International Master of Public Health

Master international de Santé Publique

Residential proximity to industrial facilities in France: an environmental justice study in the Lille Metropolitan Area

Presented by

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Master 2 Student -2008-2009

Location of the practicum
EHESP- Rennes- France

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Acknowledgment

There are several institutions and individuals who have made this learning experience possible and I would like to extend my deepest and sincere gratitude to them. First of all, I will like to thank the EHESP for giving me the opportunity to pursue a career in Public health.

This dissertation would not have been possible without Dr. Severine Deguen, who, not only accepted to supervise this work but also guided my first steps into quantitative research. Accept my wholehearted gratitude for your patience and being there whenever I needed your guidance.

I am also extremely fortunate to have having Dr. Denis Zmirou as academic supervisor. Sir, thanks for your valuable contribution to this work and especially for your advice throughout this period.

My deepest thanks go to Dr. Moise Desvarieux and Pakdaman Khashayar for accepting to examine this work. It is an honour having such an experienced scientist to evaluate a study of this nature. I know you are all very busy but I am grateful you could still find time to guide me.

My sincere gratitude goes to all the EHESP master of public health lecturers for accepting to share their knowledge with me. I was extremely fortunate to have you all as lecturers. I am confident that your teachings will guide me throughout my professional career.

My gratitude also goes to my entire classmates with whom I shared the public health experience throughout the academic year. I am particularly grateful to you all for spending pleasant time together.

I would also like to express my gratitude to all the EHESP-DSET personnel for their sympathy. To all the PhD students of the LERES department at EHESP, and to James Boniteau, receive special thanks from the bottom of my heart.

For my lovely family and friends for their inseparable support and prayers, hope this new degree will bring a new orientation in our lives.

Finally, it is a pleasure to thank all those who contributed successfully to the realisation of this work. Even if you are not cited here, I am particularly grateful to you all.

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List of Acronyms

ATDSDR	Agency for toxic substances and disease registry
EPA	Environmental protection Agency
EPER	European pollutant emission registry
EPRTR	European pollutant Release and transfer registry
GIS	Geographic information system
INSEE:	Institut National de la Statistique et des Etudes Economiques
INSERM	Institut National de la santé et de la Recherche Médicale
IPC	Industrial pollution control
IREP	Registre Français des émissions polluantes (French Registry of polluting emissions)
IRIS	Ilots Regroupés pour l'Information Statistique
LMA	Lille Metropolitan Area
LMA	Lille Metropolitan Area
PCA	Principal Component Analysis
SMA	Strasbourg Metropolitan Area
TRI	Toxic Release inventory
UNEP	United Nations Environment protection programmes.
WHO	World Health Organisation

General introduction

1 Overview of social health inequalities

The health of populations has become a major concern for researchers, clinicians, politicians and decision makers. For many decades now, efforts have been made and are still being made worldwide, in industrial countries notably, to see what types of policies could likely reduce health inequalities. The idea is to treat people equally, without any social or gender distinction as far as health is concerned. The notion of equality here implies having equal access to healthcare, resources, policies and intervention programmes. Although this equal access to health seems to be real in some settings, studies have shown that social inequalities in the health domain still remain a problematic issue in many countries (Perlin 2001; Brown, 1995; Bowen et al 1995; Briggs et al., 2008; Laurian, 2008). Health inequalities are understood as the consistent difference between socio-economic groups in relation to health. Also, although life expectancy has increased in many countries among social groups, studies also indicate that health inequalities gaps in life expectancy are still a major concern. Among the underlying indicators to explain these disparities, behavioural, socioeconomic and environmental factors are often cited.

2 Factors of Health inequalities

2.1. Behavioural Components

With respect to behavioural or "life style aspect", it is known that individual behaviour towards alcohol consumption, drug use, eating habits has a role to play in the general mortality and morbidity rate (Lahelma, 2006; Sabrina, 2008). For example, the way people eat, the types of food they consume have a great influence on their probability of becoming obese than other factors. Likewise, the smoking patterns and heavy drinking are also important elements to be considered.

2.2. Socio-economic components

Looking closely at the social determinants, studies have shown that different types of employment and the working conditions of some people render them more likely than others to contract disease such as cancers (Maunsell et al, 2004; Deschamps, 2006). Similarly, it has been revealed that people with low socioeconomic income tend to buy junk food (fatty, sugary), and live in poor hygienic conditions which then exposes them to some diseases like hypertension, diabetes, asthma, just to name a few (Dastgiri, 2006). It is however necessary to note that these health inequalities are also explained by limited access to health care facilities, poor quality of care as well as, limited level of education,.

2.3. Environmental components

The environmental indicators, namely environmental pollution is believed to be a contributing factor to health disparities (Setlow 1998; Brulle R.J, 2006; Fikret 2007). Public health scholars have worked for many years exploring the role of environment in health inequalities. The literature suggests that socially disadvantage populations such as the poor, female, children, elderly, racial/ethnic or religious groups, immigrants… who already have poor health status due to their limited access to health care, are more exposed to environmental hazard such as noise, traffic, industrial pollutants, electromagnetic fields than the privilege groups (White, better of population, etc) (Brown P. 1994; Perlin et al. 1999; Briggs et al. 2008).

Also, studies (Perlin, 1995; Bowen 1995) indicate that people of colour (black, Hispanics), and people with low socioeconomic status tend to live close to noxious environmental hazard than white and better-off populations. The principal findings of these studies show that people who are exposed to environmental nuisance (atmospheric pollution, noise, traffic density) are more likely to develop health risk than others. This phenomenon which focuses on the disproportionate burden of environmental risks that some social, economic and ethnic groups bear, or which refers to a situation in which a specific group is more affected by environmental hazard, is often referred to as “environmental racism”, “environmental injustice”, “environmental inequity” depending on where the study was carried out or on what researchers were looking for.

3 Overview on environmental justice

The concept of environmental justice is of American origin. The term *environmental racism* is commonly used to investigate environmental disparities among Africa-Americans, Hispanics, Asians, black and white, while the term *environmental injustice is* mostly used when there is environmental disparities among age, worse off and better off social groups. It is clear that whether using environmental racism or environmental injustice, what researchers usually want to focus on is to find out whether there are environmental inequities or environmental discrimination among races, classes, ages or social groups.

Obviously, since the 1970s a number of studies have been carried out (Freeman, 1972; Asch et al, 1978) on environmental justice to find out whether people are treated fairly -without any restriction or discrimination- as far as environmental risks or hazards are concerned. The term *environmental hazard* here encompasses atmospheric pollution, noise, and industrial pollution. These studies usually examine whether, access to environmental related matters such as access to information, participation in decision making, environmental health policies, exposure to noxious industries, and to healthy environment are enjoyed in the same way by everyone. In this present study, because of our internship timeframe, we will focus only on industrial pollution. The question is: What can we learn from studies that have been carried out on industrial pollution with regards to environmental justice so far?

The findings of studies carried out on residential proximity to industrial pollution so far have often been inconsistent. For example, while some researchers found that low income people, blacks, Hispanics, tend to live closer to environmental hazards than high income people do (Ash and Fetter 2004), others did not find the same evidence (Bowen 1995; Anderton et al.2000). Also, while some researchers indicated that all those who live closer to industrial facilities are people with low income or minorities (Morello-Frosch 2001) others have revealed that among those who live close to these facilities, some groups are socially deprived while others are not (Sadd et al. 1999). Some investigators have found only weak evidence for environmental injustice in this domain, while others have not found any evidence at all (Anderton et al. 1994; Anderton and Anderson 1996).

4 Environmental justice in France

Although the evidence of environmental injustice was found in some industrial countries like US in the 1970s and in some parts of Europe like United Kingdom in the 90s (Mohai and Saha, 1999; Walker, 2005) and Spain (Ramis et al. 2009), France was not part of this studies. This could probably be explained by the rank their healthcare system occupies in the world. In fact, according to the WHO, France has the best Health care system in the World. Obviously, having the top health care system does not exclude some inequalities. In spite of the French Public health Insurance system (PHIS), signs of health inequalities among social groups and gender can still be observed.

There are remarkable disparities in the maternal, perinatal, and mental health, within the French populations (Declerc et al., 2000; Saurel-Cubizolles, 2009). Some studies have been conducted in France recently to find out whether environmental components were contributing indicators to these disparities. Interestingly, evidence of environmental inequalities was found within France. As an illustration, Laurian, in a study carried out in France, found out that those hazardous facilities were predominantly located in town with high percentage of foreigners than in town with fewer foreigners. The following year, Havard (2008) revealed that population residing in socioeconomic deprived area; especially elderly women (55-74years) were at higher risk of having coronary thrombosis than those living in area with best living conditions.

5 Limitation of environmental justice studies

Though the existence of environmental injustice is overwhelmingly indubitable, the majority of studies carried out so far on this issue have had methodological “handicaps”. These handicaps could be explained by the fact that some parameters are not given consideration during the studies and interpretation of the data. These methodological limitations make it difficult to draw a tangible association between proximity to industrial facilities and related health impact. It is in this light that Bowen, (2002) when mentioning the potential influences of research results, declare that, if the geographic unit, the statistic methods, the exposure estimate, the type of environmental nuisance and the indicators of socioeconomic level are not carefully considered or estimated, the results cannot be comparable or generalized with other settings. Following the same argumentation, Sheppard et al. (1999), looking at the influence of methodology on environmental justice studies, indicated that the contrasting results in such studies is mainly due to “the failure to pay attention to the effects of measures of proximity….” This was also acknowledged by Maantay (2002) who reveals that, the critical issue in environmental justice studies is the lack of reliable risk exposure index or proxy.”

6 Work Plan

It is with regards to these Methodological difficulties that the EHESP[1], through the “Equit’area” Project, decided to carry out an environmental justice study in some French cities namely Lille, Paris, Lyon and Marseille. The study entitled *socio-spatial aggregation of exposition to environmental health risk* aims at studying the contribution of environmental hazards to health social inequalities in France. Several environmental exposures like atmospheric pollution, Noise and Industrial pollution are being considered in the study. However, because of the data available at the moment limited by our internship timeframe, we will focus, only on industrial pollution in the Lille metropolitan Area. Firstly, we will start by presenting a literature review of the commonly used methods applied to delineate exposed populations to polluted industrial facilities and give advantages and drawbacks of every method. We are not pretending to solve the entire methodological issues face by environmental justice researchers. But we intend to develop an indicator that might be useful to determine the exposure distance of our target population. Secondly we will present and describe the socio-economic characteristics of our study population. Exploring the association between proximity to industrial facilities and the socioeconomic characteristics of the Lille metropolitan area population will be our last point.

[1] Ecole Des Hautes Etudes en Sante Publique (French School of Publique Health)

Part I
Literature review on proximity indicators

1.1. Literature review method

The literature review was done using EBSCOhost, a research database that contains articles from different Journal, namely Medline, E-journals, direct science, etc. This database covers a wide variety of topics. In order to access articles dealing with our research topic, a list of key words was created. These key words were classified into two categories. Firstly, words those refer to proximity measure in one side and those evoking source of pollution in the other. About twenty key words were created for both categories and finally, only few of them were able to locate our articles of interest. These include: proximity, distance, TRI, socioeconomic status, air pollution, ethnic/racial segregation, industrial facilities, and environmental justice. Overall, hundred of articles were consulted but only about fifty were selected for this present study.

1.2. Common characteristics of proximity indicators

Overwhelmingly, studies that focus on environmental justice issues have used proximity indicators to determine population closeness to hazardous or polluted facilities. The idea here was to determine up to what distance people can be considered as exposed to a given hazard or to differentiate the exposed from the unexposed. From the literature, we identified some frequent methods used to delineate such populations, namely the Unit-coincidence method, the buffer and the cumulative proximity exposure. Though using different approaches to identify impacted population, it is important to consider that there are some common elements characterizing these methods. These include the availability of a GIS technology, the existence of a geographic unit of analysis and the geocoding of addresses locations. What does GIS and Geocoding refer to?

GIS, known as Geographic Information System, is a computer technology used to identify geographic locations such as boundary, industrial location, etc and pinpoint them on a map. In fact, on a map, GIS helps visualizing the spatial distribution of hazardous sites in a geographic unit like a block group, a census tract or an IRIS. This process of localizing locations on a map is called geocoding. Indeed, in order to geocode, two sets of information need to be available: lists of addresses and the reference layer which can be the municipality in which the study is being carried out. In this light, address information is then linked with geographic coordinates such as latitude and longitude. The idea is to highlight various address locations on a map in order to explore the relation between these locations and potential exposure to polluted facilities. It is interesting mentioning here that this is done through statistics method or test.

Also, in ecological studies, whatever data are being used (health, exposure, socioeconomic); all data have to be aggregated at the geographic level. In cases of multivariate analysis where individual and geographic data are jointly needed, the aggregated data have to be collected at the same level. It is, however, necessary to note that, in order to minimize ecological bias and increase the statistic power in such a study, the geographic unit of analysis has to be as smaller as possible to denote significance in a study of association.

Furthermore, what one should bear in mind here is that most environmental hazard studies that use GIS analysis follow the following procedure: (1) identify the geographic boundaries of the potential polluted area, (2) estimate the proximity of the population to the polluted sources (3) compare the characteristics of the population with their proximity to the various sources using appropriate statistical methods.

1.3. Various methods used in environmental justices studies

1.3.1 Spatial coincidence method

1.3.2 Description

The Spatial coincidence method, also known as the Unit-Hazard Method (UHC) (Bevc et al 2007) is one of the first approaches used to estimate impacted population in environmental justice studies. This method simply consists in identifying the presence or the absence of a polluted industrial facility within a geographic unit (fig9.a). When a facility is found within a geographic unit, it is assumed that the entire population living within this unit is exposed. Conversely, the absence of facility implies that there is no exposure. A statistic model is therefore used to compare the characteristics of the population living within this various geographic units.

Another way of defining the impacted population using the spatial coincidence method involves counting the number of industrial facilities within each geographic unit (fig.9b) In this particular case, the aim of the statistical analysis is to investigate the potential existence of a dose-effect relation. In other words, this is to find out whether the socioeconomic or health characteristics of the target population deteriorate as the number of industries increases.

1.3.3 Application

In a study carried out in Minneapolis (Minnesota), Sheppard et al (1999) tried to examine whether some groups of population were disproportionately exposed to industrial pollution than others. Demographic Data came from the 1990 Census and facilities information data was

obtained from the 1995 EPA' Toxic Release Inventory. The authors indicated that people with relative low income, especially white are more likely to live proximate to TRI than people with relatively high income and other ethnic or racial groups.
Evidence of environmental justice has also been reveal in the UK. Walker et al (2005) explored the association between the socio-economic characteristics of the population and the distribution of Industrial Pollution Control (IPC) sites. The study was carried out at the ward level using the Index of Multiple Deprivation 2000. Data from the industrial pollution control database IPC was used. It was concluded that IPC sites were predominantly located in deprived neighbourhood (area with poor living conditions).
Likewise, Anderton et al. (1994) used National survey data of 1980 at the census tract level in Massachusetts to examine the socio-spatial distribution of hazardous materials or toxic sites. TSDF[2] data was provided by the environmental service directory of 1992. No statistical significant difference was found between tracts of racial/ethnic groups that contain TSDF compare to that without TSDF.

1.3.4 Advantages and drawbacks

Not withstanding some mixing results provided when using the spatial coincidence method, it should be recognized that this approach has the advantage of facilitating statistical comparisons (Zandbergen 2006). In other words, studies conducted in several countries at approximately the same geographic level could easily be compared statistically. Consequently, the association between the facilities and the characteristics of the population is less biased.
However, despite these advantages, this method presents certain drawbacks. To begin with, the spatial coincidence method considered everyone living within a geographic unit having a polluted industrial facility as exposed whereas the pollution capacity of these industries does not necessarily affect everyone equally. Indeed, no matter the type and quantity of the emitted pollutant, it is assumed that population living far from the emitted sources are less exposed than those living proximate to the polluted facility.

Another important point ignored by this method is the "edge effect" (Zanbergen 2006). Indeed, a polluted industry might be located proximate to the boundary of two geographic units. In this case, people from the other unit could likely be more affected by the pollutant released from this facility than those of the targeted unit. Futhermore, in epidemiological studies where potential health event associated with Hazardous facilities is examined, all industrial facilities are grouped

[2] Treatment Storage and Disposal Facilities

in the same statistical analysis package, forgetting that the noxious capacity of pollutant varies from one pollutant, industry to another.

1.4. Buffers method

1.4.1 Description

The buffer method consists in estimating population or individual proximity within a certain distance of a given point, line or area (Sheppard 1999). Basically, there are three types of buffers, namely point, areal and line buffer. The point buffer refers to the method used to identify impacted population within a given point, at a predefined radius. Line buffer is used to trace or tail exposure along a railroad line carrying hazardous materials (Sheppard 1999) while the areal buffer is mainly used for large superfund sites. Applying buffer in environmental justice studies consists in drawing a cycle at a defined point with a predefined radius in order to delineate and depict the exposed population. It is, however, interesting to mention here that the point buffer better suit industrial pollution studies. In this case, the centre of the buffer refers to either the centroid of the geographic unit or an identified industrial facility (Fig.9c)

Whether using the centroid or an hazardous source as the centre of the buffer, two options are considered: (1) People living within the block groups overlapping within buffer are considered as exposed (Sheppard et al. 1999) or (2) only people living within the buffer radius of a given block are impacted (Perlin, 1999). (3)In cases where two or more buffers intersect with each other, people living within the intersected part of the buffer are considered as highly exposed that others. Unlike the spatial coincidence method, the buffer approach has been widely used not only to investigate relationship between industrial pollution and socio economic characteristic of the neighbouring population, but also between industrial pollution and related health impact (Brender et al 2008).

1.4.2 Application

Overwhelmingly, the majority of studies tackling environmental justice that used buffer method to define their impacted population have not shown consistent results. As an illustration, Neumann et al, (1998), used buffers to investigate equity issues related to proximity of households or individuals to TRI[3] facilities at the census block level in Oregon. Using data from the EPA 1992 TRI database and demographic information from the 1990 National Census, they found no relationship between the socioeconomic characteristics of population and their proximity to TRI facilities.

[3] Toxic Released Inventory

Conversely, one year later, Perlin et al (1999) used the same method, to examine the socio-demographic characteristics of people living close to polluted industrial facilities in the US at the block group level. The study was conducted in three states, namely West Virginia, Louisiana and Maryland and compared the results. Facility data was obtained from the TRI database and demographic data came from the national Census of 1990. Unlike the previous study, they found that African-Americans and population below poverty level tend to live near industrial source of air pollution than white and rich population. It is important to mention again that this result was consistent for all the three states.

In 2006, Mohai and Saha, used distance buffers to overcome the limitation of previous environmental studies which used unit hazard methods. US EPA identifier and address information came from another leading study on Hazardous waste carried out by Gupta and Been (1995; 1997). These addresses were then geocoded and location information was verified through phone call interviews. The 1990 census data was used. One, two and three miles radii buffer was drawn around each TSDFs using ArcView. The study was carried out at the census tract level. As a result, they found that racial and socioeconomic disparities are greater when using distance buffers than Unit Hazard methods.

Brender et al. (2008) conducted a case control study based on the 1996-2000 births in Texas. The aim of this study was to examine relationship between maternal residential to hazardous sites and chromosomal anomalies in births in the city of Texas in the US. They used data from the Texas birth defect registry to obtain information on the Texas state residents. Information on the various hazardous sites and contaminants came from the agency of toxic substances and disease 2005 registry (ATRSD). Also, details on industrial facilities came from the Toxic release inventory database (TRI). Their results showed no significant evidence of chromosomal anomalies associated with maternal proximity to industrial sites. Sans et al (1995) used buffer to determine the effect of petrochemical plants on cancer in Banglan Bay in the UK. Demographic and socioeconomic data came from the 1981 Census. A circle of 7.5 km radii was drawn to including people living around the plant. The study was carried out at the district level. At the end of the study, a significant increase number of cancer cases and cancer deaths were registered.

In Europe, Ramis et al. (2009) conducted a study to explore the relationship between Non-Hodgkin's Lymphomas (NHLs) and exposure to pollutant emissions in Spain. Information about the industries was obtained from the EPER-registry. Data about the cases came from the deaths records of the Spain National statistics institute for the period of 1994-2003. Also, data from the

2001 census and the electoral roll was used. Exposed population refers to all those residing in a town area with EPER-registered industries located at 200-1500-1000 meter from the municipal centroid. As a result, the authors found possible increase risk of NHL mortality risk among population residing in the vicinity of paper and pulp industries.

1.4.3 Advantage and drawbacks

Generally speaking, buffer method has the advantage that it can easily be drawn using a geographic information system and provides a straightforward visual representation through circle rings around each facility (Zandbergen 2006). It gives a clear picture of who is exposed and who is not. What can be drawn here is that buffers give a better approximation of the exposed characteristics than the unit hazard methods.

However, there are some limitations associated with this method. The main and crucial limitation of this method lies on the fact that the choice of buffer distances is usually done arbitrary, that is, without any justification. (Bhopal, 1998; Gunier, 2003; Correla, 2008). In some cases, researchers are forced to compare the influence of different radius on the results to see up to which distance people can be considered as exposed. Again here the issue of how to choose the buffer radius is still of concern in the sense that even when doing distance comparison, inconsistent results are sometimes found. For example, Ramis et al. used three buffers with respectively 2km, 1.5 km and 1km to define population exposure in their study. They found a likely increased of NHL mortality among population located within 2km from the industries compare to other distances. Whereas Sheppard 1999, using different buffer radii 100, 500, and 1000 yard to determine whether the choice of the buffer radius could influence the result of the analysis found no or little difference among the distances.

Another non-negligible issue with buffer is that, though it gives a better characteristic of the socioeconomic level of the exposed population, there is still an assumption that population are equally distributed within the geographic unit, which is not always the case. In addition, some researchers used the same buffer radius for all types of industry forgetting that the toxicity and the quantity of pollutant emitted vary from one facility to the other (Buzzelli et al ,2003; Jacobson, 2003; Zandbergen, 2006).

Neumann et al. (1999) for example, conducted a study in Oregon (US) to explore environmental equity for population living near TRI facilities. They obtain TRI data form the EPA's TRI 1992 demographic and socioeconomic data came from the 1990 National census. No evidence was found between the location of TRI and the socioeconomic characteristics of the surrounding population. They acknowledged that one of the limitations of the study could be the failure to pay attention to the type and quantity of pollutant emitted by the various TRI. The suggestion they made was that future study should take in to account dispersion modelling and environmental fate in their analysis in order to better estimate exposure potential.

Technically, the main concern with the buffer method relies on how to estimate the buffer radius. Indeed, Researchers are not always sure, when drawing their buffer to include or exclude the truly exposed population and that is what the cumulative proximity exposure seems to answer.

1.5. Cumulative proximity exposure approach

1.5.1 Description

The cumulative proximity exposure, commonly called CPE was developed by Cutter et al. (2001) to answer some limitations posed by the buffer method. The idea was to estimate impacted population of a target hazard. This was done by summing “proximal” exposure links to each hazardous facility located within a geographic unit (Fig.9d) Basically the CPE is a tool that takes into consideration diverse types of hazards when delineating the exposed population. The users of this method take for granted the fact that all industries have the same influence on the entire geographic unit. It is usually estimated through the formula presented below.

$$CPE_i = \sum_{j}^{\#facilities} \left(1.0 - \frac{d_{ij}^p}{T_j^p}\right)$$

Where $\sum_j$ is the sum of all facilities located within the geographic unit; i the location of the population or the centroid of the geographic unit; d_{ij} is the distance from the centroid i to the facility j. T_j is the distance at which exposure is negligible at the facility j and p the rate of reduction of exposure at increasing distance from j. As a reminder, the centroid of the geographic unit is considered as the location of the population. So, the distance is measured from the centroid to each facility and all the distances are summed to obtain the cumulative exposure distance. Very few studies have used this approach to delineate population exposed to industrial pollution.

1.5.2 Application

Cutter and al (2001) carried out a study in medium size cities within the US metropolitan areas to examine the relationship between location of environmental hazard and federally assisted public housing known as housing and urban development. Subsidized households database containing housing characteristics was used. In addition to this, four different EPA databases were utilized to determine the number and location of TRI. The demographic data were taken from the 1990 US census. Using all this information, a cumulative proximity exposure was performed to sum the exposure distance from all this facilities. As a result, the authors realized that minority population or non whites are significantly more exposed to locational exposure than whites.

Likewise, using CPE to examine the use of proximity in defining exposure to a given hazard, Buzzeli and Jerett (2003) conducted a study in Hamilton (Canada), at the census tract level. Following their previous study carried out in Hamilton in 2001, they used socio-demographic data from the 1996 census and obtained data on the total suspended particle (TSP) from the Hamilton air monitoring network. Road network data came from a comprehensive and topologically integrated geo-database for Canada. Distance from the census centroid to the major road and distance to the edges of industrial land parcels were estimated. Integrating these hazardous sources in their analysis, they found that proximity measures could yield significant results where emissions sources are clustered than in other areas. This meant that, using CPE in area with many facilities, exposure potential is higher than in area with few facilities.

Using a similar method called cumulative hazard density which integrates multiple hazards such as toxic emission and traffic pollutants, Bolin et al. (2002) try to examine whether hazardous sites were disproportionately located in areas with lower income and minority residents. This was done at the census tract level in the Phoenix metropolitan region (US). Demographic information came from the 1995 census data and data on the various facilities was provided by the EPA 1996 database. The result of this study indicated that hazardous sites are disproportionately located in low income and minority resident neighbourhood than in other area across the phoenix region.

1.5.3 Advantages and drawbacks

Cumulative proximity exposure has the ability to take into account many sources of hazard in an analysis (Buzelli and Jerrett. 2003) and is relatively less expensive. It also gives a better approximation of the exposed population and thus helps highlighting the spatial disparities within a geographic unit. However, a possible difficulty with this method is that, it does not take into account the quantity and toxicity of the hazard. In addition to this, it could also be very demanding and time consuming.

2 Discussion

2.1. Summary of the various methods

We have just examined the most commonly used methods or approaches used to investigate environmental inequalities among population, namely exposure to industrial pollution. These methods include the spatial coincidence, the buffer and the cumulative proximity exposure. We have realized that, statistically, the use of spatial coincidence method simplifies the comparison of results in the sense that data on the geographic unit are usually available and the geographic limits are well known. However, considering everyone living in a geographic unit as exposed could be an aberration in that, exposure depends on other parameters like the type, the quantity and the toxicity of the pollutant emitted.

We learned that buffer method was developed to overcome the limitation of the spatial coincidence method by drawing circle around each facility to determine exposed population. It is interesting saying that this method lies only on assumptions in the sense that it does not have a way of estimating the real exposure distance. The cumulative proximity exposure was performed to assist in determining the real distance at which population are exposure to environmental hazards. This is done by summing the distance from the centroid to the various hazardous sources in order to estimate population proximity to the various industrial facilities within a geographic unit. Though not taking into account the types of emission, the meteorological condition…in the analysis, the literature indicates that the few studies carried out using this approach could yield significant results.

2.2. Conclusion

This literature review on proximity indicators clearly reveal that much still need to be done at least on the methodological aspect, in order to improve the quality of studies carried out on environmental justice studies in general and on proximity to industrial facilities in particular. Undoubtedly, future researchers need to consider meteorological data in their analysis. Unfortunately, this data are not always available or easy to obtain. In the absence of such data, one could continue relying on CPE approach since studies indicated that it is a promising approach. In the present study, considering the results of studies presented by the CPE users, we developed a similar approach call Multi-Site Proximity Index (MSPI) which consists in summing all the distances from the centroid to the various polluted industrial sites located within the Lille Metropolitan area. Unlike the CPE, the MSPI does not consider the T distance; that is the distance at which the exposure is considered as negligible. However, the applicability of this method will be discussed in the result section.

Part II
Materials and methods

This section describes the Lille Metropolitan Area (LMA) and presents all the tools and types of data collected to establish the relationship between industrial sites and the demographic and socio-economic characteristics of our target population.

1.1. Presentation of the study site

The present study was carried out in the Lille Metropolitan area (LMA), located in the Northern region of France, near the French border with Belgium. It is the fourth-largest metropolitan city in France after Paris, Lyon and Marseille and the capital of the Nord-Pas de Calais Region. During the 1999 French National census, it was composed of 85 municipalities subdivided into 504 Census Blocks also known as IRIS[4] in the French context. The LMA has approximatively 1091483 inhabitants spread over its 612 km². With a population density of 1783/km², varying from one municipality to the other. It covers 61200 hectare. The principal municipalities here are Lille, Villeneuve D'ASCQ, Roubaix and Tourcoing. The Capital city, Lille has approximately 212597 residents (1999 Census). The LMA is neither too hot nor too cool and is generally described as enjoying a temperate oceanic climate. This site was chosen for our study because of the amount of data that was already available at the moment of our internship.

1.2. Presentation of the EPER system

The European pollutant emission registry (EPER) controls and prevents pollution within the 25 European Union member states. It informs the public about the pollutant release into the environment in order to reduce the amount of substances that affect both the environment and human beings. The EPER was established in 2000 and included only information on air and water release of 50 industrial facilities. Since information on other activities and pollutants needed also to be reported, it became necessary to expand the aim of the EPER, hence the creation of the EPRTR (European pollutant release and transfer register) in 2007.

This Register contains information on industrial and non-industrial releases into the air, water, land and off-site transfers of waste water and waste including information from points and diffuses sources. The EPRTR focuses on 91 pollutants, but only 23 of them have available data (E-PRTR website). A fixed or specified threshold limit value is attributed to all these pollutants. Industrial plants whose pollutant emission reach or exceed this value have to report their activities to the EPRTR. As part of this EPRTR, the French pollutant emission registry known as IREP aims at increasing awareness and facilitating public access to environmental issues. This registry contains yearly information of industrial facilities emissions.

[4] Ilots regroupés pour des informations statistiques

1.3. Justification and choice of pollutants

Following the EPRTR regulation, a list of approximately 52 industrial facilities in our study site Lille is known to have reached or exceed the threshold limit set by the EPRTR. Among these industries, given the information available on IREP[5], about 17 pollutants were identified but only five of them, belonging to 9 industries considered as highly polluted were finally retained. The retained pollutants include lead (Pb), mercury (Hg), sulphur oxide (SO2), nitrogen oxide (NOx) and Volatil organic compound (VOCs). The reasons for retaining these five pollutants were twofold: firstly they had sufficient information necessary to carry out statistical analysis. Secondly, they are known to have tremendous impact on people's health.

1.4. Presentation of the socioeconomic data

Information on the demographic and socioeconomic level of our study population came from the French National Census (1999) for which data is available. More recent data will likely be available by the end of 2009. The 1999 National census was conducted by the National Institute for Statistics and Economic studies known as INSEE. According to this institution, the socioeconomic characteristics of the French population are grouped into "umbrella" topics which include sub-topics also called variables. These "umbrella" topics known as domains cover information on employment, educational level, housing, and immigration status, income, family and household. These domains include about 1500 variables but only 52 of them are considered by the literature as likely to better estimate the socio-economic status or the deprivation index of a group of population (Krieger et al. 1997; Pampalon et al. 2000; Jordan et al. 2004).

In the French system, these data are available at the IRIS level which is the smallest geographic unit of analysis. This IRIS can be compare to the census Block of the US system and correspond to a neighbourhood of 2000 inhabitants on the average (INSEE, 2008). According to the INSEE, there are three types of IRIS, namely Housing IRIS, activity IRIS and miscellaneous IRIS. The Housing IRIS refers to population with approximately 1800 to 5000 inhabitants. The activity IRIS encompasses more than 1000 employees with twice more salaried workers than the local residents and finally, the miscellaneous IRIS correspond to large surface with very low density of population.

[5] Registre Français des émissions polluantes

1.5. Use of principal component analysis

Havard et al. (2008) developed a French deprivation index at the IRIS level using a Principal component analysis (PCA). This analysis transformed a number of possible correlated variables into smaller number of uncorrelated variables called principal components. In fact, the PCA groups common variables together in order to avoid repeating the same information or citing redundant variables. Using PCA, the later authors found that only 19 variables better reflect the multiple aspects of the socioeconomic status of a given group. These variables are presented by domain as follow: **Employment** : Blue collar workers in the labour force(1), people in the labour force with insecure jobs(2), people in the labour force with stable jobs(3), unemployed people in the labour force(4) and people in the labour force unemployed for more than 1 year (5). **Housing** : primary residences that are houses or farms(6), primary residences that are multiple dwelling units(7), Households without a car(8), non-owner-occupied primary residences(9), subsidised housing among all primary residences(10), primary residences with more than one person per room(11), mean number of people per room(12), Households with two or more cars (13) . **Educational level**: people aged 15 years or older with general or vocational maturity certificates (14), people aged 15 or older who did not go beyond an elementary education (15), and people aged 15 or older with at least a lower tertiary education (16). **Family and household**: single parent families (17) **Immigration status**: Foreigners in the total population (18). Income**:** Median income per consumption unit (in euros per year) (19. A single index for the above mentioned variables was constructed to maximise the variance of the PCA. This simply consists in bringing together social, economic and housing aspects of deprivation into a single deprivation score for each IRIS. The same index will be used in our study area to describe the socioeconomic level of our study population.

1.6. Description of the LMA block groups

Among the 504 census blocks of the LMA, only 453 were retained for our study. The fifty others were merely activity blocks composed of workers and for the most part inhabited. Consequently, none or very few socioeconomic data were provided for these blocks. We characterized the socioeconomic level of the 453 census blocks for which data were available using the same index of deprivation applied in a previous similar study carried out in Strasbourg. It is worth saying here that this deprivation index was successfully used to access the socioeconomic gradients of the Strasbourg area resident (Havard, 2008).

1.7. Presentation of the various categories of deprivation in the LMA

The various block groups of the LMA were grouped into five classes of deprivation according to their values as follow: C1 (<1.46), C2 (1.46-2.04), C3 (2.04-2.42), C4 (2.42-3.00), C5 (>3.00). The first class refers to privileged blocks made up of population with best living condition while the fifth class point out deprived residents. For details, see (Havard et al.2008). Overall, 102 blocks were considered as deprived compared to only 36 privileged. In fact, only few blocks have residents with relatively good demographic and socioeconomic characteristics. This number treble when looking at deprived population insofar as up to 102 blocks have residents with relatively poor demographic and socioeconomic conditions. We will explore this various classes of deprivation in the LMA which appear or seems to be more deprived than Strasbourg at least; looking at the concentration of deprived and privileged on the map (see fig. 2 and 8).

1.8. Cartography

The various maps used in this work were conceived using ArcView and exported to Word. In fact, ArcView is a Geographic Information System (GIS) software used to create and visualized spatial or geographic data. In environmental justice studies, it is commonly used to map and depict the spatial distribution of hazardous sources within a region.

1.9. Statistical Analysis

We used the multi-site proximity index (MSPI) to sum distances from the centroid to the various industrial facilities located within the Lille Metropolitan Area. We calculated the Mean, the Maximal (Max), the Median and the Minimal (Min) of the resulting data according to the various class of deprivation. Using this information, we drew the distribution curve of the various class of deprivation and found that our data had a non-normal distribution. In fact it was difficult to communicate the results. We could not perform classical statistic tests like a parametric test with such a distribution. We had to transform data mathematically using a logarithm function to normalize our distribution, in others word, to have a log-normal distribution. The idea was to calculate appropriate indicator necessary to compare our values.

What we did was that, we calculated a 95% Confidence Interval (CI) for the mean of each class of deprivation using the LN value of our MSPI data in other to compare the distribution of each class of deprivation. First of all, we logarithmized our MSPI value for all the classes of deprivation. After that, we calculated the mean and the standard deviation of the MSPI per class (C1, C2, C3, C4, C5) In fact, we refer to the standard deviation to assess to degree of dispersion of our data around the mean, to see if our data are clustered around the mean or not. The formula we used to obtain the CI of the lower and upper limit of the mean of every class of deprivation is presented as follow:

$$\mathbf{CI = [\ \bar{x} - z\left(\frac{\sigma}{\sqrt{n}}\right),\ \ \bar{x} + z\left(\frac{\sigma}{\sqrt{n}}\right)\ ]}$$

Where $\bar{x}$ stands for the mean of our log MSPI according to our class of interest, σ the standard deviation of the log MSPI per class, n the number of block group per class and Z the degree of confidence (95%), with a -risk risk equal to 5%. Furthermore, we also calculate the exponential of the upper and lower limit of the Confidence interval of our mean LN (MSPI) value. The reason behind such an idea was to be able to convert our results back into the appropriate unit of measurement.

In addition to this, in order to test the strength of the association between the socioeconomic status and population distance to industrial facilities, a Moran Index statistic test was performed using ArcGIS.

Part III
RESULTS

1 Descriptive analysis of the results

Table 1 describe the nineteen socioeconomic variables selected from the 1999 French National Census using a Principal Component Analysis (see above) whereas the second table give the mean values of the selected variables according to deprivation class. These variables were chosen as they better reflect a snapshot of the socioeconomic characteristics of deprived population. More so, they are good indicators to determine the socioeconomic characteristics of census blocks level. It is however interesting mentioning that they include our various initial domains, namely immigration, employment, family and household, housing, income and educational level. The majority of them, (seventeen) reflect the material or economical dimensions of deprivation while only two of them refer to the social aspect (single–parent family and foreign population).

1.1. Descriptive analysis of the socioeconomic variables

Table 1 point out the remarkable variability observed in the socioeconomic characteristics of our study population. Basically, substantial gaps are observed between the minimum and the maximum of some variables. As an illustration, data indicate that 100% of the populations in a census block have their personal residence compared to a percentage of 99.58% of the population in another block who live in subsidized houses. This information let one to believe that the proportion of owner in certain blocks is comparable to the fraction of non owner in other settings. Also, the minimal proportion of unemployed people in some blocks differs markedly from that of people with stable jobs in others settings. Findings show remarkable information with regards to median income. What is interesting to note here is that, the median income per consumption unit is ten times lower is some blocks than in others. For example, while a block has a median income of 3203 Euro per year and per consumption unit, another block approximates 30355 Euro.

Data also pointed out interesting information with respect to the educational level of our study population. While a setting has only 0.54% of population who do not exceed the elementary education, another setting has an equivalent percentage approximating 50%, meaning that half of the population in a block group did not go beyond an elementary education. Furthermore, some settings have very few numbers of foreigners whereas almost one third of the populations in other blocks are not of LMA origin. Data also revealed that up to about 70% of households in a block do not have a car compared to 80.61 who have more than two cars in another. It is necessary to assert here that the percentage of households with more than two cars in certain area is three times the median households without car in the whole LMA. In addition to this, there is a block showing a percentage of approximately 40% of single parental home compare to 3.92% in another. What can be insinuated here is that the percentage of single parental homes in some census blocks is ten times that of other blocks.

1.2. Descriptive analysis of the variables according to deprivation index

Looking at the table 2, our findings revealed that an average of 91% of the LMA population who are owner of their residence, live in privilege blocks compare to an average of only 34 % of owners in deprived blocks. These findings insinuate that the proportion of owners in privilege blocks treble that of deprived blocks. Data also show that the C5 class is overwhelmingly made up of relatively low income people and those with elementary education. For example, table 2 indicates an average income per consumption unit approximating 22000 Euro in privilege blocks compare to only 8300 Euro in deprive blocks. Also, findings pointed out that 29.24% live in deprived area (C5) compare to only 7.77% in privilege area (C1).

What is interesting to note here is that, the percentage of uneducated population increases as one move from the most deprived to the less deprived groups. This can be observed in table 2 where the average mean of people aged 15 years or older who did not go beyond an elementary education per class is 7.77, 11.62, 15.74, 19.32, 29.24 respectively for Class 1,2,3,4 and 5. It is useful to consider that, this particular variable was highlighted among all the variables of the educational domain as we believe it better depict the educational level of our study population and also because of the high variation observed on his data.

Overwhelmingly, the vast majority of single parental families and foreigners in LMA reside in deprived blocks. As noted in table 2, the proportion of foreigner in a geographic unit varies considerably from one block to the other and this difference increases significantly as one move from privileged to deprive blocks. This table shows high percentage of foreigners in class 5, (12.72%) compare to class 1, (1.46%). Also, about an average of 25% of the population live in poor neighbourhood in contrast to only 7.68% who live in area with best living conditions. As observed in table 2, this percentage increases markedly from class 1 to 5.

1.3. Descriptive analysis of proximity to industrial facilities

As mentioned above, we used a MSPI to determine the proximity of the population living within the various block groups of the Lille Metropolitan Area. This was done by totalling the distances from the centroid to each industrial facility located within block groups or IRIS. As presented in table 3, deprived blocks are more likely to host polluted industrial facilities than privileged blocks. In others words, industrials facilities are more likely to be located closed to deprived blocks, than privilege ones. As an illustration, data indicated on average that there is 95% probability for polluted industries to be located within 531.031km (95% CI 516.836-545.615) from blocks groups of disadvantage population compare to 588.531km (95% CI 560.944-617.475) from block groups of better off population or those with good living conditions. When expressing our confidence interval in only one direction, what caught our attention is that the upper limit of the CI for the mean distance at which deprived blocks are located from polluted industrial facilities is 545.615 km. What is interesting to highlight here is that this distance is far below the lower limit 560.944km of the average distance at which privilege blocks are located from these facilities. Also, our findings show that the farthest deprived block is located at 830.794 km whereas the farthest privileged block is situated at 1.151.441 km from hazardous industries. This data indicates that some deprived blocks are approximately 300 km closed to polluted facilities than some privilege ones.

1.4. Spatial analysis of data

The data indicated an unequal distribution of population across the Lille metropolitan area. There is a high concentration of population in some municipalities than other. The spatial analysis of data show a high density of population in the Centre, the North East and the western part of the region, respectively Villeneuve-D'ASCQ, Lille and Suburb, Roubaix, Tourcoing and Armentières. As seen in fig2, the spatial analysis of findings according to socioeconomic status show that populations with low or poor socioeconomic status are for the most cases located in these areas. Data also show that industrial facilities are scattered across the region with high concentration in the center that is, in Lille and surrounding areas (fig1).

Considering the various scores assign to each industry in our analysis to identify the most polluted industries, the spatial analysis reveal that polluted industries are mainly located in deprived block groups (see fig2). What is also interesting to highlight here is that population with unstable jobs, low level of education, high proportion of single parental families and strangers reside proximate to this polluted industries. See fig (3, 4, 5, and 6) Also, as mentioned earlier, we performed a Multi site proximity index (MSPI) to locate the proximity of the various block groups to industrial facilities. The spatial distribution of the MSPI data show that deprived blocks are located at close distances to industrial facility compare to privilege blocks (See fig.1). This map indicates that the most privilege blocks are situated very far from industrial facilities and distance to industries reduces as one move from the most privilege to the less deprived blocks.

1.5. Correlation between socioeconomic status and proximity to industrial facilities

The use of a classic autocorrelation test known as Moran's Index (MI) showed systematic pattern in the distribution of spatial data in the LMA. The MI test performed for socioeconomic status and the proximity to industrial facilities show relatively low values, respectively 0.11 and 0.23 but with the associated p-value of < 0.001. Although it is known that low Moran's I value lead to absence of spatial autocorrelation, the highly significant p-value we have here let one to assume that there is evidence of spatial autocorrelation within this area. More so, the spatial distribution of findings evidences some signs of spatial dependency. For example, the various classes of deprivation tend to be grouped together, therefore, located at approximately the same distances from industrial facilities, with the most deprived class situated at shorter distance compare to other classes. Considering this values, the inference is that there is a strong correlation between socioeconomic status and proximity to industrial facilities in this region.

General conclusion

1 Discussion

1.1. Results interpretation

Data collected and analysed during our study seem to suggest that there is environmental injustice in the Lille Metropolitan Area. We used demographic and socioeconomic data from the 1999 National French census and industries data from the French Emission pollutant registry known as IREP to test whether minority groups, or population with relatively low or poor socioeconomic status were more likely to reside close to industrial facilities than population with high socioeconomic level. The descriptive, spatial and statistic analysis has confirmed our hypothesis by showing that those who live near industrial facilities in the LMA are people with poor socioeconomic status. Our data was classified according to categories of deprivation: from the less deprived to the most privilege census blocks. Deprived blocks referred to population with poor living conditions including lower educational level whereas privileged blocks were blocks with better off population or population with good living conditions. Our findings indicated that polluted industrial facilities were more likely to be localized in socially deprived blocks than in privilege blocks. In other words, polluted industrial facilities were predominantly located in neighbourhoods occupied by immigrants, single parent-families and workers.

Our findings also showed that population with lower educational level and population with unstable jobs were more likely to live near industrial facilities compared to those with high educational level or with stable jobs. We noted a correlation between socioeconomic status and proximity to industrial facilities. We used the Moran's I statistical test to examine the presence of spatial autocorrelation in the distribution of spatial autocorrelation as well as the proximity to industrial facilities. We noted that neighbourhood belonging to the same class tend to have similar features and to be located in the same areas, hence the presence of spatial autocorrelation with an associated p-value of <0.001. It is important to mention here that the evidence of environmental inequalities observed here agrees with earlier environmental justice studies carried out in other industrial countries like the US (Morello-Frosh R et al. 2002; Perlin et al.1999) and Canada (Jerrett et al. 2001) where it was revealed that minority groups and socially deprived population were more likely to be exposed to air pollution and suffer from the resulting effect than people with higher socioeconomic status. Our result also corroborated recent studies carried out in France by Laurian (2008) revealing that towns with high percentage of immigrants are more likely to host more hazardous sites than towns with fewer immigrants.

1.2. Limitations of our study

Although our findings show a highly significant association between the socioeconomic level of the LMA population and their proximity to industrial facilities, we can not rule out the various limitations associated with this study. The limitations were twofold: first of all with the data used and later with the method put in place to carry out this work.

1.2.1 Data limitations

With respect to data, there is a ten-year difference between the collection of the socio-economic and demographic data used and the time this study was conducted. We used data from the 1999 French National Census for a study carried out in 2009. It is obvious that the socioeconomic and the demographic characteristics of people living in this region today might have changed over time. However, even if the demographic and social characteristics of the corresponding residents might not be the same, what is sure is that people with higher socio-economic status cannot leave areas with good living conditions to relocate in an area with poor living conditions. Instead, one could expect people of deprived neighbourhood, who might have raised enough money, or whose socioeconomic status might have changed with time, to join the privileged area and not the reverse. In this light, our association still hold in that, it is more likely that, those remaining near industrial facilities might still be people with lower socioeconomic level.

Another limitation could be associated with the ecological aspect of this study. In fact, we used data at the group level assuming groups as being homogenous, forgetting that people living in a geographic area can not have the same socioeconomic level. They might be some disparities among the socioeconomic characteristics**.** We believed that using both neighbourhood (context) and individual data (composition) could yield more accurate results as they might mutually influence each other (Diez Roux, 2001). Also, a non-negligible limitation of this study could be linked to the type of industrial data used. As mentioned earlier, industrial data came from the French registry of polluting emissions (IREP). This institution has a threshold report limit for a wide variety of pollutants. In this light, only industries who reach or exceed this threshold limit report their emission to the IREP. So the IREP database we used had only few industries (53) for the LMA compared to the myriad of industries existing in this region. Many other highly polluted industries like the petrol stations, the washing machines, etc, do not figure on the IREP database. As an illustration, there are industries that release different types of pollutants but since these emissions do not reach or exceed the threshold limit, IREP does not care about those. Conversely, some industries might release only one pollutant but figure on IREP database. Therefore, industries that figure on IREP database are not essentially the most polluted and consequently not those that could necessary impact population's health. We believed that this limited number of industries could have somehow biased our result.

1.2.2 Methodological limitations

Looking at the method used, though our Muti-site proximity index (MSPI) approach was similar to that used by Cutter et al (2001) and Buzzelli and Jerrett et al (2003) called Cumulative proximity exposure, we do not consider the T distance, which is the distance at which exposure is considered as negligible in our analysis. These types of data need some modelling techniques that we were not able to perform. However, we were told there are some specialists such as those in charge of air quality control called AASQA[6] in France who might provide such data. We did get in touch with them but unfortunately, our time frame was to short for them to provide us with such data. We intend to take into account such data in the next part of this study. In addition to the T distance handicap, our MSPI fall in the limitations of other methods like the spatial coincidence approach in that, it does not consider the edge effect. The MSPI is exclusively limited to the geographic unit where the study is being conducted, whereas an industry could be located at the boundary of the unit and be more likely to affect people from the other unit. In addition to this, we grouped all industries in the same package, as being equal.

Indeed, the MSPI considered all industries has having the same polluted capacity whereas all facilities do not release the same pollutants. The next part of this study intends to calculate and attribute a score to each industry. This score will be including as weighting factors in the MSPI analysis. Likewise, the meteorological conditions were not considered is this analysis although the literature indicates that pollutants could be transported at long distances from the industries. Furthermore, indoor and personal exposures were not taken into account in this analysis whereas they can be particularly higher in some cases than industrial pollution. What should be noted here is that environmental justice studies hardly use this method given that it is not only costly, but also very demanding (Morello-Frosch, 2006). However, in the Equit'area project, atmospheric pollution will be modelled by the AASQA and allowance would be given to the meteorological conditions, the topography and many others pollutants influencing factors.

1.3. Conclusion

Although these limitations could have possibly impacted our results, it is interesting to note that our defined hypothesis consisting in exploring whether those who live proximate to industrial facilities are socioeconomically deprived holds and is highly significant ($p<0.001$). The spatial

[6] Associations Agréées pour la Surveillance de la Qualité de l'Air.

analysis clearly shows a clustering of socioeconomic deprived population near polluted industries. Event if the number of industrial facilities we used was not exhaustive, what is important to reveal is that among the 53 industries provided to us by the IREP, the 9 we considered as highly polluted are localized in deprived areas. Again, the MSPI approach we used indicated that distance to industries is associated with the deprivation categories. The less socially deprived blocks are situated at shorter distance from industries compare to privilege ones. As seen in figure 1 deprived groups are located at the borders of the geographic unit where there are few or no industries at all. It is possible that they might be some industries in the other geographic zone which might impact them but since we do not have any information about those, we cannot say much about that. Given the information we have at the moment, we can conclude that population with lower socioeconomic status are more likely to reside near industrial facilities in the LMA and to be exposed to the related health impact than population with higher socioeconomic status. What could be the potential explanation of such unequal exposure to environmental hazard in the French context in general and specifically in the Lille Metropolitan Area?

1.4. Possible explanation of environmental injustice in LMA

Historically, Lille is an industrial town which was specifically meant for the sitting of industries. In this light, residences were built around each industry for the workers. This could likely explain why more workers are found around industrial facilities. It is also known that people who work in industries are for the most cases, unskilled labour and consequently have only a low level of education. This can be confirmed looking at our data as a high percentage of those who live proximate to industrial facilities are labourers and people with relatively low level of education. In the other hand, we can be tempted to believe that the installation of population around this industrial area was simply done through migration as an earlier study suggested that immigrants are more likely to locate close to environmental hazard than other groups (Laurian, 2008). It is known for example that many people come to France to look for jobs and are unskilled for the most cases. It is known that industrial facilities usually offer plenty of jobs for the unskilled. These could probably explain why there are many immigrants or foreigners in this area.

Another possible explanation for why people with lower socioeconomic level live close to industries could be their limited financial resources as the literature suggest that industrial neighbourhood might offer cheaper houses (Clark D. et al, 1994; Brid Gleeson, 2007) It may also be that because many labourers do not have a personal means of transportation, they may choose to reside near their job site to avoid paying transport fees. This can be confirmed using our finding as a very high proportion of those who live near industries in Lille do not have a car. Furthermore, social networking could also likely explained why clustering of blocks is observed in this area. For example, people with the same social characteristics tend to live together because they share the same worldview (life style, same religious or ethnic identities). This could likely explain the high concentration of deprived population around industrial facilities.

1.5. Perspectives

This study evokes the need to carry out additional studies in order to improve the quality of these findings or to obtain more accurate results. For example, we used data at the group level, considering all those living in the geographic unit as having homogenous characteristics which might be a bias to our findings. It would be interesting to conduct a field survey in order to collect individual data. Having individual data might give accurate information on the characteristics of those living in various neighbourhoods. Also, future studies using the MSPI method should make allowance for the meteorological conditions, the concentration of the pollutants, the type and the quantity of pollutant emitted by each industrial facility. Likewise, studies on proximity to industrial pollution in LMA should consider making a comparative study with neighbouring cities to found out whether the privileged are not affected by the industries from the neighbouring cities. Alternatively the LMA should be increased to include a part of neighbouring cities to explore the potential exposure of privilege blocks.

Considering that people are exposed to diverse sources of exposure, industrial pollution might not be the only exposure pattern affecting the health of population? Researchers should consider carrying out an epidemiological study to compare industrial exposure to other types of exposure. It will also be interesting to find out about the procedural social inequalities with regards to environmental hazard in LMA. To obtain formal information as to whether government deliberately decide to sit polluting industries in deprived block or whether deprived population choose to stay in this region. This could help us better explain the type of environmental injustice prevailing in this area in order to guide health policy makers and town planners.

1.6. Originality of the study

The originality of this study lies on the fact that very few studies have been carried out on environmental justice in France. The first studies were carried out by Laurian (2007) and the second by Havard et al (2008). This study is to first study exploring proximity to industrial pollution in France. We suggested and performed a new method to sum cumulative industrial exposure called Multi-site proximity exposure which has never been used before. Also, unlike other environmental justice studies that used a common deprivation index to depict the socio-economic and demographic gradient of population, we used a French deprivation index exclusive to the French context. In addition to this we used the French registry for polluting emissions which has never been used to assess environmental injustice in France.

1.7. Public health relevance of the study and recommendations

This study is of public health relevance in that, the reduction of health social inequalities is one of the top priorities of the WHO (World Health Organisation). Likewise, environmental impact on population health is on the main agenda of the French National strategic plan set by the National assembly in 2004. Furthermore, the impact of industrial pollution in populations' health is highly documented (Glorennec P et al 2006; Hu et al 2006; Wasserman et al. 2000; Hyman M. 2004), It is known for example that people who are exposed to industrial pollution are more likely to develop disease such as cancer, asthma or to have some neurological or developmental disorders which are all major public health concerns.

Through the present study, we intend to raise awareness of researchers, decision makers and the general population on the existence of environmental injustice in France. We are confident that it is only through this strategy that the fight against social inequalities can be done as improving health also passes through the reduction of social inequalities. This study could for example help town planners to rethink their town planning policy. Possibly, they could for example, locate social houses in high income people neighbourhoods so that people with low income could at least leave in healthy environment. Public health practitioners could for example educate the deprived groups on the potential health impact of industrial pollution on their health, so that when residing near industrial facilities, they could at least be aware of the potential risk they are facing. It is obvious than people with low income might also have limited choice. It this light, the French government could why not considered creating more jobs for the unskilled and people with limited level of condition so that deprived population could also affording renting houses in "healthy" neighbourhoods. In addition to this, it would also be interesting to empower the socially deprived community by involving them in decision making with regard to town planning.

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Annexes

List of Tables and figures

Table 1: Value of socio-economic variables

Variables (proportions unless otherwise stated)	Census domain	Min ¹	Median	Max ²
Foreigners in the total population	Immigration	0.23	4.02	33.23
Unemployed people in the labour force	Employment	4.85	14.22	57.24
People in the labour force unemployed for more than 1 year	Employment	2.06	7.95	36.35
People in the labour force with stable jobs	Employment	26.25	67.18	82.77
People in the labour force with insecurejobs	Employment	5.17	11.69	23.09
Blue collar workers in the labour force	Employment	0.47	21.12	51.34
Single parent family	Family and household	3.92	14.17	39.31
Non owner occupied primary residence	Housing	4.59	43.85	100
Households without a car	Housing	0.9	24.41	69.39
Households with two or more cars	Housinng	2.95	22.52	80.61
Primary residence with more than one person per room	Housing	0.6	5.41	46.65
Mean number of person per room	Housing	0.52	0.64	1.14
Primary residence that are house or frams	Housing	0	68.82	100
Subsidised housing among all primary residences	Housing	0	9.85	99.58
Primary residence that are multiple dwelling unit	Housing	0	26.28	99.85
People aged 15 or older with at least a lower tertiary education	Educational level	2.33	9.88	15.97
People aged 15years or older who did not go beyond an elementary education	Educational level	0.54	17.03	46.19
People aged 15 years or older with general or vocational maturity certificates	Educational level	1.41	8.1	22.74
Median income per consumption unit (in euro per year)	Income	3203	14207	30353

[1] Minimum

[2] Maximum

Table 2: Mean value of variable according to deprivation class

Class of variables	C1	C2	C3	C4	C 5
Number of census blocks per class	35	102	83	131	102
	Mean per Class				
Foreigners in the total population	1.46	1.85	3.46	6.14	12.72
Unemployed people in the labour force	7.17	8.92	12.41	17.1	30.7
People in the labour force unemployed for more than 1 year	3.73	4.79	7.08	10	11.02
People in the labour force with stable jobs	71.57	73.72	70.27	63.78	48.84
People in the labour force with insecurejobs	7.14	8.82	10.83	13.24	16.67
Blue collar workers in the labour force	10.16	16.67	21.31	23.24	27.24
Single parent family	7.68	10.37	13.6	16.21	24.79
Non owner occupied primary residence	16.69	24.42	38.62	56.37	77.54
Households without a car	8.01	13.09	19.91	31.02	41.09
Households with two or more cars	53.16	40.13	27.84	18.05	11.55
Primary residence with more than one person per room	2.43	4.18	5.1	6.27	12.82
Mean number of person per room	0.59	0.61	0.62	0.65	0.76
Primary residence that are house or farms	90.28	83.67	70.58	51.03	34.02
Subsidised housing among all primary residences	0.8	3.77	11.8	20	48.87
Primary residence that are multiple dwelling unit	7.54	13.65	25.72	44.32	62.46
People aged 15 or older with at least a lower tertiary education	13.33	11.9	10.53	8.97	7.73
People aged 15years or older who did not go beyond an Elementary education	7.77	11.62	15.74	19.32	29.24
people aged 15 years or older with general or vocational maturity certificates	12.54	10.31	8.83	7.25	5.08
Median income per consumption unit (in euro per year)	21946.03	17558.69	15124.57	13491.84	8295.49

Variables (%)

Table 3: Multi-site Proximity Index Values

	Categories of deprivation				
	C1	C2	C3	C4	C5
Number of block Group per class	**36**	**101**	**83**	**131**	**102**
		ln MSPI Value			
Mean	13,24652348	13,28538471	13,2367183	13,20405608	13,18257496
Standard deviation	0,223620893	0,246162768	0,236084241	0,241532188	0,139609761
Min	12,94642609	12,93117005	12,93042539	12,930041	12,93651596
Max	13,95652478	14,00891694	14,090517	14,0557085	13,63013706
lower limit CI	13,17347399	13,23737625	13,18592762	13,16269466	13,15548104
Upper limit CI	13,31957298	13,33339316	13,28750898	13,2454175	13,20966887
95% CI	13,18-13, 32	13,24-13,34	13,19-13,29	13,17-13,25	13,16-13,21
			EXP MSPI Value		
EXP Mean	566098,5649	588530,898	560574,9881	542561,1491	531030,6156
EXP Min	419335,287	412986,4466	412679,0262	412520,4239	415200,1432
EXPMax	1151441,024	1213375,782	1316539,161	1271500,803	830793,9297
EXP Lower limit CI	526219,6517	560943,9395	532813,9716	520577,8145	516836,0782
EXP Upper limit CI	608999,6528	617474,5702	589782,427	565472,8118	545614,996
95% CI	526,220 - 609	560,944 - 617,475	532,814 - 589,783	520,578 - 565,473	516,836 - 545,615

Table4. Polluted industries in LMA and scores

	Pollutants emitted					
Threshold report (Kg/year)	Lead and compounds (Pb)	Mercury and compounds (Hg)	Non Methanic volatil organic compounds	Notrogen oxide(NO2)	Sulphur oxide (SO2)	Total score
	200	10	100000	100000	150000	
	Idustrial facilities					
CEAC	1960					
CVE Antares		10				
Produits chimiques du Loos		12				
Rhodia Operations		20		114000		
Guy Demarle - Siret			307000			
FLINT Group France SAS			102000			
Pennel et Flipo			119000			
Centrale thermique du Mont de Terre - Resonor				106000	208000	
Holliday Pigments S.A.					194000	
Scores	9,8	4,2	5,28	2,2	2,68	**24,16**

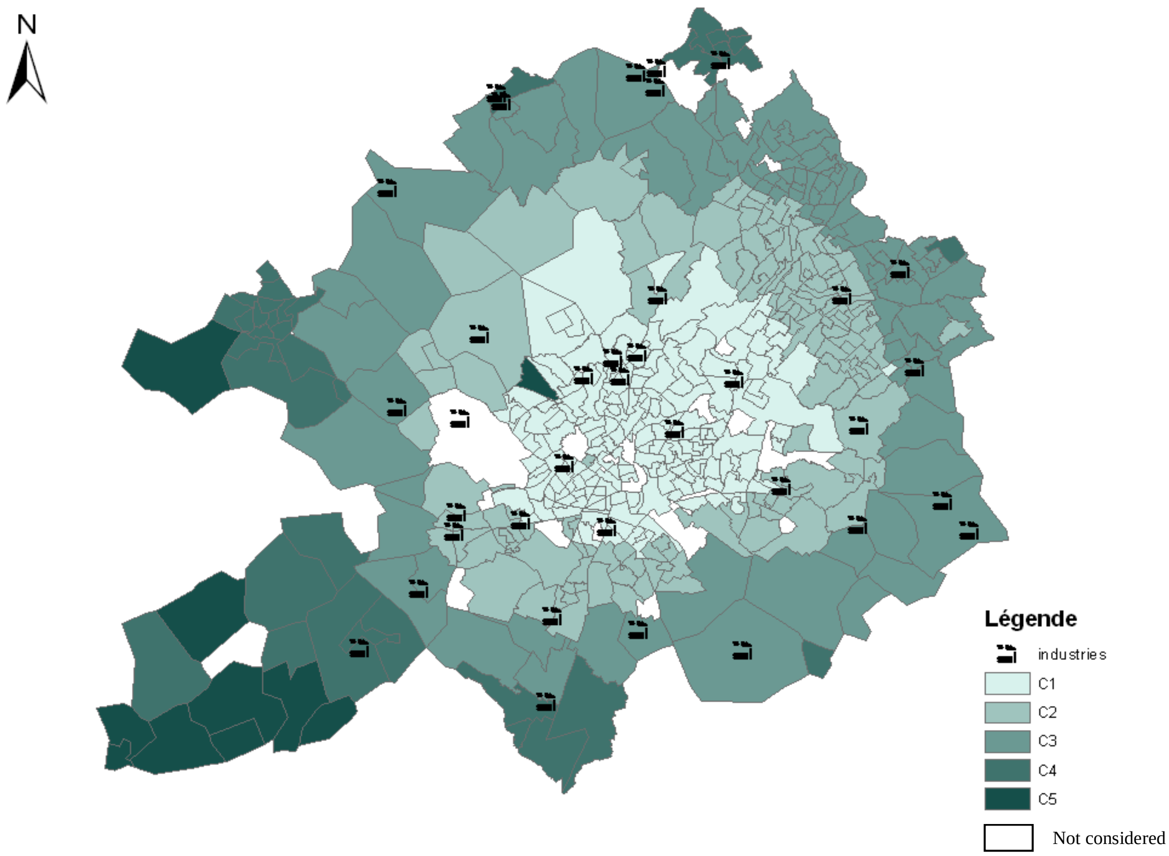


Fig.1: Distribution of industrial facilities and MSPI in LMA

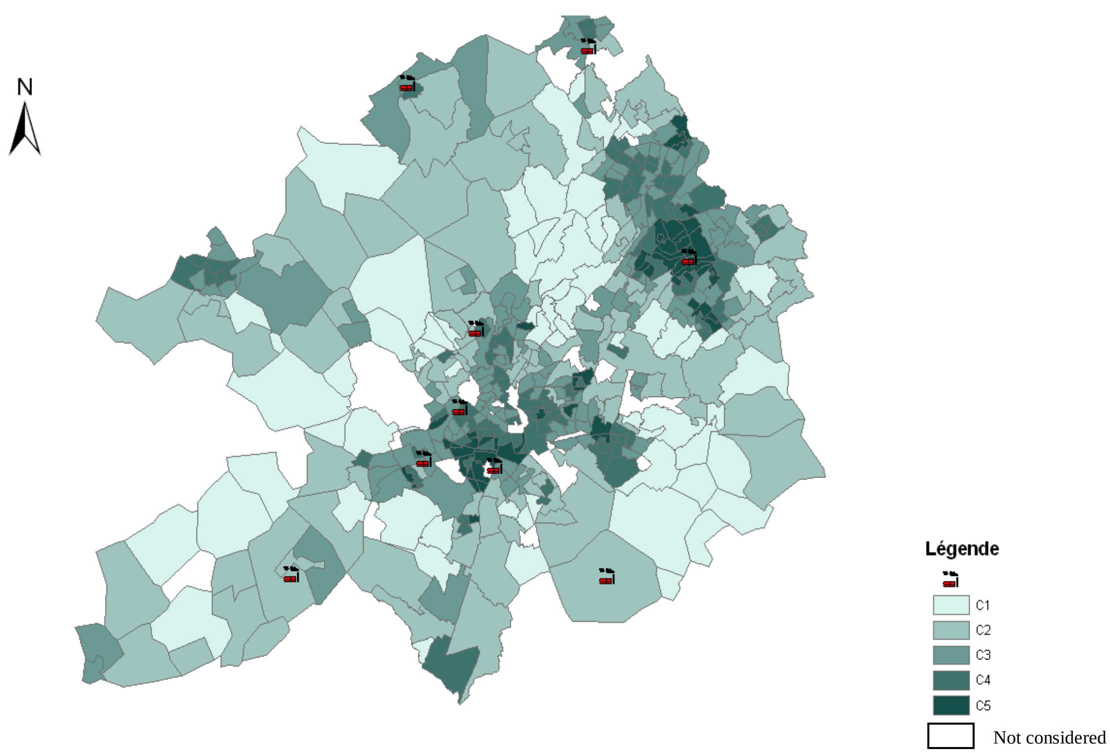


Fig. 2: Distribution of deprivation categories and polluted facilities in LMA

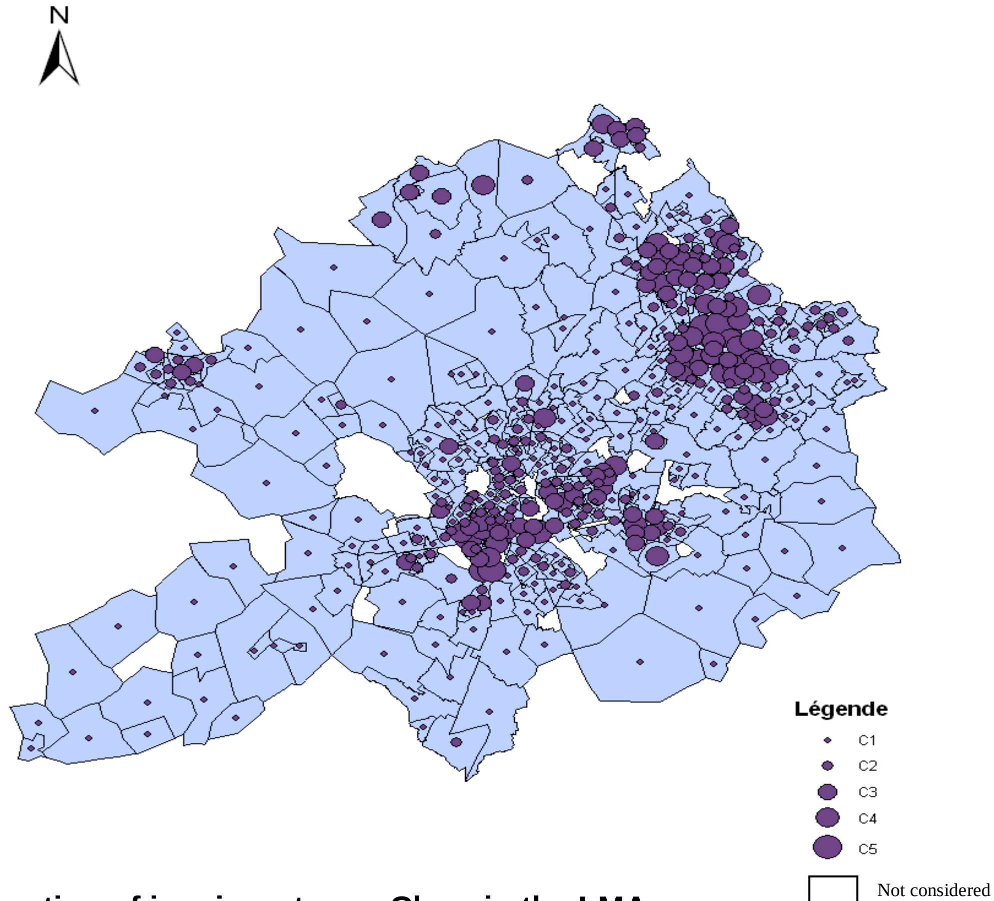


Fig.3: Proportion of immigrants per Class in the LMA

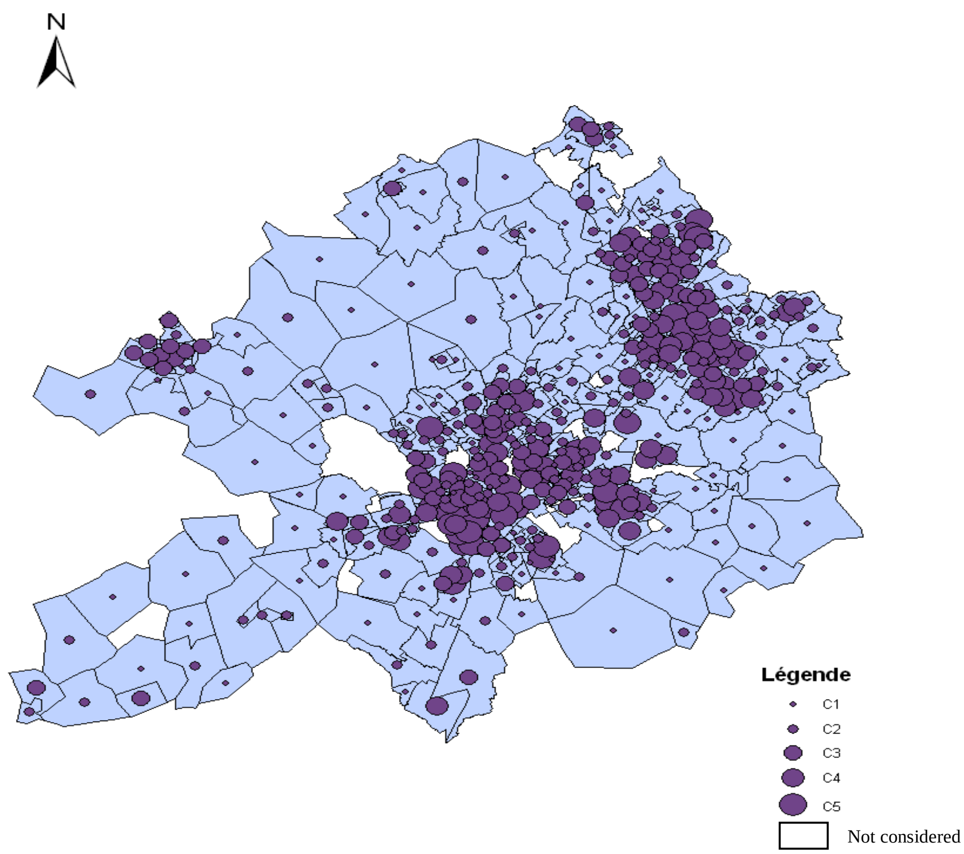


Fig.4: Proportion of single parental families per class in the LMA

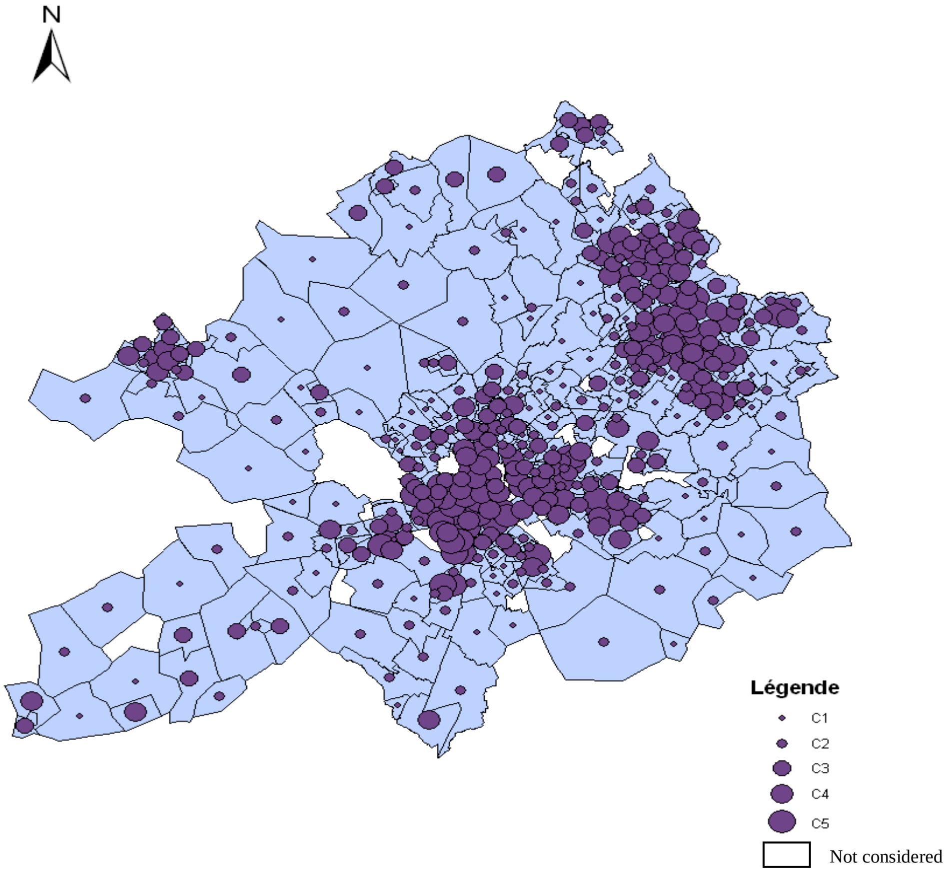


Fig.5: Proportion of population with unstable jobs per class in the LMA

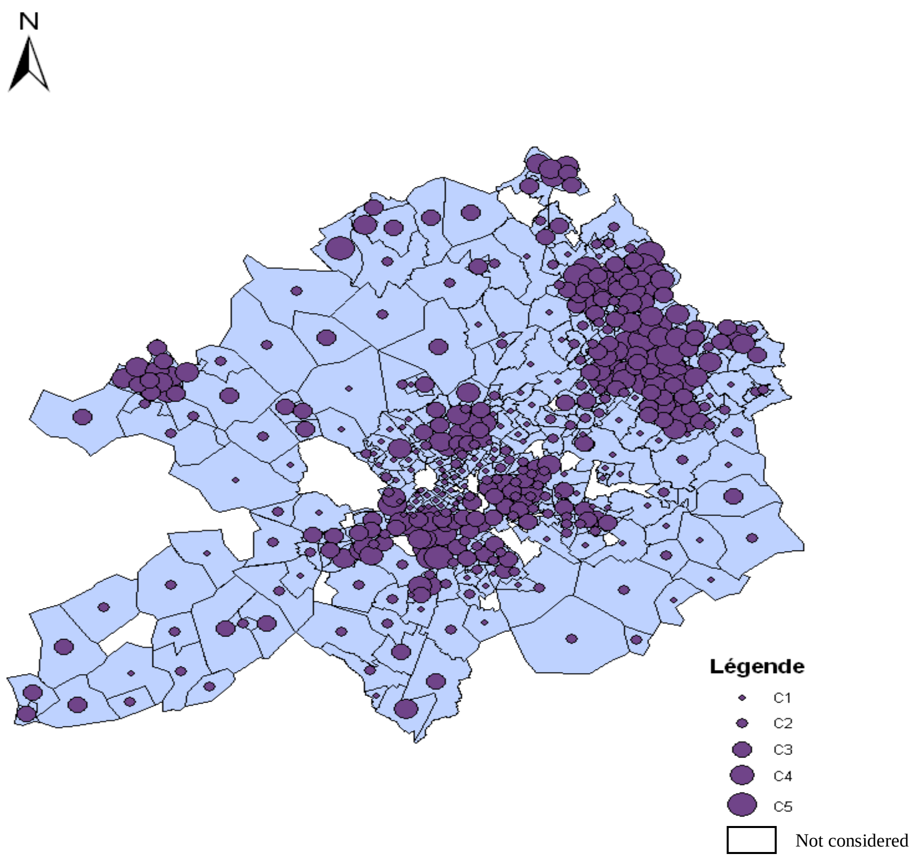
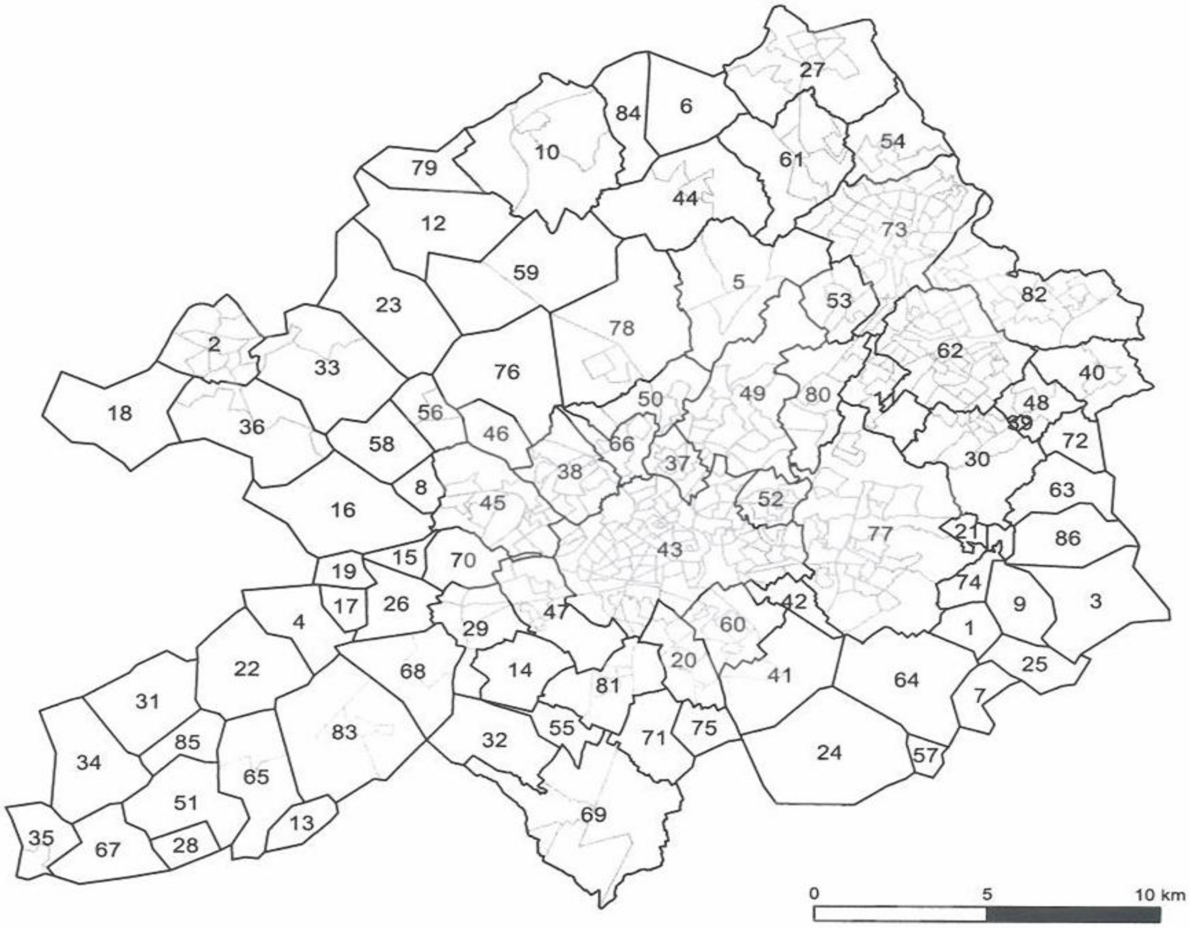


Fig.6: Proportion of population with low educational level



1 : ANSTAING
2 : ARMENTIERES
3 : BAISIEUX
4 : BEAUCAMPS-LIGNY
5 : BONDUES
6 : BOUSBECQUE
7 : BOUVINES
8 : CAPINGHEM
9 : CHERENG
10 : COMINES
11 : CROIX
12 : DEULEMONT
13 : DON
14 : EMMERIN
15 : ENGLOS
16 : ENNETIERES-EN-WEPPES
17 : ERQUINGHEM-LE-SEC
18 : ERQUINGHEM-LYS
19 : ESCOBECQUES
20 : FACHES-THUMESNIL
21 : FOREST-SUR-MARQUE
22 : FOURNES-EN-WEPPES
23 : FRELINGHIEN
24 : FRETIN
25 : GRUSON
26 : HALLENNES-LEZ-HAUBOURDIN
27 : HALLUIN
28 : HANTAY
30 : HEM
31 : HERLIES
32 : HOUPLIN-ANCOISNE
33 : HOUPLINES
34 : ILLIES
35 : LA BASSEE
36 : LA CHAPELLE-D'ARMENTIERES
37 : LA MADELEINE
38 : LAMBERSART
39 : LANNOY
40 : LEERS
41 : LESQUIN
42 : LEZENNES
43 : LILLE
44 : LINSELLES
45 : LOMME
46 : LOMPRET
47 : LOOS
48 : LYS-LEZ-LANNOY
49 : MARCQ-EN-BAROEUL
50 : MARQUETTE-LEZ-LILLE
51 : MARQUILLIES
52 : MONS-EN-BAROEUL
53 : MOUVAUX
54 : NEUVILLE-EN-FERRAIN
55 : NOYELLES-LES-SECLIN
56 : PERENCHIES
57 : PERONNE-EN-MELANTOIS
59 : QUESNOY-SUR-DEULE
60 : RONCHIN
61 : RONCQ
62 : ROUBAIX
63 : SAILLY-LEZ-LANNOY
64 : SAINGHIN-EN-MELANTOIS
65 : SAINGHIN-EN-WEPPES
66 : SAINT-ANDRE-LEZ-LILLE
67 : SALOME
68 : SANTES
69 : SECLIN
70 : SEQUEDIN
71 : TEMPLEMARS
72 : TOUFFLERS
73 : TOURCOING
74 : TRESSIN
75 : VENDEVILLE
76 : VERLINGHEM
77 : VILLENEUVE-D'ASCQ
78 : WAMBRECHIES
79 : WARNETON
80 : WASQUEHAL
81 : WATTIGNIES
82 : WATTRELOS
83 : WAVRIN
84 : WERVICQ-SUD
85 : WICRES
86 : WILLEMS

Fig7. Municipalities and IRIS of the Lille Metropolitan Area (source Declerc C. 2007)

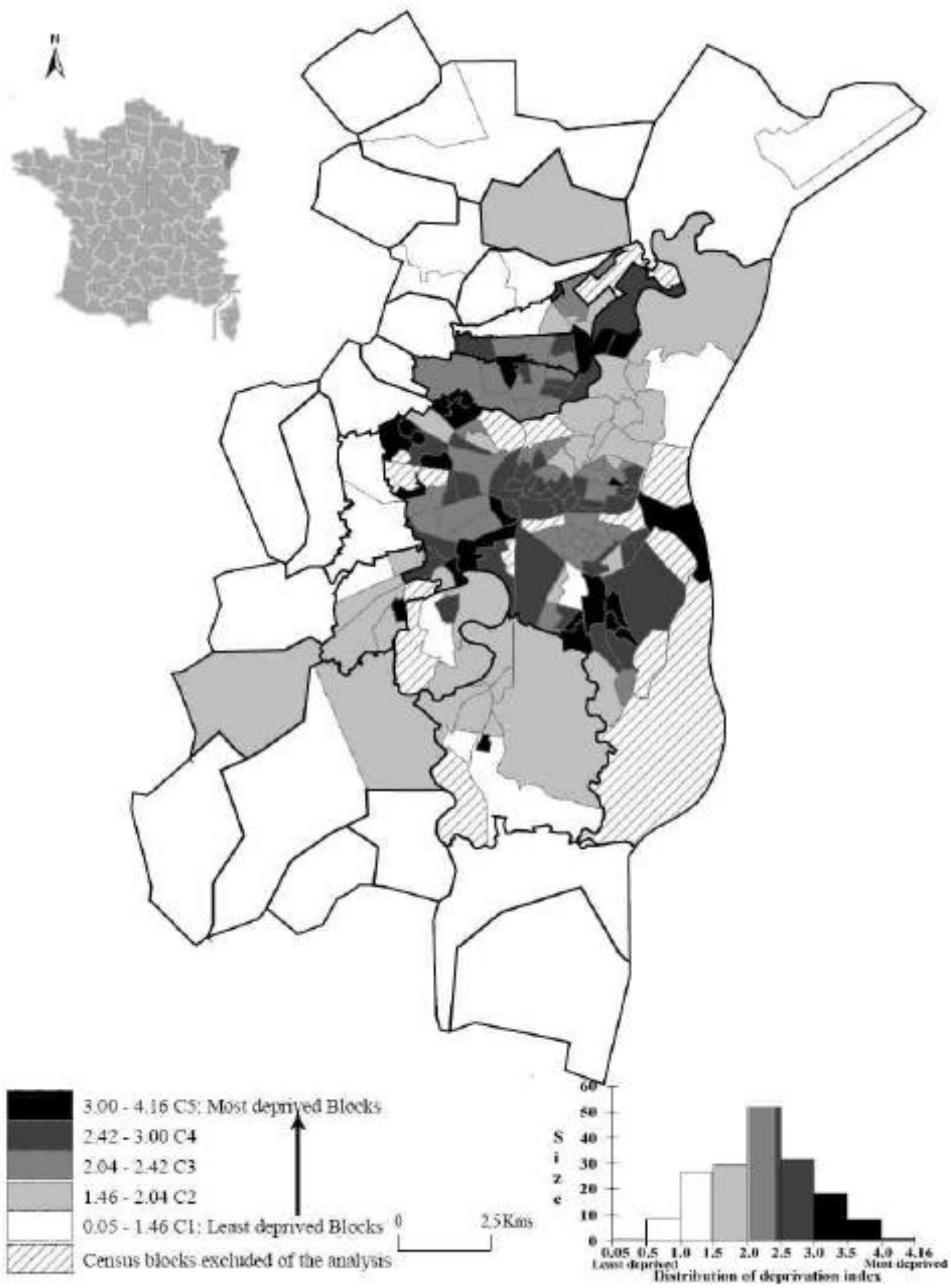


Fig.8: Distribution of deprivation categories in Strasbourg metropolitan area

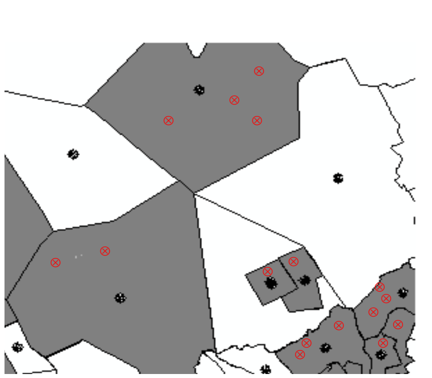


Fig. 9a: Spatial coincidence illustration 1

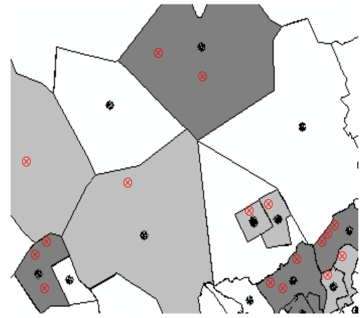


Fig.9b: Spatial coincidence illustration 2

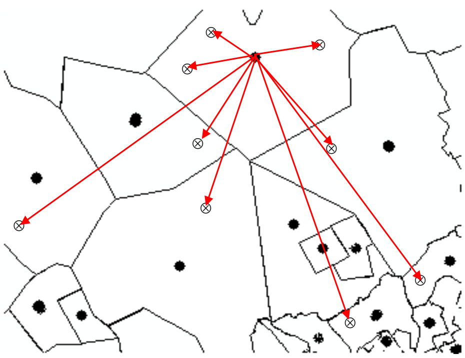


Fig.9d : MSPI Illustration

Fig.9c : Buffer illustration

Legend

▭	Not exposed	→	Distance from centroid to industy
▬	Slightly	o	Industry
■	Exposed	•	Centroid

Fig.9: Illustration of proximity indicator methods

Abstract

This study examines the demographic and socioeconomic characteristics of people living close to industrial facilities in the Lille Metropolitan area. The idea was to test whether population with lower socioeconomic status are more likely to reside proximate to industrial polluted facilities in France as it is established in other industrial countries namely the US, Canada, UK, Spain, etc. Demographic and socioeconomic data came from the 1999 National French census and industrial data were obtained from the French pollutant emission registry (IREP).

The study was carried out on a small geographic unit known as IRIS in the French context, which can be assimilated to a census block. A deprivation index, applied to the French context, successfully used in a previous environmental justice study in another French neighbourhood called Strasbourg was used to determine the socioeconomic level of our study population. We developed a new approach summing exposure from a range of industries located within an IRIS called Muti-site Proximity exposure (MSPI). The reason behind this was to explore neighbourhood distances from industrials facilities. With the aim of exploring the association between neighbourhood socio-economic level and proximity to industries, we examine whether neighbourhood located at shorter distances from industrial facilities were socially and economically deprived compared to neighbourhood located farther.

Our descriptive, statistics and spatial analysis showed a highly significant association between the neighbourhood demographic and socioeconomic characteristics and their proximity to industrial facility. Our Moran's Index test was highly significant ($p<0.001$) indicating presence of spatial autocorrelation in this area. This study clearly indicate the presence of environmental injustice in France in that, socially deprived population like labourers, immigrants, single parental families, low income people and people with lower level of education are more likely to live close to industrial facilities in France than other groups. Future research in this domain should consider including spatial autocorrelation in their analysis and why not exploring the causes of such inequalities.

Keywords: industrial air pollution, environmental justice, social heath inequalities, socioeconomic status, spatial analysis, immigration.

Résumé

Proximité aux industries en France : une étude de justice environnementale dans l'agglomération de Lille

Plusieurs études menées dans les pays industrialisés relèvent l'existence d'injustice environnementale, notamment aux US, et dans certains pays d'Europe. L'objectif de ce travail était de vérifier hypothèse selon laquelle les populations socio-économiquement défavorisées seraient plus exposées à la pollution industrielle en France et précisément dans l'agglomération de Lille. Nous avons utilisé les données socioéconomiques et démographiques du recensement général de la population française de 1999 et les informations industrielles recueillies auprès de l'IREP (Registre Français des Emissions Polluantes).

L'étude a été menée à l'échelle du Quartier de résidence : IRIS. L'indice de défaveur utilisé dans une étude précédente conduite dans l'agglomération de Strasbourg a été utilisé pour déterminer le niveau socioéconomique des IRIS. Afin d'estimer la distance aux industries, une méthode appelée Muti-site proximity index (MSPI) prenant en compte l'exposition de toutes les industries localisées dans les différents IRIS a été développée. L'objectif était de voir si les populations vivant proche des industries étaient socio-économiquement plus défavorisées que celles vivant à une distance plus éloignée.

Notre Indice de Moran était très significatif ($p<0.001$) suggérant la présence d'autocorrection spatiale. Par ailleurs, nos analyses descriptive, statistique et spatiale révèlent une forte association entre le niveau socioéconomique des IRIS et leur proximité aux industries. Les résultats de cette étude montrent que les ouvriers, les étrangers ainsi que les populations ayant un revenu ou un niveau d'éducation faible auraient plus tendance à vivre à proximité des industries que les autres groupes sociaux. Il serait intéressant d'explorer les déterminants de la proximité aux industries en France et les futures études de justice environnementale gagneraient à inclure l'auto-corrélation spatiale dans leur analyse.

Mots clés : Pollution industrielle, justice environnementale, inégalités sociales de santé, niveau socioéconomique, analyse spatiale, immigration.