower income level in unhealthily high exposure areas. Including $PM_{2.5}$ is also an addition to research by Fecht et al. (2015), as the health consequences of $PM_{2.5}$ are just as, if not more detrimental than PM_{10} (Liu et al., 2019). It is, therefore, an important addition to research; Especially when it can have such significant importance in current issues, as mentioned in the previous section.

Nevertheless, several limitations should be addressed and could be improved on in future research. The data used ($100 \times 100\,m$ square; CBS, 2016b) had some limitations, as it lacked figures on education and included a lot of missing data for several categories. This was partially overcome through sensitivity analyses, but the data still does not provide a full picture. The missing data is likely so prevalent due to difficulties obtaining data on income levels and other social characteristics. Looking only at income level and unemployment rate also gives a rather limited and overgeneralized picture of socio-economic status. More detail and more aspects that play into SES would be useful to include in analyses. As SES is such a complex factor, further investigation into it might also be beneficial, as indicators are very simplifying. Similarly, ethnic backgrounds are quite generalized ('western' and 'non-western'), not allowing much differentiation or sound conclusions on racial inequalities. While the prevalent results on the Dutch/ non-Dutch distinction do give an indication of some ethnic inequalities, no concrete conclusions about racial inequalities should be drawn from such data, as a Dutch background does not have to mean a specific race or ethnicity. Notable is also the unemployment figures, which proved to be troublesome in the analyses, as there were no true zero values in the complete dataset and a large chunk of data was unavailable. This means that the results for unemployment rates should be regarded critically as well. Generally, the investigation of social characteristics should always be looked at critically, as it is a very complex topic area. However, some indications can still be useful to draw even from imperfect data.

6. Conclusion

To answer the initially posed research question: how do different social factors (income, unemployment, & migration backgrounds) characterise high levels of exposure to $PM_{2.5}$, PM_{10} and NO_2 in the Netherlands on a $100 \times 100\,\text{m}$ scale? Nationally, urban characterising qualities are dominant, as urban areas experience higher levels of air pollution. However, in unhealthily high exposure areas (according to WHO guidelines), lower income levels and migration backgrounds are overrepresented with Dutch backgrounds being the most reliable characterising factor, whilst differences between mean unemployment rates are minor. These findings indicate a level of environmental inequality, especially regarding migration backgrounds in the Netherlands.

Findings showed that unhealthy air pollution disproportionately hit more vulnerable groups despite opposing national outcomes for income levels. The national income level patterns can be explained by urban demographic patterns, with more high income level people moving to city centres. Still, they largely do not experience their same share of unhealthy air pollution as lower-income groups, as the distribution is not equal. However, this relationship is quite complex and could benefit from further investigation. For different migration backgrounds, the results are more consistent. Non-Dutch migration backgrounds characterise higher levels of air pollution exposure nationally but are also significantly overrepresented in unhealthy exposure areas, indicating further environmental inequalities. While the overall trend can be explained by patterns where more people with a migration background live in Dutch cities rather than rurally, this does not explain the overrepresentation in unhealthy exposure areas. Therefore, there are indications of environmental inequality both regarding ethnicity and SES in unhealthy exposure areas. This should show that there is a need for both social and environmental issues to be addressed for a more sustainable society in the Netherlands.

These findings support those of previous studies, highlighting that environmental inequality is still an issue in the Netherlands even though national patterns would suggest otherwise. It also addresses the relevance of this issue currently as unhealthy $PM_{2.5}$ concentrations could even indicate higher cases of COVID-19. This study adds to the discussion of the interconnection of social and environmental problems but has some limitations that need to be taken into consideration.

6.1. Further research

Further research is possible and would be beneficial in this area. It could expand on more pollutants and more recent data, as well as investigate the underlying reasons for environmental inequality and the interconnection of social and environmental issues. Investigations into the complex income variable, as well as other social indicators and race, could help provide more concrete results. Furthermore, more complete data and SES indicators could give a more robust picture of the environmental inequality in air pollution exposure.

7. References

Agyeman, J., Schlosberg, D., Craven, L., & Matthews, C. (2016). Trends and Directions in Environmental Justice: From Inequity to Everyday Life, Community, and Just Sustainabilities. *Annual Review of Environment and Resources*, *41*(1), 321–340. https://doi.org/10.1146/annurev-environ-110615-090052

Andrée, B. P. J. (2020). Incidence of COVID-19 and Connections with Air Pollution Exposure Evidence from the Netherlands. In Fragility, Conflict and Violence Global Theme. Accessed through: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3584842

Atlas Leefomgeving (2016). Kaarten. Accessed through: https://www.atlasleefomgeving.nl/kaarten

Beelen, R., Hoek, G., van den Brandt, P. A., Goldbohm, R. A., Fischer, P., Schouten, L. J., … Brunekreef, B. (2008). Long-term effects of traffic-related air pollution on mortality in a Dutch cohort (NLCS-AIR study). *Environmental Health Perspectives*, *116*(2), 196–202. https://doi.org/10.1289/ehp.10767

Bontje, M., & Latten, J. (2005). Stable size, changing composition: Recent migration dynamics of the Dutch large cities. *Tijdschrift Voor Economische En Sociale Geografie*, *96*(4), 444–451. https://doi.org/10.1111/j.1467-9663.2005.00475.x

Briggs, D., Abellan, J. J., & Fecht, D. (2008). Environmental inequity in England: Small area associations between socio-economic status and environmental pollution. Social Science and Medicine, 67, 1612–1629. https://doi.org/10.1016/j.socscimed.2008.06.040

CBS (2016a). *Annual Report on Integration 2016 Summary.* Statistics Netherlands. https://www.cbs.nl/-/media/_pdf/2016/47/ji2016s_web.pdf

CBS (2016b). Kaart van 100 meter bij 100 meter met statistieken. Accessed through: https://www.cbs.nl/nl-nl/dossier/nederland-regionaal/geografische-data/kaart-van-100-meter-bij-100-meter-met-statistieken

Clark, L. P., Millet, D. B., & Marshall, J. D. (2017). Changes in transportation-related air pollution exposures by race-ethnicity and socioeconomic status: Outdoor nitrogen dioxide in the United States in 2000 and 2010. *Environmental Health Perspectives*, *125*(9), 1–10. https://doi.org/10.1289/EHP959

European Environment Agency (2019). Netherlands - Air pollution country fact sheet. Accessed through: https://www.eea.europa.eu/themes/air/country-fact-sheets/2019-country-fact-sheets/netherlands

Fecht, D., Fischer, P., Fortunato, L., Hoek, G., De Hoogh, K., Marra, M., … Hansell, A. (2015). Associations between air pollution and socioeconomic characteristics, ethnicity and age profile of neighbourhoods in England and the Netherlands. *Environmental Pollution*, *198*, 201–210. https://doi.org/10.1016/j.envpol.2014.12.014

Fischer, P. H., Marra, M., Ameling, C. B., Hoek, G., Beelen, R., de Hoogh, K., … Houthuijs, D. (2015). Air pollution and mortality in seven million adults: The Dutch environmental longitudinal study (DUELS). *Environmental Health Perspectives*, *123*(7), 697–704. https://doi.org/10.1289/ehp.1408254

Fischer, P. H., Marra, M., Ameling, C. B., Velders, G. J. M., Hoogerbrugge, R., de Vries, W., … Houthuijs, D. (2020). Particulate air pollution from different sources and mortality in 7.5 million adults — The Dutch Environmental Longitudinal Study (DUELS). *Science of the Total Environment*, *705*. https://doi.org/10.1016/j.scitotenv.2019.135778

Flanagan, E., Stroh, E., Oudin, A., & Malmqvist, E. (2019). Connecting Air Pollution Exposure to Socioeconomic Status : A Cross-Sectional Study on Environmental Injustice among Pregnant Women in Scania, Sweden. *Environmental Research and Public Health*, *16*(24), #5116.

Gehring, U., Heinrich, J., Krämer, U., Grote, V., Hochadel, M., Sugiri, D., … Wichmann, H.-E. (2006). Long-Term Exposure to Ambient Air Pollution and Cardiopulmonary Mortality in Women. *Epidemiology*, *17*(5), 545–551. https://doi.org/10.1097/01.ede.0000224541.38258.87

Goodman, A., Wilkinson, P., Stafford, M., & Tonne, C. (2011). Characterising socio-economic inequalities in exposure to air pollution: A comparison of socio-economic markers and scales of measurement. *Health and Place*, *17*(3), 767–774. https://doi.org/10.1016/j.healthplace.2011.02.002

Hall, J. V. (1996). Assessing health effects of air pollution. *Atmospheric Environment*, *30*(5), 743–746. https://doi.org/10.1016/1352-2310(95)00014-3

Hoek, G., Brunekreef, B., Goldbohm, S., Fischer, P., & Van Den Brandt, P. A. (2002). Association between mortality and indicators of traffic-related air pollution in the Netherlands: A cohort study. *Lancet*, *360*, 1203–1209. https://doi.org/10.1016/S0140-6736(02)11280-3

Jerrett, M., Burnett, R. T., Kanaroglou, P., Eyles, J., Finkelstein, N., Giovis, C., & Brook, J. R. (2001). A GIS - Environmental justice analysis of particulate air pollution in Hamilton, Canada. *Environment and Planning A*, *33*(6), 955–973. https://doi.org/10.1068/a33137

Künzli, N., Kaiser, R., Medina, S., Studnicka, M., Chanel, O., Filliger, P., … Quénel, P. (2000). Public-health impact of outdoor and traffic-related air pollution : a European assessment. *Lancet*, *356*, 795–801.

Liu, C., Chen, R., Sera, F., Vicedo-Cabrera, A. M., Guo, Y., Tong, S., … Kan, H. (2019). Ambient particulate air pollution and daily mortality in 652 cities. *New England Journal of Medicine*, *381*(8), 705–715. https://doi.org/10.1056/NEJMoa1817364

Liu, Y., Wu, J., & Yu, D. (2018). Disentangling the Complex Effects of Socioeconomic , Climatic , and Urban Form Factors on Air Pollution : A Case Study of China. *Sustainability*, *10*(3), 1–14. https://doi.org/10.3390/su10030776

Marshall, J. D. (2008). Environmental inequality: Air pollution exposures in California's South Coast Air Basin. *Atmospheric Environment*, *42*(21), 5499–5503. https://doi.org/10.1016/j.atmosenv.2008.02.005

Mayer, H. (1999). Air pollution in cities. *Atmospheric Environment*, *33*, 4029–4037.

Mikati, I., Benson, A. F., Luben, T. J., Sacks, J. D., & Richmond-Bryant, J. (2018). Disparities in distribution of particulate matter emission sources by race and poverty status. *American Journal of Public Health*, *108*(4), 480–485. https://doi.org/10.2105/AJPH.2017.304297

Milojevic, A., Niedzwiedz, C. L., Pearce, J., Milner, J., MacKenzie, I. A., Doherty, R. M., & Wilkinson, P. (2017). Socioeconomic and urban-rural differentials in exposure to air pollution and mortality burden in England. *Environmental Health*, *16*(1), 1–10. https://doi.org/10.1186/s12940-017-0314-5

Morello-Frosch, R., Pastor, M., Porras, C., & Sadd, J. (2002). Environmental justice and regional inequality in Southern California: Implications for furture research. *Environmental Health Perspectives*, *110*(SUPPL. 2), 149–154. https://doi.org/10.1289/ehp.02110s2149

Musterd, S., Hochstenbach, C., & Boterman, W. (2020). Ripples of structural economic transformation: The changing social geographies of Dutch metropolitan regions. *Applied Geography*, *116*, 1–12. https://doi.org/10.1016/j.apgeog.2020.102151

National Research Council (2010). Global Sources of Local Pollution: An Assessment of Long-Range Transport of Key Air Pollutants to and from the United States. Washington, DC: The National Academies Press. https://doi.org/10.17226/12743

O'Neill, M. S., Jerrett, M., Kawachi, I., Levy, J. I., Cohen, A. J., Gouveia, N., … Zanobetti, A. (2003). Health, wealth, and air pollution: Advancing theory and methods. *Environmental Health Perspectives*, *111*(16), 1861–1870. https://doi.org/10.1289/ehp.6334

Samoli, E., Stergiopoulou, A., Santana, P., Rodopoulou, S., Mitsakou, C., Dimitroulopoulou, C., … Katsouyanni, K. (2019). Spatial variability in air pollution exposure in relation to socioeconomic indicators in nine European metropolitan areas : A study on environmental inequality *. *Environmental Pollution*, *249*, 345–353. https://doi.org/10.1016/j.envpol.2019.03.050

Schlosberg, D. (2004). Reconceiving environmental justice: Global movements and political theories. *Environmental Politics*, *13*(3), 517–540. https://doi.org/10.1080/0964401042000229025

WHO (2006). *WHO Air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide - Global update 2005.* World Health Organization, Geneva, Switzerland. Retrieved from: http://whqlibdoc.who.int/hq/2006/WHO_SDE_PHE_OEH_06.02_eng.pdf

Appendix I: Abbreviations

List of Abbreviations:

- GIS - Geographic Information System
- SES - socioeconomic status
- WHO - World Health Organization
- CBS - Centraal Bureau voor de Statistiek (Central Bureau for Statistics)
- $PM_{2.5}$ - Particulate Matter with a diameter of 2.5 micrometres or less
- PM_{10} - Particulate Matter with a diameter of 10 micrometres or less
- NO_2 - Nitrogen Dioxide

Appendix II: Supplementary Results

1. Full National Linear Regressions

1.1. NO_2

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	28.29	0.46		61.32	0.00
Income Level	0.38	0.03	0.07	11.29	0.00
Unemployment (%)	-0.09	0.00	-0.22	-35.02	0.00
Dutch (%)	-0.10	0.01	-0.38	-21.48	0.00
Western (%)	0.05	0.01	0.07	9.54	0.00
Non-Western (%)	0.01	0.01	0.04	2.39	0.02

1.2. $PM_{2.5}$

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	12.37	0.13		95.69	0.00
Income Level	0.13	0.01	0.09	13.78	0.00
Unemployment (%)	-0.02	0.00	-0.14	-20.68	0.00
Dutch (%)	-0.02	0.00	-0.29	-15.60	0.00
Western (%)	0.02	0.00	0.09	11.65	0.00
Non-Western (%)	0.00	0.00	0.01	0.78	0.44

1.3. PM_{10}

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	19.98	0.16		125.46	0.00
Income Level	0.28	0.01	0.16	24.02	0.00
Unemployment (%)	-0.03	0.00	-0.18	-28.79	0.00
Dutch (%)	-0.03	0.00	-0.31	-17.29	0.00
Western (%)	0.02	0.00	0.07	9.38	0.00
Non-Western (%)	0.01	0.00	0.07	3.79	0.00

2. Full Urban Linear Regressions

2.1. NO_2

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	28.79	0.56		51.39	0.00
Income Level	0.35	0.04	0.08	9.19	0.00
Unemployme	-0.08	0.00	-0.22	-25.99	0.00
Dutch (%)	-0.08	0.01	-0.37	-14.55	0.00
Western (%)	0.05	0.01	0.07	7.43	0.00
Non-Western	0.01	0.01	0.05	2.10	0.04

2.2. $PM_{2.5}$

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	12.54	0.16		80.84	0.00
Income Level	0.14	0.01	0.12	13.33	0.00
Unemployme	-0.01	0.00	-0.09	-10.39	0.00
Dutch (%)	-0.02	0.00	-0.32	-11.91	0.00
Western (%)	0.02	0.00	0.09	8.58	0.00
Non-Western	0.00	0.00	-0.03	-1.15	0.25

2.3. PM_{10}

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	20.26	0.20		101.43	0.00
Income Level	0.30	0.01	0.18	21.91	0.00
Unemployme	-0.02	0.00	-0.16	-19.13	0.00
Dutch (%)	-0.03	0.00	-0.35	-13.67	0.00
Western (%)	0.02	0.00	0.08	8.03	0.00
Non-Western	0.00	0.00	0.05	2.04	0.04

3. Full No Missing Variables Linear Regressions

3.1. NO_2

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	27.72	0.05		547.58	0.00
Income Level	1.00	0.01	0.22	94.40	0.00
Dutch (%)	-0.14	0.00	-0.51	-218.48	0.00

3.2. $PM_{2.5}$

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	12.51	0.02		733.55	0.00
Income Level	0.28	0.00	0.20	78.49	0.00
Dutch (%)	-0.03	0.00	-0.36	-146.77	0.00

3.3. PM_{10}

	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	20.26	0.02		1037.20	0.00
Income Level	0.41	0.00	0.24	99.97	0.00
Dutch (%)	-0.04	0.00	-0.43	-178.56	0.00

4. Urban Pearson's Correlations

	NO_2	$PM_{2.5}$	PM_{10}	Population	Income	Unemployment (%)	Dutch	Western	Non-Western
NO_2	1.00								
$PM_{2.5}$	0.72	1.00							
PM_{10}	0.82	0.87	1.00						
Population	0.33	0.24	0.34	1.00					
Income	-0.06	-0.04	0.01*	-0.20	1.00				
Unemployment (%)	0.02	0.00*	0.00*	0.10	-0.43	1.00			
Dutch	-0.38	-0.26	-0.35	-0.45	0.44	-0.36	1.00		
Western	0.08	0.12	0.10	-0.09	0.11	-0.19	-0.19	1.00	
Non-Western	0.18	0.10	0.15	0.19	-0.45	0.37	-0.91	-0.27	1.00

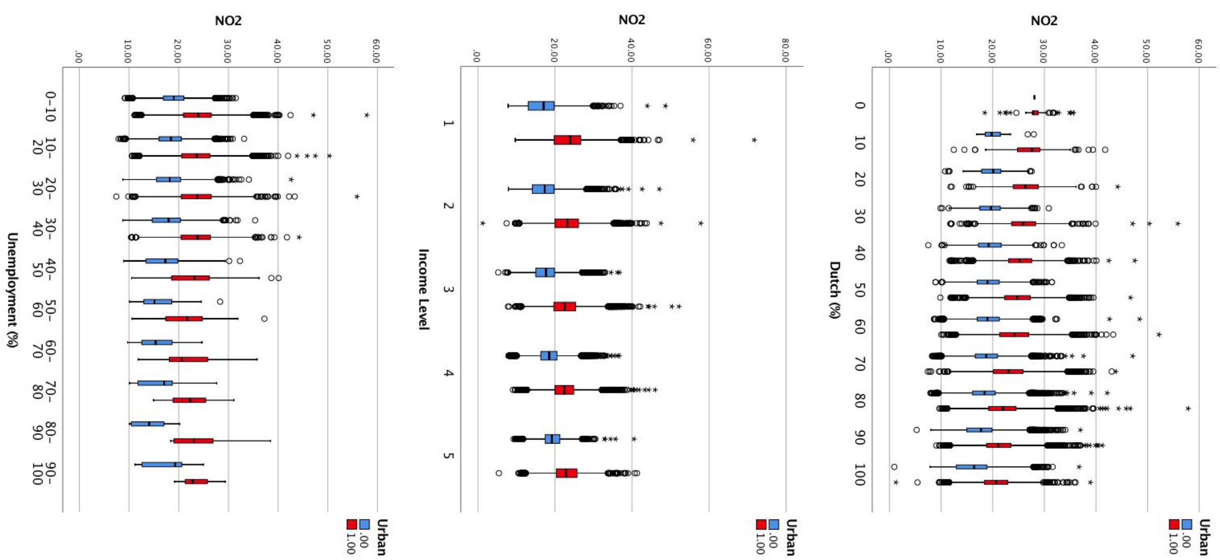
*not a significant correlation (p>0.05)

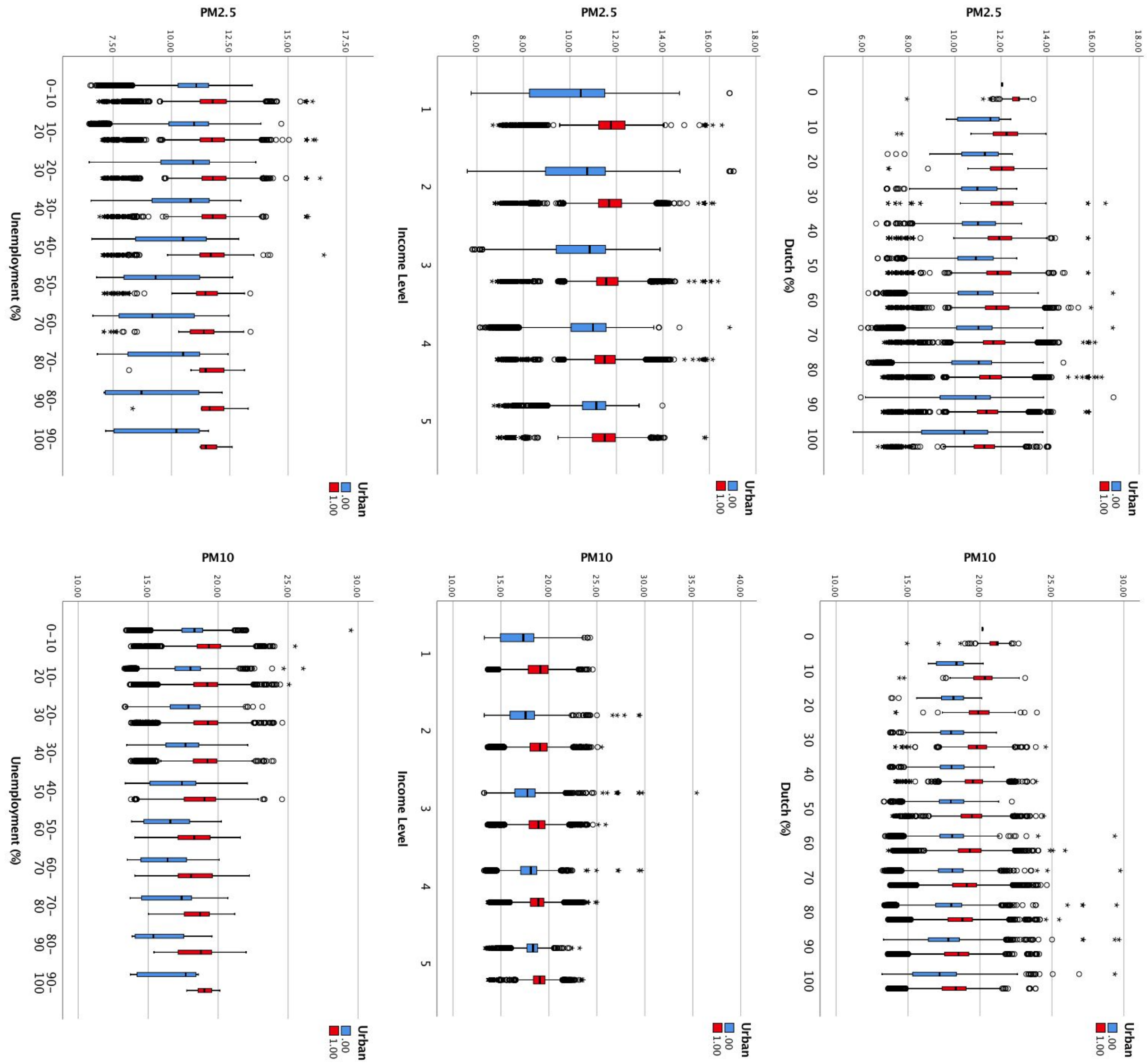
5. No Missing Values Pearson's Correlations

	NO_2	$PM_{2.5}$	PM_{10}	Population	Income	Dutch
NO_2	1.00					
$PM_{2.5}$	0.80	1.00				
PM_{10}	0.85	0.92	1.00			
Population	0.42	0.28	0.38	1.00		
Income	0.05	0.08	0.10	-0.13	1.00	
Dutch	-0.44	-0.30	-0.35	-0.47	0.33	1.00

all correlation are significant ($p<0.05$)

6. Box-plot Comparison National and Urban




PM2.5
Dutch (%)
Urban
.00
1.00
PM2.5
Income Level
Urban
.00
1.00
PM2.5
Unemployment (%)
Urban
.00
1.00
PM10
Dutch (%)
Urban
.00
1.00
PM10
Income Level
Urban
.00
1.00
PM10
Unemployment (%)
Urban
.00
1.00

Appendix III: Cities included in Metropolitan Agglomeration Data

- Amersfoort
- Amsterdam
- Apeldoorn
- Arnhem
- Breda
- Dordrecht
- Eindhoven
- Enschede
- Geleen/Sittard
- Groningen
- Haarlem
- Heerlen
- Leeuwarden
- Leiden
- Maastricht
- Nijmegen
- Rotterdam
- ‘s-Gravenhage
- ‘s-Hertogenbosch
- Tilburg
- Utrecht
- Zwolle