RISK ASSESSMENT OF A PEDESTRIAN-ORIENTED ENVIRONMENT

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ABSTRACT

Audrey de Nazelle: Risk Assessment of a Pedestrian-Oriented Environment
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Health professionals and urban planners are increasingly calling for new approaches that involve changes in the built environment to address complex health and environmental problems. In particular, community designs to promote walking and cycling are seen as potential solutions to the obesity epidemic in the U.S. Yet, the net health effect that results from neighborhood transformations is not known today. Competing risks may be involved, particularly when considering the effects of encouraging people to be active in areas with significant air pollution and fraught with risks of traffic injuries.

This dissertation proposes a conceptual framework for assessing risks and benefits that ensue from the improvement of the pedestrian environment, and investigates some of these relationships in a quantitative application.

The probabilistic model developed for this work consists in simulating the movement of individuals in a case-study area that undergoes hypothetical changes in land use and street network. Resulting changes in energy expenditure due to active travel and in pollutant inhalation dose are estimated. The model uses an activity database, travel models from the transportation literature, and ozone and PM_{10} fields developed for this work using the Bayesian Maximum Entropy framework and a combination of monitored and modeled data. Daily individual inhalation intake is thus calculated accounting for specific activities, locations, and times of day. Uncertainty and population variability is analyzed through MonteCarlo simulation.

Results show great uncertainty associated with estimating risks and benefits. For

example, two travel models yield a four-fold difference in predicting the fraction of population with significant increases in PM_{10} inhalation dose. Conservative estimates demonstrate a significant increase in the fraction of days above a PM_{10} threshold across the population, and potential for some individuals to more than double their inhalation intake of both pollutants on certain days. Clear benefits in terms of physical activity, however, cannot be established by the conservative exposure model.

This work is an innovative risk assessment method for analyzing health impacts of built environment policies. The dissertation concludes with suggested policies to address increased risks, and a research agenda for future work in this area.

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LIST OF ABBREVIATIONS

BE: built environment

Cerv: Cervero transportation model

CHAD: consolidated human activity database

DOT: department of transportation

EPA: environmental protection agency

LU: land use

NAAQS: national ambient air quality standards

Rod: Rodriguez transportation model

1 INTRODUCTION: PURPOSE OF THIS DISSERTATION

No one would call pedestrian-friendly designs a panacea, but some will go as far as talking about a “Third Public Health Revolution” (Scutchfield 2004) others a “paradigm shift” (King et al. 2002; Killingsworth et al. 2003). From proximal to distal causes of health status, experts from a broad spectrum of fields are looking into the advantages of creating health-supportive built environments[1]. Physical activity enhancing, air-pollution reducing, social interaction inducing, traffic injury-preventing… pedestrian-oriented community designs are thought to respond to many of the qualities called for to improve residents’ health. Yet, the net health effect that results from changes in communities aimed at improving the walking and cycling environment is not known today. Competing risks and benefits may be involved, particularly when people are encouraged to be active in streets that may be polluted or fraught with risks of traffic injuries. **The purpose of this dissertation is to propose a conceptual framework for assessing relative contributions of risks and benefits that ensue from the improvement of the pedestrian environment, and to test some of these relationships in a quantitative application. The overall goal is to aid decision making for more health-promoting communities.**

The thesis explored in this dissertation is that transforming the built environment towards more pedestrian-friendly designs triggers health benefits in the form of healthy active travel while simultaneously increasing detrimental exposures to air pollutants.

Current environmental and health policy in the US, like modern urban planning, consists in the aggregation of specialized elements, with little blending and overall framework for

[1] The built environment refers to the bundle of features that characterize communities’ physical aspects: land use patterns, transportation systems, neighborhood characteristics, building orientation and design.

balancing competing considerations of sustainability. The segregation of these entities in planning the urban environment is carried over in the way its environmental and health impacts are assessed. Whether due to regulatory requirements or to research and practice specializations, typically the approaches used to analyze the effects of the built environment are piecemeal and selective. Themes considered mostly in isolation of one another include air quality, water pollution, traffic congestion, traffic safety, physical activity, crime, social cohesion and nutrition. Despite a diversity of theoretical and methodological frameworks to capture concepts such as quality of life in relationship with the community environment, little research has been undertaken on the interaction of these different items and their overall effect on the health and well-being of people.

Yet, not only is it important to consider comprehensively and dynamically the effects of community plans on the full gamut of benefits and risks associated with them in the decision making process, but also it is necessary to evaluate possible unintended consequences. Indeed, as for most policies, plans to change the built environment can carry competing risks that are not systematically considered in traditional evaluations and, hence, fail to address risk-risk tradeoffs (Graham and Wiener 1995).

Of particular interest for the current research on pedestrian-oriented environments, is how encouraging active lifestyles may unintentionally compromise people's health by increasing exposures to air pollution and traffic hazards. There is a clear need to understand and quantify these risk tradeoffs so policy can be better informed.

The first objective of this dissertation is to provide a conceptual framework for analyzing disparate health impacts of the built environment, in support of the policy goal of health-promoting environments. Secondly, this work will offer estimates of changes in factors of risks and benefits, in terms of exposure to air pollution and of active travel, following a change in the community design. The factors of risk and benefit quantified in this work are meant to form the basis for evaluating in a further study net health impacts resulting from the competing effects of a pedestrian-oriented built environment – specifically physical activity and exposures to air pollution and traffic hazards.

The proposed analysis comprises important theoretical contributions to the fields of risk assessment and policy analysis. Theoretical challenges stem from the combination of a variety of fields that employ different constructs and data types in their areas of study, and from decision making in the face of uncertain knowledge.

This introduction first provides a brief review of existing frameworks for the study of the built environment and its effects on health and quality of life. Next a conceptual model of the overall impacts of the built environment on health is presented, accompanying an overview of why communities may want to implement policies to improve their pedestrian environment. The rationale for conducting a risk assessment of such policies is then stated, followed by a section on the research objectives for this dissertation, and this chapter ends with a discussion on the theoretical contribution of the proposed work. Guided by the conceptual model, a more detailed description of current knowledge and gaps in understanding the health impacts of the built environment follows in the next chapter. Proposed methods to undertake a health impact assessment of a pedestrian oriented environment are covered in Chapter III. The dissertation ends with an analysis of results of the computation model, and a discussion of policy avenues for addressing potential risks and for enhancing benefits.

1.1 Conceptual frameworks for the analysis of the built environment

Different fields of study have had varying interests and used diverse approaches in the study of impacts of the built environment. Nevertheless, no research has offered a rigorous quantitative assessment of disparate impacts of pedestrian-oriented environments, including an analysis of risk-tradeoffs. Comprehensive assessments of the built environment emerging from different fields have laid the foundations that make a formal quantitative analysis possible., these approaches have at times been criticized, however, for their lack of a theoretical framework including explicit mechanistic pathways, or have remained at a conceptual stage. For example, human ecology offers a broad perspective on the interactive influence of physical, economic and social factors on livability, quality of life and sustainability (Lawrence 2003), but quantitative analyses in that field typically are restricted to simple correlations of these indicators and outcomes, without further modeling of mechanistic pathways (Smith et al. 1997; Hancock 2002; Paccione 2003). The social ecological framework used in public health refers to explicit theories to explain behavioral pathways to health (Glanz et al. 1990), and its quantitative applications generally use rigorous statistical techniques. However, ecological models developed to assess comprehensively impacts of the built environment have mostly remained conceptual, have not raised the issue of risk trade-offs tackled in this paper, and have not suggested computational approaches to test or estimate effects of changes in the built environment (Stokols 1992; Northridge et al. 2003). Health Impact Assessment (HIA) offers another framework allowing comprehensive assessments of changes in the built environment. It is a tool, used mostly in Europe and increasingly in the US, meant to help in decision-making processes by assessing negative and positive effects of proposed policies or programs. Decomposing overall impacts of proposed projects is an important focus for HIA, and the study of unintended consequences of community planning is at the forefront of the European branch of the World Health Organization's Healthy Cities initiative concerns to be addressed by HIA (Duhl and Sanchez 1999). However, it is a pragmatic tool, mostly geared towards stakeholders' involvement in decision-making, and often constrained by short time frames (Mindell et al. 2004). It is therefore not meant for rigorous research endeavors which may include developing new methods and complex multi-attribute modeling of mechanisms of change in health, behavior, and the environment. Hence, HIA is not appropriate for the risk tradeoff analysis proposed here.

Risk assessment, the framework used to guide this research, is chosen because it is used for rigorous scientific analyses of health impacts of hazardous exposures, allowing for multiple pathways and multiple contaminants. An important focus of risk analysis is assessing sources of uncertainty and its impact on model outputs. This is an especially important feature in an analysis that combines results from different fields that use different analytical methods, metrics, and scales of analysis. Although it has not traditionally considered the effect of “place” on health - especially in terms of how it may affect behavior - there is nothing in the theoretical underpinnings of risk assessment to prevent such extension[2]. Thus, determinants of physical activity and travel behavior may be part of a risk analysis. The field has been criticized for typically ignoring competing risks or comparisons of health impacts in risk (Graham and Wiener 1995; Ponce et al. 2001; Murray et al. 2003). Nevertheless, methods integrating health metrics such as quality adjusted life years (QALY) or disability adjusted life years (DALY) can be used for this purpose (Ponce et al. 2001). The health metrics approach used in risk assessments can also facilitate the inclusion of behavioral health outcomes into the comprehensive assessment (such as those resulting from physical activity behavior). Therefore, risk assessment is an appropriate framework to study the competing risks associated with changes in neighborhoods towards pedestrian-friendly designs, because it affords the flexibility to integrate both behavioral components and health metrics that allow comparative risks analysis, and allows for the analytical rigor necessary to tackle complex multi-attribute problems and assess the uncertainty associated with the results.

1.2 Background: analysis of a bicycle- and pedestrian-friendly environment policy

1.2.1 *Rationale*

The broad framework used in this dissertation to describe the impacts of the built environment is presented in Figure 1.1, and the major issues that justify the call for implementing urban design changes are overviewed here. The built environment impacts human health, both

[2] Albeit perhaps not with all the subtleties the word “place” signifies in the fields of environmental psychology or geography.

directly and indirectly through its influence on behaviors, environmental quality, and the functioning of society. In particular, building more pedestrian-friendly communities may have positive effects on residents' health by increasing physical activity in the form of active (non-motorized) transportation (Ewing and Cervero 2001) or leisure-time exercising (Humpel et al. 2002), possibly decreasing vehicle use (Ewing and Cervero 2001) hence reducing air, water and noise pollution and traffic injuries. In addition, building compact communities as opposed to sprawl development reduces the amount of impervious surface per inhabitant, allows the preservation of open space and prevents land fragmentation – all of which may benefit human health indirectly by protecting water quality and natural habitats (which may prevent the spread of vectors of disease such as deer, mice and mosquitoes). Furthermore, pedestrian –oriented designs are analogous to principles used to prevent crime (Crowe 2000; Mair and Mair 2003); encourage social interaction (Leyden 2003) which may lead to a better functioning of society (Langdon 1994) and better health (Putnam 2000); increase the availability of food stores which is associated with healthier diets (Morland et al. 2002); and improve the mobility of those who cannot drive because they are too old, too young, or do not own a car, thus leading to a more equitable society.

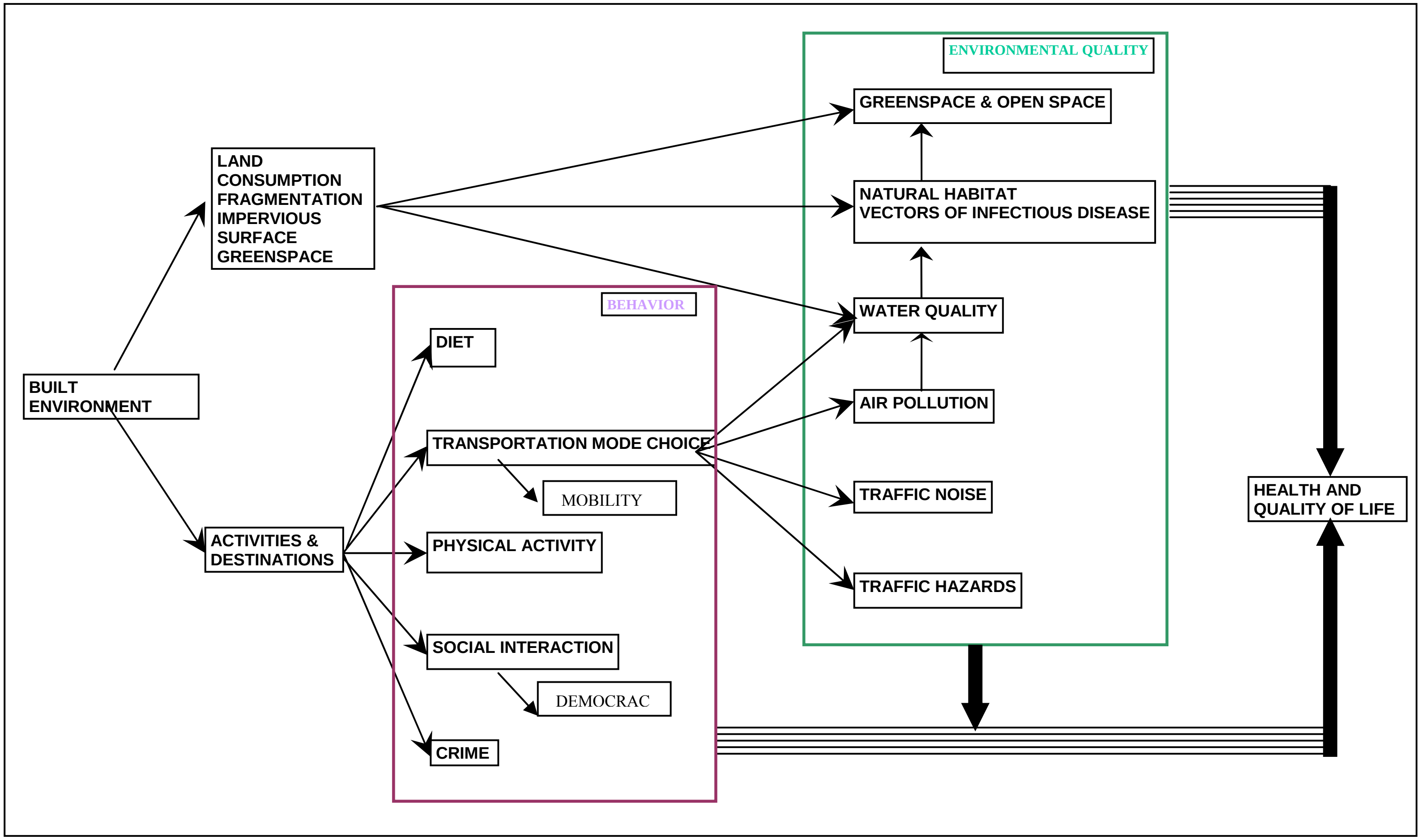

Figure 1-1 Framework for conducting a risk assessment in a pedestrian-friendly environment

1.2.2 *Context*

The growing popularity of urban design policies that improve the walkability and bikeability of communities (Myers and Gearin 2001) comes at a time of great concern with obesity, and with vehicle-use related afflictions such as air pollution, congestion or oil-dependency. With obesity[3] and overweight[4] prevalence reaching over 64% in the US (Flegal et al. 2002), corresponding to a 50% increase in less then a decade in the 90s, health officials are now calling the trend an epidemic. One study has estimated around 300 000 deaths were attributable to obesity every year (Allison et al. 1999). Finkelstein et al. (2003) estimated a 14.5 % ($247) total per capita annual increase in medical spending due to overweight, representing a total of $78.5 billion in 1998 - 9.1% of annual US medical expenditures. Some studies have suggested that the trends could possibly be more due to decreases in energy expenditure than increases in energy intake (Jebb and Moore 1999). Obesity, and even more so the health risks associated with obesity such as hypertension and diabetes, can be prevented or mitigated by the practice of regular physical activity. Moreover, reduced physical fitness has been shown to be associated with mortality independently from body mass, meaning that public health campaigns might more appropriately be focused on physical activity rather than solely on weight loss (Welk and Blair 2000). Two hundred thousand deaths a year, a third of US deaths from CHD, diabetes and colon cancer, are attributed to inactivity (Powell and Blair 1994). Only 22% of US adults engage in the recommended 30 minutes/5 days a week of physical activity, and 25% are completely inactive (U.S. Department of Health and Human Services 1996).

It is not surprising therefore, that public health officials and practitioners are looking for new ways to promote physical activity in light of the lack of success traditional interventions have had in reversing trends. Changing the built environment to help individuals easily integrate

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[3] Body mass index above 30; nearly one in three American is obese (Flegal 2002).

[4] Body mass index ranging from 25 to 29.9

physical activity into their daily routine is seen as a more practical and sustainable approach than the traditional exercise programs (Koplan and Dietz 1999; Carnall 2000; Badland and Schofield 2005). Hence, agencies and health and environmental organizations are increasing their calls to action for creating more pedestrian-oriented environments. The Robert Wood Johnson Foundation, for instance, has launched a series of programs and initiatives to help communities create plans to improve their walkability and bikeability in order to encourage “active living” – a concept referring to a lifestyle that easily integrates physical activity into daily routines (Robert Wood Johnson Foundation). The Center for Disease Control and Prevention has also promoted such policies through its Active Community Environment initiative (CDC 1999).

In addition, some health organizations such as the WHO encourage an interdisciplinary approach to public health promotion, helping advance policies that demonstrate a synergy of effects on health (Dora 1999). Pedestrian-oriented community design policies precisely fit this description, as they are seen as solutions to problems associated with vehicle use. The EPA for example has recommended such strategies to mitigate air pollution and other environmental degradation due to common auto-oriented land use practices (U.S. Environmental Protection Agency 2001b; U.S. Environmental Protection Agency 2001a). Indeed, traditional strategies to improve air quality by reducing tailpipe emissions, improving highways, and proposing travel alternatives have proven insufficient to bring many areas into attainment (Kessler and Schroeer 1995; OECD 1997). In 2002, 136 million people lived in US counties exceeding the ozone standard, potentially contributing to widespread asthma attacks, chronic bronchitis, and other respiratory disorders. Particulate matter standards violations are also widespread, and the evidence of its multiple deleterious effects on health is growing, particularly of traffic-induced fine particulates. The American Lung Association (American Lung Association 2004) evaluated the total cost of asthma alone in the US at $14 billion a year (including direct health care costs and loss of productivity). Vehicle emissions also contribute to climate change and its potential for irreversible global health and environmental impacts, for which there is a quasi-worldwide concern. Pervasive vehicle use imposes other charges to society, such as an estimated total cost of congestion in 85 urban areas in the US amounting to $62 billion in 2002, due to time loss and fuel wastage (Schrank and Lomax 2004). The list goes on. It is in this context of broad concerns regarding physical activity and auto-oriented communities that pedestrian-oriented design policies and their possible multiple benefits may seem appealing to communities.

1.2.3 *Special populations at risk*

The issues associated with community design discussed above are compounded when looking at some specific sub-populations. Children, for example, are particularly affected by the environment in which they live. In terms of physical activity, in addition to forming lifetime habits during childhood (Tudor-Locke et al. 2001), overweight children have risk factors which become debilitating chronic diseases in adults (Must et al. 1999). Children today do not have the opportunities for exercise most of their parents did in their childhood; in the last 30 years, the proportion of children walking or cycling to school has dropped from 48 to 16% (US Environmental Protection Agency 2003b). A survey conducted by the CDC showed 84% of parents reporting barriers to their children walking or biking to school (CDC. 2002). Moreover, pedestrian-oriented community design would provide mobility to the youth independent of parents driving them places[5], possibly affecting their psychological development by conferring a higher sense of autonomy and allowing more explorations into the world (Frumkin et al. 2004).

Auto-dependency similarly affects other populations' mobility such as the elderly, the disabled and lower-income people. Driving cessation has been associated with reduced social activity and depressive symptoms (Marottoli et al. 1997; Marottoli et al. 2000), possibly affecting a fifth of adults over age 65 (Surface Transportation Policy Project (STPP) 2004). More than a quarter of households earning less than $20,000 do not own a vehicle (Pucher and Renne 2003), thus limiting their ability to participate in economic activities in car-dependent environments.

[5] For 70% of their trips, children rely on adults driving them places (Pucher and Renne 2003)

Yet, community designs can reduce these disparities in mobility by allowing people to replace auto-trips by walk, bike or transit trips.

In addition to having reduced mobility, possibly because of having to rely on their feet to go places in environments unsafe to the pedestrian[6], children, the elderly and minorities are particularly at risk of automobile crashes as pedestrians. For instance African Americans are the victims of more than 20% of pedestrian deaths, even though they only represent 12% of the US population (Surface Transportation Policy Project (STPP) 2002). Similarly, death rates from asthma are close to three times higher for African Americans than for white Americans (US Environmental Protection Agency 2003a). This could in part be due to disproportionate exposures to traffic for minorities. Gunier et al. (Gunier et al. 2003) showed for example that in California Hispanic children, followed by African American and then Asian children were each significantly more likely to live in a high-traffic area than White children. The study also found household income to be inversely related to living in a high traffic area, and the trend of white children being less exposed to traffic than other children held true in every income group.

Another theme of perpetuated inequality in the US that would be addressed by improving the pedestrian environment in certain neighborhoods is the disproportionate lack of parks and recreational facilities in low income communities and low income communities of color, possibly contributing to disparities in physical activity rates (PolicyLink 2002). In fact, older adults, women, ethnic minorities, and persons with lower education levels show the lowest prevalence of physical activity (U.S. Department of Health and Human Services 1996), which could be specifically addressed by facilitating the integration of walking or biking as a lifestyle for such subpopulations in communities.

[6] Pedestrians are 23 times more likely to die in a car crash than car riders per kilometer traveled (Pucher and Renne 2003).

1.2.4 *Design strategies*

Concepts implemented for pedestrian-friendly communities are akin to those of new urbanism, and traditional, neo-traditional, or transit-oriented development - all thought to encourage non-motorized transportation. The most basic principle of pedestrian-oriented design is that destinations are made more accessible to pedestrians by shortening distances from home to retail, employment or schools, and by creating a more "human scale" environment. This begins with mixed and dense land uses. The transportation system must comprise a dense, safe and efficient street network, characterized by a well-connected fine-grained street or walkway and bikeway pattern, small block sizes, continuous sidewalks of widths commensurate to that of the roadway, regularly spaced and well signalized crosswalks, traffic calming measures, and ideally containing available transit. A human-friendly neighborhood microscale design can be accomplished with attention to: building orientation such as shortened set-backs; parking location, preferably on-street and small lots behind buildings rather than seas of parking lots between the street and building; landscaping such as vegetative street buffers to protect pedestrians from vehicular traffic and trees for shade; and pedestrian amenities such as street lighting, benches, public art, parks, gathering places, and signage to facilitate way-finding.

Implementation of these measures is straightforward in new developments, but existing sites can also be retrofitted for a pedestrian-friendly environment. This may entail, in addition to what is feasible in the above treatments, for example: accommodating parking lot entrances to shopping centers for safe pedestrian access; providing gates in fenced-in commercial or residential areas; creating cut-throughs in cul-de-sac developments to allow pedestrians and cyclists to take the shortest route to commercial or employment destinations from their home; providing well-signalized crosswalks at the entrances of commercial centers, housing concentrations and schools even if no intersection exists – all of which must be connected by a marked walkway and bikeway network resembling a simple grid.

1.3 Rationale for conducting a risk assessment of a pedestrian-oriented environment

While government agencies, foundations, and experts from health and transportation fields call for the improvement of the pedestrian environment in towns and cities, the actual overall health benefit of such policies is not known. The possible benefits were listed in the previous sections, yet some of these gains may also pose risks. It is these competing risks that drive the need for this proposed research. A preview of relevant research supporting the claim of concern for competing risks associated with increasing activity in an urban environment is offered below, and reviewed more thoroughly in Chapter 2. The conceptual framework for assessing the competing risks of built environment transformations considered in this dissertation is then presented. This section concludes with a further discussion of the relevance of this dissertation research.

On the one hand air pollution might indeed be reduced from a shift in travel modes, but on the other hand, people may increase their exposure and their inhalation dose by being physically active in streets that may still experience high pollution levels, all the more so if the activity is held near busy roads. There is a growing body of evidence to suggest that living or going to school near heavy traffic roadways is associated with increased incidences of respiratory infections, asthmatic and allergic symptoms, and childhood cancers such as leukemia (Wyler et al. 2000; Buckeridge et al. 2002; Hoek et al. 2002; Lin et al. 2002; Maheswaran and Elliott 2003; Nicolai et al. 2003; Crosignani et al. 2004). However some work has suggested that cyclists and pedestrians in many cases are less exposed to urban air pollutants than those traveling by car or bus on the same route (Adams et al. 2001; Rank et al. 2001; Duci et al. 2003). Furthermore they may at times have the capability to choose less congested routes where exposure is reduced (Adams et al. 2001), if the street layout permits it. However, not only is the minute ventilation increased when exercising, but also, at least in the case of ultra fine particles, the deposition fraction may increase. Daigle et al. (2003) showed that the combination of both effects may multiply the total ultrafine particle deposition during moderate exercise by up to five times compared to resting. Two recent review articles (Carlisle and Sharp 2001; Sharman et al. 2004) on the effects of major urban air pollutants concluded by recommending that people avoid exercising near roadways.

Moreover, as in the US it is generally more dangerous to be a pedestrian or a cyclist than being in a vehicle[7], individuals changing their behavior for more active forms of travel or outdoor leisure might increase their risk of traffic injuries. Even though an increase in pedestrian and cyclist activity in the streets and the improved engineering treatments in the new built environment design may increase the safety of pedestrians and cyclists, the higher exposure to traffic hazards must be accounted for to determine the overall benefits.

A risk assessment framework, schematized in Figure 1.2, is thus proposed to guide an analysis of health impacts of competing risks associated with neighborhood changes towards a more pedestrian-friendly environment. The competing risks refer specifically to the interrelations between in-street physical activity behavior (for leisure or utilitarian travel) and hazardous exposures (traffic hazards and air pollution). This framework integrates into a single model perspectives from research fields: the impacts of the built environment on travel mode choice and physical activity; the hazardous exposures due to the interaction between these behaviors, the built environment and the spatial-temporal distribution of air pollution and traffic hazards; and their respective effects on health. The interrelation between behaviors and exposures is complex; it includes the simultaneous effects of: physical activity behavior on the time and location of exposure; transportation mode choice in combination with features of the neighborhood built environment on the time and location of vehicles on the road, hence the microscale air pollution dispersion and traffic hazard conditions; and more macroscale (regional) built environment

[7] Ibid. footnote 5.

factors on traffic intensity and ambient air pollution concentrations. In short, the model highlights the unintended health consequences that may occur when encouraging an outdoor active lifestyle.

This framework, which guides the ensuing literature review as well as the computational component of the dissertation, can be viewed as following a risk assessment model, enhanced with a behavioral component.

This short discussion has shown that there are indeed tradeoffs that need to be accounted for when implementing policies of improvements in pedestrian-oriented environments. The objectives of such policies are all worthy, therefore the purpose of this dissertation is not to discourage such initiatives, but rather calls for a comprehensive approach to assessing and implementing such policies, considering all risks and benefits involved.

Ultimately, as a pedestrian-friendly environment addresses a diversity of policy objectives, it calls for a comprehensive approach to assess its effects. Its outcomes may not be determined in isolation of each other, as trade-offs and synergistic effects must be taken into consideration to evaluate overall effects of community design on health. While many parts of the picture have been studied before and much is known about different elements, no overall built environment health impact assessment has been performed before in the US. It is timely to undertake such work at a time of great interest in such community design solutions to many current health and environmental problems.

From a policy perspective, the result of a comprehensive analysis may bring about some further recommendations to improve the resident's health which perhaps would not have otherwise been considered. For example, conclusions could support a policy as simple as urging people to choose one route over another to reduce exposures while walking, cycling or jogging outdoors. In more serious cases, a community may decide to first tackle its air pollution problems before encouraging active transportation and leisure.

More generally, there is a societal need for this research because important health concerns are currently not integrated in the planning decision-making process. Government agencies have a piecemeal and selective approach to assessing health or environmental repercussions of plans or programs. Policies that regulate planning decisions for example are mainly concerned with how transportation and land use will impact environmental quality for regulatory compliance purposes. Moreover, while legislation such as the Safe Accountable Flexible Efficient Transportation Equity Act: A Legacy for Users (SAFETA-LU, US DOT, 2005) does consider both pedestrian and cycling enhancement and air quality, it does not suggest any joint analysis to estimate possible health outcomes. The pedestrian-environment risk assessment framework suggested in this dissertation proposal could serve as a basis for making the case for a systematic comprehensive assessment of community plans.

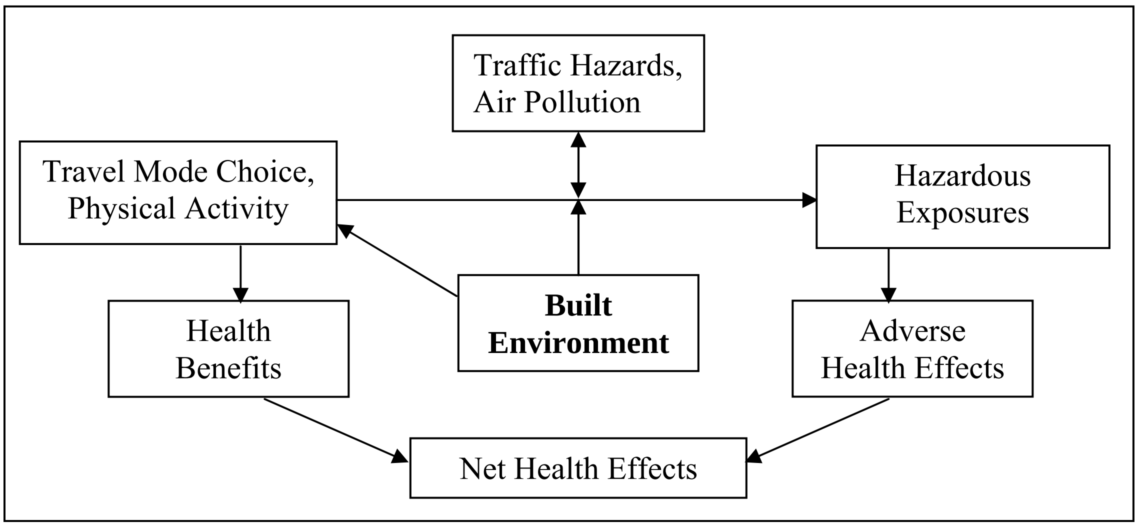

Figure 1-2 Conceptual model for a risk assessment of a pedestrian-oriented environment

1.4 Research objectives

The goal of this dissertation is to advance research and policy for a comprehensive approach to creating health-promoting environments through urban design, land use and transportation plans. More precisely, this research aims at providing a framework and a computational example for assessing risk and benefits trade-offs resulting from changes in the built environment that propose to improve the walking and biking environment of communities. This work has several potential audiences: local planners and health practitioners, the research community, and State and Federal decision-makers. As highlighted in the decision framework outlined below, various outcomes of the computational model lead to different audience targets. If the tool developed is able to give high quality precise results, then it will benefit the local planning and health community involved in making decisions for more health-promoting environments. In the case of poor resolution because of overriding uncertainty, this dissertation will mostly be useful for researchers, to offer directions for improving the ability to estimate health impacts in a demonstrated area of need. Regardless of the quality of the tool, the work is also directed more generally towards State and Federal-level decision makers. As the work raises important issues of competing policy goals (increase physical activity and curb air pollution exposure) it will serve as a plea to have health-promotion considered comprehensively in setting nation- or state-wide health and environmental policy strategies.

The first objective is therefore to develop multi-attribute models of the relationship between community design and human health and well-being. This objective contains both a theoretical component stemming from the integration of constructs from different disciplines, and a computational endeavor linking empirical results from different fields associated with the competing risks concomitant to urban active living. The intent is to develop a theoretically-based strategy for supporting the policy goal of health promoting environments. The framework will aid decision makers in assessing comprehensively built environment policies, and guide them in designing optimal solutions.

Secondly, the model is applied to scenarios of change in a case study area to provide an example of an assessment of expected factors of health risks and benefits ensuing from improvements of the pedestrian and bicycle environment. The following hypotheses are tested in the case study:

1. A change in the built environment to create more pedestrian- and bicycle-oriented communities yields both a healthy surge in active travel and detrimental increases in inhalation of air pollution in the population.

2. Population changes in physical activity and air pollution exposures may not be adequately quantified to provide useful policy information, due to the extent of uncertainty associated with the simulation process.

More specifically, the outcomes of the computational model are evaluated within the context of a decision framework, characterized by three possible paths, as follows:

1. Risk results mandate action to reduce risk
   - At local levels – actions on the built environment and health communication
   - At the state or federal level – actions on emission standards and transportation/land use policies, and on comprehensive health risk assessment for setting state and national environmental and health policies
2. Risk is deemed acceptable and benefits clearly outweigh risks
   - Local and state/federal level decision makers must act to enhance built environment policies
3. More analysis is required to inform decision-making for immediate action

The decision framework outlined above warrants discussions on risk metrics, on judgments on the ‘acceptability’ of risk, and on decision-making in the face of uncertainty. These issues are considered in Chapter 3.

The third objective for this dissertation, a sequel to the second hypothesis tested and third decision path is to develop research recommendations for generating better assessments of the built environment’s health impacts. The uncertainty analysis is used for that purpose, uncovering the areas of scientific knowledge where gaps create the greatest hindrance to precise and reliable estimates of health impacts.

The study concludes with policy recommendations for planning healthy communities. These may not be limited to whether and how to develop pedestrian-oriented environments, but may also be more nuanced or broader, such as recommendations to support further efforts to reduce vehicle use through a different set of policies before encouraging outdoor activities, to develop recommendations for safer use of the environment (e.g. create “hazard maps” of the area with recommended routes for cycling or walking), to use social marketing techniques to encourage healthier and more sustainable behaviors, or more generally to support new legislation requiring a comprehensive health impact assessment of community plans. The policy aim is to identify opportunities to improve overall health in the population by increasing healthy behaviors and restrain risks due to hazardous exposures. The policy component of this work thus also contains a theoretical aspect integrating perspectives from different fields in practical policy applications.

1.5 Theoretical contribution

The proposed dissertation contains several layers of theoretical discussions. The first and overarching theoretical contribution is the combination of constructs from different fields to create a unified conceptual model of the impacts of the built environment on health and quality of life. The framework schematized in Figure 1.1 is the result of a logical assembly of linkages studied and explained in different fields, and reviewed in the next chapter. The challenge of this effort is to make the necessary conceptual leaps to bring together perhaps apparently unrelated themes.

Within this broad conceptual analysis of built environmental impacts, a second and more precise theoretical contribution is to provide a framework for analyzing risk tradeoffs within the context of improving the walking and cycling environment in communities. While methods for risk tradeoff analysis have been developed in a wide array of domains (Graham and Wiener 1995), none have considered built environmental policies targeting physical activity behavior versus air pollution and vehicular traffic hazardous exposures. A particularly novel feature of the proposed analysis within the chemical risk assessment field is the integration of determinants of behavior component as the first source of exposure.

The proposed risk tradeoff framework introduces important theoretical challenges due to the incorporation of different environmental, behavioral, and health metrics stemming from the different fields involved. Because data regarding the various aspects of the model are collected and explained for different purposes in each field, they do not necessarily match to resolve the issues targeted in the current analysis. Questions revolving on the applicability and methodology to bridge disparate metrics thus arise. The proposed approach to handle in a consistent and rational way these issues is to systematically and diligently track the uncertainty associated with applying data from a particular field in an alternative context. The dissertation will address questions on the sufficiency of this approach to reconcile different risk metrics and uncertainties.

A policy-oriented theoretical contribution of this work concerns decision making in the face of uncertainty regarding competing risks of the built environment. Several layers of uncertainty, from uncertainty in the overall health status to relative uncertainties of the competing risks, need to be considered in the policy decisions. In particular, do the differences in uncertainties associated with competing risks allow us to make a judgment? Should less uncertain risks matter more than more uncertain risks? These questions will be explored, along with questions about what policy framework should be used to make decisions (e.g. the precautionary principle, acceptable risk levels and benchmark dose levels), and which are supported by the analysis. Guidelines will be proposed to judge the adequacy of model results needed to support decision-making.

In addition, by proposing and testing a framework that moves away from the prevailing "target risk" decision making paradigm (Graham and Wiener 1995), to consider overall risks and benefits expected from policy change, this dissertation contributes theoretically to another facet of the risk-based decision-making field. The concluding chapter discusses the feasibility and worth of such approaches given available knowledge and understanding of competing risks.

Applied policy recommendations also offer theoretical contributions, in the form of the integration of multi-disciplinary policy perspectives. In particular, intervention procedures from the health behavior field are considered along with urban design solutions and with environmental science and policy standard-type approaches to develop comprehensive and targeted sets of policy proposals.

The final theoretical contribution concerns future work recommendations, identifying most important gaps and data and research needs for the improvement of health-promoting environment analysis. In particular, theoretical questions on the value of increased knowledge are raised. This includes discussions on both estimating the benefit of integrating more information versus the cost (effort) associated with obtaining it, and on deciding how to weigh these elements.

2 LITERATURE REVIEW

This literature review covers the fields of transportation, planning, design, public health and environmental health/risk assessment. It presents a broad overview of impacts of the built environment, beyond the scope of the quantitative assessment presented in the following Chapters. The chapter begins with an overview of existing frameworks used for the analysis of the built environment, followed by a review of the relevant themes to characterize impacts of community design: environmental determinants of active lifestyle and transportation choices; exposure to urban air pollutants, traffic hazards and other potential hazards in an urban environment given daily activities; health impacts of lifestyle choices, hazardous exposures, and potential mental health effects of the built environment. The intent of the review is to first present the current state of knowledge on the different theoretical and empirical links found between pedestrian-oriented built environments and final health outcomes presented in the conceptual model in Figure 1.1. It is designed to demonstrate both the need and the feasibility of conducting this research. It addresses the challenges presented by this effort, in particular that of reconciling measures and associations developed at different spatial-temporal scales and under different perspectives. It also serves to inform the risk assessment, by providing the basis for quantifying the different relationships under study, and the level of uncertainty associated with them. In some cases, the relationship between different endpoints is already well established and factors can be directly derived from the literature. In other cases, factors are calculated by synthesizing the literature to provide the best estimate given the current knowledge. The goal is to then integrate these constructs and empirical findings to propose a unified assessment of health and quality of life impacts of improving the pedestrian environment in a community. The most applicable segments of this review for informing the quantitative risk assessment are sections 2.2.2 and 2.3.1; the rest of the chapter is relevant for the broader conceptual framework this analysis fits it.

2.1 Conceptual Frameworks

This section reviews conceptual frameworks that have been or can be used to investigate the built environment and health and quality of life. First are described disciplines that specifically integrate characterizations of built environment and human health relationships, and then approaches such as health impact assessments and risk assessments that have a broader or different application setting and can be used in particular for built environment and human health analyses.

Built environment and quality of life interactions have generated research from a variety of disciplines, each with different perspectives and choice of indicators. Some have focused primarily on social-psychological issues of livability, happiness, or satisfaction, others have considered physical health outcomes specifically, and some have attempted comprehensive assessments. Human ecology is perhaps the broadest approach, with the interaction of physical, economic and social indicators of the environment used to explain livability, quality of life and sustainability (Lawrence 2003). Lawrence (2003) contends however that rarely are both natural and social sciences incorporated in the same human ecology analytical framework. The urban health framework, perhaps a subset of human ecology, is described by Vlahov and Galea (2002) as the study of the health impact of the social environment, the physical environment, and health and social services, along the dimensions of urbanization (growth of cities) and urbanicity (impact of living in urban areas at a given time). The ecological model used in public health also uses a multilevel framework, integrating perspectives of intrapersonal, social and cultural, and physical environment levels of influence (Stokols 1992; Sallis and Owen 1997), it is however usually applied to specific health outcomes such as smoking of physical activity behavior. An example of a more narrowly focused area is residential satisfaction research, where environmental quality is measured by individuals' appraisal, perception, evaluation and coping behavior in their residential environment (van Kamp et al. 2003). Another example is the city planning field which associates physical form to criteria associated with needs such as livability, character, connection, mobility, personal freedom and diversity (van Kamp et al. 2003).

These different disciplines invoke more or less explicitly theoretical frameworks to relate place effects to health or livability. The public health ecological framework for example draws from health behavior theories such as the health belief and precede-proceed models to explain behavioral pathways (Glanz et al. 1990). In addition, in a seminal article on the social-ecologic framework, Stokols (1992) called for the development of interdisciplinary models within that framework to explain specific mechanisms such as geographic, architectural, technological and sociocultural factors affect health. Theories of environmental psychology such as behavior setting or environmental load (Bell et al. 2001) are applied in residential satisfaction research or social geographic research on the urban environmental quality and human wellbeing (Pacione 2003). The human ecology and urban health frameworks borrow theories from the diverse disciplines they incorporate in their studies. The city planning field on the other hand is described by van Kamp et al. (2003) as having a set of visions rather than theories.

However, whether theoretical constructs are available to explain the phenomena or not, in its application, explicit mechanistic interpretations of relationships are at times bypassed. Further, van Kamp et al. (2003) contend that the dynamic process of person-environment relationships has had little application or theoretical development, despite general acceptance that individual components do interplay, affecting the total system. Human ecology assessments of built environments may for example typically restrict the analysis to correlating indicators of the physical or social environment to indicators of human health and wellbeing outcomes (Smith et al. 1997; Hancock 2002; Pacione 2003), with no further modeling of mechanistic pathways. While the identification of relevant indicators is an essential step, insufficient use of theory may lead to contrasting results and diminish the effectiveness of policy applications (Mitchell et al. 2000; Bauman et al. 2002). Researchers have called for greater theorizing and testing of hypotheses on local social and physical environment influences on health in applied place effect research (Macintyre et al. 2002). Perhaps an influencing factor in the inadequate conceptualization of behavioral and health pathways in comprehensive empirical research is the lack of a unified or coherent theoretical model of people-environment relations, also solicited by authors (Lercher 2003; van Kamp et al. 2003).

In recent years there has been an upsurge of calls for transdisciplinary approaches to model built environment impacts on health (Frumkin 2001; King et al. 2002; Corburn 2004). Several authors have proposed transdisciplinary conceptual models synthesizing mechanisms of action between people's environment and their health, integrating specifically perspectives from different fields. For example, in their model of social determinants of health and environmental promotion, Northridge et al. (2003) emphasize the built environment, placed as a intermediate level of influence on health and well-being. They describe interactive and dynamic relationships between domains of fundamental, intermediate, and proximate causes of health and well-being, identifying the relevant research in the planning and health fields associated with them. While Diez Roux's paper is focused on cardiovascular disease, it uses a similar multidisciplinary and comprehensive approach to explaining health status. The author identifies factors of the social and physical environments, and reviews the literature from different fields explaining links with behaviors and stress and psychosocial effects, leading to the biological factors that result in the disease.

However, transdisciplinary efforts to describe mechanisms of action in explaining the built environment impact on health and well-being have mostly remained conceptual. Researchers in this area of study have raised important issues on the difficulty of applying such conceptual models, and they have generally not suggested computational approaches to test or estimate effects of built environment changes. Analytical frameworks that could be applied for that purpose are reviewed next.

Frameworks that are more specifically geared towards analyzing effects of policies in a community include health impact assessment (HIA), community impact assessment (CIA), and risk assessment (RA). These frameworks offer a platform to develop computational models evaluating effects of policy changes.

The relatively new concept of health impact assessment strives to consider comprehensively the determinants of health to judge proposed policies or programs. The Merseyside Guidelines of Health Impact Assessment (Scott-Samuel et al. 2001) group such determinants into biological factors, personal/family circumstances and lifestyle, social environment, physical environment, public services, and public policy. Although health impact assessments (HIA) are generally not rigorous scientific endeavors, typically do not consider the interaction of competing risks, and are often applied without a clear theoretical framework (Krieger et al. 2003), they at least attempt to decompose the overall impacts of policies, programs, or projects. HIAs are at the core of the European branch of the World Health Organization's Healthy Cities initiative, and the study of unintended consequences of community planning at the forefront of its concerns to be addressed by the assessments (Duhl and Sanchez 1999). The HIA framework however is geared towards stakeholder involvement in the decision making processes rather than scientific analytical processes. It does not provide a theoretical base for linking various elements of policies and plans to health endpoints, and it has not yet produced a rigorous analysis of competing risks and tradeoffs resulting from community plans.

Similarly to the HIA but restricted to transportation projects, Community Impact Assessments (Federal Highway Administration 1996) in the US emphasize public involvement in the decision making process. Although enhanced quality of life is one of the intended benefits of the approach, it does not require a comprehensive and rigorous health assessment and focuses on concerns raised by the community. While the guidelines specify the need to consider direct, indirect, and cumulative impacts of the proposed project, analysts are typically planners and transportation engineers and the investigative process does not necessarily involve multidisciplinary teams, thus limiting the scope and depth of the assessment.

The risk analysis field could also theoretically provide an adequate framework for the analysis of competing health risks in a population. The advantage of the risk assessment framework is that it offers a scientifically rigorous approach to estimating health impacts of hazardous exposures, allowing for multiple pathways and multiple contaminants. In addition, although it does not usually consider social determinants of health, there is nothing in theoretical underpinnings to prevent such extension, and it at least permits stratification by socio-demographic variables in the analysis. However, risk analyses have been criticized for typically ignoring competing risks or comparisons of health impacts in risk (Ponce et al. 2001; Murray et al. 2003). Nevertheless, methods integrating health metrics such as quality adjusted life years (QALY) or disability adjusted life years (DALY) can be used to such effect (Ponce et al. 2001). The health metrics used in risk assessments can also facilitate the inclusion of behavioral health outcomes, such as those resulting from physical activity behavior, into the comprehensive assessment.

The risk analysis framework however, usually is designed to relate exposure to health outcomes, but not to assess the behavior that leads to the exposure or the health effect. A risk assessment begins with the identification of hazardous contaminants and the estimation of exposure to such contaminants, and does not include any concept of risk emanating from the determinants of behavior that lead to the exposure. The behavior however may be accounted for, although air pollution risks assessments have in fact typically not done so in great detail. Most often, measures of ambient concentrations in a broad geographic area (e.g. a city) averaged over a period of time (e.g. a year) have been used to estimate the exposure of the residential population in the area (ref). Yet, methods to assess the spatial and temporal variability of individuals' exposure throughout their daily patterns of activity have been developed (Johnson 2002), and may be more appropriate in assessing competing risks and benefits associated with designs and lifestyles promoting active living. Provided data are available, such information can be integrated in risk assessment framework.

In summary, frameworks that have been or can be applied to the study of the built environment on health are unsatisfactory, as different disciplines have generated models describing their part of the picture, yet no coherent comprehensive model exists to evaluate quantitatively the person-environment system. Indeed, while some models aspire to be comprehensive, they have not been applied in a rigorous analysis setting. Other models are guided by sound and coherent theory, but either focus on one part of the overall picture, or have not been translated into computational models. Yet all these approaches show promise in that together they can shape a useful computational model. The assessment methods reviewed (HIA, CIA, RA) all provide a possible platform for bringing together the knowledge and understanding from the relevant fields. Given the analytical rigor provided by the risk assessment framework, and its flexibility allowing the integration of both behavioral components and health metrics that enable comparative risk analysis, it is the approach chosen for this dissertation.

2.2 Effects of the built environment on behavior

The built environment is thought to influence where and how we travel, but also our levels of physical activity, crime rates, nutrition, social interaction, and perhaps more. The design fields address these issues from a theoretical perspective – contemplating how individuals experience and react emotionally to the environment they are surrounded by. This literature review begins with an overview of design themes to serve as a general theoretical backdrop neither usually explicit nor considered in the more empirical research presented later on behavior changes conducted in different disciplines.

2.2.1 *Design fields*

Environmental psychologists conceptualize how the physical environment is a source of sensory information, how we react to the amount of control we feel we have in different environments, how some places trigger "programmed" behavior, etc. Urban designers and architects describe settlement form and explain the connection with human values. They have normative theories for building good cities or good neighborhoods. They relate the physical environment to psychological and emotional reactions such as feelings of anxiety, sense of security, stability and continuity, awe and pride, alienation, wonder and delight (Lynch 1996)**.**

As Hillier (1996) writes: "A design is not simply a picture of a building, but a picture of a potential object and of a potential social object – that is an object that is to be experienced, understood and used by people". In other words the notion of design includes how people relate and behave in relation to it. Architects, designers and environmental psychologists explain how different designs impact behavior because:

- They *afford* different functions for their users
- They provide different *meanings* to the human mind.
- They offer different levels of *imageability* and *legibility*
- Their *aesthetic* values contribute to different cognitive and emotional human experience.
- They provide different means of *natural surveillance* ("eyes on the street")
- They give different senses of *control* and *territoriality*

Affordance refers to the functional values perceived given physical characteristics of the environment. Walking, socializing, or driving occasion different perceived environmental demands (Gehl 1987). The concept could be compared to "cues to action" in health behavior theories. A wide road surrounded by a strip mall development, as pictured in Figure 2.1, would afford vehicular traffic, while human-level interesting scenery such as complex, detailed and irregular features are inviting to pedestrians and afford walking behaviors, as well as conversation with neighbors and friends in the streets (figure 2).

Likewise, people react to the *meaning* the environments have for them. According to Rapoport (1982), built forms are expressions of the way our minds organize and schematize the world to impose meaning onto it, and thus project a representation of the self and of group identity. An auto-oriented scenery may thus reflect an image of us as drivers rather than pedestrians, as can be contrasted in Figures 2.1 and 2.2.

Kevin Lynch (1960) writes about the importance of the *imageability* and the *legibility* of our physical environment: the identity, structure and meaning of an environment help us identify a useful structured image of the environment. This impacts our behaviors by facilitating way-finding, giving us a sense of social roles, providing emotional security, and a level of depth and intensity of human experience within the environment. For instance, way finding takes a different significance whether one is driving or walking: taking the wrong direction as a pedestrian may have costlier effects in terms of time and effort than while driving, and may also provide a feeling of anxiety of walking in unknown and possibly unsafe territories. Therefore human-scale legibility is a key component of pedestrian oriented environments. Similarly, spaces in cities can create different images through the sense of distance they project. Moderate size buildings, narrow streets and building details provide a sense of a warm, intimate and personal space, while wide streets and tall buildings with no detail are cold and impersonal (Gehl 1987). The perceived distances that result from such spaces matter in pedestrian transportation choices – a straight dull road might give a sense of unacceptable length while the same distance in a sequence of small and contrasted spaces will seem shorter (Gehl 1987). Speed is also related to scale – small dimensions and detail invites slow speeds, and according to Gehl, slow traffic means lively cities because events happen with people looking at each other and interacting.

Using similar concepts, Skjaeveland and Gärling (2002) explain how *aesthetics* of space – both in content (symbolic meaning) and structure (formal aesthetics) - impact the human experience and thus affect evaluations of persons and behaviors within the environments. For instance a structured setting such as fine-grained gridded street patterns might facilitate the cognitive organization of a neighborhood and make walking seem feasible by facilitating way-finding and reducing the perception of distance.

Natural surveillance, control and *territoriality* are concepts that are used in crime prevention through environmental design (Crowe 2000; Mair and Mair 2003) as well as to enhance the pedestrian experience. Territorial enforcement through building design, maintenance and landscaping that clearly delineate public and private places, provide spaces that residents control, maintain and care for, projecting a positive image of residents, thus offering a pleasing environment at the human-scale that calls to be respected. Natural surveillance is reached by the concept of "eyes on the street": the visibility of people's activity is facilitated by building orientation, windows, front porches, continuous sidewalks, lighting, and locating housing near areas of safe activity through mixed land uses (Crowe 2000). The eyes on the street convey a sense of security essential for an agreeable pedestrian experience. In a related issue, environments that encourage pedestrian activity re-enforce themselves as seeing other people in the streets conveys a feeling of safety and pleasantness (Gehl, 1987) leading to more walking behavior.

The design fields are mostly based on theories, and empirical support for these concepts have been mostly limited to laboratory experiments, some specific client-based studies not meant to establish scientific principles on environment and behavior (Gifford 1997), and a few well-known natural experiments such as the Pruitt-Igoe housing project in St Louis Missouri (Newman 1996). Data attempting to show a relationship between the built environment and travel or physical activity behavior is found respectively in the transportation and public health literature.

Figure 2-1 An auto-oriented environment

Figure 2-2 A pedestrian-oriented environment

2.2.2 *Transportation Research*

In the transportation literature on travel behavior, the theoretical reference is the micro-economic theory of utility, embedded in the theory of travel as a derived demand. Transportation analysts do not consider the emotional and experiential factors that intervene when making travel choices, but rather assume travel choices are made to minimize the different types of costs involved in travel alternatives, given preferences, presumed to depend solely on socio-demographic characteristics, and given available resources. However, Boarnet and Crane (2001a) and others have criticized travel behavior research for commonly lacking a clear behavioral theoretical framework. They contend that much of the research in the field has essentially been ad hoc with no explicit reference to an underlying theory. The estimation methodologies employed by researchers in the field include aggregate statistical analysis, disaggregate multivariate regression-type analyses, and individual or household-based discrete choice analysis using logit, logistic or probit regression.

Although the type of analysis used could be the guiding thread for this literature review on empirical travel behavior research, instead this section is organized according to the type of data that enters travel models, because it is a more useful approach for the purpose of this dissertation. Three categories of data are generally included in empirical travel research: a) socio-demographic, b) land use and transportation network, c) microscale design data. In an explicit travel choice theory framework as described by Boarnet and Crane (2001a) for example, the data would generally be categorized as the costs of each travel alternative and the demographic characteristics of the trip maker. Cervero (2002) would add built environment variables (land use diversity, density and urban design) as a separate direct influence on mode choice, while Boarnet and Crane (2001) would consider them as part of the cost variables.

2.2.2.1 *Theoretical considerations*

The built environment indeed affects the costs of alternative modes of transportation through its effect on time and distance of travel. Connected transportation network and mixed and dense land uses reduce in principle the costs for all modes of travel by shortening distances between origins and destinations. While it may affect all modes in a same manner in terms of reduction in time required to travel, the resulting change may make some modes more viable. Implementing transit for example becomes possible when the transit lines are guaranteed to reach a sufficient amount of people to be efficient. Walking and cycling are feasible options when reaching destinations can be done in a reasonable amount of time and effort. As options become viable, individuals' preferences for a mode under different circumstances are realized. If each individual has a different utility function based on costs and preferences for each travel mode, then a reduction in costs might change the optimal solution for that person's choice and they may change travel habits.

Cervero (2002) contends on the other hand that for travel mode options, land use and other built environment variables may have a *direct* effect on choice rather than through its impact on travel time. Although he doesn't generalize this particular reasoning in his article on a normative framework for travel behavior research, Cervero proposes two examples as justifications: workers may be liberated from the need for driving their car to work if their midday activities can be done at the workplace thanks to mixed uses at the employment location; transit use may be stimulated by an attractive access to transit stops. It could be argued that Cervero's first example doesn't show any *direct* influence of the built environment on travel mode in the sense that the land use patterns still affect the costs of travel for other trips during the day. It does show nevertheless how built environment factors matter at different destinations, and not just at the place of residence. The second example however, may allude to a theoretical reasoning of how the emotional experience influences mode choice. It is conceivable that individuals want to fulfill goals other than cost minimization while traveling – such as feelings of freedom, or well-being, of happiness, moral obligation, or inner harmony in interaction with the built and natural environment (Gärling 1998). The principles of environmental psychology and architecture reviewed in the previous section may be more useful than economic theory in explaining how the perception of one's environment and how it is processed might affect mode choice. This conceptualization may indeed support a *direct* and independent effect of built environment factors on mode choice, and be interpreted as such in empirical research testing these factors. Another way in which land use variables have at times entered travel models is through their theoretical influence on residential location. Boarnet and Crane (2001) and Boarnet and Sarmiento (1998) have for example used land use variables as instruments in mode choice models, as a means to test the hypothesis of residential choice affecting travel behavior. However, the issue of self-selection remains largely unresolved as this method has given inconsistent results depending on the scale and location of the analysis (Boarnet and Crane 2001). Other sociologically and psychologically meaningful behavioral concepts might help explain other parts of the transportation decision making process such as habit formation and social support/pressure. Such constructs however are not generally considered in travel behavior research. Exceptions are the works by Kitamura et al. (1997) and Bagley and Mokhtarian (2002) who have tested attitudinal factors in their travel behavior models, or experimental work such as Fugii and Kitamura's (2003) analysis of changes in habits and attitude following a temporary structural change in transit service.

Beyond different conceptions on how data should be categorized in levels of influence of travel behavior, the grouping chosen here reflects practical reasons, since our purpose is to study the effect on health of changes in land use and the microscale environment. Following a review of how socio-demographic, land use and transportation network, microscale design data have been shown to affect behavior, this section on travel behavior ends with a description of travel research that has tested attitudinal factors and residential location preferences.

2.2.2.2 *Socio demographics*

Socio demographic characteristics are often shown to dominate the explanatory power of travel models (Cervero and Kockelman 1997; Kitamura et al. 1997). In particular, in their synthesis of built environment impacts on travel behavior, Ewing and Cervero (2001) identified household socio economic status as the most determining factor in explaining trip frequencies, with land use variables having little or no consistent pattern of influence.

Travel behavior varies considerably across socio demographic groups, as analyses of the National Household Travel Survey shows (Pucher and Renne 2003). Income and vehicle ownership are perhaps the most consistent socio economic characteristics in explaining travel. For instance, households with less than $20,000 income a year take on average 3.2 trips per day and travel 17.9 miles per day, while over $100,000 yearly income households take 4.8 trips a day and travel 31.8 miles. In addition, auto-ownership, possibly the most influential factor in mode choice, is primarily determined by income. While more than a quarter of lower income households (less than $20,000 a year) do not own a car, only 1.5% of households earning over $100,000 a year have no cars and 38.5 percent of these have three or more cars. Auto use for each household auto ownership category jumps from close to a third of trips for those with no cars, to 82% when the household owns one car, to 90% of trips for households with three or more cars. In the same categories for vehicle ownership, walking rates drop from 41% to 12.5% to 6.3%, and transit use from 19% to 2.7% to 0.5%. Cycling represents 2.4 % of trips in 0 car households, is reduced close to three-fold when one car is present, then stabilizes. Race variation also shows to be associated with mode share patterns, probably due to income differences. Age represents an important factor in mobility levels: children and the elderly tend to take fewer trips and travel less far than the rest of the population. All age groups however rely mostly on the car for travel, with children having a lesser reliance with 71% of vehicle mode share compared to the 86% general population auto share for all trips. With a few exceptions, only slight differences exist between genders on mode choice patterns in descriptive analyses, although some regression models have shown a significant gender effect in different studies, but with inconsistent results and depending on the specific outcome considered. Education level and household composition variables also enter travel behavior models as significant at times, but not consistently.

2.2.2.3 *Land use and transportation network variables*

The measures of density and mix use take various forms in travel behavior studies. Densities are typically measured by population or employment density. Gross densities use the total land area, while net densities exclude areas devoted to parking lots, roads, public open space, or other un-developed land. Although often net densities are used because they refer to land available to development, gross densities may be more useful in measuring the quality of a pedestrian environment (Krizek 2003a). Some authors such as Cervero and Kockelman (1997) have also used accessibility to jobs as a measure of density. They used a gravity model form measuring the relative proximity to activities and compactness, to derive their accessibility index[8]. While densities can be proxies for other variables that might affect travel such as income and transit availability, most travel models control for these other measures in their models as well.

Measures of land use mix often referred to as the "diversity" dimension, have taken a variety of forms in travel behavior research. Krizek (2003a) would argue that land use mix is important to travel behavior, especially walking, to the extent that it offers a complementary functional mix of uses close to each other. In its simplest form, a binary variable is used and the

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[8] Specifically, accessibility index=$\{\sum_j (\text{jobs})_j \exp[\lambda t_{ij}]\}$, where i = origin; j = destination, t_{ij} travel time between i and j, and λ = empirically derived impedance coefficient (Cervero and Kockelman 1997)

mixed use classification is attributed to neighborhoods from visual inspection of self-reported presence of nonresidential activities within a certain distance of a household. Cervero and Kockelman tested a series of diversity measures in their San Francisco Bay area study (1997), ranging from an entropy index measuring the balance of mix within an area (hectare grid cell) within a neighborhood (census tract), to a dissimilarity index quantifying a more fine-grained inter-mixing of dissimilar uses among abutting grid cells, to measures of intensities of uses as well as vertical mixing.

In a comprehensive review of the literature on the effect of travel behavior on the built environment, Ewing and Cervero (2001) came to the conclusion that regional accessibility, a measure of access within the region (for employment, shopping, recreation) from the home, is the most important factor in determining vehicle miles traveled.

There is a general consensus that when neighborhood land uses are mixed and dense – and both ends of the trip matter – trips are shorter, and modes alternative to the private vehicle are more likely (Ewing and Cervero 2001). In fact, Cervero (2002) in his sets of fully specified discrete choice models in analyzing Montgomery County, Maryland, data showed that above and beyond price and time factors, land use variables were significant determinants of mode choice. Specifically, his analysis[9] showed that increased density and mixed land uses at both ends of the trip reduced solo-commuting and increased transit use, given prices and time for travel for each mode.

In terms of non-motorized transportation, studies have generally found that dense, accessible, and mixed land uses generate more walking and cycling mode utilitarian trips (Cambridge Systematics 1994; Frank and Pivo 1994; Cervero 1996; Cervero and Duncan 2003). Regional densities on the other hand were found by Greenwald and Boarnet (Greenwald and Boarnet 2001) to have no impact on walking behavior, and only local densities were shown to positively impact pedestrian travel. According to Ewing and Cervero (2001), the choice to walk is

[9] Cervero's analysis did not consider non-motorized modes,

primarily a result of land use mix, and secondarily of densities, and the order is reversed for transit use.

Although Ewing and Cervero conclude that trip frequency is a matter of household sociodemographic characteristics rather than land use factors, some research points to higher vehicle trip generation associated with mixed use in the home tract (Crane and Crepeau 1998; Frank et al. 2000).

In addition to land uses, the transportation network that connects different destinations is also thought to be an important factor in travel behavior. For example the 2001 EPA report (U.S. Environmental Protection Agency 2001b) on land use, transportation and environmental quality explains how typical modern communities' hierarchical street networks of cul-de-sacs leading to collector streets, leading to major arterials, make biking and walking difficult because of the circuitous routes and the high-traffic volumes of the wide arterial streets. Pedestrian-friendly communities in contrast include well-connected street networks, which shorten distances and remove physical barriers to walking and biking (such as busy arterials, walls, and other obstacles). However, research that has tested transportation network variables has not always found consistent or significant results (Ewing and Cervero 2001). In one study, two different measures of grid patterns (proportion of four-way intersections and proportion of blocks that are quadrilateral) pointed to opposite impacts on total vehicle miles traveled (Cervero and Kockelman 1997). In another, walking and cycling was shown to be more prevalent in neighborhoods with sidewalks, yet the sidewalk presence was not correlated with the share of non-motorized modes (Kitamura et al. 1997). This result could mean that even though more walking trips are generated, they do not substitute other trips. Frank et al. (2000) found in the Puget Sound that while street network density was negatively and significantly associated with vehicle miles traveled (VMT), it was also positively and significantly associated with vehicle trip generation. In this case, even though more vehicle trips are produced, the shortened distances resulting from the street network leads to an overall VMT reduction. In contrast, Crane and

Crepeau (1998) found that a dense street network was associated with fewer vehicle trips generated at the household level, using a fully specified ordered logit regression model including trip distance and speed variables to explain non-work travel. The association did not remain when looking at person level trips however, and another grid pattern network variable was not significant in either model. Another half dozen studies have found no significant relationships between travel outcomes and transportation network indicators (Ewing and Cervero 2001).

Such discrepancies could be explained by the contention of some researchers that compact and mixed developments might theoretically increase overall vehicle miles traveled by reducing distances and thus improving accessibility for vehicles as well as for non-motorized modes (Crane 2000; Boarnet and Crane 2001b). The rationale is that increased accessibility means that more can be accomplished in a single shorter trip, and the effective reduction in the cost of each additional trip results in higher trip generation. Nevertheless, part of the pedestrian environment equation is missing at this stage; the urban design element discussed next can further feed the analysis.

2.2.2.4 *Microscale design*

Although density and mix often have the most explanatory power in travel models, they are not exhaustive measures of neighborhood accessibility. Hess et al. (1999) for instance found in their study of pedestrian behavior that sites with comparable density and mix but different design characteristics resulted in different travel behavior. The importance of urban design could be explained by experiential factors with mode choice as discussed earlier, or from an econometric perspective, could be explained by a change in duration of travel. The same way grid systems and compact mixed use developments may decrease the cost of travel by shortening distances, design treatments such as traffic calming measures may increase travel duration for vehicles, but not for cyclists and pedestrians.

There have been different approaches to estimating microscale design impacts on travel. Some studies have used a general qualification of neighborhood type, such as "urban" versus "suburban" or "pedestrian-oriented" and "neo-traditional" versus "auto-oriented" or "sprawl", to compare travel patterns. Other studies have looked at the influence of specific microscale factors, and a few have investigated travelers' perceptions about their neighborhood environment.

A rationale for the neighborhood type analysis approach is to counter the problems of high colinearity between indicators of the built environment (density, mixed-use and pedestrian amenities), and lack of rich and objective data for small scale land-use and urban design indicators (Cervero and Radisch 1996; Cervero and Kockelman 1997).

For example, in Cervero and Radisch's San Francisco Bay area study, two neighborhoods were chosen because of similar aggregate socio-economic and transit accessibility characteristics, but very different urban designs. Detailed contrasted descriptions of the level of pedestrian friendliness in the *neo-traditional* neighborhood and the *conventional* suburban community are provided in the analysis[10], but only a simple dummy variable representing the neighborhood is used in the travel behavior regression analysis to indicate the difference in built environment. The household survey analysis showed that residents of the *neo-traditional* neighborhood were less dependent on their car, especially for non-work trips, and non-work trips less than one mile. Furthermore, because of the statistically different rates of walk and auto trips in the two neighborhoods, but similar total trip rates, the authors assert that walking substitutes rather than supplements auto trips in the neo-traditional neighborhood. Interestingly however, the neighborhood dummy variable was not significant for the work trip binomial logit model. The authors suggest that the neighborhood quality did have an influence on the BART station access mode to go to work, but it was not modeled. This study clearly shows the positive impact of

[10] The differing indicators of the neighborhood types reported are housing density, percent housing that is single-family detached, (in the BART vicinity:) blocks per square mile, intersections per square mile, T-intersections, four-way intersections, cul-de-sacs, (in the retail district:) average block length, percent of blocks with curb cuts. The data was obtained from census data and field surveys.

pedestrian-friendly neighborhoods in reducing car-use, although the specific attributes that matter are not known.

Hess et al. (1999) categorized twelve neighborhoods of 0.8km radius around commercial centers in the Seattle area as either "*urban*" and supportive of pedestrians, or "*suburban*" and not supportive of pedestrian behavior, depending on their mean block size, sidewalk continuity, and location of car parking (on-street or not, and large or small lots). They found on average three times higher pedestrian volume in the *urban* sites, controlling for density, income and land use mix. They explain the difference by the lack of efficient pedestrian route structure in suburban neighborhoods, noting that land use distribution and intensity could otherwise be as conducive to walking in *suburban* sites. Walking distance from homes to shops was on average 66% higher than airline distance in *suburban* sites, verses 27% higher in urban sites. This study shows the potential for retrofitting suburban neighborhoods to encourage walking, as the authors demonstrate that the supportive land use structures exist, but designs need to be reconsidered for supportive pedestrian environments in *suburban* sites. No travel demand modeling framework is used however in this study.

Srinivasan and Ferreira (2002) investigated how trip chaining behavior differed by neighborhood type, classified using factor analysis on measures of densities and transportation network characteristics. Comparisons of residential location type showed that in urban neighborhoods households tend to integrate their non-work activities within their work tours more than more suburban locations. This is interesting because it goes against the study results that have shown that mixed use and accessible environments generate more trips (Crane and Crepeau 1998; Krizek 2003b). They also showed higher proportions of all non-auto tours in urban areas than suburban areas. These results point in the direction of urban neighborhoods generating fewer vehicle trips altogether.

Handy's 1996 study of pedestrian travel in Austin neighborhoods also used the categorized approach, in addition to some perception measures. She distinguishes between *traditional, early-modern*, and *late-modern* building periods in six different neighborhoods of otherwise similar income levels. Some differences included: low transit service, wide curvilinear street layouts, auto-oriented commercial center, dominance of the garage in the *late-modern* streetscape; multiple bus routes, front porches, design variations, grid patterns, pedestrian-oriented commercial center and the integration of single and multi-family housing in the *traditional* neighborhoods; the *early-modern* neighborhoods tended to be in between the two for most of these measures. Strolling frequency was found to be higher in the *traditional* neighborhood, where people walked for pleasure or to go to the store, than in the *late-modern*, where exercise and health was the dominant reason for walking. Walking to the store varied from less than once a month in the *late-modern* neighborhoods to two to six times a month in the *traditional* neighborhood. Handy used in addition an uncommon approach to investigating travel behavior: investigating residents' perceptions of the environment. She found that feeling safe walking at night and seeing neighbors in the street were the variables most highly correlated with walking behavior. The authors also noted that the walk trips appeared to substitute other trips, but that there was a possibility of self-selection among residents of the traditional neighborhood in their desire to be able to walk in their neighborhood.

In a follow up study, Handy and Clifton (2001) modeled the frequency of walking trips to the store in these six neighborhoods as a function of residents' perception of the local shopping and walking environment, controlling for socio-demographics, distance to the store, and strolling frequency. Residents who rated positively the *walking incentives* (within walking distance and hard to park) and *walking comfort* (comfort, safety, busy streets to walk along and cross) were more likely to walk to the store. A dummy variable for one of the traditional neighborhoods was also significant and positively associated with walking frequency; so was the strolling frequency. More important however was the distance to the stores: each additional mile reduced the walking frequency by 2 to 4 trips a month. This study shows that although land use measures (distance to shopping) may still be more important, design, as measured by people's perception of their environment, is also an independent significant determinant of walking behavior.

A classic example of a study on the impact of pedestrian environment features on travel behavior is Portland's Land Use-Transportation-Air Quality (LUTRAQ) study conducted by Parson, Brinckerhoff, Quade and Douglas (1993), in which 400 travel analysis zones (TAZ) were subjectively rated according to a "Pedestrian Environmental Factor" (PEF). The four parameters of the PEF, each rated on a three-point scale, were: (1) ease of street crossings; (2) sidewalk continuity; (3) local street characteristics (grid versus cul-de-sac); (4) topography. The PEF proved increased the model's explanatory power in explaining auto ownership, mode choice, and destination choice. For example, a unit increase in the composite PEF factor (simple sum of the ratings of the four parameters) was shown to decrease on average 2.5 percent of household VMTs once other land use and demographic variables were accounted for.

A similar approach to gauging the pedestrian-environment effect on travel behavior is Holtzclaw et al.'s (2002) paper on "location efficiency", investigating how socio-economic and neighborhood characteristics determine auto ownership and use. The authors develop a measure of "pedestrian/bicycle friendliness (PED)" in the TAZ, based on street pattern, the mean year the housing was built and some features of bicycle and pedestrian amenities such as bike lanes and traffic calming. The regression models developed for data in Chicago, Los Angeles and San Francisco showed a significant negative contribution (but not a very high effect) of the PED variables to explain VMT per vehicle, once variables of residential density household size and per capita income were accounted for.

In addition to the elaborate measures of density and diversity used in the Cervero and Kockelman (1997) study mentioned earlier, the authors used detailed descriptors of microscale design to explain travel behavior. The list includes street characteristics (e.g. grain and pattern), pedestrian and cycling provisions (e.g. sidewalks, trees, lights, crossings, signalized intersections, block length), and site design (e.g. location and proportion of off-street parking, drive-ins). Both the contribution of individual variables and composite measures derived by factor analysis were tested in travel demand models (controlling for sociodemographics and other density and diversity land use variables). The “walking quality” factor (including measures of sidewalk and street light provisions, block length, planted strips, lighting distances and flat terrain, with18% of total variation explained), was not significantly associated with household and personal VMT. Of the design variables, only the grid pattern indicator was significant in explaining VMT, interestingly with a positive association. However, the walking quality factor, an indicator of a grid pattern, and sidewalk width all favored a non-single occupant auto mode for different trip purposes, while an indicator of auto-oriented commercial center design[11] increased the likelihood of driving for non-work home based trips[12].The authors note that these micro-scale environmental factors are less influential on mode choice than land-use and demographic factors, although this could be partly explained by the comparatively lower variation amongst the variables.

Rodríguez and Joo (2004) looked a few specific features of the physical environment in Chapel Hill, NC to explain commute mode choice to the UNC campus, using a fully specified mode choice model, including the cost of all mode alternatives. They found that a greater slope in the terrain was a significant deterrent to non-motorized modes (controlling for travel time), and that sidewalks significantly increased the likelihood of walking to campus. Their results also suggest that time spent walking or cycling to campus is perceived as more costly than time spent traveling by motorized modes[13].

Kitamura et al. (1997) attempted to provide a complete picture of the effect of the built environment on modal splits, combining different approaches of analysis – neighborhood type, urban micro-environmental factors, and perceptions and attitudes. The authors surveyed residents

[11] “proportion of non-residential parcels with front- or side-lot on-site parking”.

[12] The authors provide useful elasticities between measures of the built environment and travel demand.

[13] It would be interesting to determine where the different perception of costs originates – perhaps different urban designs generate different cost perceptions, or perhaps the physical effort reduces the appeal of non-motorized modes for some people.

of five Bay Area neighborhoods, chosen for their contrasting levels of density, land use mixing and transit accessibility, and in which were also recorded attributes of the micro-scale environment through site surveys. Area descriptors included: macro-scale descriptors (density, mixed land-use); pedestrian/bicycle facilities; housing choices (home ownership, parking, backyards); accessibility indicators (proximity to transit and land uses); perceptions on neighborhood quality (reason to move, walking/biking environment quality, level of transit service, parking and congestion difficulties). Models explaining different mobility measures were tested. The authors conclude that there is a significant impact of neighborhood characteristics in explaining travel behavior. However, most of the area descriptors added low explanatory power to the models, and had low or insignificant t-tests. In most models the area dummies were the most significant neighborhood factors. The perceptions of the quality of the pedestrian and bicycle environment are only significant in explaining the fraction of auto trips. In the case of bike perception, it leads to a surprising positive association of high quality with fraction of auto trips, possibly due to high biking facility safety standards in suburban divisions where auto use is high. The presence of sidewalks and bike paths on the other hand explains a higher number of non-motorized trips.

2.2.2.5 *Attitudes*

In addition to the microscale design variables described above, Kitamura et al. (1997) also investigated the effect on travel behavior of residents' attitudes about aspects of urban life. 39 questions were asked, and their answers reduced to eight factors which explained 43.3% of the variation: pro–environment, pro-transit/ridesharing, suburbanite (e.g. like low density), automotive mobility (relying on autos), time pressure, urban villager (e.g. value walking distance to shops), TCM (belief in transportation measures to solve problems), workaholic. Attitudes indeed vary across neighborhoods in the direction consistent with the patterns associated with them: for example pedestrian friendly neighborhood residents scored highly on the "pro-environment” and “urban villager” factors, and suburban neighborhoods scored lower. Suburbans scored highly on “suburbanite” and “automotive mobility” and urban pedestrian-oriented neighborhood residents did not. The regression analysis further supported this coherence: for example pro-transit attitudes are positively and significantly associated with the number of transit trips and non-motorized trips, the pro-environment factor is positively and significantly associated with the number of non-motorized trips, the auto-motive mobility is positively and significantly associated with the fraction and the number of auto trips and negatively and significantly associated with non-motorized and transit trips. In addition, the attitude factors added to the explanatory power of all models. In fact, the authors show that the attitude factors account for more of the variation in the fraction of auto trips than neighborhood descriptors do, even though neighborhood descriptors also have their own association (they add significantly to the model in the presence of attitudinal factors) with the fraction of auto trips. The authors conclude from these findings that “attitudes are certainly more strongly, and perhaps more directly, associated with travel than are land use characteristics”. Their deduction is that land use policies may not change travel demand unless attitudes are changed as well.

Another study that has included attitudinal variables is Bagley and Mokhtarian’s (2002). As they discuss attitudes in relation to residential location, their work is described in the next section.

2.2.2.6 *Residential location*

Kitamura’s (1997) study may imply that people choose to live in neighborhoods that correspond to their travel preferences resulting from their attitudes about transportation, the environment, or other factors. Of course, the possibility remains that the inverse is true: that attitudes are formed by land use itself and the environment one lives in, so that changing land use will change travel behaviors by having an impact on attitudes. The choice of residential location in relation to travel behavior is important to understand in the context of implementing policies that improve the pedestrian environment. One attempt to elucidate the question of causality is Bagley and Mokhtarian's (2002) study using the same data set as Kitamura et al.'s, and a structural equation modeling approach to account for different possible causal directions. The method allows the simultaneous modeling of attitudes and lifestyles affecting both residential location and travel behavior, as well as the reverse. In addition to the attitudinal factors described above, 11 lifestyle variables were also grouped by factor analysis, using data about respondents' different types of activities and interests. Continuous and disaggregate measures of neighborhood traditionalness is preferred by the authors to the simplified dichotomous measure of neighborhood type, and leads to two factors grouped by principal component analysis: *traditional* and *suburban*. These factors are used as continuous variables, and represent the individual's score of their neighborhood environment. Results show that traditional residential location is explained by attitudes and lifestyles such as being a culture lover, an outdoor enthusiast, pro- transportation mode alternatives, pro-growth, pro-pricing strategies, time-satisfied, work-driven or pro-high density, while suburban living is associated with being an adventurer, a homebody, a nest-builder, a relaxer, pro-driving, pro-environment or pro-transit. The greatest effect found on travel demand is from attitudinal and lifestyle variables, but no or little effect of residential location is shown on travel demand[14], thus supporting the view of self-selection in travel behavior and built environment studies. However the authors note that the limitations of the study prevent the results from being considered definitive.

More recently, Schwanen and Mokhtarian (2005) tested the residential location choice factor by studying mode choice of dissonant urban and suburban dwellers. Using data on attitudes and travel behavior in the San Francisco Bay area, they studied the mode choice of urban dwellers with suburban attitudes and suburban dwellers with urban attitudes (i.e. dissonant cases). They suggested that if the neighborhood type still had an effect on mode choice after accounting

[14] Except surprising positive effect suburban neighborhood on transit miles, probably due to the particular condition of the BART rail system availability to suburban residents in this sample.

for the dissonance or other lifestyle and attitude factors, then it would mean that the physical structure of the neighborhood had an independent effect on travel. They found that indeed, suburbanites living in an urban neighborhood are more likely to commute by car than non dissonant residents, but not as much as much as true suburbanites. The reverse relationship however was much weaker (urbanites living in suburban neighborhoods driving less than true suburbanites), possibly because the physical constraints of the suburban environment prevail over travelers' preferences. Integrating travelers' attitudes about travel freedom and pro-environment policies in the multinomial logit models made the impact of dissonance disappear, showing the inter- relationship between attitudes and neighborhood type mismatches.

Several authors have attempted to control for residential location in explaining travel behavior by entering land use variables as instruments in travel models, to test whether these variables are correlated with the error term. The method has lead to inconsistent results. Greenwald and Boarnet (2000) claim the success of the instrumental variable routine in accounting for residential choice in their non-work walking trip models. Three of four individual land use variables were found to be valid instruments, and two of the former (block group population density and a PEF score adaptation of the LUTRAQ project PED score) remained a significantly positive influence on walking trips. Some studies have shown that the instrument is valid for some land use measures (e.g. retail and service employment density) and not others (e.g. population density or grid pattern), and varies according to the scale of analysis (block group verses zip code) (Boarnet and Sarmiento 1998, Boarnet and Crane 2001). In a case presented by Boarnet and Crane, the instrument variable routine actually changes the interpretation, reversing the direction in which the grid pattern is thought to influence vehicle trip generation (from more to less), and changing the significance of other land use variables (e.g. land use mix proxy becomes a significant negative influence on vehicle trip frequency). These authors conclude that these methods are promising, but that caution should be taken on interpreting them at this point.

In a different, quasi-experimental approach to residential location and travel behavior analysis, Krizek (2003b) studied the changes in travel behavior following a move to a different location in the Seattle area. Urban form descriptors of density, land use mix and street patterns within 150 meter grid cells are combined into a single neighborhood accessibility (NA) measure by factor analysis. A gravity model is used to determine the regional accessibility for each grid cell. Krizek's modeling approach uses neighborhood and regional accessibility variables before and after the move for both the home and the work locations (work variables averaged for multi-worker households), to explain vehicle miles traveled (vmt), person miles traveled (pmt), number of tours, and number of trips per tour (accounting for sociodemographics before and after the move). Results show that the most influential factor is the baseline travel behavior: the more a household traveled, the more they reduce their travel. Interestingly, urban form at the previous home location matters: the higher the baseline NA, the higher the decrease in miles traveled and number of trips per tour, and increase in number of tours. An increase in commute distance explains an increase in vmt, pmt, and decrease in the number of tours. Households who relocate to neighborhoods with higher NA reduce vmt and pmt, and number of trips per tour, but increase the number of tours. An increase in regional accessibility from the home also reduces vmt, pmt, and number of trips per tour. No statistically significant association was found for mode choice.

These results support in part the proposition of some authors that new urbanist designs may generate more vehicle trips, since households that move to neighborhoods with higher NA are shown to increase the number of tours while decreasing the number of trips per tour (in other words they are more likely to travel for single purpose trips rather than group trips together). However, contrary to the same authors' contention, total vmt is reduced in this example, presumably because the number of miles per trip is reduced in the higher NA neighborhood. It is also interesting to note that baseline and changed neighborhood accessibility have the same type of influence on the change in travel behavior. Could this possibly point to urban form factors shaping people's preferences?

In summary, we note that it is difficult to capture the different elements that intervene in the decision making process, but the built environment does seem to affect travel behavior. Different studies show inconsistent results on the question of vehicle trip generation and total VMT, while mode share results are generally similar. There are diverging indications on whether there is a trip substitution effect or not, but there is definitely more non-motorized transportation in walkable neighborhoods. The discrepancy in results may be due to the variety of designs present in the different study locations and lack of adequate systematic description of the built environment used in travel models. Identifying the appropriate scale of analysis also appears to matter, as some elements of design can explain travel at one level of resolution and not another (for e.g. Boarnet and Crane 2001), as would be theoretically expected given different scales of perception at different speeds (walking versus driving) (Gehl 1987). The problem is compounded by the difficulty of collecting data at the desired scale. Also, the issue of causal relationship between urban design and non-motorized travel is not yet resolved, as studies accounting for residential location have led to inconsistent results. However, such designs do seem to respond to a part of the US population's preferences, whether it requires that people move to these places[15], or whether people's behaviors adapt to their surroundings. Therefore creating such places and offering people the choice to live in such environments would be expected to change travel behavior in the overall population.

Despite these uncertainties, Cervero and Ewing (2001) provide elasticities as synthetic measures of the effect of land use and design factors on vehicle travel. They derive these factors from the re-analysis of four databases used in different travel behavior studies. They report that the typical elasticities for vehicle miles traveled with respect to local density (residents and employees) and to local diversity (jobs-population balance) are each -0.05. For vehicle trip frequency, these numbers are respectively -0.05 and -0.03. Regional accessibility (index derived

[15] Myers and Gearin (2001) contend that the supply of compact development and walkable neighborhood is short and that the current sprawl-style housing market responds to the demands of a population that goes against the driving force population in coming years.

by a gravity model) has a more important effect, with an elasticity of -0.2 for vmt. Finally, the elasticity for local design, measured by a combination of sidewalk completeness, route directness, and street network density, with respect to the number of vehicle trips is -0.05, and with respect to vmt is -0.03. Ewing and Cervero suggest an additive effect of their elasticities; therefore, although each element may have a relatively small impact on behavior, overall an appreciable effect can be expected. Several authors (e.g. Ewing, Cervero, Kockelman, Radisch) note that more than the individual factors of the built environment affecting travel behavior, it is more likely to be the synergistic effect of the three dimensions – density, diversity, design – that overall determines choices on when, where, how and how often residents travel.

2.2.3 *Traffic Safety*

Traffic safety is a major public health concern, representing the leading cause of death for people ages 1 to 34 in the US (Natl. Cent.Injury Prev. Control. 2001). Moreover pedestrians are 23 times more likely to die in a crash than car riders per kilometer traveled; bicyclists 12 times (Pucher and Dijkstra 2003)[16]. Therefore encouraging more people to walk and bike may increase health risks in the community. However, comparing traffic safety statistics in the US and in Europe, Pucher and Dijkstra have shown that increasing pedestrian and bicycle travel while decreasing traffic fatalities is possible. In addition, travel behavior studies and traffic analysis research point to roadway features and community designs that can reduce pedestrian and cyclist traffic hazards.

Hess et al. (1999) in their description of pedestrian behavior accessing commercial centers in different community environments show that suburban communities generate riskier pedestrian behaviors than urban communities, because of the lack of adequate amenities. While 98% of pedestrians entered the commercial center walking on a sidewalk in the urban

[16] Pucher and Dijkstra (2003) report per billion kilometers traveled 140 fatalities for pedestrians, 72 for cyclists and 6 for car occupants. Injury rates are 2.1 per 500 000 km traveled for pedestrians and 25 per 500 000 km traveled for bicyclists.

neighborhoods, only 60% did so in the suburban communities. Jaywalking was also more prevalent amongst suburban walkers than in urban centers (32 versus 20%). These findings are corroborated by Ewing et al.'s (2003) investigation into sprawl's impact on traffic fatalities. The authors showed that a higher degree of sprawl, measured by a county-level sprawl index, was significantly associated with greater traffic fatality rates for all modes. The association was found to be greater for pedestrian fatalities, with a 1% increase in the sprawl *index*, which indicates a decrease in sprawl (the index ranges from 1 to 448 indicating the least to highest sprawling county), explaining a decrease in pedestrian fatalities ranging between 1.47% and 3.56 %, depending on the type of exposure accounted for.

Campbell et al. (2004) reviewed the literature on pedestrian safety in the US, and summarize crash rates by when and where they occur, for whom, how, and how severe they are. Statistics include crash rates varying by time of day, light condition, traffic control measure, speed limit, intersection vs. non-intersection, etc. The authors review impacts of pedestrian safety measures such as crosswalk treatments, signage, and traffic calming measures. They conclude with recommendations for enhancing pedestrian safety such as providing raised medians on multiway roads, sidewalks and walkways, limiting right turn on red in some settings, converting two-way to one-way streets in some circumstances, developing traffic calming measures in neighborhood streets, as well as enforcement and education programs. The detailed statistics and impact analyses provided in the document can be used along with other travel behavior data to develop traffic injury probability functions associated with different roadway treatment and community design options.

Another determinant of pedestrian and bicycle safety demonstrated by some recent research in the US is the amount of non-motorized activity present in the streets. Jacobsen's (2003) analysis of crash data showed that the more people walk and cycle in communities, the more walking and cycling was safe. The author conjectures that it is the driver's behavior that adapts to the greater presence of pedestrians and cyclists rather than the reverse.

An additional benefit of taking people out of their cars is a possible reduction of road rage. Although evidence on this issue is scarce, Wells-Parker et al. (2002) indicate that driving more than 14 000 miles a year and driving every day have both been associated with higher scores for self-reported road rage behavior compared to those driving fewer miles and those driving less frequently.

2.2.4 *Physical activity research*

2.2.4.1 *Theoretical framework*

Health behavior research can follow a variety of conceptual models that target different levels of intervention, such as the individual, organization, community or population levels. Particularly interesting for the study of physical activity in the context of this dissertation is the social-ecological framework, which integrates these different levels of influence and their theories into one model to provide ways of understanding how the different determinants interact and reciprocate to influence behavior (Stokols 1992; Sallis and Owen 1997).

The health belief model (Strecher and Rosenstock 1997) illustrates well the psychosocial theories used to understand individual behavior and change in behavior. Its basic assumptions are that individuals behave rationally, and that they want to take action to reduce or prevent illness. According to the model, a person is more likely to become more physically active depending on five conditions: 1) her perception of risks of developing a condition and perception of the seriousness of the condition if not action is taken (perceived health threat, a combination of perception of susceptibility and severity); 2) her belief about the effectiveness of physical activity in reducing the health threat (perceived benefits); 3) her belief about the negative aspects of physical activity (perceived barriers); 4) the cues to action that stimulate and remind her to become more physically active; 5) her belief about her ability to become physically active (self efficacy). The transtheoretical model (Prochaska et al. 1997) recognizes that individuals go through a cognitive process before actual behavior modifications. The stages of change described in the theory are categorized as "precontemplation", "contemplation", "preparation", "action" and "maintenance". They describe the individual's path from having no intention of changing behaviors, to recognizing the benefits of changing, then acknowledging that the pros outweigh the cons and having a plan, to finally taking action, and in the end reaching a point of confidence in the ability to continue the behavior. The theory maintains that interventions should be stage-appropriate to be successful.

These individual cognitive and emotional factors interact with the social, cultural and physical environments provided by organizations such as the work place, the school or the church, by the community, and by society as a whole, to either re-enforce or discourage healthy behavior. The Precede-Proceed planning model for community intervention for example offers a systematic way to look at antecedent conditions – the influences of influences – that lead to better health and quality of life (Daniel and Green 1995). In this model, policies, regulations, and education programs at the community or organizational level are examined with regards to their influence on "predisposing", "reinforcing" and "enabling" factors that lead to behavior and lifestyle choices. Predisposing factors refer to one's knowledge, attitudes, beliefs, values and perceptions, while reinforcing factors bear on the attitudes and behaviors of others in the community. The availability of opportunities and accessibility of resources represent the enabling factors. A pedestrian-oriented community design analysis lends itself particularly well to the application of the model with regards to these enabling factors and opportunities for walking and cycling. Finally, the population level of influence can be described for example through the political economy of health theory (Linnan et al. 2001), by the pressures exerted by economic, social and political forces on people's behavior. In terms of physical activity behavior, these pressures can be perceived through the auto-industry marketing power, the relative pricing of alternative modes of transportation (both out-of pocket and time costs due to built environment factors), and perhaps a culture of freedom which somehow has been amalgamated with the freedom to drive.

The social ecological model provides a good framework for looking into specific levels of influence using the relevant theories, but within the context of other levels of influence. The physical activity literature reviewed here is targeted specifically on how the physical environment affects the behavior. However, it is important to keep in mind the interaction of other levels of influence for a more complete understanding of lifestyle choices, and also for planning better policies for a successful use of the pedestrian environment.

2.2.4.2 *Determinants of physical activity*

There has been an explosion of physical activity research on built environment factors in the recent years. Humpel et al. (2002) provide a good synthesis of the literature up to 2001. The authors find that the research shows overall a significant relationship between leisure time physical activity behavior and measures of *accessibility* to physical activity facilities, *opportunities* for physical activity and *aesthetic* attributes of the environment. They conclude on the other hand that weather and safety issues are not strong determinants of physical activity.

The built environment-related *accessibility* measures found to be significant in explaining physical activity in Humpel's review include access to parks, beaches or shops within walking distance. In particular, Troped et al. (2001) found that increased distance to a bikeway (both perceived and GIS-measured), perception of a busy street to cross (but not "objectively" measured), and having a steep hill to negotiate ("objectively" measured but not perceived), were all negatively associated with the use of the bikeway. In more recent articles, accessibility measures such as land use mix and ease of walk (Boureaudhuij et al. 2003), living within walking distances to shops, a park, or trail (King et al. 2003), access to public attractive open space (Giles-Corti and Donovan 2003), were all positively associated with some measure of physical activity. Giles-Corti et al. (2005) tested 3 different accessibility indices to measure access to public open space (POS), and found that very good access to POS measured by the size, attractiveness and distance to the POS was associated with a 50% greater likelihood of walking more than 180 minutes a week compared to a very poor access to POS. However, despite a significant relationship between accessibility to POS and its use, and a significant relationship between the use of POS and reaching recommended levels of activity, they found no direct significant relationship between any of the accessibility indices and attaining the recommended levels of activity. Hoehner et al. (2005) recently studied the impact of both subjectively and objectively measured attributes of the environment on the odds of leisure-time and transportation-related physical activity behavior, with each measure adjusted for age, gender and education (and not other environmental variables). They found that living in the highest quartile of the number of non-residential destinations, either measured objectively or subjectively, more than doubled the odds of being physically active while traveling conducted. In addition, the objective measure of greater numbers of residential destinations yielded a significantly higher likelihood of attaining the recommended levels of physical activity through active transportation in that study. However, measures of accessibility to recreation facilities lead to weak or inconsistent associations with recreational activity.

In Humpel's review (2002), measures of *opportunities* for activity such as perceived neighborhood environment (safety and ease of exercising and frequently seeing others exercise) and sidewalk presence were in general not found to be strongly related to leisure time physical activity; only measures related to the facilities themselves explained the behavior. Since then, however, other studies have found such measures to be significant contributors to physical activity levels, such as a neighborhood rating score function of the convenience, safety, aesthetics and overall quality of the neighborhood for walking (King et al. 2003) and sidewalk presence (Brownson et al. 2001; Boureaudhuij et al. 2003), well maintained sidewalks and safe areas for walking or jogging as well as knowledge of routes for cycling, walking or jogging (Sharpe et al. 2004). Nonetheless Hoehner et al.'s (2005) recent study found no association between the perceived measure of sidewalk presence and transportation or recreational activity, and found furthermore an objectively measured high proportion of well maintained sidewalks to be inversely related to transportation activity. The latter finding may be explained by the lack of accounting for income levels or characteristics other than age, gender and education in their estimates, especially since both low and high income neighborhoods were surveyed.

In articles reviewed by Humpel et al. (2002), in general the more people seem to appreciate the *aesthetics* of their neighborhood, such as finding it “friendly”, “pleasant”, “attractive”, with an “enjoyable scenery”, or a “living environment”, the more likely they were found to be physically active. Boureaudhuij et al. (2003) also found a positive association with activity levels with a neighborhood perception measure based on the resident’s “emotional satisfaction”. Unexpectedly, the presence of hills and heavy traffic were found to be associated with leisure time physical activity by Brownson et al. (2001), perhaps because they are respectively correlates of enjoyable scenery (also significant in the model), and of urbanicity. Heavy traffic, as well as unattended dogs, were also counter-intuitive significant predictors of leisure time physical activity in a study by Huston et al (2003), who explain the relationship by a possible increased awareness of such nuisances by active respondents. More counter-intuitive associations were found by Hoehner et al. (2005), who showed an inverse relationship between objectively and subjectively measured aesthetic attributes of the environment – well maintained and free of garbage neighborhoods – and transportation activity. Similar to their findings on sidewalks, this could be explained by the limited adjustments included in the models.

Some authors found gender differences among behavioral impacts of neighborhood quality. For example Humpel et al. (2004) found in a multivariate analysis on walking for different purposes that men who had the most positive perception of their neighborhood aesthetics were 7 times more likely to walk in and around their neighborhood, and close to 4 times more likely to walk for exercise, while these relationships did not hold true for women. Weather on the other hand was shown to affect walking in a similar way for both genders, with perceiving it as not an inhibiting factor associated with higher likelihood of walking around the neighborhood and for exercise. Surprisingly a high perception of safety and of accessibility decreased the odds of walking in men respectively for a neighborhood walk and for pleasure, and did not affect women. Walking to and from places was not found to be affected in either group by any of the environmental measures.

Another approach taken by some authors has been to use an overall objective rating of the neighborhood environment in their analyses. Saelens et al. (Saelens et al. 2003) for example compared activity levels amongst residents recruited in a "high-" and a "low-walkability neighborhood". The high walkability neighborhood, characterized by higher levels of residential density, land use mix, connectivity, aesthetics and traffic safety, generated on average 70 minutes more moderate to vigorous activity in a week. Moderate intensity and total physical activity measured by activity monitors were significantly higher in the high-walkability neighborhood ($p<.05$), however no significant differences were found for self-reported activity of different levels and walking for different purposes, or for objectively measured strenuous activity.

Giles-Corti and Donovan (2003) combined into a single multivariate summary score three measures of the physical environment: an environmental appeal score based on the interviewer's assessment of street type and tree coverage; a functional environment score measuring whether sidewalks and visible shops on the street were present; and a spatial access to attractive open space score. Following a social ecologic framework, similar summary scores were developed for individual and social determinants and entered into a logistic regression model explaining walking at recommended levels. Results show that the highest (of three) environmental score generates more than twice as much walking at recommended levels than the lowest score. Overall the model showed similar relative impacts of the three levels of influence, with highest scores of both social and individual determinants generating around three times more walking at the recommended levels than the lowest scores.

Ewing et al. (2003) developed a county level sprawl index function of residential density and street accessibility to explain physical activity and health outcomes associated with inactivity. The hierarchical modeling showed the sprawl index to be a significant predictor of the number of minutes walked for leisure, body mass index, obesity and hypertension. In particular, a decrease in two standard deviations in the index (i.e. increase in sprawl) resulted in a 14 minute decrease in leisure time walking.

The same way home age has been used in transportation studies as a way to typify the built environment, Berrigan and Troaino (2002) used that approach to examine walking behavior (for all purposes) as a function of neighborhood type. They found that people living in older homes were more likely to walk more, however other forms of physical activity were not associated with home age.

Looking specifically at trips on foot to work, Craig et al. (2002) used hierarchical linear modeling to create a latent environmental score to explain the behavior. The neighborhood score was based on 18 environmental variables collected by a trained observer, such as existence of walking routes, variety of destinations, and safety of crime, of which only visual interests and aesthetics were not significant contributors. The environment score was significantly related to walking to work, even after controlling for the degree of urbanization, which moderated the relationship.

Recently, Frank et al. (2005) developed in Atlanta a walking index based on land use mix, residential density, and intersection density, within a 1 km network buffer surrounding each survey participant's residence, to explain objectively measured physical activity. They found that people living in the highest quartile of the walkability index, indicating a more walkable neighborhood, were 2.4 times more likely to attain the recommended activity levels than those in the lowest quartile of the index (confidence interval 1.18-4.88), adjusting for sociodemographics[17]. The index also explained total minutes of physical activity, with a small but significant effect. As only 10.7% of the variance in amount of activity was explained by the socio-demographic variables and walkability index, the authors hypothesize that further integrating environmental measures such as the presence of sidewalks would increase the amount of variance explained by the model.

One study examined not only walking behavior, but also the stages of change described in the transtheoretical model, in relationship to neighborhood environment factors. Carnegie et al. (2002) used factor analysis to combine perceptions of residents' neighborhood into an aesthetic factor ('pleasant", "friendly", "attractive", and "safe for walking during the day") and a practical convenience factor ("shops within walking distance" and "beach, park, or cycleway nearby"). Three variables could not explain either of the factors ("safe walking at night", "traffic in neighborhood", and "dogs barking as a deterrent"). Both factors were shown to be significantly associated with the stages of change measure. However only contemplators perceived their environment for both factors significantly more negatively than those in maintenance did, and all other difference between stages were not significant. A more positive perception of the aesthetics and of the practicality of their neighborhood environment were also associated with more walking. In addition, those who walked more perceived the traffic in their neighborhood to be more of a nuisance than those who walked less.

Yet another approach is to examine health status as the modeling outcome rather than the physical activity behavior, as in Ewing et al.'s previously mentioned sprawl index study (2003). Giles-Corti et al. (2003), looked at environmental factors' impact on overweight and obesity in Perth, Australia, using physical activity along with other lifestyle factors, as one of the independent variables rather than the outcome. They found living on a highway (compared to a cul de sac), and poor access to sidewalks, walk/cycle paths (perceived), and shops within walking

[17] Eighteen percent of those living in the lowest quartile attained the 30 minutes or more of moderate activity on at least one day (of the 2 day survey), compared with 28.1% , 32.3% and 37.5% in the second, third, and fourth quartiles respectively.

distance (perceived) to increase significantly the odds of being either obese or overweight. Physical activity, however, was not associated with either outcome, and having access to motor vehicles all the times was associated with a lower likelihood of obesity. This study also showed the influence of the social environment, with the comparison with peers' physical activity behavior also significantly associated with both obesity and overweight. Timperio et al. (2005) also used perceived measures of the neighborhood environments, to study their impact on childhood overweight and obesity. None of the children's perception variables were significant at the 95% level in adjusted logistic regression models, and only the perception of heavy traffic and road safety concerns on the part of parents showed to be positively associated with odds of being overweight and obese respectively.

Several obesity and built environment studies were published in the year 2004. Sturm and Cohen (2004) find a positive association between sprawl and chronic diseases, using Ewing's sprawl index in a logit regression with random effect. In particular, they find that two standard deviations increase in the sprawl index (i.e. less sprawl) implies 96 fewer chronic medical problems per 1000 residents, which they compare to the difference in the outcome made by a 4-year difference in age, or by the difference between black and white populations, or by the doubling of income. They also find street accessibility, land use mix, and population density to be significant predictors of chronic illnesses, but not the degree of centering. Lopez (2004) developed another sprawl index, based on the percentage of the metropolitan population living in low density areas, and found a small but significant association between sprawl and overweight and obesity. In their study in the Atlanta region, Frank et al. (2004) showed land use mix was a strong negative predictor of obesity in their logistic regression model, with each quartile increase of land use mix explaining a 12% decrease in odds of being obese. Contrary to Giles-Corti (2003), the authors also found that each additional kilometer walked decreased the odds of being obese by 4.8%, and that time spent in cars also predicted obesity odds significantly. Connectivity and residential density on the other hand were not significant at the 95% confidence level, possibly due to the spatial colinearity between them and land use mix. The authors also noted that the observed relationships were stronger for white than for black populations.

One of the common limitations in these studies on the built environment and physical activity is they use a cross-sectional survey design, meaning that causation cannot be established. One recent exception to this is Merom et al.'s (2003) surveys of residents living in proximity of a new trail, pre- and post- trail opening and promotion campaign. They used data on monitored cycling activity in four locations along the trail collected during 5 months comprising the campaign and trail opening, as well as self reported walking and cycling activity and awareness of the trail promotion or other physical activity promotion campaigns. They found that cyclists residing within 1.5 km of the trail increased cycling hours between pre- and post- campaign (but not significantly) while at the same time those living between 1.5 and 5 km slightly decreased their hours of cycling, and that the difference between the two groups was statistically significant. The increase was found to come mainly from one neighborhood, where residents rode long distances, including work commutes. Monitored cycling counts revealed an increase in mean daily cycling counts after the trail opening. Humpel et al. (2004) also used a prospective study design, to determine changes in perception of the walking environment following an increase in walking behavior, but unrelated to any environmental change. The study showed that an increase in perception of aesthetics (men only), convenience (men and women) and traffic as a problem (opposite directions for men and women) were significantly associated with increases in time walking. However, despite the prospective design of the study, no causal relationship can be established from such findings.

An interesting approach to investigate causation in obesity research is Bell et al.'s (2002) study on the effect of motorization in China. Of course a comparison with the US is not entirely relevant because of cultural or historical factors that may confound results; still, China, with its increasing reliance on automobiles for travel, provides a broad-based natural experiment of the evolution of transportation behavior and its effect on body mass. The authors show that indeed, acquiring a vehicle lead to Chinese men gaining weight and increased their odds of becoming obese controlling for diet and socio-demographic factors. Odds of being obese were found to be 80% higher in households owning a car.

A novelty in the more recent studies reviewed here compared to the majority of older research, is that many of them considered utilitarian walking - and sometimes cycling - in addition to leisure time activity, therefore providing a more complete picture of the influence of the built environment. In their 2004 review specifically on environmental influences on walking behavior, Owen et al. (2004) conclude that the patterns of results are consistent in their diagnosis of positive relationships between the two, although they note that the body of literature is still too small to give definitive prognoses. The associations found hold promise for the promotion of physical activity using built environment policies, which is enhanced by findings that walking in the streets fits well existing preferences. Indeed, neighborhood streets have been reported as the most common location for activity (Brownson et al. 2001; Eyler et al. 2003; Huston et al. 2003), and walking as the most popular form of physical activity (U.S. Department of Health and Human Services 1996; Giles-Corti and Donovan 2003). In particular, the relative prevalence of leisure time walking is highest in low SES subgroups, which are also the least active subpopulations (Siegel et al. 1995). Walking can be a practical element of everyday life, and can be financially accessible for most people, if the appropriate environment exists. The greatest public health benefits could be gained by encouraging the most sedentary people to participate in regular activity of moderate intensity, and walking shows promise for such population shifts, confirming the relevance of improving the pedestrian environment as a public health target for physical activity promotion.

However most of these studies hold limitations that prevent definitive resolution of the impact of the built environment on behavior. Possibly the greatest one is the previously mentioned cross-sectional design employed in most studies. In the past a typical issue had been the restriction of physical activity studies to leisure time activity, but more recent research is addressing that issue. Although we have shown some studies that use objectively collected data, a frequent limitation in physical activity studies stems from the use of subjective perceived measures of built environment attributes (e.g. distances to destinations, perceived aesthetics and neighborhood quality). Although studies that have tested the reliability of the measures with a test-retest method have shown acceptable levels of agreement (Kirtland et al. 2003; Saelens et al. 2003), the lack of standardized measures prevent the generalizations across studies and populations. More problematic is the limited validity of the perceived compared to objective measures (Kirtland et al. 2003), which makes policy applications more difficult.

This review has shown that there is potential for an improvement in health status through pedestrian-oriented environment improvement policies, and that data are available to assess effects of such changes, albeit with much uncertainty.

2.2.4.3 *Health effects*

Benefits of physical activity are multiple, however the dose-response relationships with the different effects are often unclear, as reported by Rankinen and Bouchard (2002) following the consensus symposium on such matter. All cause mortality, cardiovascular disease, coronary heart incidence and mortality, and incidence of type 2 diabetes mellitus show the strongest inverse linear relationships with regular activity (Rankinen and Bouchard 2002). Other documented health benefits for which there is possibly less support of a dose-response relationship include: reduced colon cancer, reduced blood pressure, increased insulin sensitivity, more favorable lipid profiles, reduction in weight gain, bone mass maintenance in pre-menopausal women, decreased bone loss after menopause, increased peak bone mass in adolescents and young adults, decreased platelet adhesiveness and aggregation at rest and during exercise (hemostatic system benefits), quality of life and independent living benefits in the elderly, and reduced depression and anxiety (Mayer-Davis et al. 1998; Rankinen and Bouchard 2002; Houmard et al. 2004).

On the other hand, physical activity at times may increase health risks, especially high intensity exertions in people with underlying cardiovascular diseases, and potential musculoskeletal injuries with increased intensity and volume of exercise.

Although the built environment is shown to impact leisure time physical activity, including high intensity exercise such as jogging or team sports playing in a park, the effects of walking and cycling are of particular interest here, since these activities represent the particular targets of the pedestrian environment policy. A further distinction is made between utilitarian and leisure time walking or cycling, because they may represent different levels of exertion. As Shepard notes (1997), active commuting may be more beneficial than leisure time walking, as people are more likely to walk as fast as they can to get to work, possibly attaining an optimal heart rate of 70% max or greater for 90% of women and two thirds of men.

Walking to work was associated with significant decreased risk of hypertension, adjusting for covariates including leisure time physical activity, in a prospective study of Japanese men walking to work (Hayashi et al. 1999). Wagner et al. (2001) used a large cohort of middle-aged men in Europe to study the effects of physical activity, especially regular walking or biking to work or activity of moderate intensity, on body weight and body fat. The cross-sectional analyses revealed significant inverse relationships between cycling or walking to work and body mass index (BMI) and waist circumference, accounting for leisure time physical activity expenditure and high intensity leisure-time activity. Regular cycling and walking to work was found to be negatively associated with a change in BMI, while leisure time exercise was not, in their longitudinal analysis. High intensity leisure time activity however was significantly associated with decreased BMI. Andersen et al. (2000) in a large prospective study in Copenhagen showed that those who did not cycle to work experienced a 39% higher mortality rate than those who did, after multiple adjustments, including leisure time physical activity. The authors also provide gender and age-specific statistically significant estimates of reductions in relative risks of dying associated with different levels of leisure time exercise. Manson et al.

(1999) examined associations between physical activity and coronary events, defined as nonfatal myocardial infarction or death due to coronary disease, in a large prospective study of US nurses. They analyzed in particular the effects of walking on women who reported no vigorous exercise. They found that women who participated in three or more hours of brisk walking per week reduced their multivariate risks of subsequent coronary heart disease by 35% compared to sedentary women. In addition, walking pace was shown to be an independent predictor of coronary events, and the participation in both vigorous exercise and regular walking demonstrated greater reductions in coronary events than participation in either one of them.

Oja et al. (1998) developed a pilot study on physiological effects of walking and cycling to work by conducting a randomized controlled experiment involving a 10-week walk or cycle to work intervention. They found that health-related fitness and several indices of metabolic health improved during the intervention. Both groups experienced small but statistically significant net increases in $VO_{2\,max}$ -with larger increases for cyclists than walkers- HDL cholesterol increased, and substandard work load heart rate and blood lactate decreased significantly. No changes were observed however in serum total cholesterol or triglyceride concentration, or in body weight.

The results described above show that walking or cycling trigger health benefits independently of other physical activity. Another approach to investigating the question of the relative contribution to health benefits provided by regular walking or cycling is to compare the effects of exercises of different intensity and duration.

Kraus et al. (2002) used a randomized controlled trial of sedentary overweight or obese subjects to study the physiologic effects of exercise regimes differing by intensity and amount. They found benefits in terms of plasma lipoprotein occurred in all exercise groups, and was independent of intensity in low-amount groups. However, only subjects in the high amount and high intensity exercise group increased their high density lipoprotein (HDL) levels, and had large decreases in low density lipoprotein (LDL) levels. The amount and not the intensity of exercise were associated with clear benefits when looking at 11 variables of plasma lipoprotein within the low-amount group. The lipoprotein improvements observed in this study are of interest because of their known beneficial effects on body weight, subcutaneous abdominal fat, atherosclerosis and risk of myocardial infarction (Tall 2002).

Houmard et al. (2004) observed in the same study that while the control group experienced a decrease in insulin sensitivity, those who exercised at low volume/moderate intensity and high volume/high intensity increased their insulin sensitivity more than those exercising at low volume/high intensity levels, and that sensitivity was improved when exercising longer, regardless of the intensity. They conclude that a variety of exercise volumes and intensity will trigger the highest benefits. Using the same study, Slentz et al. (2004) examined effects on body weight and body composition. They found a distinct beneficial effect on weight change of the amount of activity, with a dose-response relationship. Intensity seemed to influence lean body mass rather than weight change. The authors conclude that most overweight sedentary individuals can maintain or lose weight with just 30 minutes of brisk walking or 20 minutes of jogging a day.

Another question that has arisen in the field regards the issue of effects of longer continuous sessions versus the accumulation of bouts of activity that add up to the same amount. Lee et al. (2000) used data from the Harvard Alumni Health study to show that when adjusting for the total amount of energy expenditure, the duration of exercise per session did not affect the risk of coronary heart disease (CHD). In other words, the accumulation of bouts produces the same effect as longer periods in terms of CHD effects. In addition, the authors noted that given the same total energy expenditure, and regardless of the duration of exercise per episode, participation in sports or other recreational activities did not produce any additional benefits in terms of protection from CHD than did solely walking and climbing stairs as a form of exercise.

A limitation in many of the studies is the common use of self-reported physical activity levels, and in particular relying on perceived measures of exertion. People with different fitness levels might regard differently for example activities of “moderate” intensity, thus hindering the generalizability of such measures. However, research on health benefits of exercise is consistent, and this issue may only affect the level of precision that can be expected when generalizing results. It can be concluded from these studies that larger amounts of exercise is always better, and that since the intensity of exercises trigger different types of benefits, a variety of forms of exercise including walking or cycling will maximize improvements in health.

2.2.5 *Social Capital*

2.2.5.1 *The built environment and social capital*

Social capital can be defined by the social networks and interactions that inspire trust and reciprocity among citizens. Jane Jacobs (1961), new urbanist, and other thinkers and architects, believe that one of the benefits of mixing land uses is to offer neighborhood amenities that bring more life to the streets by increasing pedestrian traffic and offering spaces for spontaneous interaction and gathering amongst neighbors. They also argue for higher density to facilitate walking, transit, and the creation and use of public open space. They note that in lower density neighborhoods space is privatized and people have no need for public parks as they use their own back yard instead. In other words, they assert that pedestrian-oriented environments will increase face-to-face contact and thus may increase resident's social capital.

Some empirical research has shown that indeed the built environment may impact resident's level of social capital, which in turn triggers health effects. In a simple analysis on the amount of destinations within walking distances in Galway, Ireland, neighborhoods, Leyden (2003) found that for each additional place a resident can walk to in their neighborhood, odds of knowing their neighbors is increased by 28%, odds of participating politically by 14%, odds of trusting others by 15%, and odds of social engagement by 20% .

Skjaeveland and Gärling (2002) note in their review of research on neighboring that social contact between neighbors is enhanced when there are opportunities for passive social contact, proximity between neighbors, and an appropriate space in which to interact. Baum and

Palmer (2002) conclude from their analysis of a survey of residents' perception of "place" and its effect on their levels of social interaction and health in Adelaide, Australia, that social contact would be enhanced by the improvement of the environment such as through the presence of local shops and cafés, parks with facilitators, and attractive places to walk. Although density may increase opportunities for social contact, too much density can also give a sense of crowding which may weaken social ties. Relationships between the built environment and social interaction and neighborhood satisfaction are therefore often difficult to capture and generalize. In addition, cultural and geographical factors may affect results, limiting the applicability to US conditions of some empirical research such as Skjaeveland and Gärling's in northern Europe.

In the US, Langdon (1994) notes that most suburbs built in the last 50 years do not have gathering places where people can interact with neighbors. Effects of fewer gathering places were tested at the building-level by Nasar and Julian (1995), who found that apartment buildings with outdoor courtyards triggered a higher sense of community than those with interior corridors. Freeman (2001) attempted to operationalize dimensions of sprawl to study its effect on social ties. The author's logistic regression analysis showed that the number of neighborhood social ties was not related to density, but that that the percentage of people in the neighborhood who drove alone to work was a strong predictor of meaningful interaction with neighbors. Every 1% increase in the proportion of individuals driving alone to work was shown to be associated with odds of individuals having neighborhood social ties equal to 0.28 (p-value=0.02).

Another perspective on the issue can be seen through the lens of Uslaner's (1999) contention that optimism is what builds trust, leading to democratic participation - both of which can be seen as expressions of social capital. The author asserts that that people need to be put in situations where they feel they can control their environment and fix problems together in order to build trust. Although Ulsaner's suggestion is that people should play sports and attend sports events to achieve this, it seems that keeping the same premise, more can be explored in the direction of environmental control through urban design possibly leading to a greater sense of optimism and trust. Theories of environmental control as part of the Crime Prevention Through Environmental Design framework (Crowe 2000) and Newman's (1996) defensible space principles could be applied to building trust and social capital for enhancing democratic participation.

2.2.5.2 *Social capital and health*

Social capital, in turn, has been linked to health outcomes. To summarize, Putnam (2000) and Kawachi and Berkman (2000) have associated higher levels of social capital and activity participation with good health, crime prevention, enhanced economic development, and to the proper functioning of democracy.

At the collective level, Kawachi (1999) explains how participation in social institutions help develop skills (organizational and communications) leading to increased political activity, and eventually to better health because governments become more responsive to people's needs when political mobilization occurs across the socioeconomic range. At the neighborhood level, Kawachi's reasoning is that social capital affects health through informal social control (e.g. monitoring street activities), maintenance of healthy norms (e.g. neighbor's intervention to prevent delinquent behavior), and access to different forms of social support. Social support at the individual level can be through instrumental support (e.g. ability to borrow needed money or car for access to health care), emotional support, and the provision of information.

Comparing state-level social capital measures, Kawachi (1999) found that living in states with the low social capital was associated with 22% to 48% higher odds of fair to poor health than residing in a state with the highest social capital indicators (after adjusting for individual sociodemographics and lifestyle characteristics).

Looking specifically at the elderly, Glass et al. (1999) found that social and productive activities for the elderly were both shown to be associated with longer survival, independently from physical activity (risk of death for highest versus lowest category of activity participation was respectively 0.81 and 0.77 for social and for productive activities, in models adjusted for sociodemographic and individual risk factors). Re-enforcing the argument of the built environment effect, auto-oriented communities may limit the mobility of the elderly in particular, which could explain why driving cessation in the US has been associated with a reduction in social activity, a measure of social capital, and the increase in depressive symptoms (Marottoli et al. 1997; Marottoli et al. 2000).

Rather than the built environment, however, Kawachi (1999) holds the widening socioeconomic disparities responsible for the reduction of social capital. His perspective is that as the rich get richer, they indulge in more “conspicuous consumption”, and the poor, who are getting poorer, in order to maintain a relative status also increase their levels of spending, but to do that need to work more and reduce their times with family and friends or volunteering in the community. In support of this argument, Kawachi (1997) finds that variations in social capital stocks are correlated with levels of household income inequality. The author does note however that social capital is not a panacea, especially considering possible negative impacts such as the exclusion of some people, the restriction of liberties, and unhealthy socialization (e.g. smoking or gangs)

2.2.6 *Crime*

Crime is not only a direct cause of deterioration of health, (in the US, crime was the 13th leading cause of death in 2001, and the 2nd for the 15 to 34 age group (Natl. Cent.Injury Prev. Control. 2001)), it can also affect health indirectly because of stress and inhibitions that accompany fear of crime. Although fear of crime may not be related to crime itself, it can act for example as a deterrent to outdoor physical activity such as walking (Saelens et al. 2003).

Certain environmental design traits can be used both to deter crime and reduce fear of crime. The design principles are those that cater to the sense of “place”, of territorial enforcement, and the sense of a community controlled, maintained and cared for by its inhabitants (Crowe

2000; Mair and Mair 2003). These can be achieved through landscaping, designing and maintaining buildings, grounds and streets that give a positive image of residents, and reducing vehicle speed. The concept of "eyes on the street" is particularly relevant to crime prevention design, the idea being that facilitating the visibility of people's activities through building orientation, windows, front porches, continuous sidewalks, lighting, and mixed-uses to locate housing next to areas of safe activities, provides natural surveillance.

Crime prevention through environmental design (CPTED) principles implemented in a few neighborhoods in the US were shown to be effective in reducing crime (Taylor and Harrell 1996; Mair and Mair 2003). The landscaping, building designs and mixed use development concepts used are similar to those thought to increase walking and other forms of physical activity, as well as social interaction.

2.2.7 *Nutrition*

Recent research has shown that the built environment may even have an impact on resident's eating habits. Morland et al. (2002) determined that healthy diets were associated with the availability of supermarkets in a resident's census track. In particular, fruit and vegetable intake was shown to increase by 32% for each additional supermarket for Black Americans. Recommended levels of fat and saturated fat intake among Black Americans were also associated with the presence of supermarkets. The associations found for White Americans however were either weaker or not observed, possibly due to the greater availability of private vehicles among the white population.

Thus, one of the key elements of pedestrian-oriented environments, a greater land use mix, may also benefit healthy eating habits, especially in Black Americans, who tend to suffer more from the ailments of inactivity and poor nutrition than White Americans do.

2.3 Air pollution

We now turn to the impacts of transportation behavior on health through its effect on air pollution exposure. We review in particular the literature on spatial-temporal variation of traffic related pollutants, as it will inform decisions on the degree of resolution that will be needed to capture health effects due to neighborhood-level changes in community design.

Nationally, on-road mobile (trucks and vehicles) emissions represented in 1999 (U.S. Environmental Protection Agency 2002; US EPA 2005):10% of particulate matter (PM2.5), 34% of nitrogen oxides (NOx), 51% of carbon monoxide (CO), 29% of hydrocarbons (HC), 31% of national air toxics emissions (includes188 toxic air pollutants, 1996 data). In urban areas however, the contribution of vehicle emissions to these pollutants is typically higher than these national figures (e.g. Schauer et al. 1996). In addition, NOx and HC react in the presence of sunlight to form ozone, and the ubiquitous, low altitude emissions from vehicles make them a higher contributor to ozone formation in urban areas in general. In the case of hazardous air pollutants (HAP), not only may vehicles be responsible for a greater share of emissions in some areas, but also they may emit HAPs that are more toxic than other sources. Such is the case for example in California, where mobile sources are estimated to contribute the most to the hazard index (56%) and the excess lifetime cancer incidence (52%) derived from census track ambient level exposures (Morello-Frosch et al. 2000).

A major question in estimating health effects of air pollution is that of the exposure measure to be used. Ambient levels may not be representative of the concentrations people may be exposed to throughout the day, particularly certain pollutants by the roadside of heavy traffic streets. For instance ultrafine particulate matter or polycyclic aromatic hydrocarbons (PAH) concentrations decay as the distance downwind from a busy road increases (Levy et al. 2003). In addition, with toxic effects greater than their larger size counterparts for similar chemical composition and mass concentration, ultrafine particle exposure assessment by the road side deserves higher attention in exposure studies in the US (Zhu et al. 2002). It is also thought that physical activity while inhaling pollutants may increase its effects, because higher ventilation and deeper breathing augment respiratory deposition, and fractional penetration is higher while breathing through the mouth than through the nose (Sharman et al. 2004).

Given the importance of choosing an appropriate level of resolution in estimating exposure, this section first reviews the literature on traffic-related air pollution dispersion and exposure assessment methods. The literature on health impacts of traffic-related exposure is then reviewed.

2.3.1 *Pollution spatial-temporal variation*

Some traffic-related air pollutants have been shown to vary significantly from near heavy-traffic roadways to background ambient levels. Nitrogen dioxide (NO_2) for example seems to unequivocally demonstrate small-scale variations associated with traffic emissions, especially in the summer months when high ozone levels favor the conversion of NO into NO_2 (Roorda-Knape et al. 1998; Janssen et al. 2001; Monn 2001). Coppale et al. (2001) estimated that traffic volume accounted for 74% and 37% of observed NO and NO_2 concentrations respectively in a French city, and that spatial variability of these pollutants is high over short time periods (15 minutes) but not over long periods (months).

The spatial distribution of all particulate matter may not be generalizable, as local conditions such as weather, topography, and variety of pollutant sources seem to play an important role; some studies have found for example greater variance in PM_{10} than in $PM_{2.5}$, some studies the reverse, and others a fairly homogeneous distribution of both (Monn 2001). When focusing specifically on particulates associated with traffic emissions, studies have perhaps been more consistent, although not entirely. Several studies have been conducted in the Netherlands measuring pollution as a function of the distance to and the intensity of road traffic, in particular in how it affects levels inside and outside of schools. Janssen et al. (2001) found that $PM_{2.5}$ and soot (both indoors and outdoors) significantly increased with increasing truck traffic density and significantly decreased with increasing distance to traffic. Roorda-Knappe et al. (1998) on the other hand found no spatial gradient related to distance from road for PM_{10} and $PM_{2.5}$ in six Dutch districts. Roemer and van Wijnen (2001) compared in Amsterdam background sites to street and motorway sites; motorway followed by street sites consistently showed higher concentrations than background sites for PM_{10}, $PM_{1.0}$ and black smoke[18], in ascending order of spatial gradient strength. In Boston, Massachusetts, Levy et al. (2003) showed higher concentrations of ultrafine particulate matter, $PM_{2.5}$, and PAH at shorter distances from the road and with downwind wind direction, with a higher gradient for PAH, but not very robust statistical associations for all relationships. Their regression models predicting pollutant concentration at the road side as a function of traffic count only yielded statistically significant results for “large diesel vehicles” explaining PAH levels, and “fraction large diesel” explaining ultrafine PM. As the authors note, the limited predictive power of the models however does show that traffic counts may not be a good indicator of short averaging period emissions levels in busy urban areas, probably because of low counts during congested periods of time. Levy and other authors (2001) had previously noted in the same study area a significant trend of higher PAH concentration near bus stations and on bus routes, but no such pattern for fine PM.

As the examples above showing a different trend for particle-bound PAH and PM suggest, rather than particle mass concentrations, other indicators may capture the variation of traffic-related pollutants better. Hoek et al. (2002) for instance come to that conclusion in their study showing a comparatively higher level of $PM_{2.5}$ absorption coefficient by the roadside than of $PM_{2.5}$ contrasted to background levels (31% to 55% and 17 to 18% respectively). Similarly, comparing pollution outside of homes in high- and low-traffic intensity streets in Amsterdam, Fischer et al. (2000) showed a 15 to 20% higher PM_{10} and $PM_{2.5}$ concentrations in the former, yet the particle components BaP, total PAH, soot, gas phase benzene and total VOC were about twice

[18] An indication of elemental carbon

as high in the high traffic street compared to the low traffic street. In the streets of Harlem[19], New York City, Kinney et al. (2002) found little association between $PM_{2.5}$ and proximity to local diesel traffic, however they found a strong spatial gradient for elemental carbon (EC)[20] – a four-fold increase in mean concentration values going from the lowest to the highest diesel traffic counts. In reverse, the authors noted some temporal variation across days for $PM_{2.5}$ and little for EC.

Particle number concentration, as opposed to particle mass concentration, has been shown to decrease dramatically as the downwind distance from a heavy traffic road increases, with about 70% drop in the first 30 meters, and an additional 50% drop in the next 60 to 120 meters (Shi et al. 1999, Zhu et al. 2002). A shift in particle size distribution accompanies the drop in number concentration, with a drastic decrease in small size ultrafine particles (<50nm) compared to an only slight decrease in larger size particles (>100nm) (Zhu et al. 2002). Zhu et al. (2002) in addition show a similar exponential decay pattern for CO and BC as for number concentration. Hitchins et al. (2000) also observe an exponential decrease for ultrafine particles away from a heavy traffic road, and an average of maximum total number concentration of fine and ultrafine particles 7 times higher by the road side than the average urban ambient levels.

Benzene concentration gradients away from roads have also been observed, but only very close to the road (within 15m) (Roorda-Knape et al. 1998; Janssen et al. 2001). Vardoukalis (2002) found both vertical and horizontal gradients for benzene in street canyons in Paris, with 5th floor measures averaging 20 to 30% lower than first floor concentrations, and curbside levels 2 to 6 times higher than background levels. The street configuration, in this case that of typical Parisian street canyons, plays an important role in pollutant dispersion.

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[19] In the summer to avoid combustion emissions from heating.

[20] Elemental carbon represents close to 60% of the mass of diesel exhaust particles in LA, California (Cass and Gray quoted in Kinney et al. 2000).

Ozone displays a strong temporal pattern, with peak levels happening on sunny afternoons in the spring and summer. Small scale variations in urban areas depend on the proximity to NO emissions such as traffic, with lower ozone mixing ratios observed near traffic arteries because of the scavenging effect of NO on ozone. However, NOx emissions from vehicles are more effective in making ozone than power plants are, as they are ubiquitous, released below the mixing height, and accompanied with VOCs for immediate participation in the chain of photochemical reactions. The complexity of ozone formation in a chain of photochemical reactions dependent on other conditions (weather, VOC emissions, altitude) prevents generalizations on spatial patterns.

In addition to outdoor ambient spatial variation, some studies have investigated concentrations in different microenvironments, including indoor vs. outdoor and in different transportation mode, as well as overall personal exposures. In terms of different indoor environments affected by traffic pollution, some pollutants are thought to penetrate from the outdoors, while others are generated within the microenvironment. Levy et al. (2002) studied these patterns for $PM_{2.5}$, ultrafine particles and particle-bound PAH, in different indoor and outdoor environments along a high traffic street in Boston, Massachusetts. In general, their results showed that all three pollutants had outdoor concentrations which were fairly poor predictors of indoor environments[21], except for ultrafine particles but with a regression slope close to zero. Ultrafine particles were shown to be fairly low indoors except when cooking was involved, and where there was cooking or human activity indoor levels of $PM_{2.5}$ and PAH were greater than outdoors. In transportation mode environments, the investigators found $PM_{2.5}$ and PAH levels greater in the bus and in the car following the bus than outdoors, and no difference for ultrafine particles.

[21] The authors' regression models showed that outdoor ultrafine particulate matter was a significant predictor of all indoor microenvironments chosen except the food court (i.e. non air-conditioned apartment, coffee shop, mall, hospital, and library), however the regression slope was generally close to zero. $PM_{2.5}$ on the other hand only showed significant predicting power for the apartment and coffee shop, and PAH only for the apartment.

In a school-based study conducted in the Netherlands, Roorda-Knape et al. (1998) found indoor NO_2 to be significantly correlated to traffic intensity, percentage of time downwind and distance to motorway. They also saw a significant correlation between indoor black smoke and truck traffic intensity and percentage of time downwind, but they determined no such associations for PM_{10}. In a like-study Janssen et al. (2001) observed similar patterns for NO_2, and found indoor soot and $PM_{2.5}$ to significantly increase with increasing truck traffic density and significantly decrease with increasing distance to road.

In-vehicle concentrations have generally been found to be higher than outdoors. In Hong Kong, Chan et al. (1999) found NO, CO and NOx concentrations to be lower on the pavement by the roadside than in trams, buses and private cars in increasing order, and only slight differences for ozone and NO_2. Relative CO concentrations in different transportation modes exhibit similar patterns in Athens (Duci et al. 2003). Riedeker et al. (2003) compared pollution levels inside patrol cars to roadside and ambient levels in North Carolina, and also found CO, in addition to elemental carbon and VOCs and many metals, to have several times higher concentration in the vehicle than on the road side or in the ambient air. In-vehicle ozone and $PM_{2.5}$ levels on the other hand were lower in-vehicle than outdoors.

Adams et al. (2001) included the bicycle mode on a study of personal exposure to $PM_{2.5}$ in transport microenvironments in London. They found significantly lower exposure levels when traveling by bike than by car and by bike than by bus when looking at both winter and summer seasons together (differences lose significance when looking at summer and winter seasons separately). They also showed that cyclists using side streets as opposed to the more congested main streets were exposed to lower $PM_{2.5}$ levels. In general, exposure levels calculated using personal sampling devices in different transportation modes were about twice the levels given by the urban center monitor, although the authors note that different measuring devices may have affected that result.

The research reviewed above shows that pollutants have different patterns of dispersion and transformation in the environment, depending on the pollutant type, meteorological conditions, traffic intensity and street configuration. Another aspect to consider in spatial variation of pollutant concentrations is how the street environment affects driver behavior. Emission factors are second in importance, behind total vehicle miles traveled, in determining total emissions. The emission factors depend in part on driving patterns such as speed, amount of jerkiness in the driving style, acceleration and deceleration. According to Boulter et al. (1999), lower speeds increase emissions of CO, HC and particulates, while increasing average speed increases NOx emissions, and in general transient cycles generate more emissions than constant speeds. Therefore, traffic calming measures may reduce traffic volumes and enhance the pedestrian experience in different ways, but this may have to be balanced with possible emission factor increases due to higher oscillations in the speed curve (Boulter et al. 1999; Ericsson 2000).

2.3.2 *Personal exposure*

Finally, the same way variation is found in the spatial-temporal dispersion of air contaminants, there is a high level of variation in exposure to the pollutants due to human movement throughout the air pollution field. Studies such as Kousa et al.'s (2002) based in 4 European cities have shown that ambient fixed-site air concentration can be a poor predictor of personal exposures to particulate matter, explaining only 48% of the personal leisure time exposure variation, and as little as 15% of the personal workday exposure variation. Payne-Sturges et al. (2004) found that most of 11 VOCs personal exposure measures were underpredicted by a residential indoor air sampler, and even more so by either an outdoor air sampler set outside of the residence or ambient air concentration modeled by EPA's Assessment System for Population Exposure Nationwide (ASPEN).

Yet, air pollution risk assessments do not typically or systematically take into account daily activities; residential location is commonly used as a surrogate for exposure to the contaminants. For example recent air pollution health impact assessments conducted in European cities for the WHO and the European Community, in the UK to predict benefits of urban air quality management, or in the US to estimate effects of changing PM standards, have used city-wide ambient concentrations as exposure indicators (Deck et al. 2001; Martuzzi et al. 2002; APHEIS 2004; Mindell and Joffe 2004).

Beginning in the early 80s, however, researchers began to use activity pattern data to characterize exposure (Klepeis et al. 2001); the EPA started developing a national daily activity database for use in exposure studies in the late 90s (McCurdy et al. 2000). The Consolidated Human Activity Database (CHAD) developed by the EPA's National Exposure Research Laboratory is currently used by the agency for risk assessments such as air toxics exposure modeling nationwide. Burke et al. (2001) for instance estimate exposure to PM in Philadelphia using CHAD to weigh the time individuals spend in different microenvironments. Demonstrating the relevance of the use of activity patterns, they found that the median exposure to $PM_{2.5}$ in indoor residential environments is more than 4 times that of outdoor or in-vehicle $PM_{2.5}$ exposure. They do not use the energy expended in each activity, however, in their estimations.

2.3.3 *Traffic-related air pollution health Impacts*

There is an increasing amount of research showing health impacts resulting from exposures to traffic-related air contamination. These studies suggest that exposure specifically to traffic emissions can trigger health impacts that may not be captured in analyses that use city-wide or region-wide ambient concentrations. Several approaches are used to investigate the contribution of traffic emissions to health risks, including epidemiology studies that use different measures of traffic-related pollution exposures, and experimental studies.

One recent study attempted to link traffic pollution to adverse health by investigating opportunities for exposure such as while traveling. Using a case-crossover design to analyze the effect of traffic on nonfatal myocardial infarction, Peters et al. (2004) collected diaries from the hospitalized survivors for the 4 days preceding the infarction in Augsburg, Germany. The authors found that time spent in a car, in public transportation, on a motorcycle or on a bicycle was associated with an increase in risk of myocardial infarction (2.6 odds ratio for being in a car, 3.94 for being on bike). After adjusting for severe exertion, being outside, and getting up in the morning, the odds ratio associated with being on a bike lost its significance at the 95% confidence level; however, the risk associated with overall traffic exposure remained high (odds ratio 2.73, with confidence interval 2.06-3.61). No data on actual pollution concentrations were reported for that study.

A number of studies, mostly in Europe, have used a measure of traffic intensity as a proxy for exposure to traffic-related emissions. After various forms of adjustments, living in proximity to heavy traffic roads compared to living further for instance has been associated with a risk of mortality from stroke in the UK (Maheswaran and Elliott 2003); and with chronic cough, rhinitis, wheeze in children in the Netherlands (van Vliet et al. 1997). However no association was found between the measure and children's hospital admissions for asthma or respiratory illness in North West London (Wilkinson et al. 1999). Traffic exposure indicated by traffic counts at a resident's home was shown to be associated in Munich with cough, current asthma and wheeze in children (Nicolai et al. 2003), and in Basel with increased pollen sensitization in adults, especially for those who lived 10 years in the same residence (but not with hay fever, asthma symptoms and pollen-related rhinitis) (Wyler et al. 2000). In Erie County, NY, children hospitalized for asthma were shown to be more likely to live in proximity of heavy traffic roads compared to controls (Lin et al. 2002). Looking specifically at heavy duty vehicles, Ciccone et al. (1998) observed an increase in risk of recurrent bronchitis, broncholiotis and pneumonia in children living in streets with high frequency of truck traffic in Italian metropolitan areas. In school-based studies in Nottingham, UK, at first a traffic activity index characterizing the school location did not explain very significantly wheeze in children (Venn et al. 2000). However the authors noted that the scale used (1 km^2) may have been too large to detect traffic-related exposure variation, as they showed in a subsequent study in the same area an increase in the risk of wheezing in children living within 90 meters of busy roads compared to living further away (Venn et al. 2001). In a recent study in California, Reynolds et al. (2004) found no evidence of increased risk of cancer for children whose mothers lived in high traffic density areas.

To estimate traffic effects on health, instead of simply using a measure of traffic intensity, some studies actually estimate the air pollution associated with it, often as a function of traffic density and ambient measures. Continuing with cancer effects, in Denmark, Raaschou-Nielsen et al. (2001), using a complex traffic exposure index based on a combination of ambient pollution levels, traffic, and street configuration measures, revealed some evidence of Hodgkin's lymphoma in children for mothers exposed during pregnancy. Crossignani et al. (2004) recently uncovered in northern Italy a significant increase in risk of childhood leukemia associated with the highest exposure to benzene outside the home compared to the lowest, measured by a model based on vehicle emissions information and traffic data.

Nicolai et al.'s (2003) work in Munich mentioned above also used traffic information and monitored data to develop traffic-related air pollution models: cough was found to be associated with soot, benzene, and NO_2; current asthma with soot and benzene; current wheeze with benzene and NO_2. In the Netherlands, Hoek et al. (2002) developed regression models using as independent variables a combination of background and local pollutant estimates and an indicator for living near a major road. They showed a more significant contribution of the proximity to the road than background concentrations in explaining cardiopulmonary and all cause mortality for both the black smoke and NO_2 models (Hoek et al. 2002). In an interesting school-based study in the San Francisco Bay area, Kim et al. (2004) chose an area of good regional air quality but high traffic density to isolate the effect of traffic-related pollution on health outcomes in children. They found that school sites within 300 meters downwind of the freeway had higher levels of black carbon, NOx, NO, and somewhat NO2, than schools further away, and that NOx and NO2 at the more distant schools were similar to monitored levels at the regional sites (less variation was observed for $PM_{2.5}$). In terms of health outcomes, the authors found small but significant increased risk of bronchitis and asthma for children attending schools where higher traffic related pollutants were observed.

The Olympic Games in Atlanta provided a natural experiment setting for analyzing the effect of reduction in vehicle use on health, as great efforts were made to reduce road traffic congestion. Friedman et al. (2001) estimated that during that time, the 22.5% decrease in peak weekday morning traffic counts was accompanied by 27.9% drop in peak daily ozone concentration (81.3ppbto 58.6ppb), and by a range of 11 to 44% decrease in emergency visits for asthma-related care. Regression analyses revealed a significant reduction in asthma events as recorded in the Medicaid database associated with observed decreases in ozone mixing ratio.

Another method to assess health impacts of traffic related exposure is air pollutant source apportionment. It is the method used for example by Laden et al. (2000) in a re-interpretation of the classic US 6 city study, in which they demonstrate that a $10\mu g/m^3$ increase in $PM_{2.5}$ from mobile sources accounts for a 3.4% increase in daily mortality (confidence interval 1.7-5.2), while increase associated with coal combustion is 1.1% (CI 0.3-2).

These epidemiological studies show an effect of traffic-related exposure on health. They are to a certain extent more precise in terms of traffic-related air pollution exposure than epidemiological studies that use ambient city-wide or region-wide concentrations as “blanket” exposures. However they are inconsistent in their methods of assessment of both traffic-related exposures and health endpoints – contributing to their variable results, and making it difficult to generalize for use in a risk assessment study. In addition, none provide combined detailed information on the distribution of pollutant concentration and activity patterns or physical exertion and health outcomes.

Very few epidemiological studies on air pollution have taken into account physical exertion as part of their diagnosis. McConnell et al. (2002) specifically considered physical activity when assessing the effects of air pollution in a prospective study in California. They found a 3.3-fold increase in the risk of developing asthma in exercising children in high ozone areas compared to children not playing sports in the same areas. They also showed a larger effect of high activity compared to low activity, and an independent effect of time spent outdoors in the development of asthma. As the authors note, while the issue may partly be exercise-induced asthma (athletes have been shown to have high asthma rates), the study demonstrates that ozone at least acts as a modifier.

Another attempt to consider activity patterns in pollution exposure is Künzli et al.'s (1997) pilot retrospective study in California on lifetime effect of ozone exposure on lung function. The authors used a convenience sample of 130 college students to compare different approaches of exposure assessment – from a more detailed approach accounting for exercise periods and time spent outdoors, to an ecologic approach that only assigns ambient concentrations at the places of residence. To factor in activity level, the authors simply count the time in moderate and in heavy levels of activity respectively as twice and three times the remaining time spent outdoors. The study showed a significant influence of lifelong exposure to ozone on small-airway airflow, which could be an indicator of pathologic changes that may lead to obstructive lung disease. A stronger and more significant effect was observed when considering lifelong residential exposure rather than exposure at the last residence only, however there were no appreciable differences in effects according to the exposure assessment approach. Nevertheless, the authors conclude that not accounting for activity patterns may still result in misclassification, especially as they show that the variance in exposure estimates according to the approach used increases as ambient concentrations increase.

In both McConnell's and Künzli's study, the physical exertion measures are rather crude, the only pollution concentration accounted for is at the residence location, and the activity is not matched with time or location information.

Overall, although these epidemiological studies show a pattern of adverse health outcomes associated with traffic emissions, they are not sufficiently informative to provide clear dose-response relationships for an assessment that accounts for the variability in both activity patterns and pollution dispersion. Other sources of information, such as experimental studies on exercise and air pollution, must be used to be able to take into consideration inhalation doses as a function of activity level and pollutant concentration.

Daigle et al. (2003) for example conducted chamber experiments in which healthy subjects were exposed to ultrafine particles during sequences of exercise and rest. They have shown that the highest deposition fraction is seen with the smallest particles, and that the deposition fraction increases with exercise in all particle size bins, with a total of 32% increase. They estimate that with a combination of increased minute ventilation and increased deposition fraction, particle number deposition is increased more than 4.5-fold while exercising compared to resting, during a one hour exposure at 25 $\mu g/m^3$ ultrafine particle concentration.

2.3.4 *Air pollution and climate change*

The built environment is in large part responsible for the emission of climate-changing pollutants, from the buildings themselves to the layout of neighborhoods, cities, and regions. Although naturally a single neighborhood-level type of a change will not affect either the local or global climate, in a broader model of the effects of community design, these emissions would have to be considered. Therefore health effects of climate change are summarized here. Risks to human health could arise from (WHO 2002; McMichael et al. 2003): the increased exposures to thermal extremes; increases in weather disasters; changing dynamics of disease vectors; the seasonality and incidence of various food-related and waterborne infections; the yields of agricultural crops; the range of plant and livestock pests and pathogens; the salination of coastal lands and freshwater supplies resulting from rising sea-levels; the climatically related production of photochemical air pollutants, spores and pollens; the risk of conflict over depleted natural resources.

According to the WHO (2002) health affects attributed to climate change in 2000 included 2.4% of diarrhea worldwide, 6% of malaria in some middle-income countries and 7% of dengue fever in some industrialized countries.

2.4 Other health and environmental quality stressors associated with the built environment

2.4.1 *Noise, traffic, congestion*

Vehicles do not only create crash hazards and emit air pollutants, they can also be an important source of noise exposure for residents, especially in large arteries with heavy traffic near residential areas. Noise due to traffic also has detrimental health consequences, it has been shown to cause stress and sleep disturbance, affecting mood, functioning and symptoms such as headaches, and fatigue (Fletcher et al. 1996). In particular, children's exposure to ambient noise due to traffic and railways has been associated with mental health problems, characterized by poor classroom adjustment as rated by teachers, and self reported mental health problems in children with early biological risk (low birth rate and preterm birth) (Lercher et al. 2002).

More generally, Kaplan and Kaplan (2003) postulate in their reasonable person model that "people are more reasonable when their environment supports their basic information needs". They explain that people prefer to acquire relevant information at their own pace to make sense of things, and dislike being confused. An example they give in the transportation realm is how being surrounded by traffic precisely contributes to the confusion that brings mental fatigue in people. They hypothesize that road rage may result from such fatigue. Some research has related congestion with high levels of stress, which in some people results in aggressive behavior while driving (Hennessy and Wiesenthal 1997).

2.4.2 *Open space, green space*

Kaplan and Kaplan (2003) describe how, contrary to the traffic environment, natural environments have a restorative quality, shown in different studies to provide health benefits in settings such as hospitals, prisons and at home. In particular, access to walkable green space was shown to be associated with longevity in older people by Takano et al. (2002). Kuo et al. (1998) found that vegetation in common spaces was associated with neighborhood social ties, and that both were related to a resident's sense of safety and adjustment.

These findings may raise questions then on the appropriateness of urban living, since suburbs are often thought to allow more exposure to trees and open space. However, suburban green spaces are not often walkable, while urban parks may provide the adequate environment. In addition, suburban and sprawl developments precisely encroach on open space. In fact, farmland, forests, wetlands and open space are being lost to urban uses at a faster rate than population growth rates due to low-density dispersed suburban development across the US (U.S. Environmental Protection Agency 2001b).

Furthermore, beyond the loss of open space, land fragmentation due to dispersed development patterns further deteriorate natural habitats, affecting the habitat of more than 95% of species listed under the Endangered Species Act (U.S. Environmental Protection Agency 2001b). This not only puts ecosystems at risk and contributes to the loss of biodiversity, but also can pose a direct health risk when it results in the increase in vectors of disease. Lyme disease for instance has been related to sprawl, due to the greater presence of white footed mice in comparison to other species in fragmented low-diversity habitats (LoGiudice et al. 2003).

2.4.3 *Water quality*

Development options can also affect water quality. Urban development increases the amount of impervious surfaces, essentially from roads, parking pavements, and roof tops. Different development types induce particular impervious surface patterns. Urban centers tend to consist almost strictly of impermeable surface with only urban parks and landscaped areas providing open soil surfaces. Suburban developments on the other hand tend to display a mixture of impervious and soil surfaces. One would expect a compact and well-contained town to consist of a concentration of impervious surfaces in the center, with only little beyond the urban boundaries. Conversely, a low-density dispersed development might extend its impermeable surfaces further, and have soil surfaces throughout. Therefore while compact developments might have a higher density of impervious surfaces in a contained area, sprawl would generally bring about a higher amount of impervious surfaces per capita.

An increase in impervious surfaces is a concern for water resources because it reduces the land's ability to filter water, causes increased siltation and causes polluted runoff into water bodies. Pavement on roads and parking lots collect pathogens, metals, sediments, chemical pollutants and transmit them to water bodies. Gaffield et al. (2003) describe the routes by which stormwater runoff might pose human health risks. In particular vehicle exhausts are an important source of nitrogen in water bodies and of deleterious concentrations of polyaromatic hydrocarbons in urban lake sediments. Nitrogen exacerbates algal bloom as well as poses a direct risk to health due to nitrate concentrations. Polyaromatic hydrocarbons are known carcinogens and disrupt aquatic ecosystems. Runoff from urban and suburban areas is thought to be in large part responsible for the transmissions of parasites such as Giardia and Cryptosporidium in water supplies, causing waterborne diseases such as gastrointestinal illnesses. Bacteria and parasites also make their way to recreational water bodies and expose swimmers to risks of ear and eye discharges, skin rashes and gastrointestinal problems. Algal bloom can generate marine biotoxins, which can contaminate seafood along with viruses, leading to diarrheal and paralytic disease. Furthermore, drinking water treatment with substances such as chlorine and ozone can in turn create unhealthy by-products. Gaffield et al. report that the EPA estimates 1100 to 9300 cases of bladder cancer each year caused by disinfection byproducts, as well as neural tube defects, spontaneous abortion and small size for gestational age.

Bhaduri et al. (2000) calculated that in Indianapolis, Indiana, an 18% increase in urban area was responsible for an 80% increase in annual average runoff and 50% increase in average annual loads for lead, copper and zinc. The EPA (2001b) estimates the runoff from a parking lot to be 16 times higher than that of an undeveloped meadow. As Gaffield et al. (2003) describe, the total impervious surface area of low-density developments is generally much larger than that of high density development, more than 60% of which are due to roads and parking lots. They point out that even lawns in such developments can act as impervious surfaces, generating as much as 90% as much runoff as pavement, because they are typically compacted by construction equipment.

Gaffield et al. conclude that a compact development (narrow streets, reduced parking, mixed land use, increased density and open space) with significant open space can reduce by a half the amount of stormwater runoff that a conventional development would produce.

Gaffield et al. also report that low-density construction can lead to up to 40 000 times higher erosion rates than before the soil was disturbed, because of the destruction of the protective vegetative cover. The resulting accumulated sediments can hold large amounts of bacteria and other pathogens. The authors also note that as impervious surfaces reduce the land's natural ability of filtering water down to groundwater, groundwater supply is reduced, possibly leading to increased health risks due to increased arsenic concentration. In addition, paved areas and compacted earth result in the land becoming more prone to flooding. Similarly, the impervious surfaces can create pools of stormwater, which then act as breeding grounds for mosquitoes, which apart from being a nuisance, are also vectors of diseases such as West Nile Virus, Dengue fever and Malaria.

Although this discussion may not be entirely relevant for a neighborhood-level re-development, it can be clearly seen that at a wider scale development choices may have important consequences on human and ecosystem health.

2.5 Societal Impacts

2.5.1 *Social activity and democracy*

The section on social capital has already alluded to the built environment influencing the amount of social interaction that occurs in neighborhoods. Social capital is not only a direct determinant of personal health, but also impacts health indirectly through its effects on the ways society functions. Jane Jacobs (1961) linked the ability of people to engage spontaneously in conversations in the street setting to building trust and respect for each other. Langdon (1994) suggests that when people have public gathering spaces they get together and discuss problems within the community, exchange ideas, and find solutions together. It thus enables people to handle concerns without the involvement of government, giving power to individuals to influence the conditions they live in.

Not only can an unfriendly built environment hinder this type of encounter amongst neighbors, but also auto-oriented developments can increase the amount of time spent driving, thus reducing the time to interact with others. Polzin and Chu (2003) calculate that the amount of time spent driving in the US has risen steadily at a rate of 2 minutes per year in the past 20 years, to reach 78.5 minutes per day per person in 2001. According to Putnam (2000), each additional 10 minutes in daily commuting time cuts the involvement in community affairs and informal social interaction by 10% each for both the commuter and the high-commute community as a whole (Putnam 2000, pg 213).

Some thinkers have linked neighborhood interactions to the democratic process. Dewey (1927) for example believed that face-to-face contact and dialogue with neighbors and family were essential for people to develop an understanding of the world and test ideas, leading to a greater social intelligence.

2.5.2 *Inequities*

The built environment can also create, and in most cases perpetuate, social inequities in our society. Mobility, injuries, illnesses, and access to resources affect some populations more than others.

In auto-oriented environments, people who do not or cannot drive have reduced mobility compared to others. The disproportionately affected by this problem are children, the elderly, the disabled, and low-income people. Children are driven by adults to places for 70% of their trips (Pucher and Renne 2003). In particular, in the past 30 years, proportion of children walking or biking to school has dropped from 48 to 15%. (US Environmental Protection Agency 2003b). This type of dependence not only hinders the ability of children to participate in some activities, it also puts a strain in their parents' lives, and results in much time spent inside vehicles. In addition, some authors suggest it may affect children's development, as they are not able to go on their own to safely explore the world and develop the knowledge and skills necessary to adapt as they grow up (Frumkin et al. 2004). The elderly also see their activity participation limited in auto-oriented environment when they stop driving, affecting more than 1 in 5 adults over 65 in the US (Surface Transportation Policy Project (STPP) 2004). Foley et al. (2002) estimate that on average, drivers aged 70 to 74 will be dependent on alternative sources of transportation for 7 (females) to 10 years (males). According to the Department of Transportation, half a million people in the US are homebound because they cannot get the transportation they need (US Department of Transportation 2003). Low income people also get particularly affected by transportation issues. In the US, 26.5 person of households earning less than $20 000 do not own a vehicle (Pucher and Renne 2003), which becomes a problem in car-dependent environments for people who cannot even access jobs or other needed places of activity.

Possibly due to lower auto-ownership rates and a higher reliance on feet as a means of transportation, or because of poor walking conditions in certain neighborhoods, African

Americans are disproportionately affected by traffic injuries. While representing only 12% of the US population, African Americans are the victims of more than 20% of pedestrian deaths (STPP 2002). African Americans also have higher exposure to contaminants, such as traffic exposure in California (Gunier et al. 2003), perhaps explaining their three-fold higher rate of death from asthma compared to white Americans (US Environmental Protection Agency 2003a)

Poorer communities suffer from disinvestments, compounded by planning policies that increase fragmentation and marginalize the impoverished communities, leading to the deterioration of social ties and at times housing loss (Wallace and Wallace 1997; Duhl and Sanchez 1999). In particular, low income communities and low income communities of color have less access to parks, recreational facilities, well-funded schools and playground structures, possibly contributing to disparities in physical activity rates (PolicyLink 2002).

On a more global scale of inequities, the adverse effects of climate change are likely to be felt more strongly in countries with scarce resources and inadequate technology, infrastructure and institutions to adapt to the changes (WHO 2002; McMichael et al. 2003).

Disparities in our society may lead to social unrest and lack of respect and trust within society. These constitute important health determinants, not only because of the risk of violent retributions and costs associated with it, but also because of coping mechanisms and stress levels that may result from it. For example John Henryism, or high effort coping of psychological – especially racially-based - stressors has been linked to hypertension in African Americans (Geronimus and Thompson 2004).

2.5.3 *Economic issues*

The built environment choices impose costs to society, both at an individual level and collectively. Individual costs include for example the individual costs of auto use, which are difficult to avoid in auto-oriented communities. The American Automobile Association estimated an average mid-sized car cost 24.6 cents a mile to own and operate in 1991. Congestion bears a cost in terms of time loss and fuel waste, appraised at $62 billion in 85 urban areas in the US in 2002 by the Texas Transportation Institute (Schrank and Lomax 2004). There are also both collective and individual costs resulting from health care needs associated with inactivity and with air pollution. The cost of asthma alone was estimated at $14 billion a year by the American Lung Association (2004). Finkelstein et al. (2004) calculated that in 2003 in the US, obesity-attributable medical expenditures amounted to $75 billion, including $17 billion financed by Medicare, $21 billion by Medicaid. This sum represented about 6% of total adult health expenditures. The authors suggest that if a tax were to be allocated to cover theses costs it would have be set at about $350 per person (half if only Medicare and Medicaid expenditures were financed). Other costs include environmental damage caused by air and water contamination, and perhaps also the cost of oil dependence.

These figures are important not only because of the burden imposed on society in terms of expenditure, but also because of opportunity costs. Money spent on those issues may not be spent in other sectors such as health care and prevention programs.

As we have seen, the good functioning of society is another important impact of the built environment choices. A healthy society in terms of respect, trust, peaceful understanding of each other, and democratic process, has important health consequences. Direct health impacts include possible violence and psychological stressors associated with social unrest. The democratic process may affect health care and prevention choices and spending priorities that lead to these choices.

3 CONCEPTUAL FRAMEWORK

The literature review covered the issue of how to design humane and healthy communities. The links between the built environment, behaviors, environmental quality and health schematized in figure 1.1 were overviewed to provide the broad context within which pedestrian-oriented environment policies fit, with their far-reaching impacts on human health. Within this comprehensive framework however, the issues proposed to be addressed computationally in this dissertation are limited to the ones that lead to competing health impacts: active travel and exposures to air pollution. Although this dissertation ends at the assessment of physical activity rates and exposures to ozone and PM_{10}, the model is built with the aim of an application to eventually (in future research) estimate the competing health impacts of outdoor physical activity, exposure to air pollution, and traffic hazards. The conceptual framework for the model is therefore presented including these final outcomes, to state clearly the general goal of this dissertation work and preparation for follow-up work. These outcomes are also possibly those that have most contributed in the interest in building pedestrian-friendly design. The other impacts of the built environment such as social cohesion, democracy, healthy nutrition, or crime control, are important to keep in mind because they are part of the overall rationale in the current movement that supports built environmental policies to improve pedestrian-friendliness. However, operationalizing these relationships in the computational model may introduce a level of complexity and uncertainty which may interfere with the more primary goal for this computational application of assessing the competing health risk factors of the built environmental changes. Other restriction proposed for this assessment is to limit the study population to adults, and air pollutants to ozone and particulate matter less than 10 microns, to make the work more manageable. The addition of air toxics such as benzene and acrolein would be particularly relevant in future work however, as they are associated with automobile emissions. The aim of the computational part of this work is thus to study the effects of changes in the built environment at the street and neighborhood level, on adults' physical activity behavior and air pollution exposure levels, with the future aim of assessing health impacts associated with these hazardous exposures and healthy activity behaviors.

The literature reviewed in the previous chapter justifies the need for such analysis, as it showed that indeed, the built environment, through its effect on behavior, impacts human health in both an adverse and a beneficial way. It also showed that a detrimental change in exposures due to changes in the built environment is dependent on personal activities and street-level exposures, warranting a detailed assessment. The research reviewed for this work has uncovered no such comprehensive risk assessment - or rigorous and detailed health impact assessment - of a neighborhood built environment undertaken in the US as of yet.

There are three methodological components to the proposed analysis: 1) establish the conceptual framework for the analysis, then 2) build the computational model, describing the links between different aspects of the built environment and exposure and/or health endpoints, and 3) apply the model to scenarios of change in a case study area. The overall goal is to construct and apply a suite of methodologies needed to understand the net health benefit or decrement resulting from changes in travel mode and physical activity.

3.1 General approach

The analytical framework proposed for this dissertation is depicted in Figure 3.1. Activity patterns, namely transportation choices and physical activity, are first projected to change as a consequence of built environment scenarios. The daily activities then lead on the one hand to exposures to air pollution and traffic crashes producing adverse health effects, and on the other to increased healthy active behaviors. These two health impacts combined result in a net health effect estimated as the final outcome of the analysis. To reiterate, while the full conceptual model is presented here for clarity of purpose, the computation model for this dissertation ends at quantifying energy expenditures and exposures to air pollution (in terms of inhaled pollutant dose).

The links schematized in Figure 3.1 are explained theoretically or empirically (or both) in the literature in different disciplines. The first part of this research is to abstract the relevant constructs and findings from the literature in different fields to develop these relationships. While some of them are rather straightforward, others, especially the ones dealing with human behavior, can be rationalized or partly explained through different reasonings. A major challenge is to determine how to apply the constructs of one field to phenomena observed in another, especially in the computational application. An example of this could be using design and health behavior theories to explain daily choices of transportation modes. A question raised by this task is whether the same phenomenon described in different disciplines can be equated or whether issues of scale or interpretation hinder any valid comparison. Other issues include how to synthesize and perhaps prioritize different constructs, and identify missing links. A suite of models that interpret the theoretical constructs and link specifically descriptions of the built environment to behaviors and to health effects is thus constructed here. These relationships then inform the computational part of the risk assessment, discussed in Section 3.2.

3.2 Suite of models

Each numbered arrow in Figure 3-1 is described by a more specific model, schematized in Figures 3-2 to 3-7, and explained in this section. The arrows in dashed lines represent the parts of this model that will remain conceptual for this dissertation, while the others are operationalized in a computational model described in the next chapter.

To increase the readability and the usefulness of the models, each of the interconnections are simplified to characterize only certain aspects of the phenomena. Indeed, the literature review has revealed how daunting it would be to describe in a single model the full gamut of relationships between the myriads of indicators of the environment, behavior, or health, that have either been observed or theorized. Consequently, the suite of models explained below display the relationships most relevant to the task at hand (assessing competing risks involved with the community design), and a list of indicators that have most prominently been used and proven to be significant in explaining the phenomena of interest.

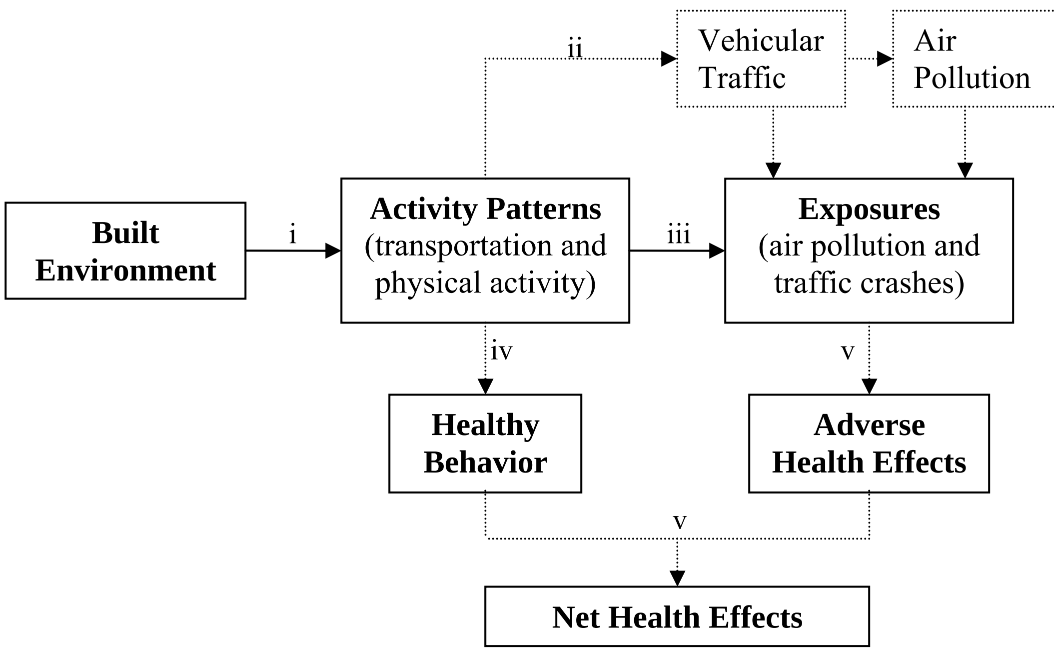

Figure 3-1 Conceptual Model for Assessment of Competing Risks Associated with Creating a more Pedestrian-Friendly Built Environment

3.2.1 *Built environment – activity patterns model*

The first arrow (i) of the model in figure 3-1 characterizes the behavioral component of our framework, linking the built environment to activity patterns. Figure 3-2. displays a more detailed model of this relationship. In this conceptualization, the density and mix of land uses such as residences, commerce, shopping, and restaurants, determine where an individual will undertake activities throughout the day, given a pre-determined activity pattern. This represents a simplification in that in actuality the availability of, and destination to, different locations may influence the activity pattern itself. That withstanding, the relationship holds that one is more likely to choose a location that is closer to the origin of the trip or to the home location compared to other locations, and a location that has a high amount of the sought good or service compared to other locations. In other words there is an inverse relationship between distance to a location and probability of choosing that location, and a direct relationship between the density of the entity representing the purpose of the trip (such as number of employees for employment, or number of shops for shopping trips) and the choice of location.

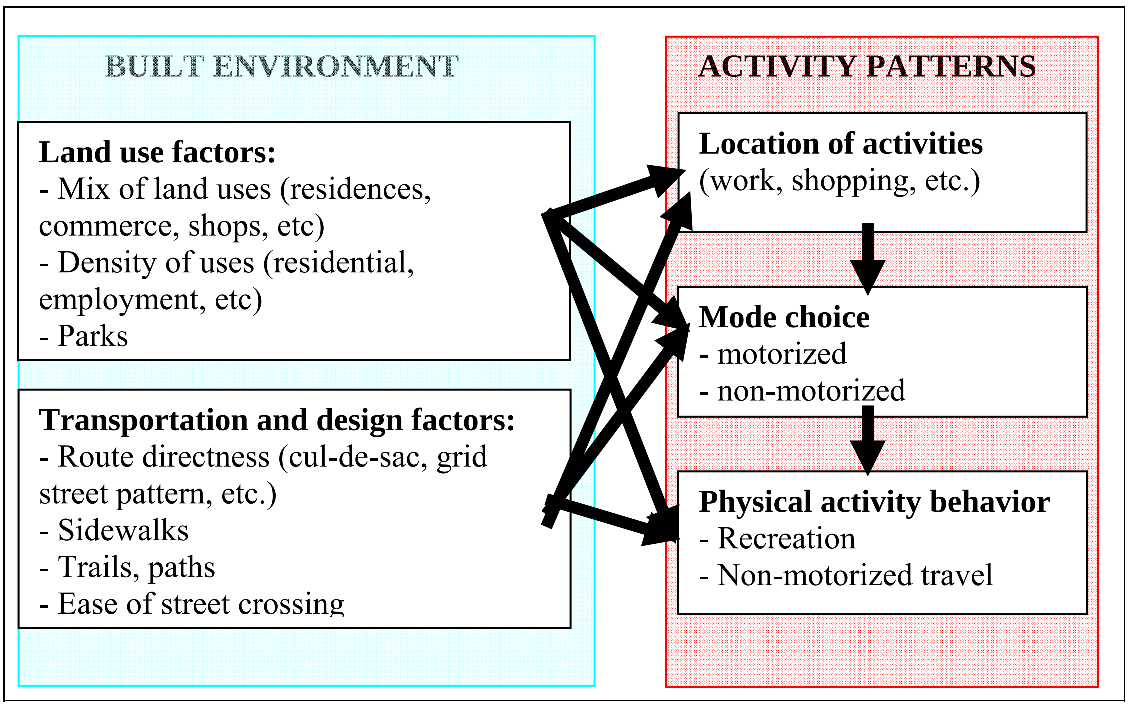

Figure 3-2 Built environment – activity patterns model

An other conceptual approach to link the built environment to activity patterns could be in the vein of activity based models which account for opportunities and constraints afforded by the physical infrastructure to predict simultaneously which activities are undertaken, in what order, where, at what time, and with what travel mode. These models are developed using local samples and applying principles of utility maximization or decision heuristics. A review of such models can be found for example in Veldhuisen et al. (2000).

In terms of mode choice, theoretical and empirical research holds that the more direct the route is, the more sidewalks, trails and paths there are, and the safer the street crossings are, the more likely one is to walk or bike rather than used motorized vehicles. Again, this is a reduction of the complexity of the phenomena, and these elements have not consistently been found to be as significant as other features of the built environment. However, all indicators of the built environment are simplifications of the reality, with certain factors masking or acting as a surrogate for others – for instance a gridded street pattern with sidewalks may in fact denote a pre-world war II traditional neighborhood, implying other determinants of behavior such as interesting diverse architecture and tree coverage. The choice of indicators for a quantitative application will necessarily depend not only on their common presence in non-motorized travel behavior research, but also on their relative simplicity for data collection and policy implementation.

In addition to travel-related physical activity behavior (‘active travel’), the built environment may also increase leisure time physical activity (‘active recreation’). The presence of opportunities for outdoor leisure activity such as parks, trails, paths, and also neighborhood streets with sidewalks, increase the likelihood of recreational physical activity.

In both cases of active leisure or active travel, the literature reveals much more abundant evidence of a “static” (cross-sectional) effect of the built environment on behavior than on the potential changes in individual behavior following neighborhood transformations. However, since in both fields the little longitudinal or quasi-experimental type of studies do tend to indicate a potential change in physical activity bheavior, this assumption is adopted in this research. The uncertainty associated with this step, however, must be noted.

Socio-demographics and other personal factors are also shown to influence activity patterns and mode choice. Hence the chosen approach must match local population composition to characteristics of individuals in the activity database (or other source of activity data) such as gender, age, or income, to moderate; these factors may then be used as moderators of the built environment effect on travel choices. An important consideration for the particular interest in non-motorized transportation is the health status of individuals. Indeed, it is possible that individuals with compromised health would be less likely to walk or bike to go places. Conversely, active travel behavior is likely to be more beneficial to individuals with certain health ailments, such obesity, diabetes, and cardio-vascular conditions. Therefore including such circumstances in the model would be extremely relevant for the scope of this work. However, the availability of data linking health status, activity patterns, travel mode choice, and the built environment effect on activities is poor to inexistent. Moreover, predicting changes in behaviors as a result of changes in the built environment is a difficult proposition to begin with, and it becomes prohibitively uncertain when considering specific populations such as sedentary, diabetic, or obese people.

3.2.2 *Activity patterns – vehicular traffic and air pollution model*

The scale of the built environment considered matters in how the resulting activity patterns are conceived to affect vehicular traffic and air pollution. Regional land use patterns and transportation networks drive the background regional air pollution field resulting from vehicle emissions, which in most cases is the greatest contributor to local air pollution. A rather microscale level of analysis is the focus of this work on pedestrian-friendly design, hence changes at the neighborhood level are considered more closely, particularly regarding the potential for changes in emissions and the spatial distribution of air pollution. This model is summarized in Figure 3.3.

Ideally, the computational approach would account for activity pattern choices and travel mode choice to determine traffic flow on specific routes at all times of the day. Veldhuisen et al. (Veldhuisen et al. 2000; Veldhuisen et al. 2005) for example use an iterative approach to estimate congestion levels and travel speeds as a function of road capacity, activity patterns, activity location and mode choices. These traffic flow predictions could then be used as inputs in an emissions model such as EPA's MOBILE6 (U.S. Environmental Protection Agency 2003), which in turn feeds into air quality models. This is very involved computationally however, as it requires modeling activities of the entire population in the region.

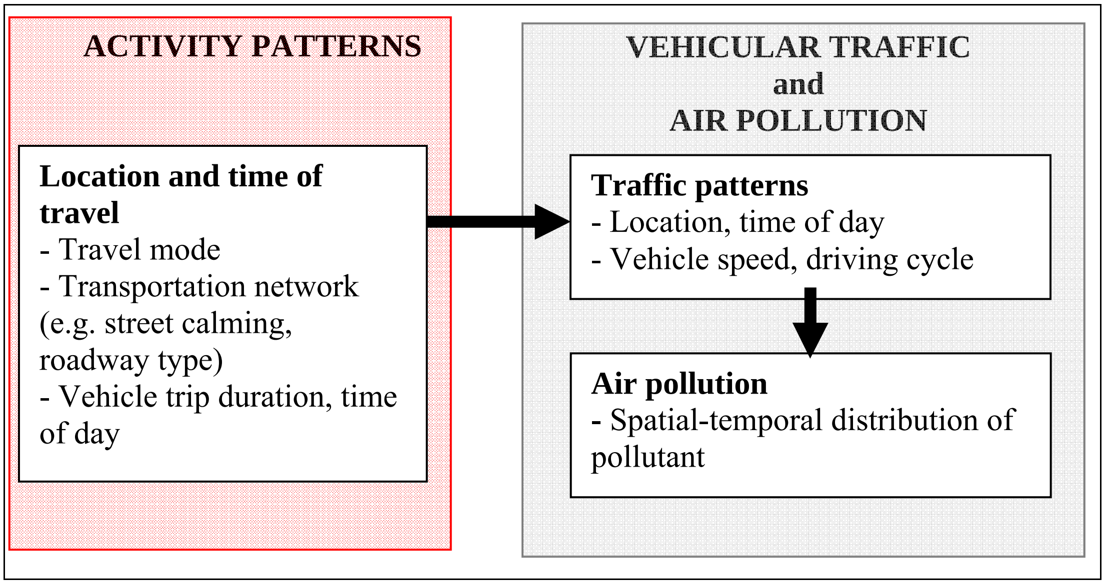

Figure 3-3 Activity patterns – vehicular traffic and air pollution model

Another approach is to use existing data on air pollution fields in the region, and estimate potential changes in vehicle emissions as a result of changes in location and travel mode choices. For example, an analysis undertaken by the author of this dissertation for a Master's thesis (de Nazelle 2001) estimated reductions in vehicle emissions that could be expected from the conversion of short auto trips to non-motorized modes, accounting for engine start and running modes. The upper bound scenario of feasible mode shift produced approximately 2% reductions in VOC and CO emissions, and 1% reduction in NOx. Changes in the built environment as conceived in this framework may have the double impact of converting short car trips to walking and cycling, but also to reduce trip length, thus increasing the potential for non-motorized modes. Moreover, reducing auto trip lengths also has the impact of lowering vehicle emissions, despite the disproportional contribution of short trips due to engine starts (and hot soaks).

On the other hand, certain microscale design features typically used to enhance the pedestrian experience by reducing vehicle speed or discouraging vehicular traffic may have a "backlash" effect of increasing emissions. Indeed, as shown in the literature review, engineering treatments such as bulbouts, 4-way stop signs, or speed humps may result in increased emissions due to stop-and-go driving cycles.

Another element important to conceptualize in this framework is air pollution dispersion. The previous chapter revealed that certain pollutants such as nitrogen oxides and particulate matter have been found to have higher concentration by heavy traffic roadways than away from the road. Therefore the type of road with regards to speed and traffic intensity will affect microscale air pollution concentrations, and proximity to different roadway types will affect exposures. Approaches to model this dispersion include using line-dispersion models which account specifically for traffic intensity in their prediction of pollutant concentrations along roadways, or to update regional air pollution fields with factors of proximity to roads. These approaches are discussed in the computational model chapter.

3.2.3 *Activity patterns-exposures model*

Figure 3-4 schematizes the activity patterns – exposure model, which is the third (iii) arrow of the general conceptual model in Figure 3-1. The two main exposures conceptualized in this model are traffic hazard and air pollution exposures due to traveling or active recreation. Other hazards such as exposure to crime or noise could also be logically considered here, but are not for the sake of simplicity.

The traffic hazard exposure is dependent on the mode and duration of travel, the duration of in-street physical activity (if present), on traffic intensity at the time and location of the outdoor activity, and on features of pedestrian safety such as ease of street crossing.

Air pollution exposure first depends on the concomitant spatial temporal distribution of the pollutants and of an individual's activity pattern. In particular, the pollutant concentrations may be higher in proximity to busy streets. Secondly, a higher inhalation rate due to higher physical exertion leads to a greater exposure, for a constant pollutant concentration. In all, the total pollutant dose inhaled is the product of the inhalation rate (activity energy expenditure), the activity duration, and the concentration at the time and place of the activity.

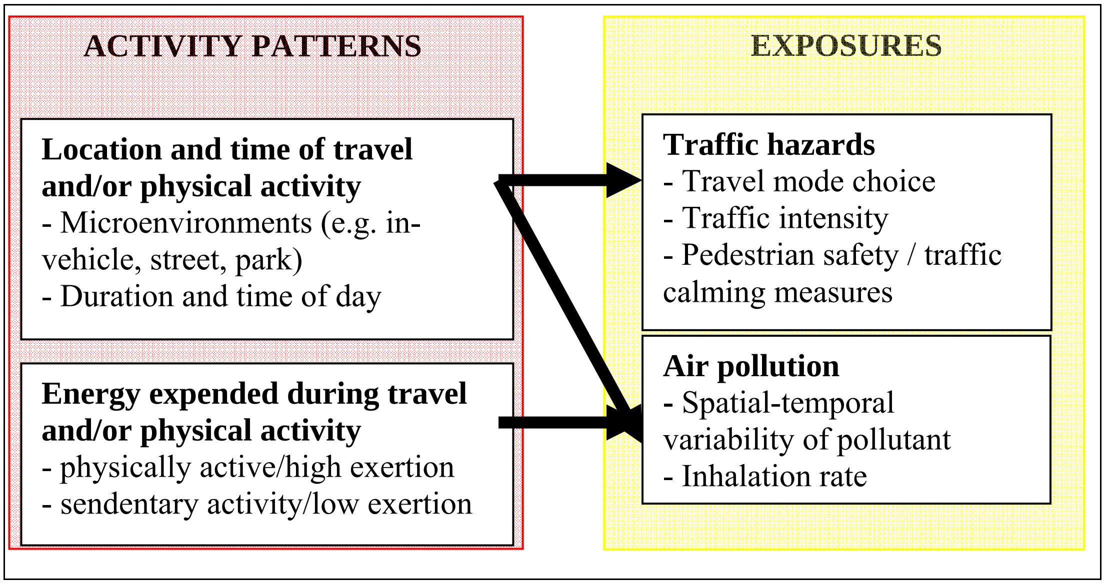

Figure 3-4 Activity patterns - exposures model

3.2.4 *Activity pattern– healthy behavior model*

Physical activity, whether through active travel or recreational activity, is associated with a variety of health endpoints. These are not estimated in the computational application of this work, but are discussed briefly here for the sake of clarity of the overall picture the model fits in. The health outcomes of physical inactivity behavior shown in Figure 3-5. are those found to have the strongest dose-response relationship or highest prevalence. The Surgeon General Report on physical activity (U.S. Department of Health and Human Services 1996) report in particular dose response relationships for reduction in risk of coronary heart disease (CHD) mortality and non-insulin-dependent diabetes mellitus (or type II diabetes). Cardiovascular disease (CVD, includes both CHD and stroke) and CHD incidence are reported elsewhere to have clear dose-response curves. The dose response functions may be a function of absolute energy expenditure levels, or may be in terms of increases from different baseline activity level. The general consensus is that increases in physical activity are more beneficial at the lower end of the energy expenditure spectrum in the population. In addition to having dissimilar impacts according to baseline activity status, the magnitude of benefits may vary for individuals of different ages or with different health status, such as cardiac patients. Therefore the most desirable modeling approach would categorize individuals into baseline activity groups (e.g. sedentary, low activity, recommended activity) and health status before estimating health effects of possible relative increases in physical exertion following changes in behavior.

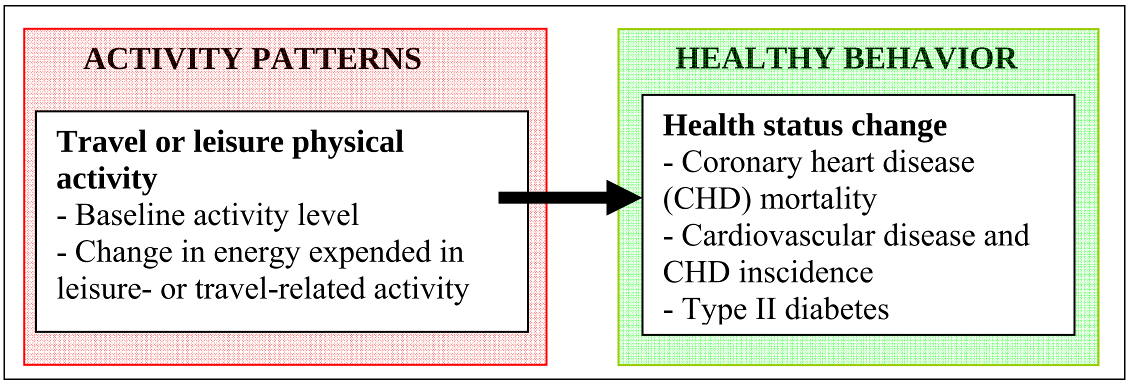

Figure 3-5 Activity patterns – healthy behavior model

3.2.5 *Exposures – adverse health effects model*

Figure 3-6 summarizes the effects of traffic and air pollution exposures on health used in the built environment model. The probability of either injury or death from a traffic crash depends on mode choice and traveling conditions. Driving, walking and biking bear respectively increasing risks of death or injury from traffic crashes per mile of travel. In addition, the more vehicular traffic, the higher the vehicle speeds, and the less safe the street crossing, the greater the risks of walking or cycling compared to driving. Research has also shown that greater numbers of pedestrians and cyclists in the street increases safety for these modes. Quantification of these relationships are however hampered by the limited research in this area.

Air pollution health outcomes depend on the pollutants chosen, and the type of exposure considered – either short term, or long term (repeated or prolonged) exposures. Functional and symptomatic responses may result from short term exposure to ozone, such as change in forced expiratory volume in 1 second (FEV_1) for the former, and wheeze and cough for the latter. Long term exposure to ozone may trigger effects such as lung dysfunction and lung cell injury and inflammation. Both short and long term exposure to PM may result in cardiovascular and respiratory mortality and morbidity (hospital visit, development of chronic respiratory disease, reduced lung function growth). As for exercise benefits, air pollution exposure has varying effects on healthy people and those with impaired respiratory systems, which could be accounted for in a computational model.

The greatest challenge in quantifying a change in air pollution-related health effect due to a change in active living behavior may be finding studies that use similar scales of exposure assessment. Indeed, the scale of analysis used in studies that measure air pollution health effects does not generally match with the scale used for this assessment, which is a further reason why the present assessment focuses on measures of exposure and not health outcomes.

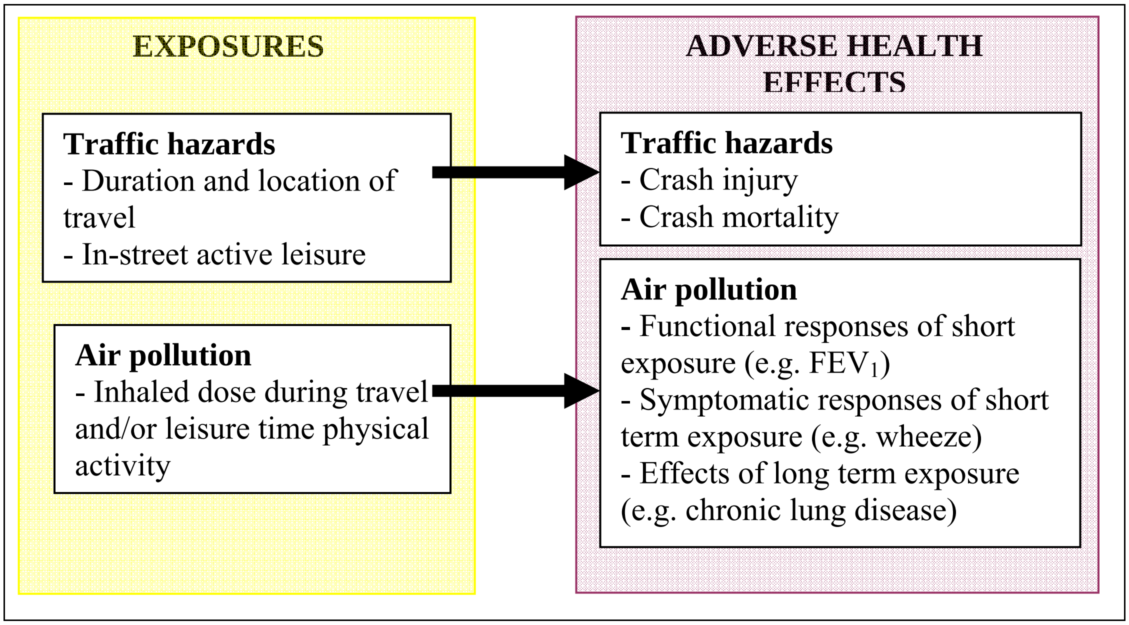

Figure 3-6 Exposures – adverse health effects model

For air toxics, the EPA developed the Integrated Risk Information System (IRIS) to allow an analysis at any level of temporal resolution of exposure assessment. The database details quantitative information such as inhalation reference concentrations for chronic noncarcinogenic health effects, and hazard identification and inhalation unit risks for carcinogenic effects, as well as the quality of the evidence, assumptions made, and uncertainty factors used, to reach consensus on the toxic's potency. The information provided by IRIS, combined with the knowledge provided by a detailed exposure assessment on energy expenditure for each activity and body mass index, allow the derivation of a precise measure of the inhalation dose.

Such consensus information, however, is not available for all pollutants. Epidemiological studies, such as those reviewed in this document, are often used as the basis for assessing health risks, because observed and quantified relationships between exposure or behavior and outcome can be both practical and powerful. As evidenced in the literature review, many use fixed locations (most generally the residence, but at times schools or workplace) as a surrogate for exposures, and assume concentrations and inhalation doses to be homogeneous throughout the city or the region and the population. This not only may result in exposure misclassification, especially for local sources of pollutants with small-scale variations and for populations with variable activity rates, but also hinders applications for higher resolution assessments.

Toxicology and human experiment studies, on the other hand, provide precise information; however they are based on small sample size, which limits their generalizability to other populations. In addition, in the case of human studies exposures are naturally related to intermediary outcomes of health such as changes in FEV rather than to morbidity and mortality outcomes which are more useful for assessing impacts on quality-adjusted years of life. There are therefore tradeoffs to be measured between uncertainty that follows from extrapolating results from epidemiological studies with imprecise exposure classifications, or from generalizing results from small sample size toxicology studies or from animal studies, and from resolving to quantifying intermediary outcomes.

It is likely that the greatest uncertainty stemming from a model linking the built environment and health would stem from linking the precise air pollutant inhalation dose to its health effects. ***It is in part due to the fact that these health relationships carry so much uncertainty that this dissertation will end at the exposure level.***

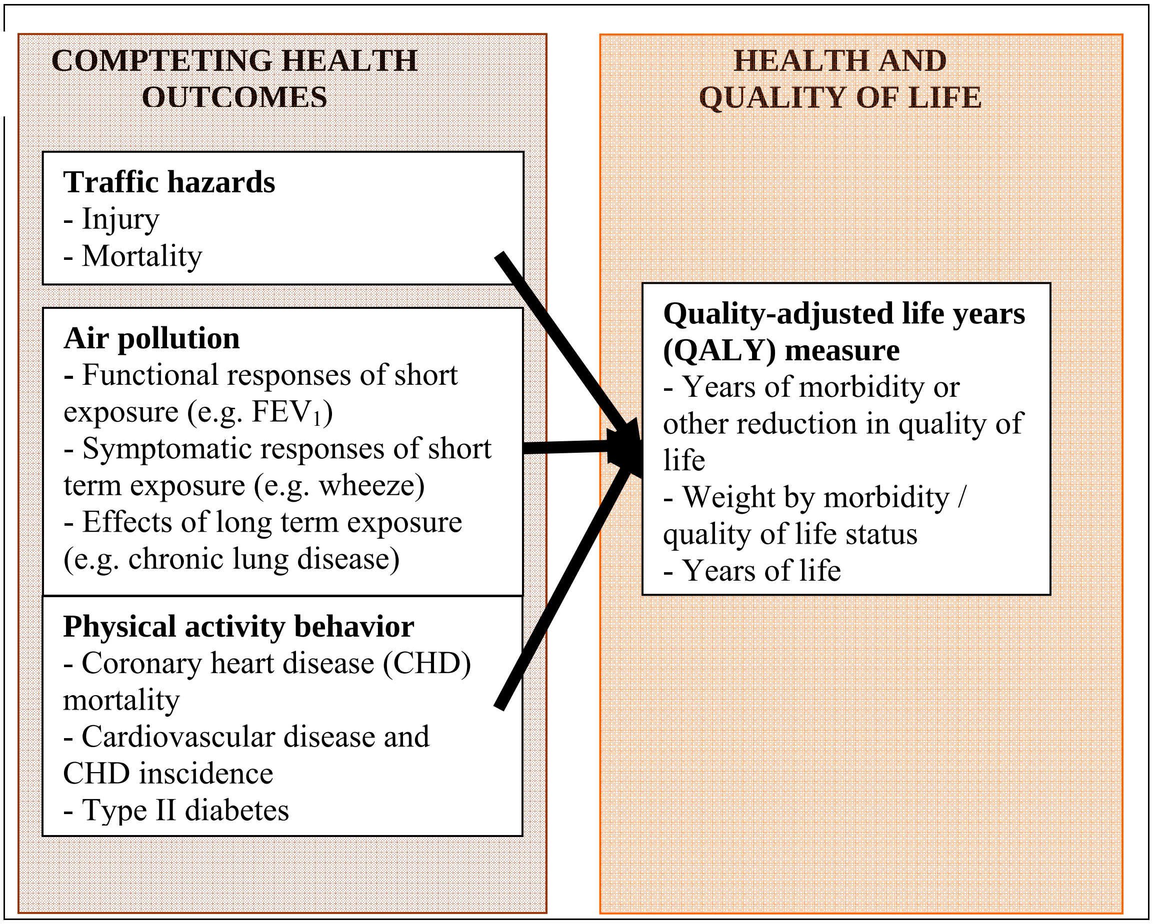

Figure 3-7 Competing health outcomes – health and quality of life measure model

3.2.6 *Competing health effects – net health effects*

To be able to compare different health endpoints, a single measure of health and quality of life needs to be developed. The individual lifelines must be projected into the future, and associated probability of death, injury, disease, or discomfort estimated for each year. Each health outcome must be assigned a weight so that a year of life with that particular ailment is equivalent to a percentage of that life year. The overall health and quality of life measure for each individual is then equal to the sum of these weighted life years. Figure 3-7 summarizes this process for the built environment conceptual model.

A theoretical discussion on approaches to weigh competing risks is necessary for this step of the analysis. Indeed, value judgments are required to determine who is to decide and how one is to process information to create a platform of comparable risks. One possible approach is to apply individual preferences using existing studies of stated preferences of disease or mortality of equi-probable risks but dissimilar cause. Revealed preferences could also be estimated by studying willingness to accept risks or willingness to pay to prevent risks in a population, assuming rational decision making. Another method could be to estimate costs to society associated with each incurring risk. Graham and Wiener (1995) suggest that relevant factors for weighing risk vs. risk include magnitude (probability of risk), degree of population exposure, certainty, type of adverse outcome, distribution and timing. These factors will have to be examined and discussed in future work applying this dissertation's computational model to net health impact analysis. In particular, points of investigation could be the disproportionate distribution of risk in the population; the uncertainty associated with each risk estimate; the use of discount rates to account for latency periods of disease and mortality and for values associated with different types of adverse outcomes. This area of research carries much uncertainty, as in health impact estimates but with added value judgments.

3.3 Conceptual model discussion

This chapter presented a conceptual approach to model competing health impacts associated with neighborhood transformations. Throughout the text, different conceptual or computational challenges for linking different parts were noted. The level of complexity involved in different steps and proposed simplifications were higlighted. The uncertainty carried through the entire model perhaps makes an assessment of actual net health impact too uncertain given the state of knowledge today to be useful for policy purposes. To reduce this uncertainty and complexity and produce results that may be reliable enough to have a policy relevance, the choice is made in this report to focus the computational analysis on linking the built environment to active travel energy expenditure and air pollution inhalation intake for healthy adults. The model has been constructed, however, to incorporate health impacts assessements at a later date as dose-response models improve.

4 THE BUILT ENVIRONMENT STOCHASTIC SPATIAL TEMPORAL EXPOSURE (BESSTE) MODEL

The goal of the Built Environment Stochastic Spatial Temporal Exposure (BESSTE) model developed for this research, is to assess quantitatively the hazardous exposure and physical activity changes resulting from an improvement in the built environment to make it more pedestrian-friendly, by simulating the daily activities of the population in a case study area where a change in the community design is hypothesized. This work is developed with the aim of assessing possible disparate health impacts of community designs. The purpose of the computational model is thus to aid decision making in communities wishing to implement urban design policies to increase physical activity and non-motorized transport. The BESSTE model allows decision-makers to begin assessing the potential competing health effects of the built environment change, and thus perhaps revise the policies for more optimal solutions. The decision framework developed for this purpose is presented next in section 4.1.

The premises guiding the computational model follow the literature reviewed in the previous sections and the suite of conceptual models depicted in Figures 3-1 to 3-7. This chapter report the type of data used for the analysis (4.2.1), the numerical functions developed to characterize the different relationships (4.2.2.), and the simulation methodology and sensitivity analyises (4.2.3).

The overall simulation structure of BESSTE is built around an exposure model inspired by the EPA's Hazardous Air Pollutant Exposure Model (HAPEM) (Johnson 1995). The BESSTE model describes the probability of a resident's activity patterns and exposures throughout the day, which can be used in estimating resulting health outcomes, and simulates these probabilities to represent the population in the study area. The simulation model is programmed in Matlab, with some functions drawn from BMElib, and input data manipulations performed in ArcGIS and Python. The model is implemented in Orange County, North Carolina, with a focus on the towns of Chapel Hill and Carrboro.

4.1 Decision framework and risk metrics

As stated in the introductory chapter, the computational model is evaluated within the context of a decision framework, which consists of three possible routes of action: 1) risk results mandate action to reduce risk; 2) risks deemed acceptable and benefits clearly outweigh risks, and 3) more analysis is required to inform decision-making for immediate action.

To support the decision framework, metrics and criteria for judgment are elaborated. The metrics reflect measures of factors of risk and benefit for specific population targets temporal patterns of activity and exposure. The criteria for judgment concern the level of acceptability of risk and sufficiency of benefit. Both are described in this section.

The choice of metrics applied in this work is guided by the desire to assess the competing risks and benefits associated with physical exertion in a changing urban environment. To characterize exposure to air pollution while accounting for energy expenditure, the outcome measured for an individual is the inhalation dose of the modeled air pollutants, PM_{10} and ozone. A measure of daily inhalation dose is developed, to allow a real evaluation of the effects of the choice of mode on overall inhalation dose. Indeed, not only are the relative contribution of travel times interesting for the analysis, but also because changes in transportation modes and activity location choices impacts the duration of the activity, a measure of inhalation dose outside of the travel activity (a form of "opportunity inhalation") is necessary to compare overall effects[22]. For

[22] Note that duration differences between activity diaries and modeled travel times are taken or added to sleep time in the model. Sleep is in most cases the activity generating lowest inhalation dose because of low activity rates.

measures of healthy physical activity however, it is not necessary to track energy expenditures throughout the day (except for the purpose of estimating inhalation dose). Energy expenditure is considered health-promoting when it is above a certain threshold – such as levels associated with walking - so a mark of physical exertion during active travel solely is sufficient for comparing incremental healthy effects of the built environment.

Thus, the metrics chosen for risks and benefits associated with each built environment scenario are for an individual in a day (hereafter referred to as the risk/benefit factors):

- Inhalation dose of PM10 throughout the day, (µg/day)
- Inhalation dose of ozone throughout the day, (µg/day)
- Energy expenditure during active travel in a day (kilocalories/day)

Both in the interest of assessing the variability in exposures and the more chronic effects of exposures, these factors are extended to yearly measures of risks and benefits by simulating 365 days of activities for an individual. For this individual, the outcomes of interest may then compare the distribution of the risk factors throughout the year for the different built environment scenarios. Selected individual metrics thus take the form:

- Change in the fraction of days above thresholds of each risk/benefit factor (graph fraction of days above certain threshold as a factor of inhalation dose)
- Difference in the distribution of each risk/benefit factor (tested using a 1-tailed Wilcoxon matched-pairs signed-rank test)
- Difference in various percentile values of risk/benefit factors

Next, as the goal of this work is to assess impacts of built environment on the entire population and not just on an individual, the individual metrics are applied to a whole population, and the final metrics considered, comparing 2 different built environment scenarios are:

- Difference in the distribution of each risk/benefit factor for the entire population (tested using a 1-sided Wilcoxon matched-pairs signed-rank test)

- Change in the intersubject variability distribution of individuals' fraction of days above different thresholds (comparison using Wilcoxon test)
- Distribution of the change in fractions of days above certain thresholds for each individual
- Change in the distribution of 95th and 99th percentile values of risk factors and 30th and 50th percentiles of the benefit factor (the intent of the policy is to generate more physical activity, and the 30th percentile value provides an estimate of the minimum amount of energy individuals expended 70% of the days in a year) (Wilcoxon test)

Different percentiles of outcomes are considered to portray both the variability and uncertainty associated with the outcomes (Cullen and Frey 1999). When possible, the measure of change is tested against the hypothesis of no change using statistical procedures, applying the classic 95 percent probability estimate and considering the p-values to provide a measure of uncertainty. The Wilcoxon matched-pairs signed-rank test is appropriate for assessing differences in built environment scenarios, as the outputs from each scenario for each individual are dependent (hence matched-pairs) and a non-parametric method is necessary for data that is not necessarily normally distributed (McGrew and Monrow 2000). In addition, uncertainty in the variability estimates is assessed qualitatively and semi-quantitatively by comparing different approaches to characterize the variability in the risk/benefit estimates, and results of sensitivity analyses on several model inputs.

The threshold used for the active travel measure is the recommended level of daily physical activity: 150kcal. For inhalation dose, no safe or unsafe thresholds have been determined in the literature (Bell et al. 2006), so a reference level is constructed in reference to NAAQS standards: an individual with a simplified activity pattern is simulated for days where the concentration in the air reaches the standard levels (see section 5.1.4).

With regards to the decision framework, an argument can be made that any deliberate move by local governments that has a potential of compromising residents' health by increasing inhalation of toxic air, albeit with the intention and the outcome of otherwise improving health through encouraging active lifestyles, warrants attention on their part to minimize deleterious exposures. Therefore, a finding that the distribution of individuals experiences a 95% probability of increased fraction of days above the inhalation dose theshold due to changes in the built environment would provoke path 1 of the decision framework (action on the part of decision makers). In addition, considering the hazards of acute exposures at the high end of the distribution, more than a 10% increase in inhalation in 5% of person-days above the thresholds would also lead to the 1st route of action in the decision framework. Finally, both because effects may occur at much lower levels than the NAAQS standards (no safe thesholds are known), and also because the simulation showing a high increase on a low pollution day could also possibly have occured on high pollution day in another simulation, one more trigger for policy making in route 1 would be the doubling of pollution intake on 5% of the days for any individual. The level of action recommended however would be commensurate to the degree of risk estimated, depending both on the magnitude and uncertainty associated with the risk. The policy discussion section tackles this issue.

Another facet of this decision path is the possibility of increased hazards as defined above, concomitant to clear benefits in terms of health-promoting lifestyles. One measure of benefits could be characterized as a significant shift to the right in the population distribution of daily energy expenditure due to active travel, as ascertained by a Wilcoxon test with 0.05 probability. Another is to test an increase in population distribution of 30th percentile value of individual's daily expenditure value (indicating the minimum level of activity undertaken 70% of the days). Reaching 150 kcal/day for 30% of the population would be a clear indication of benefits of the policy. In the case of clear benefits of the built environment policies accompanying increased hazards, actions considered would not only address limiting hazardous exposure but also expanding opportunities for active travel. The policy discussion section addresses these avenues, while also considering uncertainty and magnitude of benefits.

A consistent finding of no difference in inhalation dose for the various metrics and for the several modeling tested approaches, and ascertainment of clear benefits of the policy as described above effectuates the second path of the decision framework. In this course of action, decision-makers focus their attention to expanding policies of pedestrian-oriented environments.

A low uncertainty threshold is implemented to trigger action plan 1 (i.e. chance of detrimental effect with high risk uncertainty still brings about action), therefore decision path 3 is not exclusive of path 1, so that the course of conduct may be revised as uncertainty is reduced. The case of no significant finding of increased harmful exposures (path 2), naturally does not alleviate the need for more research for similar policies implemented in different conditions, particularly in areas with greater air pollution concerns. However, such a finding would indicate an acceptable level of risk for conditions portrayed in this case study. If no benefits of the policy can be demonstrated in this computational model, the recommendation from this study is still to develop further research on risks and benefits of pedestrian-oriented environment, as many more benefits and a few other risks than those quantified in the computational model have been identified, as reviewed in Chapter 2.

4.2 Data sources and data manipulation

This section describes the data and data manipulations used as inputs for the BESSTE model. Some perspectives on other sources of data and their manipulation, including different forms of errors, uncertainties or other challenges associated with the options, are also offered.

4.2.1 *Study location geographic, demographic, and economic information*

Orange County, NC, is chosen as the study area for implementing the BESSTE model. The towns of Chapel Hill and Carrboro are the focus of the study, with all residential locations and most destinations located within these towns, with some activities located in Hillsborough and other parts of the county, as shown in Figure 4-1. Hypothetical built environment changes only affect Chapel Hill and Carrboro.

Geographic information on the socio-demographic distribution of the population, the land use layout, including economic activity information, and the built environment features such as streets, trails, or sidewalks are needed to characterize the study location. The source of information used for implementing the BESSTE model include the Census Bureau for population demographics[23], Reference USA Business[24] for business activities, and the Chapel Hill and Carrboro Planning Department[25], for street network and land use data[26].

4.2.1.1 *Residential locations*

Although residences exist throughout the study area, a limited number of locations are chosen as residential places in BESSTE to make location and route selections manageable. Residential locations are selected with a process of population-weighted random selection of Census 2000 block groups in the Chapel Hill and Carrboro communities. Block groups[27] within 300 meters of the Chapel Hill – Carrboro street network were identified, the population counts normalized by dividing by the area covered by each corresponding block group polygon, and 19 were selected at random with probability proportional to the normalized population count. Block group polygons converted into point data using the centroid of each polygon are depicted in Figure 4-1 by the green pentagons.

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[23] http://www.census.gov/main/www/cen2000.html

[24] www.referenceusa.com, available through the UNC library system

[25] I am grateful to Scott Simons, of the Chapel Hill Planning Department, and to Jeff Grim, a Department of City and Regional Planning student at UNC, for providing the Chapel Hill data. Carrboro data can be downloaded from the Town's website .

[26] I am indebted to Amanda Henley, of UNC Libraries, for helping me import into ArcGIS census and business data and getting me started on data manipulation.

[27] Block groups are census data statistical subdivisions that contain an optimum number of 1500 people, with population counts ranging from 600 to 3000 people per block group. It is the smallest geographic unit for which the Census Bureau publishes sample data.

In BESSTE, residential locations are used as the dwelling units for the individuals' whose activities are simulated, and also as possible destinations for the purpose of visiting friends or family. Locations for other activities are described next.

4.2.1.2 *Activity locations*

All businesses in Orange County, NC, with 50 employees or more were selected from the Business Ref USA database as potential places of non-residential activity. Community parks and community centers in the Chapel Hill-Carrboro area were added to this list of activity locations, as they were considered relevant potential destinations for recreational purposes. Park data, including the number of activities available at the parks, were obtained from the Chapel Hill and Carrboro park and recreations departments' websites[28].

The different activity types were then classified into 8 categories (summarized in Table 4.1): 1) "General work", which groups any type of employment that does not fit in any of the following categories; 2) "Medical", including medical practices, hospitals, nursing homes ; 3) "Schools"; 4) "Shop/etc" groups general categories of shops, entertainment, or faith-based activities not included in the following classifications; 5) "Groceries", including grocery and convenience stores; 6) "Restaurant/bars"; 7) "Public Buildings", comprised of libraries, museums, town halls, community services; and 8) "Outdoor Rec" such as parks and golf courses. Table A-1 in the appendix shows the conversion of each of the Philippine Standard Industrial Classification (PSIC) code categories found in the Business Ref data to match the "LocCode" classification used in BESSTE.

[28] respectively: http://chapelhillparks.org/contentAdmin/images/hmpg/parks_map.pdf , http://www.townofcarrboro.org/rp/PDFs/Carbparks2003.pdf

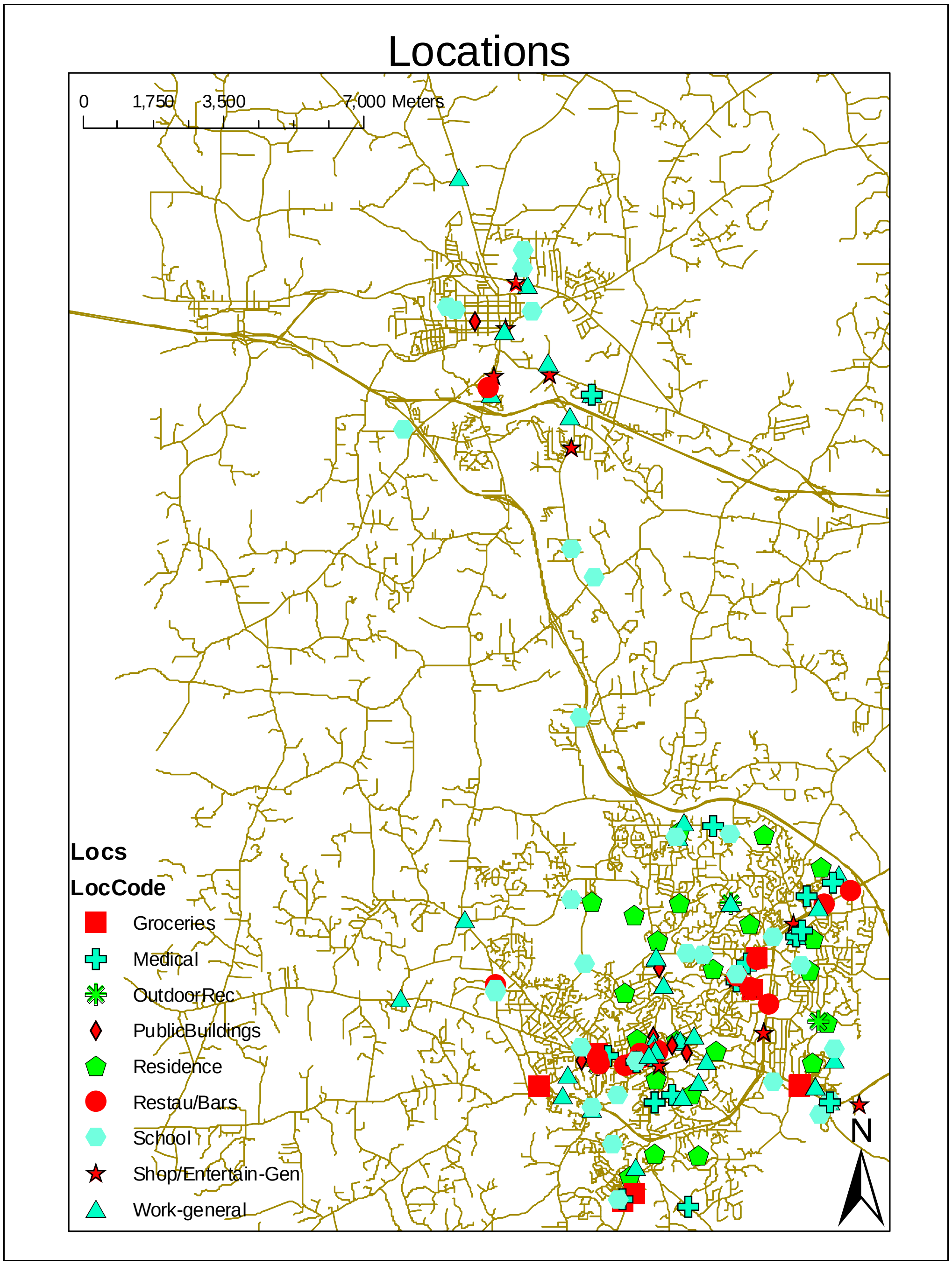

Figure 4-1 Study Area: Orange County, NC, with road network and possible locations for different activities. The concentration of activities on the South-West corner is in the towns of Chapel Hill and Carrboro, activity locations in the North-East are in the town of Hillsborough.

To simplify the activity map and thus reduce model complexity and run time, locations were consolidated by grouping them together into "activity centers" in 100-meter gridblocks. Thus all businesses within a gridblock of a 100-meter grid system overlaid on the study area were assigned to a single location. Further, activity locations in adjacent 100-meter gridblocks were also assimilated to the central activity location, if this made sense in terms of the street network (i.e. if they were located on the same road or on a road directly connected to the central location so that the route distance was below 100 meters). An exception to this rule is the Hillsborough area, where all activities were consolidated into a single location regardless of the relative distance between the businesses. This simplification was necessary to reduce model run time, and deemed acceptable since the focus of the study is on the Chapel Hill – Carrboro area.

This process reduced the 185 original business locations to 95 activity centers, including the 10 additional community parks and 19 places of residences. Figure 4.1 illustrates the activity locations, with, to provide a sense of relative attractiveness of locations, symbols for residential and for activity places respectively proportional to the number of people living there, and the number of people employed in the different businesses. For the parks locations, the number of activities available at the park is used to measure their attractiveness.

Table 4-1 Coding scheme to classify activity locations

LocCode	Description	Abbreviation
40	General work locations	WorkG
41	Medical	Med
42	Schools	School
50	General Shop/Entertainment locations	Shop
51	Groceries	Grocer
52	Restaurants/bars	Rest/bar
53	Public buildings/libraries/ museums	PubBul
60	Outdoor recreation	OutRec
10	Residential	Resid

4.2.1.3 *Land use variables*

Land use variables associated with locations are derived for two purposes: 1) to use as inputs in the transportation model, and 2) to guide the development of built environment scenarios. The transportation model issued from Cervero's work used in BESSTE is described in a later section. However, the process for obtaining the inputs into that model to characterize land use types is covered here.

Cervero's land use variables are indicators (take on the value 1 when present and zero otherwise) that describe land use types within 300 feet or 300 feet to 1 mile of dwelling units, as follows (including variable code name):

- Single family detached within 300 feet of unit	SFd
- Single family attached/low-rise within 300 feet of unit	SFa
- Mid-rise multi-family buildings within 300 feet of unit	MFmr
- High-rise multi-family buildings within 300 feet of unit	MFhr
- Commercial and other non-residential buildings within 300 feet of unit	NR
- Grocery or drug store between 300 feet and 1 mile of unit.	Groc
- Available transit	Tra

In BESSTE, these variables are derived for all location types, not just dwelling units as in Cervero. Land use data was obtained from Chapel Hill and Carrboro planning departments, and transformed to match the Cervero land use variables, using a coding scheme and Google Earth map verifications, in a process described in Appendix B.

Section 2.1.2 on built environment scenario building reviews how the land use variables are used to develop the pedestrian-friendly designs.

4.2.1.4 *Street network*

ArcGIS data on the street network, including the presence of bike lanes and sidewalks, is provided by the planning departments of the towns of Chapel Hill and Carrboro. As can be seen in Figure 4-3 representing the existing network, just above 1/3 of Chapel Hill- Carrboro streets currently has sidewalks (38%), and about 6% of Chapel Hill- Carrboro streets currently have bike lanes. Although there are several existing trails in the area, to simplify the problem these are not considered part of the existing network and are used as features of the pedestrian-friendly street patterns. This is because it requires more model run time to account for them (different distance matrices have to be calculated for a bike-ped only network, which are calculated anyhow in the more pedestrian-friendly scenario, so to simplify the existing trails are grouped with proposed additional bicycle and pedestrian paths.). Procedures for elaborating a more pedestrian-friendly street network are addressed next.

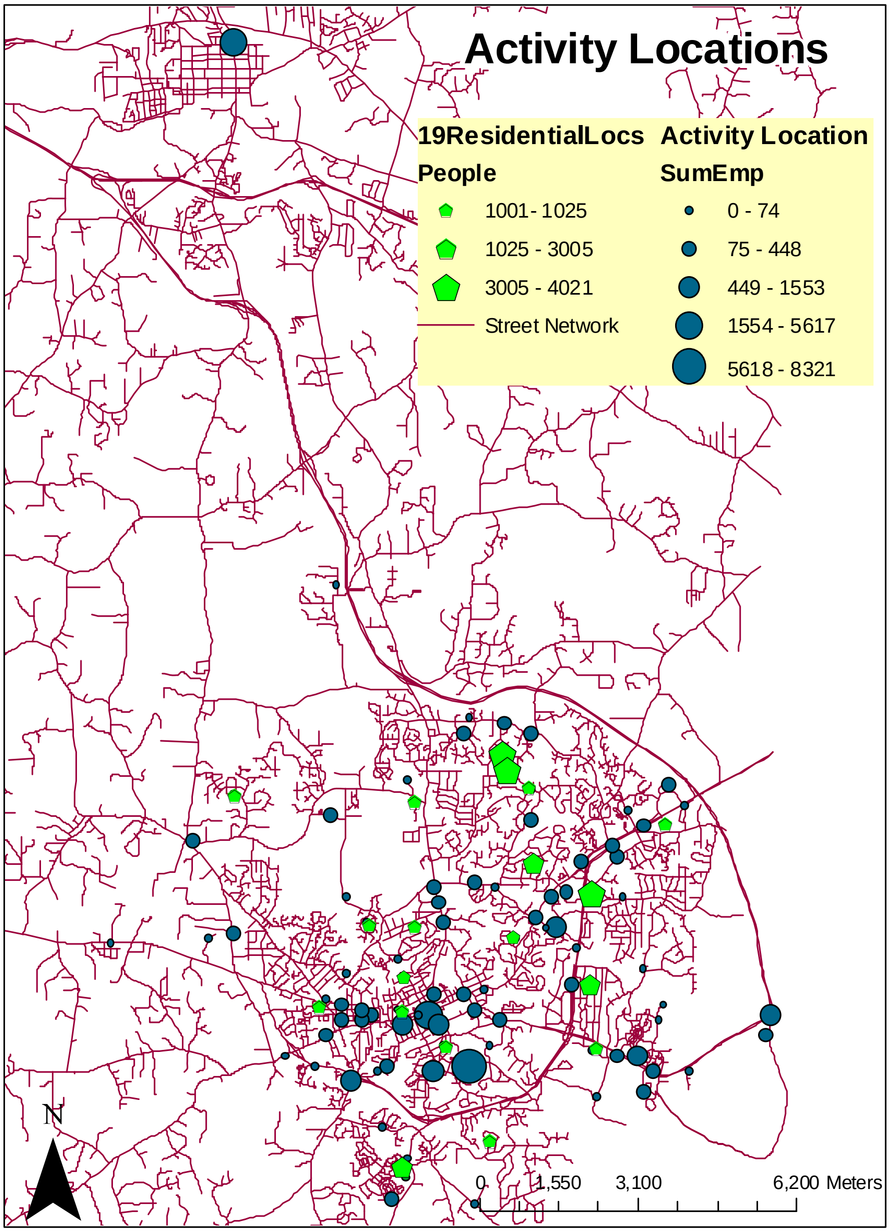

Figure 4-2 Simplified activity locations in gridblock centers. Green pentagons represent residential locations, blue circles other destinations, with symbol proportional to number of people employed in these grid blocks. Note how activities at the distant North-West location (Hillsborough) were consolidated into a single location, to improve model run time

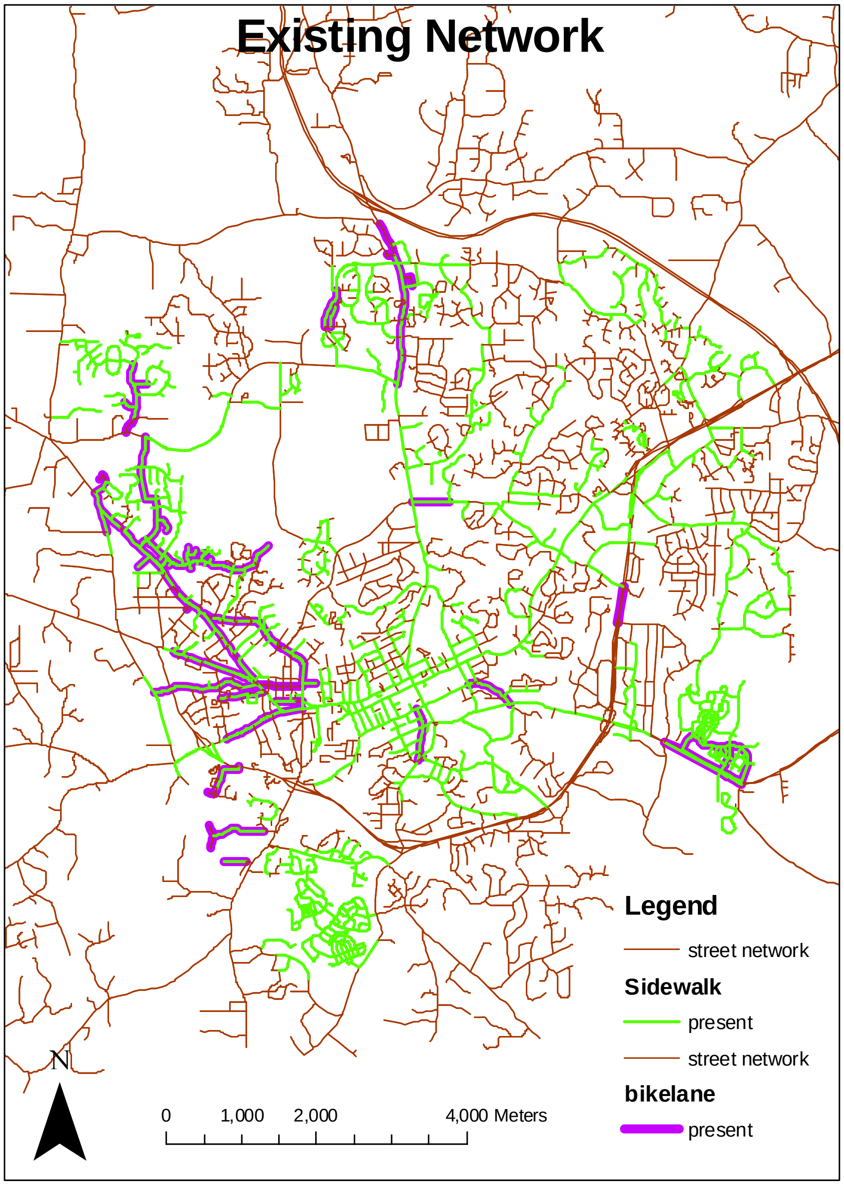

Figure 4-3 Existing street network with presence of bike (purple) and pedestrian (green) facilities

4.2.2 *Pedestrian-friendly built environment scenarios*

The geographic and socio-economic data described in the previous section is used to guide the development of pedestrian-friendly built environment scenarios for the BESSTE model. There are three directions to the proposed improvements, summarized in table 4-2, and discussed consecutively here: 1) a change in land use in terms of mixed use and density; 2) a change in the transportation network in terms of street connectivity; 3) a change in pedestrian amenities in terms of sidewalk provisions. The latter will not be considered further is this section as the pedestrian-friendly scenario simply consists in adding sidewalk on all streets. For the other two axes, the rational for scenario-building is a) to make changes that affect behavior as modeled in BESSTE, b) to devise a systematic approach of selection, and c) to suggest transformations that at least have a semblance of realism (subjectively determined). The first general principle is to target geographic areas that could be supportive of increased walking and biking because of current features that make them amenable to these modes.

Table 4-2 Built environment scenarios

Variations in the built environment are a function of the following possible changes:

- Land use variables
  - As is
  - Random locations
  - Pedestrian-friendly land use scenario (mix and density)
- Network connectivity
  - As is
  - Pedestrian-friendly network scenario
- Sidewalk presence (model)
  - As is
  - All sidewalks

4.2.2.1 *Land use changes: mixed use and density*

The land use change scenario is based on the selection of several of the existing activity locations for increased mixed use and density. Areas picked are ones that already have some mix to support a fully mixed-use and denser neighborhood. Indeed, areas that are very homogeneous would require too much change to become fully mixed, so it is more realistic to prioritize areas that can accommodate and foster more compact development.

Several approaches were attempted for selecting systematically areas where changes should occur. They involved the creation of artificial neighborhoods that were then assessed for their degrees of mixed use and density according to diverse measures, as described in the next paragraphs. A protocol for designating areas of change is then followed, and transformation scenario proposed for the selected areas.

To begin with, a 500 meter grid was overlaid on the study area, so that each 25 hectare gridblock served as the neighborhood units. One measure of land use mixed is the “number of activities”, which is a simple count of the number of activity types that are present in the neighborhood units. Each activity type was assigned a coding of 1 if it was present in the cell, and these indices summed so that the activity number measure could range from 0 to 8 (residential land uses were excluded). Appendix C shows the resulting gradient in the study area for the gridblocks in which activities take place, which varies from 0 to 4. Dashed areas in Figure 4-4 represent gridcells where more than 2 different activity types are present.

A second method to assess mixed use and density is to apply the Cervero land use variables described in section 4.2.1.3. As in the activity counts, these variables were intersected with the 500-meter grid to obtain a measure of mix and density for the neighborhood units. Areas deemed supportive of increased mixed use and density in this analysis contain mid-rise multifamily housing or single-family attached housing and non-residential uses as well. The corresponding gridblocks are highlighted with a purple border in Figure 4-4.

The protocol to pick neighborhood units for proposed changes is based on the activity count and the Cervero land use variable measures described above. Other measures such as the entropy index used by Rodriguez et al.’s and reported in Forsyth et al. 2006 were tested, however the available data did not lend itself well to these other approaches. Nevertheless, very similar selections were obtained using these alternative procedures (not shown here).

The top 20% of the gridblocks (i.e. 16 gridblocks) with the most supportive environments, based on criteria of an existing supportive environment, and need in the case of grocery stores, were selected for land use improvements. The protocol for selection is depicted in Figure 4.4. First, conditions to be met within the gridblocks are:

1) presence of medium-high residential density with at least one non-residential land use (gridblocks highlighted in purple)
2) presence of at least 2 different types of activity (hashed gridblocks)

3) Lack of grocery stores within a mile for grocery store locations (green triangles or pink circles)

All gridblocks which respond to both criteria 1 and 2 above are selected (13 gridblocks). An additional gridblock is selected as follows to add a grocery store:

a) if it responds to either criteria 1 or 2,
b) If it exists within a cluster of activity gridblocks that lack grocery stores within a mile, even after the selection of the first 13 gridblocks (above).

The remaining 2 gridblocks were chosen to specifically address the population density, selected as follows:

i) selected by criteria 1 or 2 above
ii) contains one of the population locations in the BESSTE model
iii) has the highest number of adjoining activity gridblocks, with more weight given to directly adjoining gridblocks compared to corner gridblocks

The final 16 gridblocks selected are the yellow squares in Figure 4.4. The proposed built environment scenario itself consisted of adding population density or activities in the chosen areas, following an inspection of the existing activities in the selected and adjoining gridblocks. Adding density consisted of adding people living there, and adding activities included choosing an activity type and adding a number of employees associated with the activity. The actual number of people added (residents or employees) were in keeping with numbers present in other gridcells for corresponding activities. The process is detailed in Appendix C.

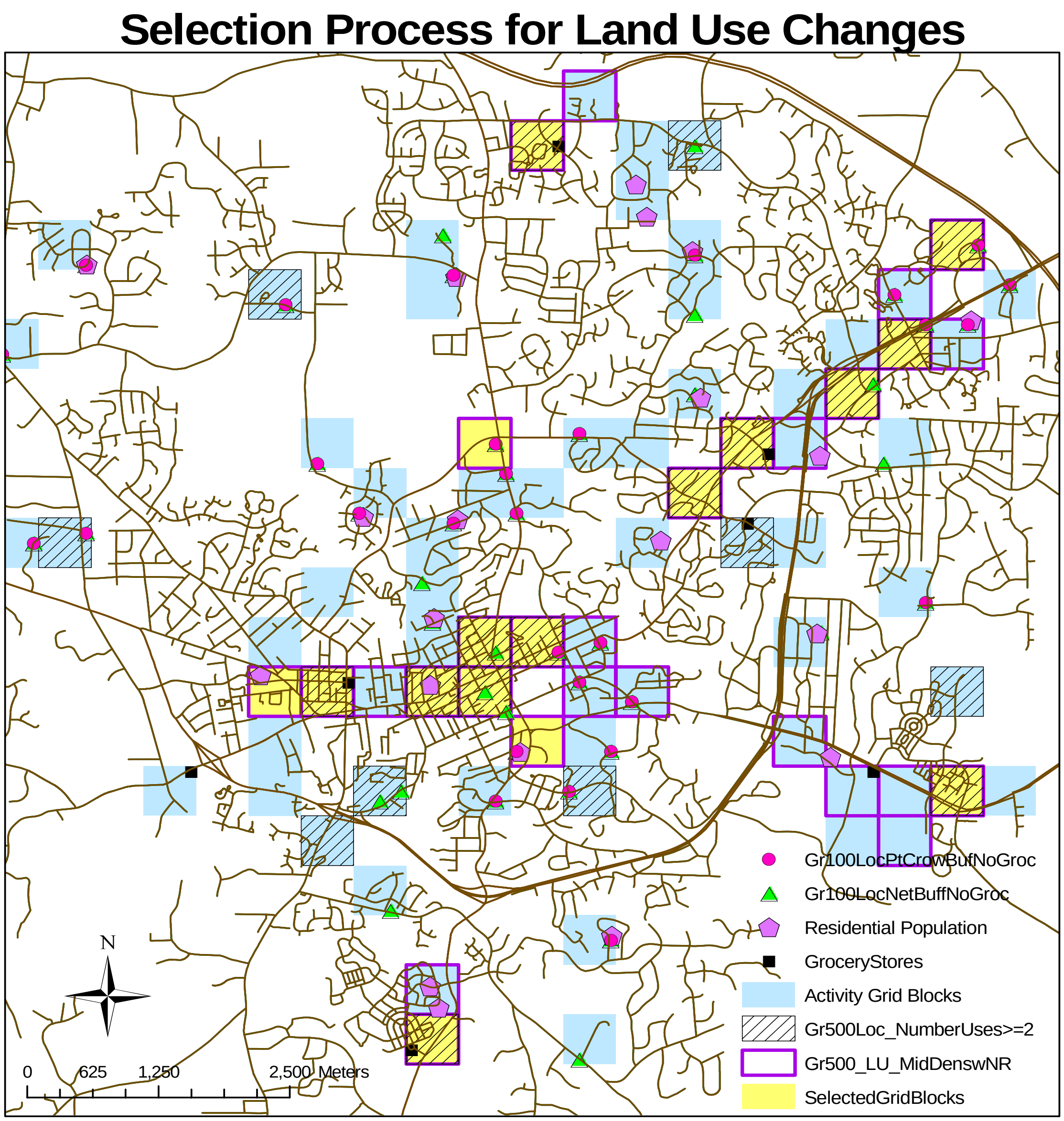

Figure 4-4 Selection Process for mixed use and density scenario: gridblocks with existing mid-densities (highlighted in purple); gridblocks with more than 2 activity types present (hashed); locations of residential population in my model (purple pentagon); selected gridblocks for scenario change (yellow gridblocks)

4.2.2.2 *Street network change: connectivity*

The proposed bike-ped friendly scenario change for the street patterns consists of adding short cuts at different cul-de-sac locations to improve connectivity in the network. As in the land use scenario, a systematic approach is devised to select areas where improvements are proposed. In brief, neighborhoods are selected based on the connectivity of the current street patterns, weighed by population data (residential population and number of people employed in different activities). A 1km-scale was chosen for the connectivity measure, to have a sufficiently big area to assess connectivity within neighborhoods as well as with adjoining neighborhoods. Next is described the means of establishing connectivity measures for the current street pattern, and the process for selecting 1km grid blocks within which changes are proposed for a more connected pedestrian-friendly scenario.

As in the case of land use, several connectivity measures were tested before choosing one that seemed appropriate for the purpose of BESSTE[29]. As can be inferred from an inspection of a Chapel Hill map, the major flaw in the area in terms of connectivity is probably the omnipresence of cul-de-sacs that prevent neighborhoods to interconnect. The proposed improved pedestrian-oriented scenario for street network is in fact to connect cul de sacs to link neighborhoods together and thus create more efficient access to destinations. Therefore a process that assesses more specifically the cul-de-sac issue was favored.

Part of the protocol for the connected node ratio from Forsyth et al. (2006) was followed to establish the intersection connectivity measure in the study area. A 150 meter buffer was applied around each 1km gridblock to consider connectivity with outside gridblocks. For each buffered area where activity occurred, the number of intersections (valence 3 and above) and the number of cul de sacs (valence 1) were calculated using the Fnode Tnode script[30] loaded into ArcGIS. The node ratio, defined as the number of intersections divided by the number of intersections + cul de sacs, was then calculated for each of these greater-neighborhood areas. The higher the ratio (i.e. close to 1), the fewer cul de sacs are proportionally present and hence the more the area is connected. The lower the ratio, the least connected the neighborhood is.

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[29] For example, first was tried a buffer ratio connectivity, equal to the ratio of the area covered by a 1km buffer around each location determined by network distance and a 1km buffer of distance covered by the crow fly (in part based on the Ratio of Area within X Street Distance to Area within X Distance Radius from Forsyth et al. (2006). The lower this connectivity measure, the lower the level of connectivity around that point. However this procedure only portrays a side of the story and doesn't account for factors such as long blocks.

[30] Author Juan Solorzano, downloaded from ESRI website

To select areas for connectivity improvements, the node ratio was weighed with population (residential population+employment) data. The goal was to choose areas with the lowest connectivity (low node ratio) and highest number of people that could be served by the proposed change (high number of employees and residences). Land use measures for the more pedestrian-friendly scenario were applied to normalize the connectivity ratio, so as to create a more efficient full pedestrian-oriented design. The top 25% of gridblocks with the lowest normalized node ratio measure were picked for network connectivity improvements, excluding the cells with no intersections (connectivity measure=0). The resulting 13 buffered gridblocks selected are shown outlined in purple in Figure 4-5.

The street network pedestrian-friendly scenario was then elaborated by adding connecting paths, mostly inside the buffered 1km grid cells, and in some exceptional cases outside the border of the cell where appropriate to connect neighborhoods. Figure 4-5 illustrates the resulting total 114 connecting segments added in the pedestrian-friendly scenario. Segments measure on average 131 meters, with standard deviation 63 meters, ranging from 5 to 342 meters each, for a total of close to 15 additional kilometers of streets or paths. In most cases these short cuts connect cul-de-sacs and neighborhoods, and some are used to cut long blocks.

4.2.2.3 *Distances and routes calculations*

Network distances and routes of travel were calculated between each location point to use as inputs in the BESSTE model. The route estimation refers to the actual location of the streets traveled. It is used for exposure assessment and conceived as the set of 100x100 meter grid blocks traversed by the route. All network distances and route-grid identifications between pairs of activity location points are calculated upfront using a Python code calling functions of the Network Analyst extension in ArcGIS 9.1.

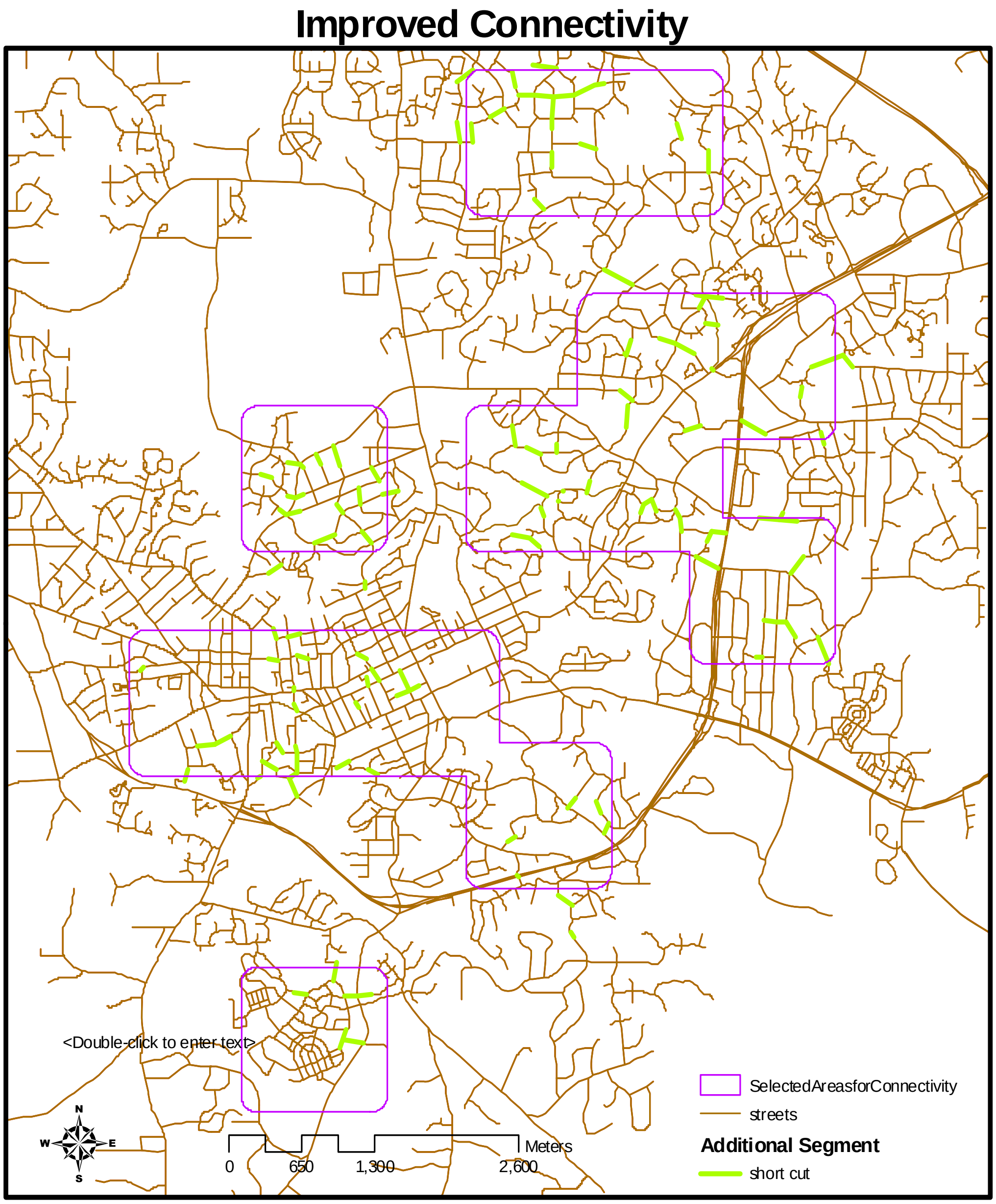

Figure 4-5 Improved connectivity for the more pedestrian friendly scenario. Green lines show added connecting segments in the selected areas outlined in purple.

4.2.3 *Activity patterns*

The source of activity pattern for the built environment model is EPA's database of activity diaries, the Consolidated Human Activity Database (CHAD). CHAD was developed by the EPA's National Exposure Research Laboratory (NERL); it is a compilation of different local and national activity datasets containing a total of close to 23,000 person days of activity. It has specific data for cities like DC, Baltimore, Cincinnati, or Denver, LA, and the Valdez area from the National Human Activity Pattern Study (NHAPS). NHAPS consists of a random sample of US residents stratified by the four major U.S. census regions (Northeast, Midwest, South, and West). While uncertainties may emerge from applying a national or regional database to estimate local activities, at least little difference was observed between mean percentage of time spent in different activities throughout the 10 EPA regions by Klepeis et al. (2001). Klepeis (2001) also states that there is a sufficient sampling rate in each of the EPA regions to perform statistical analysis in each of these regions. Thus, to capture at least some regional characteristics that may impact activity patterns, the States from EPA region 4 (Kentucky, Tennessee, North Carolina, South Carolina, Georgia, Alabama, Mississippi, Florida) are chosen for this analysis.

The subset of the database representing EPA region 4 contains 1330 individuals, for whom data is gathered for a single day of activity. For each individual record the database contains information on: the month the travel takes place in; whether that day is a week-end or a weekday; the sequence of all activities (with a choice of 144 coded activities) throughout that day; the type of location the activity takes place in; and some limited socio-economic information such as gender, age, and level of education (McCurdy et al. 2000).

The 1330 people represented in the selected database subset contain 757 females, with mean 48 years old and 573 males, with mean 44 years old. One third of the days samples (433) were week-ends, the rest weekdays. This proportion is evenly distributed throughout the year (percent ranges from 31.1 to 33.3). The months for which days were sampled are however not evenly distributed throughout the year, with a greater proportion of days sampled in the months of July, August, October and January.

For each type of activity, CHAD offers an associated probability curve of energy expenditure. These distributions were complemented with data from Ainsworth's physical activity compendium for walking and cycling (Ainsworth 2000), as explained in section 4.3.3.1.

While this national dataset is not ideal, other data source options have drawbacks as well. Health behavior surveys for example report leisure-time physical activity with their level of intensity, sometimes with information on the activity location, but do not typically encompass non-utilitarian non-motorized travel. In contrast, transportation surveys can report non-motorized utilitarian travel (although not systematically); they contain information on trip purpose, time, and destination, but they do not generally contain leisure time outdoor exercise, and have no information on energy expenditure. Neither of these latter sources of information allows a full spatial-temporal characterization of exposures throughout the daily activities.

While considering which data source is best to estimate activity patterns, it is important to remember that the final outcome of interest is the relative change in health status when improving the pedestrian environment. In other words it is not necessary to have an exact representation of current activity patterns, as long as the projected activity pattern estimates are reasonable. Therefore, the most convenient and adaptable approach to model activities was favored, given that the difference in precision provided by one approach over another might be little compared to the assumptions made during activity projections and other estimations. To capture the different errors associated with the choice of database, an uncertainty distribution[31] could have been developed and carried through the analysis, although this approach was not chosen so as not to add to the complexity of the model.

4.2.4 *Air quality*

The two pollutants chosen for exposure assessment in BESSTE are ozone and PM_{10}. For both pollutants, the space-time mapping method used is bayesian maximum entropy (BME). The BME framework allows the incorporation of different sources of information such as monitored and modeled data, or factors reflecting the knowledge on pollutant dispersion away from roads. It offers a rigorous method of processing information to spatial temporal maps of estimated pollutant concentrations as well as measures of the confidence that can be placed on the estimate. It provides the flexibility of integrating various sources of information in the analysis, in this case

[31] A source for estimating the uncertainty distribution is McCurdy and Graham's study on factors explaining activity patterns (2003).

observed data which may be considered more accurate, and uncertain modeled data for ozone and heavy traffic factors for PM_{10}. BME is a method proven to be efficient and accurate in predicting concentration fields (Christakos and Serre 2000; Christakos et al. 2001).

Briefly, in the BME implementation for this analysis, monitored data is used to develop a space-time covariance field of the pollutant in the area, providing the general knowledge of the field and giving rise to a stochastic expression of the concentration as estimation point, termed "prior" probability density function (pdf). The information is subsequently "updated" by site-specific knowledge by integrating uncertain information such as modeled data (for ozone) or road proximity factors (for PM_{10}) using a conditionalization processing rule. Each estimation point is then endowed with a "posterior" pdf, providing a probability distribution of the estimate. The spatial and/or temporal resolution of concentration estimates can thus be improved.

The next two sections cover more specifically the data and methodology used to assess ozone and PM concentrations in the study area.

4.2.4.1 *Ozone*

Ozone space-time estimates used as inputs for the BESSTE model are derived from work undertaken by de Nazelle and Serre to map ozone across the entire state of North Carolina during a high ozone episode. The methodology and data sources are reported in de Nazelle and Serre (2007). This section reviews the approach succinctly and describes the data most relevant for the study area.

The ozone mapping approach is based on the combination of monitoring data and air quality model outputs. In the framework of the North Carolina ozone analysis, measured concentrations at monitoring stations are considered exact, while model output errors are evaluated and processed to generate uncertainty distributions associated with the data. Monitoring events consist of hourly measured concentrations at 46 monitoring stations across the state for an ozone episode lasting from 8am (12:00 GMT) June 19th to 1am (5:00 GMT) July 1st 1996, collected by the Aerometric Information Retrieval Subsystem (AIRS). Predicted ozone values stem from the Multiscale Air Quality Simulation Platform (MAQSIP), and are available hourly on a 4 km grid across the State for the same period.

The monitoring stations most influential for the study area, respectively East, South, and North-West of Orange County are: the closest one, station “Duke” in Durham; in Pittsboro station “Pitt”; and the Greensboro station “CHGR”. Figures 4-6 shows for illustration the temporal trend of observed ozone values (in red with dots) at the Duke monitoring station and the temporal mean trend estimated for the entire dataset (in blue solid lines) .

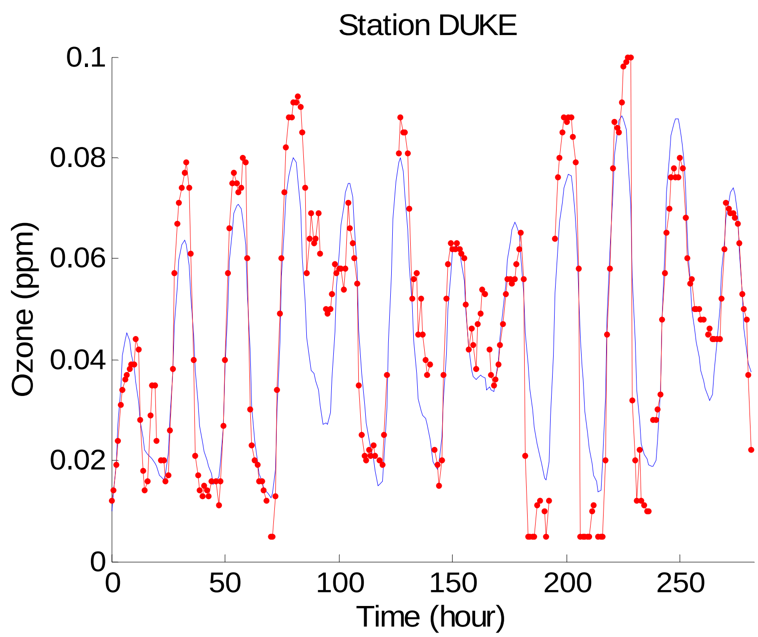

Figure 4-6 Observed ozone hourly concentrations at the "Duke" monitoring station (red dotted line), and temporal mean trend for NC (solid blue line). The Duke station, located in Durham, East of Chapel Hill, is the closest station to the study area.

The BME framework is applied to assess ozone concentrations at the locations where activities take place in the study area, and on routes between the different destinations. To illustrate, Figure 4-7 depicts the temporal trend of mean ozone estimates at a location in the study area, and Figure 4-8 renders an example of the ozone field across the Chapel Hill – Carrboro area at 4 PM on one of the ozone episode days. In the estimated ozone trend of a central Chapel Hill location, only 2 hours exceed 0.08ppm. The maximum attained at that location is 0.0811ppm, the mean 0.0450ppm, 95th and 68th percentile respectively 0.0765ppm and 0.0561ppm. Examination of temporal trends in all activity locations reveals that days 1, 4, 6 and 7 consistently have lower ozone levels than other days, however only day 7 consistently has values below 0.06ppm.

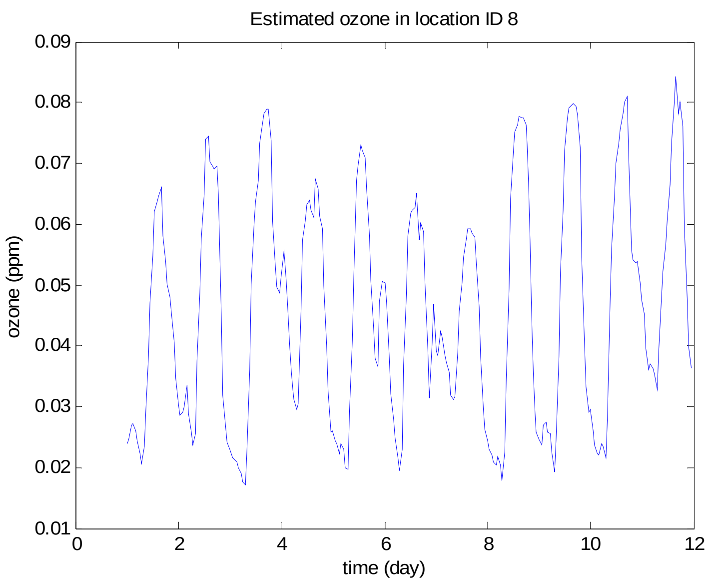

Figure 4-7 Temporal trend of ozone estimates at activity location ID 8 in the study area

As noted, the ozone data used in the analysis is for an 11-day episode. Furthermore, the episode supposedly represents a "high ozone" period and not levels throughout the ozone season. Thus, a method is proposed to apply this work to simulate ozone exposure outside of this restricted time period. First, ozone patterns available at the EPA's Airnow website[32] are surveyed to detect temporal patterns. Ozone season for the South-East is May to November, and ozone is not monitored outside of this period. A visual examination of the maps for years 2005 and 2006 reveals that from May to August four fifths to one half of the days had values below 0.06ppm, and from September to November most days (about 90%) had values below 0.06ppm.

The procedure to generate exposure estimates outside of the episode is thus to sample the days from the dataset according to the likelihood of high or low ozone on the travel day. Therefore, first from May to August, 40% of the time day 7 of the episode is sampled, and for the

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[32] Full URL for North Carolina/South Carolina ozone maps: http://airnow.gov/index.cfm?action=airnow.archivescalendar&pollutant=OZONE&map=calendar&domain=ncsc&mon=7&yr=2006&standard=US&language=EN&RegionID=3&StateID=38

remaining time in that period one of the 11 days is picked at random. From September to November a day is sampled randomly from the three lowest ozone days: days 4, 6 and 7. For days outside of the ozone season, the concentration is simply set to zero.

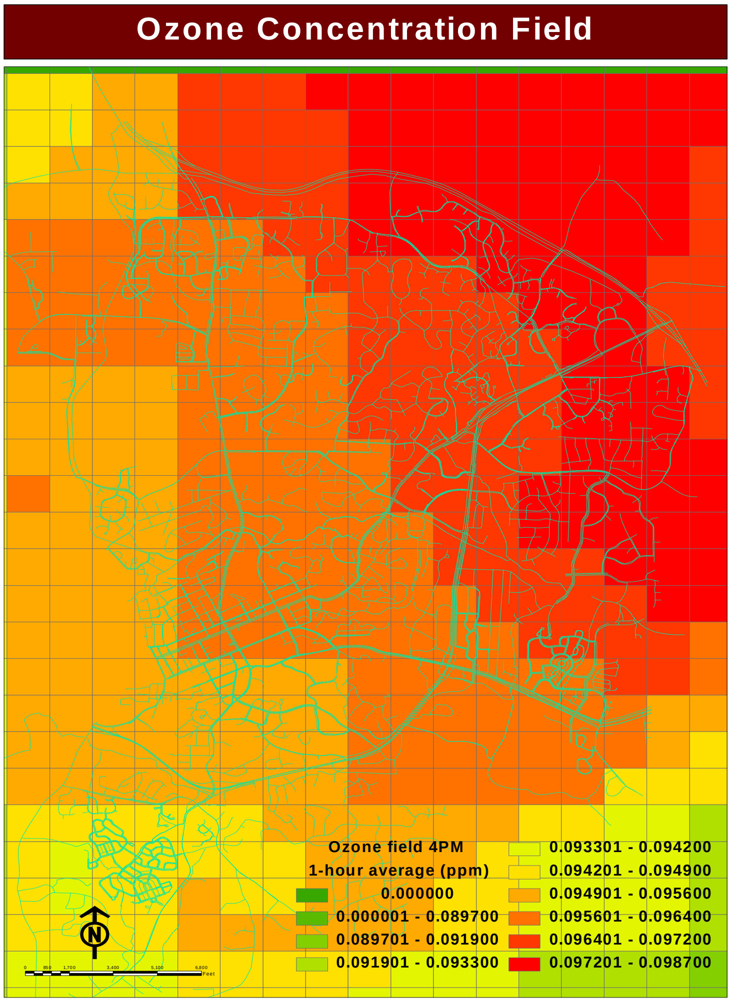

Figure 4-8 Example ozone field at 4pm on one of the ozone episode days

4.2.4.2 *Particulate matter (PM_{10})*

The framework for PM10 exposure estimates is similar to that of ozone, except for the sources of hard and soft data: the monitoring station events for PM_{10} in the study area are synthetic, and the soft information stems from factors of increased PM_{10} concentration along major roadways compared to background. Figure 4.9 summarizes the data set up, and both of these procedures are described in the sections below.

PM_{10} monitoring station simulation

Six monitoring stations are simulated in the study area (thus creating “synthetic monitoring stations”), two of which are considered rural (blue triangles in Figure 4-9), and the rest urban/suburban (red triangles). The simulation uses a covariance function and mean trends, which are then processed in BMElib using the Cholesky method (available through the simuchol function in BMElib). The covariance model originates from the work by Christakos & Serre (2000) to map PM_{10} in the entire state of North Carolina. The mean trend is elaborated using monitored data downloaded from EPA’s Air Quality System (AQS) website[33].

Separate mean trends were created for urban/suburban monitoring stations and for rural areas. Data across the State for the corresponding station type were averaged for each hour. Only the year 2006 was used, as it was the only year with data throughout for a rural monitoring station. Only one rural monitor provided data that year, and 23 urban/suburban stations. Two values of urban hourly mean concentrations seemed excessively high (185.9 and 188.7 $\mu g/m^3$), and were taken out (concentrations of the previous hour were assigned instead). Figures 4-10 and 4-11 show respectively the temporal trends of observed data at the rural station, and of the average ozone concentrations at urban/suburban stations.

[33] http://www.epa.gov/ttn/airs/airsaqs/detaildata/downloadaqsdata.htm

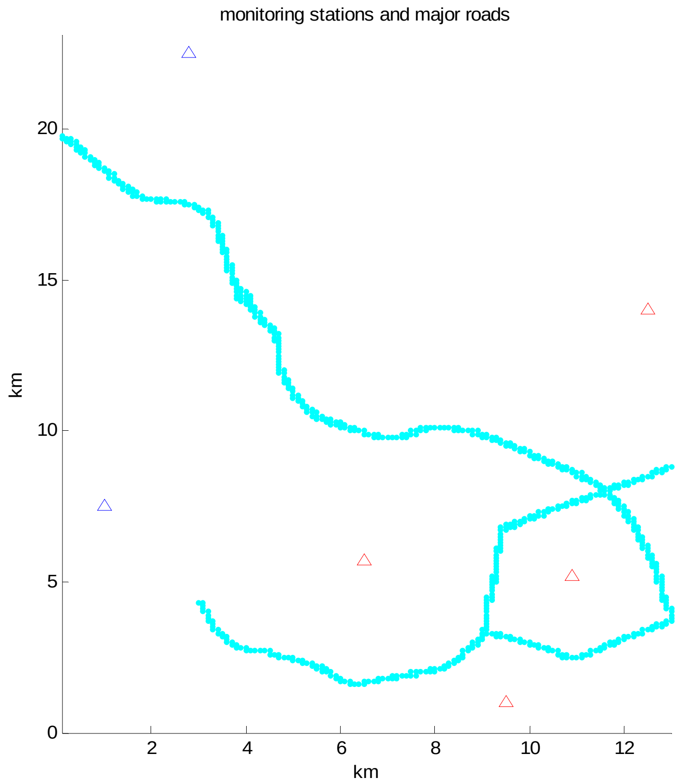

Figure 4-9 PM_{10} setup: Synthetic monitoring stations, including 2 rural stations (dark blue triangles) and 4 urban/suburban station (red triangles), and location for soft data information along major roadways (stacked light blue plus marks)

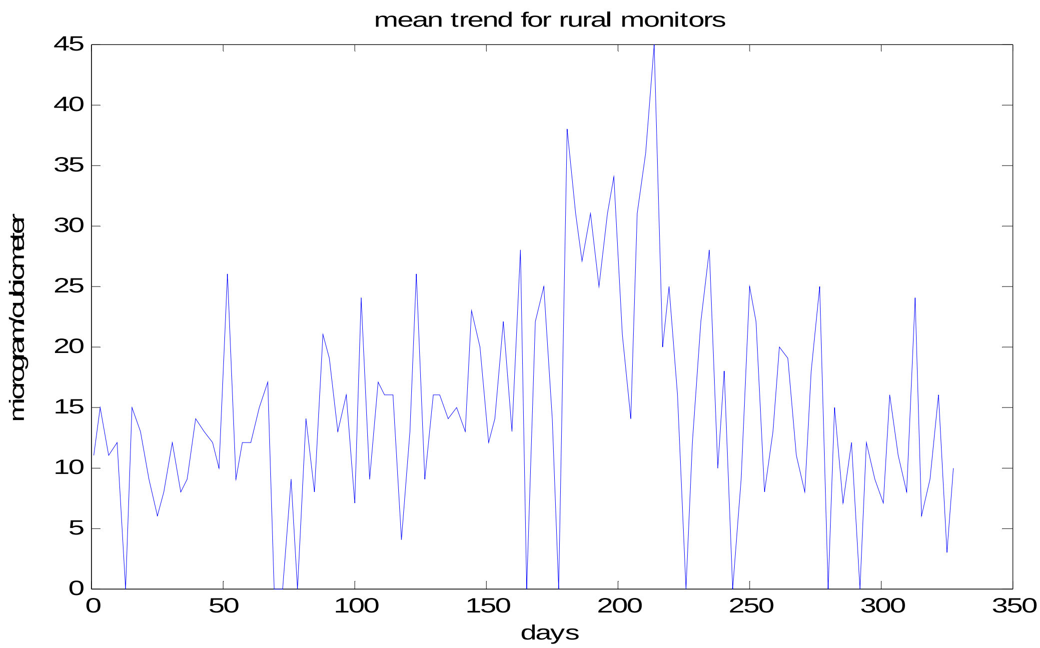

Figure 4-10 Rural station mean trend, based on the year 2006

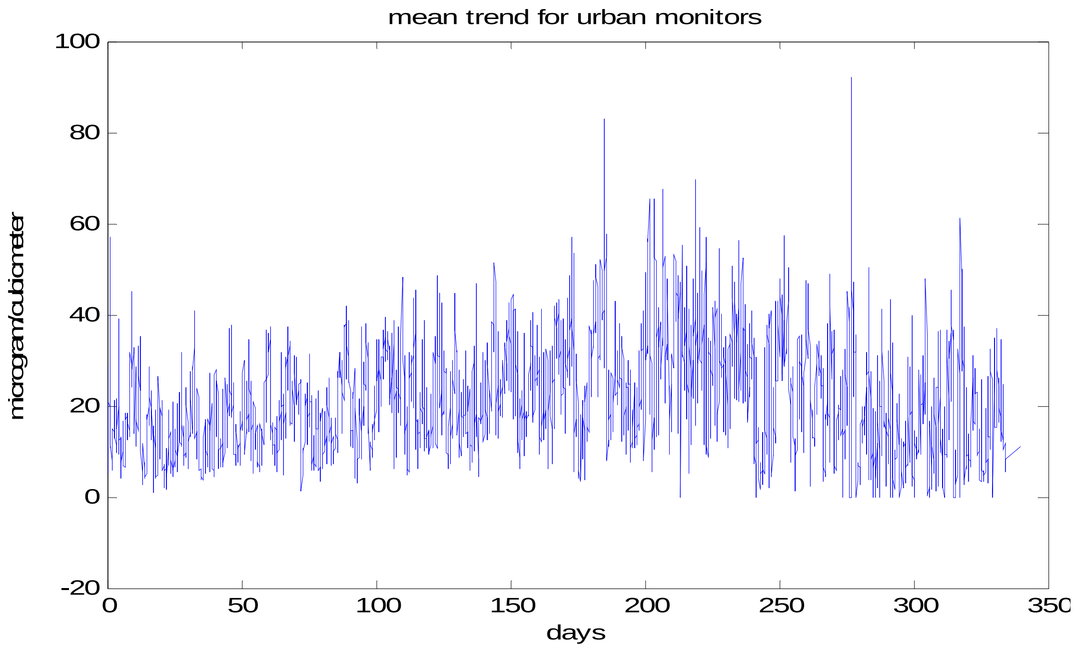

Figure 4-11 Urban/Suburban meant trend, with 2 excessive values taken out

Because hourly estimates were needed for the BESSTE model simulation, the mean trends were then interpolated to obtain outputs for every hour of the year. While many urban monitors provided hourly observations, the rural station did not; therefore the interpolated rural trend is an oversimplification of the daily variation in PM_{10}. A daily variation could have been assigned to the rural data, however it was also thought that in rural areas daily variations did not vary according to morning and evening commutes as they do in urban areas.

Selection of Major roads for PM_{10} soft data generation

PM_{10} percentage increase factors are assigned to major roads in the study area. The major roads are selected according to he following criteria: 1) arterials with posted speed limit equal or above 45 miles per hour, 2) average daily traffic observed on segments of the arterials above 30 000 vehicles per day. Figure 4-12 illustrates the selection process, with the selected roads highlighted in green, red segments are non-selected arterials, and green circles represent observed average daily traffic (obtained from the local MPO[34]) with circle size proportional to traffic intensity. Uncertainty distributions for the PM_{10} values along the roadway were created by

[34] Thanks to Felix Nwoko from the Durham-Chapel Hill MPO for providing the data.

assigning PDFs of the pollutant concentration to all 100-meter gridblocks that intersect the selected major roads.

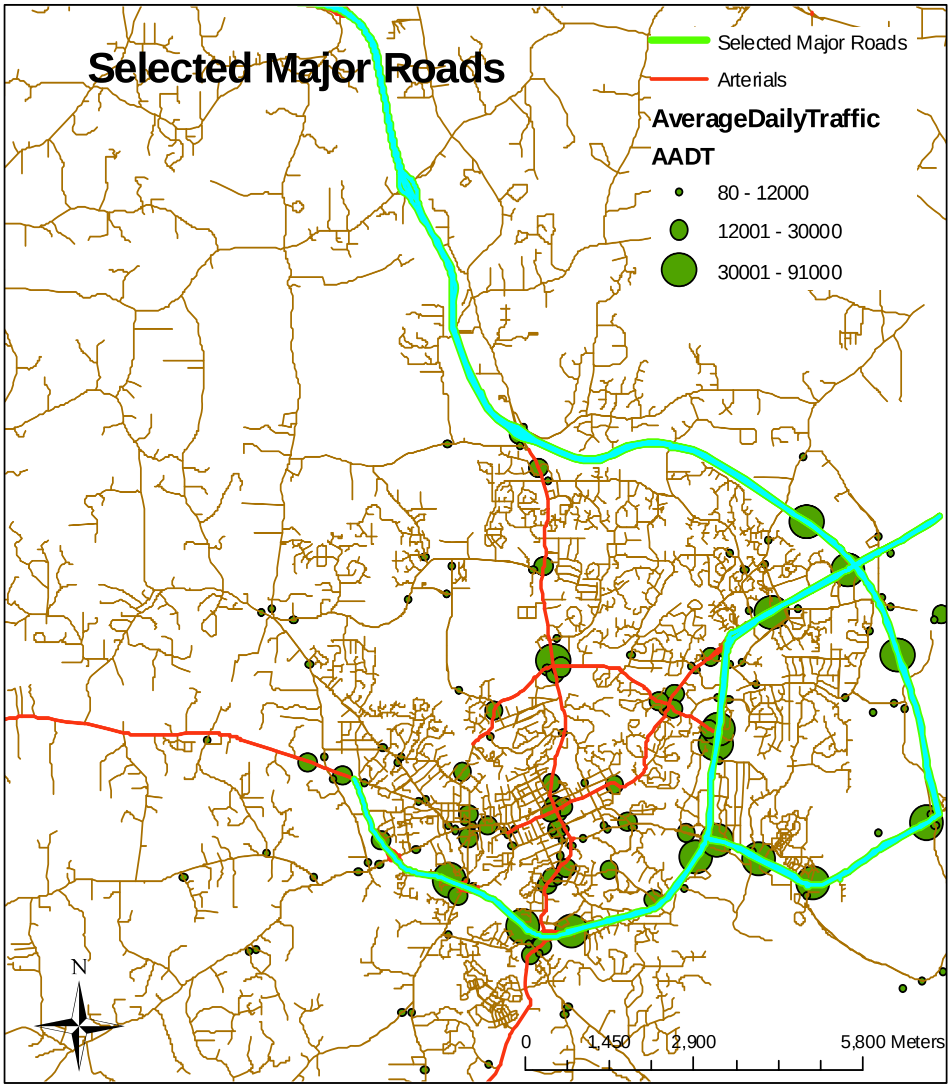

Figure 4-12 Selected major roads for soft data generation

Soft data: increase concentration percentage factors by the road side

Average PM_{10} hourly concentration at the urban monitoring stations on a given day and hour is used as representing "background" concentration on that day, and is multiplied to a percentage factor to obtain concentration in the buffer zone around the roadside. An analysis of the literature, detailed in Appendix D, led to a choice of increase factor of mean μ=20% with standard deviation σ equal to 16%. Hence the PM_{10} concentration by the selected road side is a Gaussian distribution with mean $\mu' = m(1+\mu/100)$, where m is the background concentration for that day, and standard deviation $\sigma' = m\sigma/100$.

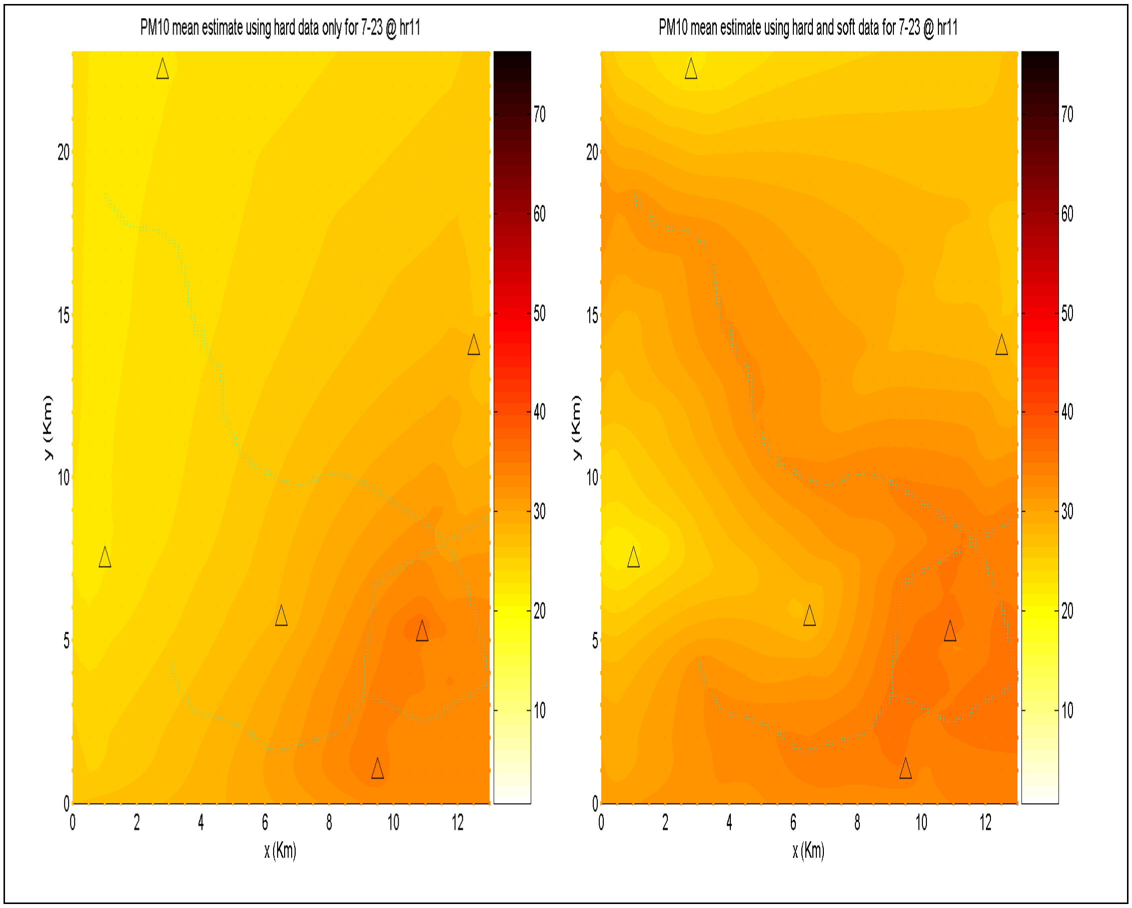

Figure 4-13 Example of a PM10 spatial field estimation in study area (July 23rd 11AM), contrasting estimation without uncertain information on roadside concentrations (left), and estimation with the uncertain information (right). Triangles represent hard data points, light blue lines are the major roads.

PM_{10} Estimations

PM10 is estimated for every activity location and every grid cell traversed by routes taken by individuals between destinations. To illustrate the data for the entire spatial field of the study area, Figure 4-13 shows an example simulation, contrasting results found when only the synthetic monitoring data was used (on the left) to maps obtained when uncertain information about road proximity concentration factors were integrated in the analysis (on the right). Synthetic monitor data is also shown on the map (in the triangles), as well as the location of the major roadways (light blue x marks). Figure 4-14 illustrates the approach to assessing exposure concentrations for an individual's timeline throughout an entire day.

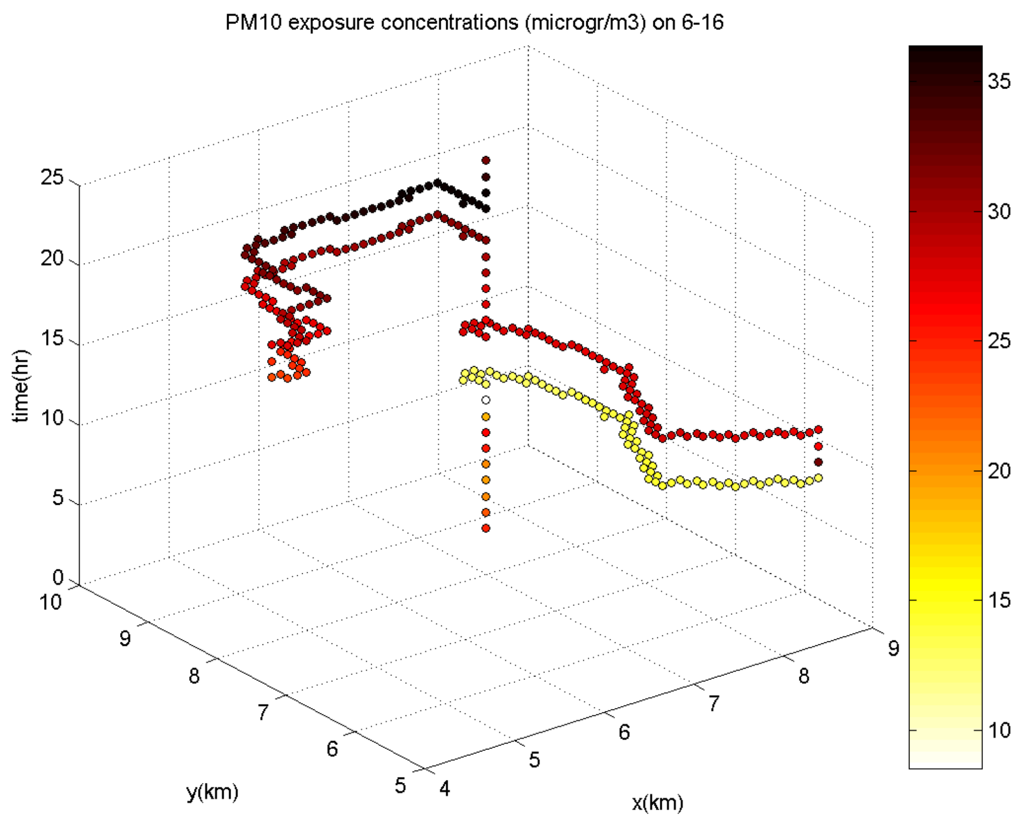

Figure 4-14 Timeline of exposure to PM_{10} for an individual throughout the day

4.2.4.3 *Scenarios of change*

As vehicle emissions may be reduced due to changes in the pedestrian environment, we could also consider mapping future air quality. Given the existing complexity of the model as it is, a simple sensitivity analysis approach is proposed. Future scenarios of uniform decreases in ozone and PM_{10} concentration across the spatial-temporal fields by certain percentage factors are tested for effects on exposure outcomes. Two scenarios are simulated: 1) 5% uniform reduction to illustrate a possible effect of neighborhood transformations, 2) 20% uniform reduction to simulate greater regional and local efforts for emissions reduction.

For future work, an appropriate way to model a shift in air pollution concentrations could be to change mobile source emissions inputs in photochemical models, typically estimated using EPA's MOBILE model. MOBILE6 produces emissions for freeways, arterials, ramps and local roadways operating at different levels of service, based on inputs such as vehicle miles traveled, speed, time of day, cold starts and hot soaks on each road segment. The inputs may be themselves a result of the network modeling process, or of a highway performance monitoring system. The network model is based on a 4 step travel model usually developed by local metropolitan planning organizations. Local roads are not taken into account in the process. To model changes in air pollution after the pedestrian improvements, first estimates of vehicle miles traveled (VMT) reductions could be drawn from the activity and travel analysis performed in BESSTE. Changes in VMT can be translated into reductions in emissions using the MOBILE6 software, and subsequently into projected ambient air quality changes using the photochemical models. If changes in travel behavior are not thought to be sufficient to change significantly MOBILE6 outputs, rather than re-run the photochemical model, factors can be applied to account for changes in vehicular traffic in selected streets thought to be affected by the pedestrian improvement scenarios.

An alternative for future work in this area would be to use line source models such as Caline (Benson 1984) as another type of air quality model; it allows the estimation of concentrations of pollutants such as NO_2, CO and particulates within 500 meters of a roadway, taking into account traffic intensity, terrain variations and land uses. Updating air pollution concentrations following improvements in the built environment then consists in changing the traffic intensity inputs to reflect the mode shifts along different routes.

It is debatable, however, whether the changes in air pollution due to the built environment is a necessary piece of the model, in that the contribution of these mode shifts to local air pollution and traffic may be dwarfed by that of other regional patterns (see discussion Section 3.2.2). Nevertheless, the effect of mode shifts on air pollution and on traffic will depend on local conditions. Depending on the study area, traffic in some local streets may change sufficiently to impact exposures to traffic and air pollution hazards. The type of modeling approach used can impact significantly whether such modifications can be captured or not (since local traffic and microenvironmental variations are not necessarily accounted for in many emissions or air quality models). Future work should consider analyses that allow the incorporation of a feedback loop of effects of mode shifts on local air pollution concentrations.

4.2.4.4 *Microenvironments*

Different layers of mapping are developed to represent the different microenvironments where activities occur, principally indoor, outdoor, and in-vehicle. Indoor concentrations are estimated in this analyses for two major reasons: 1) to obtain a relative sense of the contribution of travel-time exposures compared to overall daily exposures, and 2) because changes in travel times between different built environment scenarios lead to changes in exposure duration, the travel time differences is added to or substracted from indoor "rest" time to allow a real comparison between inhalation dose. Methods to assess microenvironment concentrations are derived from the air pollution and exposure assessment literature. However, since the core of this work is to estimate the changes in health outcomes resulting in improving the pedestrian environment, a precise estimate of indoor or other non-traffic related *sources* of pollution is not necessary, even though it may still be important to have a relative idea of the magnitude of their contribution to health risks[35]. Therefore only the penetration of ambient air pollution indoors is accounted for in microenvironment concentration simulations, and no indoor sources are modeled.

Microenvironment concentration estimations for ozone follow methods described in Johnson 2003. Simplified equations of penetration of outdoor concentrations are used, where a steady state is assumed with perfect mixing, no indoor sources and no air cleaning device. The

[35] To determine whether risks due to vehicular sources may be dwarfed by other sources.

equation accounts for air exchange rates and decay factors for ozone, and is as follows (equation 6-22 section 6.3.1. in Johnson 2003):

$C_{in} = C_{out}*(AER/(AER+Fd))$,

where C_{in} and C_{out} are respectively the indoor and outdoor air concentrations, AER is the air exchange rate and Fd the decay coefficient. The air exchange rates and decay coefficients take on different values for each type of microenvironment, for which Johnson proposes probability distributions. For non-vehicular enclosures the decay factor Fd is a normal distribution with mean 4.04 /h and standard deviation 1.35 /h, and ranging from 1.44 /h to 8.09 /h. For in-vehicles, Fd is a point estimate, equal to 7.2/h. The air exchange rate AER follows a lognormal distribution, with

$AER=GM*GSD^{Z}$,

where the geometric mean GM and geometric standard deviation GSD are provided for different microenvironment and opened window status, and where Z is a value picked from a normal distribution with mean 0 and standard deviation 1.

For residential indoor environment, with windows closed Johnson gives GM=0.53, and GSD = 1.704. For residential buildings, with windows opened a point estimate equal to 6.4 is suggested. For non-residential building: GM=1.285 and GSD= 1.891. Finally, for in-vehicle environments a point estimate is provided for the air exchange rate: AER=36.

Rather than pick at random for each iteration of BESSTE, the most likely value of microenvironment indoor/outdoor air ratio is used. Thus, the most likely value of what is called the “penetration factor”, Fi, for each type of microenvironment i, is calculated using the following equation with the most likely estimate for each element:

$Fi=AER/(AER+Fd)$.

These Fi factors were determined for the different location types in the LocCode coding scheme (see Table 4.1 for abbreviations), choosing only the closed window environment so as to simplify the model. Indeed, the open/closed window algorithm was not deemed essential enough to warrant adding complexity to the model, as it only applied to residential buildings and is not affected by the focus of the model: changes in the built environment. The resulting Fi factors for different microenvironments are shown for ozone in the first line of Table 4-3.

Table 4-3 "Penetration factors" for ozone and PM10 in different activity location types

	Resid	WorkG	Shop	Med	School	Resto/Bar	PubBul	Vehicle
Ozone	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.91
PM10	0.24	0.54	0.76	0.54	0.76	0.75	0.75	1.1

For PM_{10}, penetration factors used in this analysis stem from the diesel PM addendum in Development of Microenvironmental Factors for the HAPEM4 in Support of the National Air Toxics Assessment (NATA) prepared by ICF Consulting (2000) for EPA's Office of Air Quality Planning and Standards. When several factors existed for a single environment type (e.g. residence with no CO source, with garage, with gas stove, or both), the average was used. Resulting microenvironment indoor/outdoor ratio factors are shown for PM10 in the second line of Table 4-3. Comparisons of calculations made using other approaches (Yeh et al. 2002, EPA 2004) to estimate indoor air as a function of outdoor PM_{10} for residential buildings showed that the factors chosen provided an upper end of indoor/outdoor ratio. However, since no indoor sources were used in the BESSTE model, it was decided an upper end of the indoor/outdoor ratio was desirable, even though it wouldn't compensate for the lack of indoor sources.

The in-vehicle factors were compared to estimates found in studies of traffic-related environment. Pollutants that have been shown to be higher inside vehicles compared to the outdoor concentrations include NO, CO, NOx, PAH, elemental carbon, VOCs and many metals (Chan 1999, Duci et al. 2003Levy et al. 2002, Riedeker et al 2003). $PM_{2.5}$ has both been shown to be higher (Levy et al. 2002) and lower (Riedeker) than outdoors, while Adams (2001) found that car-drivers were more highly exposed to the pollutants than cyclists were . Riedeker found ozone to be slightly lower in-vehicle and Chan slightly higher than on the pavement. These comparisons therefore neither confirm nor reject the adequacy of the penetration factors used in the BESSTE analysis, they only show much uncertainty still remains in this area of research.

Future work in this area might also model concentrations in high-or-low local traffic streets (not just major roads as in the present work), or according to street design and traffic calming measures. Engineering devices meant to slow traffic (and thus improve the pedestrian experience) may increase local emissions because of a change in driving style from constant flow to stop-and-go. Strong variation in the driving cycle, or "jerkiness" in driving, due to street design could be specifically modeled to estimate local concentrations.

4.3 Relationship numerical algorithms

The previous sections detailed data sources and data manipulations to provide inputs in the BESSTE model. Here the numerical functions developed to quantify the different relationships described in the suite of conceptual models in section 3.1.2 are described.

4.3.1 *Location choice*

The probability of choosing a destination *i* is based on a "gravity model", which weighs the attractiveness of that location relative to that of other destinations. The approach chosen for determining the level of attractiveness of a grid cell is to equate it to the number of people employed in the grid cell for the particular trip purpose activity. Thus, the probability $PrG(i)$ of choosing gridblock *i* is:

$$PrG(i) = Att(i)/\sum_j Att(j) \quad ,$$

where $Att(i)$ is the measure of attractiveness for gridblock *i*, $\sum_j Att(j)$ the sum of attractiveness of all gridblocks. $Att(i)$ *is* defined as:

$$Att(i)=Emp(i)/SD(i) \quad ,$$

where $Emp(i)$ is the number of employees associated with the trip purpose activity in gridblock *i*, and *SD* is the distance from the previous location to gridblock i.

The general work trip purpose uses the sum of employees in all categories of activities, and the distance from the home location to the grid cell rather than the distance from the previous location. Other trip purposes utilize solely the number of people employed for the particular activity in the analysis set up, and calculates the distance from the previous location. For trips for visits to other's residences, instead of the number of employees, the number of people living within the census block represented by the gridcells are the basis of the attractiveness calculation. Park destinations do not have "number of employees" but rather the number of activities available at the park (trails, tennis courts, etc), which is the number implemented for the attractiveness measure.

The grid cell chosen for the activity location is thus picked according to the probability of each cell being chosen. A number is picked at random, and compared to the cumulative probability of choosing each of the possible destination points. The process is illustrated in Figure 4-15 with blue marks representing the cumulative probability of picking ordered locations (equal to the cumulative sum of attractiveness measures) and the red triangle indicating the selected location chosen for a particular randomly generated number (0.8214).

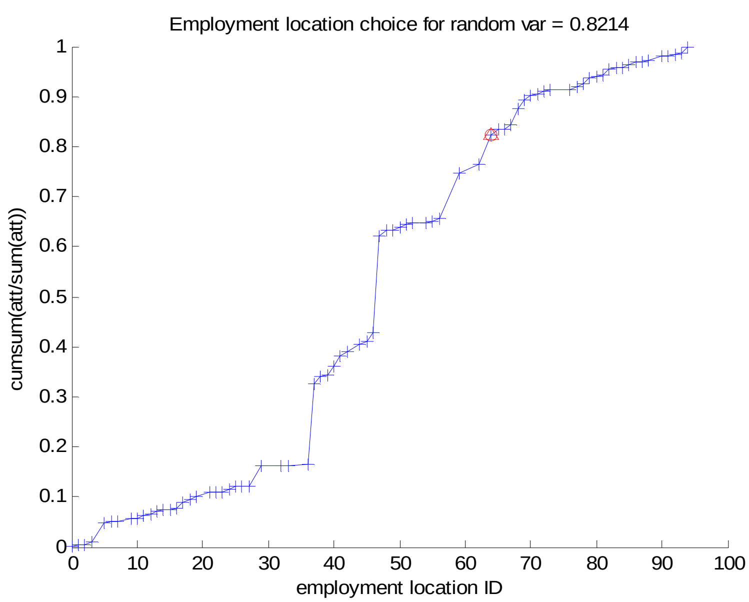

Figure 4-15 Cumulative distribution function of ordered employment locations, and location picked (red triangle) for a randomly generated number equal to 0.8214

Other forms of location choice models are tested in BESSTE in a sensitivity analysis. One approach is to not use gravity but rather fully randomly pick a location for each activity. An alternative formulation of the gravity model tested uses a different form of impedance function, inspired by Sermons and Seredich (2001) (although they use time instead of distance – the multiplicative factors are to convert distance into time, in minutes, using vehicle speed):

$$Att(i) = \frac{Emp(i)}{(SD(i)*60/20)\exp(-0.015*SD(i)*60/20)}$$

4.3.2 *Transportation mode choice*

Two competing travel behavior models are tested out for deriving transportation mode choice in BESSTE. They are chosen because they include measures of the built environment as explanatory variables, and consider explicitly the walking and cycling modes for each trip. They both suffer from the same drawback that they are derived from analyses of commuting behavior. An analysis of the 1995 Nationwide Personal Transportation Survey (de Nazelle 2001) reveals that together walking and cycling represent 2.96 percent of all trips to work, which is a low percentage compared to other trip purposes (for instance 5.89% for family and personal business purposes, 12.16% for school trips, 10.02 percent for social recreational trips and 5.75% to go shopping). Even for trips less than 3 miles, driving to work is shown to be as much as twice as likely than for trips for social and recreational purposes in a logistic regression analysis that accounts for socio-demographics, macro-level land use features and other trip characteristics. However odds are similar to those of shopping trips in the same model. Hence it is generally thought that the application of a commute model for all trip purposes would under-estimate the walking and cycling modes, but is deemed applicable to all trips for the purpose of the BESSTE simulation.

4.3.2.1 Cervero Model

The Cervero mode choice model implemented in BESSTE proceeds from Cervero's 1996 commuter travel behavior logistic regression analysis (Cervero 1996). Cervero uses the American

Housing Survey, a national survey that records data on households and their commuting patterns and contains land use information close by the respondents' housing units. The choice set of transportation modes modeled in the binomial discrete choice framework includes the automobile, transit and walking/cycling. The focus of the study is on land use variables: density measures (housing styles within 300 feet of housing unit), and land use mix (presence of non-residential buildings within 300 feet of unit, and presence of grocery and drug stores beyond 300 feet but within a mile. Mode choice is thus modeled as a function of the land use variables, distance to work, as well as control variables including the number of automobiles owned by the traveler and whether transit is adequate or not in the home neighborhood.

In Cervero's framework, the probability *PrWB* of choosing to walk or bike rather than use another form of travel is expressed by

$$PrWB = 1/(1+exp(-U)) \quad ,$$

where U is the utility function associated with the choice to walk or bike for the trip conditions, and is given by:

$$U = \sum \beta_i X_i \quad ,$$

where the β_i are the regression coefficients and X_is the values taken by the variables that enter Cervero's model.

Specifically, the variables X_is found to be significant in the non-motorized mode choice model are: distance to work, number of automobiles in the household, and dichotomous variables indicating whether the neighborhood is comprised of single family detached houses within 300 feet of the unit (home), single family attached/low-rise multi-family buildings within 300 feet of unit, mid-rise multi-family within 300 feet of unit, high-rise multi-family building within 300 feet of unit, commercial and other non-residential buildings within 300 feet of unit, grocery or drug store between 300 feet and 1 mile of unit, public transit adequate.

The variance of the probability distribution, *VarPr*, is also computed in the implementation of Cervero's model in BESSTE, using the following equations:

$$VarPr=(PrWB-CI_{68\%})^2 \quad ,$$

where $CI_{68\%}$ refers to either one of the two ends of the 68% confidence interval, calculated by:

$$CI_{68\%}=1/(1+exp(-U+/-(VarU)^{1/2}))\ ,$$

where VarU is the variance of the utility function U, computed using the formulas:

$$VarU=\sum X_i^2 Var(\beta_i\ ),\ \text{and}$$

$$Var(\beta_i)=SE(\beta_i\ )^2\ \ ,$$

and the standard errors for each regression coefficient, $SE(\beta_i\ )$, are given by Cervero.

Figure 4-16 illustrates the results of the Cervero model for different trip distances and land use scenarios. All scenarios assume 2 available automobiles in the household, adequate transit, and no grocery stores between 300 feet and a mile. Low density scenarios assume single-family detached and attached housing, high-mid density have mid- and high-rise multi-family buildings, and mixed use scenarios contain commercial and non-residential buildings within 300 feet of the household.

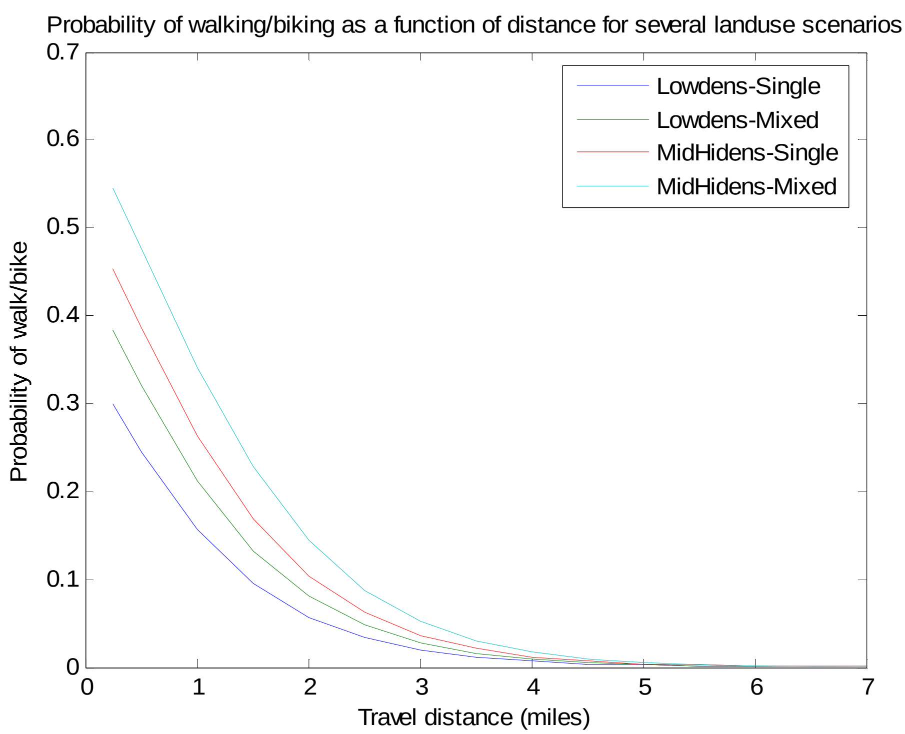

Figure 4-16 Cervero Model: probability of walking/biking as a function of trip distance and land use scenarios. All scenarios assume 2 available automobiles, adequate transit, and no grocery/drug stores between 300 feet and a mile of household

In BESSTE, the probability distribution of walking or biking on a trip is thus described by a normal curve with mean *PrWB* and variance *VarPr*, and is applied to all trip purposes from all origins and destinations. As an example, the probability distribution for a 1km trip to be made by biking or walking, under a low-density single-use scenario yields a point estimate (mean) for the probability of walking/biking of 0.2202 with 68% confidence interval (0.2197, 0.2207), while the same travel conditions for mid-high density and mixed use scenario, produce a mean probability of 0.4403, with 68% confidence interval (0.4400, 0.4406). As can be seen the uncertainty estimate is narrow, so there may not be added value in incorporating the uncertainty associated with the mean probability estimate. A test of 500 runs on mode choice pick for the first of the above two scenarios (which had wider confidence interval) showed that indeed accounting for the uncertainty around the probability estimate did not provide different results than a simple pick proportional to the probability estimate. Thus this contribution to uncertainty was no longer considered in the BESSTE model.

If a walk/bike mode choice is picked, to then distinguish between the walk and bike modes, trips less than one kilometer (0.62miles) are arbitrarily assigned the walk mode, and distances beyond that are assumed to be bike trips.

A disadvantage of the Cervero model is that it is a binomial logistic regression rather than a multinomial logit. Thus it does not allow for example the comparison of network patterns that differ between mode (example pedestrian and bicycle paths that are not permitted to motorized vehicles), which is one of the scenarios that we would like to test. The next model described and tested in BESSTE overcomes this drawback.

4.3.2.2 *Rodríguez Model*

A second transportation model is implemented in BESSTE, derived from Rodríguez' and Joo's analysis of commuting patterns to the University of North Carolina at Chapel Hill. This model performs the same task as the previous one, but is tested in BESSTE to assess the effect of the choice of travel models on results. An advantage of using the Rodríguez model is the study's focus on built environment characteristics and their impacts on non-motorized travel. Measures of the presence of sidewalks and bicycle or pedestrian paths were included, and walking and cycling modes were separately measured as outcomes. Another favorable aspect of this study is that it uses multinomial logit modeling, thus allowing one to account for characteristics of competing modes presented to the individual. For instance in this framework the difference in travel times for different modes due to the implementation of short cuts and paths in the more pedestrian friendly scenario can be accounted for. In the Cervero model used above, the probability of non-motorized versus motorized travel is a factor of the distance for all modes, not the relative distance for each mode.

An additional benefit of the Rodríguez model is that it is locally-derived in the Chapel Hill-Carrboro area. However this is accompanied by a drawback, which is that it studies solely commutes to the University campus, which must be extrapolated to all travels in the BESSTE model. These commute trips may in actuality be quite different than trips for other purposes, despite the location being the same: indeed UNC has rather restrictive parking policies, thus encouraging alternative means of transportation to the school. Free parking is widely available in Chapel Hill and Carrboro outside of the Chapel Hill center and university area. Thus it is expected that the implementation of this model for all trips may skew the results towards less driving and more alternative means of transportation.

The form of the multinomial conditional logit model used by Rodríguez and implemented in BESSTE is as follows:

$$Pn(i) = \frac{e^{V_{inO}}}{\sum_{j \in C_{nO}} e^{V_{jnO}}} \text{ for all } V_{inO} = f(a_i, d_n, E_{iO}) \text{ ,}$$

where *Pn(i)* is the probability for individual **n** to choose mode ***i***, given the choice set of modes C_{nO} at origin *O* and the systematic utility V_{inO} of mode *i* . The utility function is itself a function of attributes of the mode ***i***, a_i, of individual characteristics d_n, and of environmental factors E_{iO}. Of particular interest are the variables indicating the fraction of the route covered by sidewalks, and the presence of walking and cycling paths. The variable indicating the walking and cycling paths is the time difference between routes accounting or not for the path. No paths are assumed in BESSTE the less pedestrian-friendly network (the path variable is set to zero), while in the more pedestriant-friendly scenario the path variable is set to the difference between the route distance in the more connected pattern (pedestrian-friendly) relative to the less-connected pattern (status-quo). Although three different modeling approaches were used in Rodríguez' study, the simpler one-level logit is used for this work. All variables that were not otherwise explicitly considered in BESSTE were set at their mean value in the Rodríguez model – this includes: slope (bus and non-motorized modes); out-of-pocket costs (motorized modes), out-of-vehicle travel times (motorized modes); peak service (bus); sidewalk fraction applied to the bus alternative; path applied to the bus alternative; density (bus); number of vehicles in household (all individuals are assumed licensed). In addition, the indicator for student status is set as a random value with equal probability of 0 or 1 for respondants below 35, and no student status assumed for those above 35. The transit mode is deemed available in the model if transit lines exist within 1 km of the activity location (same indicator as used in the Cervero model). To illustrate, Figure 4-17 provides resulting probability curves of walking as a function of the fraction of the route with sidewalks for different trip distances, and Figure 4-18 depicts the probability of walking and the probability of biking, both as a function of trip distance.

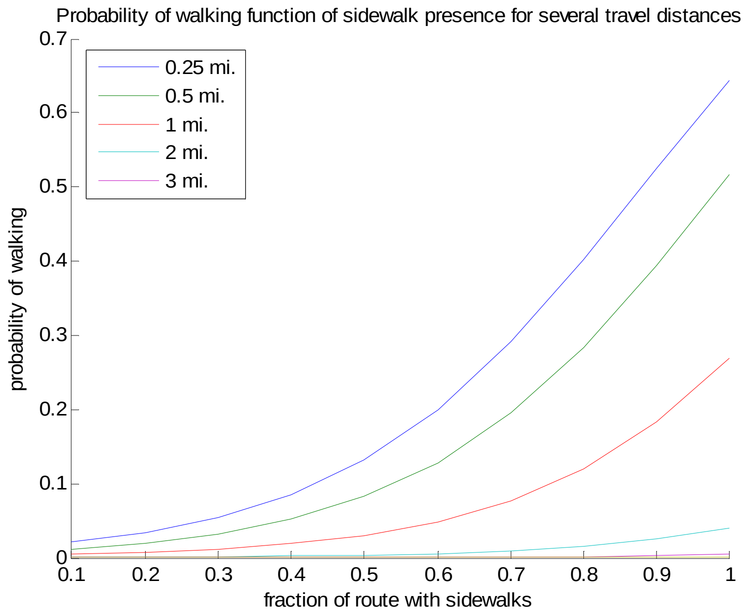

Figure 4-17 Rodríguez model: probability of walking as a function of the fraction of the travel route with sidewalks for 5 different travel distances. The scenario is for a female age 34 who is not a student, the path variable is set to 0, all other variable set to its sample mean.

4.3.3 *Physical activity and hazardous exposures*

Given an individual's daily activity patterns provided by CHAD, and corresponding spatial location for the activities and transportation mode choice to go to these places, both stochastically determined as outlined above, the person's physical activity and pollutant inhalation dose profiles can be established. First duration of travels are calculated and the time sequence of activities adjusted accordingly to obtain a 24 hour timeline of activities. Given a trip distance and mode choice, trip duration is calculated using fixed travel speeds for each mode: 20 miles an hour for car trips, 2.8mi/hr for walk trips, and 12mi/hr for bike trips. To simplify, time adjustments for travel durations are reported to sleeping times (i.e. sleep time is added or retrieved depending on whether travel duration as estimated by BESSTE is lower or greater than the duration identified in CHAD).

Each activity in each location throughout the day for an individual is matched with an energy output for that activity, and a pollutant concentration for that specific microenvironment at that time of the day. These elements are then combined to estimate inhalation rate associated with each activity.

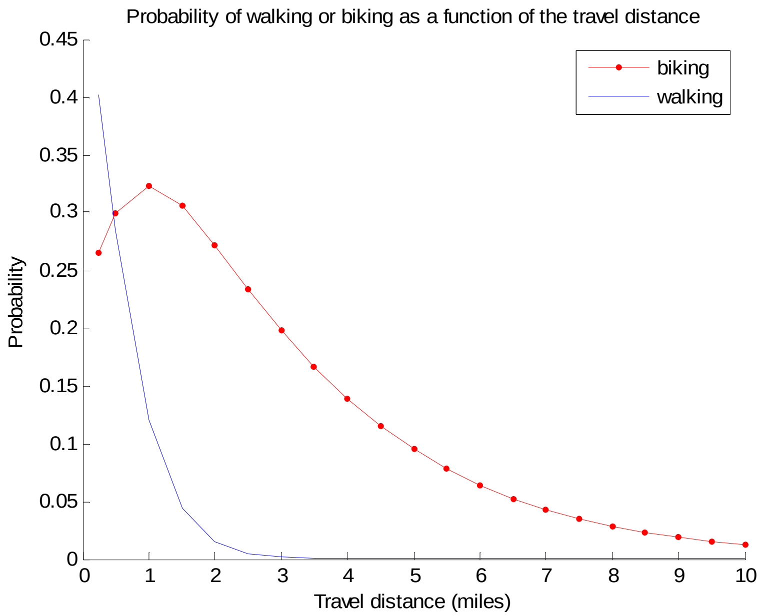

Figure 4-18 Probability of walking or biking as a function of the distance traveled. The scenario is for a female age 34 who is not a student, the path variable is set to 0, the sidewalk fraction to 0.7, all other variables set to their sample mean.

4.3.3.1 *Energy expenditure*

The rate of energy expenditure for each activity is a function of the individual's body weight, and of the "metabolic equivalent of work" [36], or MET factor, associated with each activity type:

$$Ejrt(j)=pMET(j)*BM \qquad (kcal/hour),$$

where *Ejrt(j)* is the rate of energy expenditure and *MET(j)* the MET factor, both associated with the activity at time step *j*. BM is the individual's body mass (kg).

The METs values are stochastically drawn from probability distributions associated with each type of activity and provided by CHAD, with minimum and maximum allowable values for

[36] MET *(Metabolic Equivalent)* definition taken from the University of South Carolina's Prevention Research Center: The ratio of the work metabolic rate to the resting metabolic rate. One MET is defined as 1 kcal/kg/hour and is roughly equivalent to the energy cost of sitting quietly. A MET also is defined as oxygen uptake in ml/kg/min with one MET equal to the oxygen cost of sitting quietly, equivalent to 3.5 ml/kg/min. (http://prevention.sph.sc.edu/tools/compendium.htm)

each. However, values for walking and biking from the CHAD METs chart were updated using Ainsworth's Compendium of Physical Activities (2000) as CHAD does not provide these specific modes of travel. The same distribution type as that proposed by CHAD for travel purposes is used, but mean and standard deviation values are changed, since Ainsworth provides point estimates and not distributions. CHAD holds distributions for leisure time walking, biking and jogging all combined, with mean METs ranging from 4.7 to 5.8, depending on age – these distributions are kept for leisure time walk/bike/jog, and supply the distribution type (normal, lognormal, etc.) for utilitarian walking and biking. Ainsworth's "general" biking category is used as the mean METS factor for utilitarian biking, with a value of 8 (also equivalent to bicycling, 12-13.9 mph, leisure, moderate effort). For utilitarian walking, the category "walking, 3 mph, level, moderate pace, firm surface" is chosen; it holds a value of 3.3 METs. In the CHAD leisure activity distributions the standard deviation represents 31% of the mean. This same proportion is applied for the new standard deviations for utilitarian walking and biking. However, the minimum and maximum allowable values are changed to reflect the minimum and maximum values for different types of walking, biking, or driving found in Ainsworth's compendium (for walking: 2.5 to 10.0 METs, biking: 4 to 16; other travel: 1to 3METs).

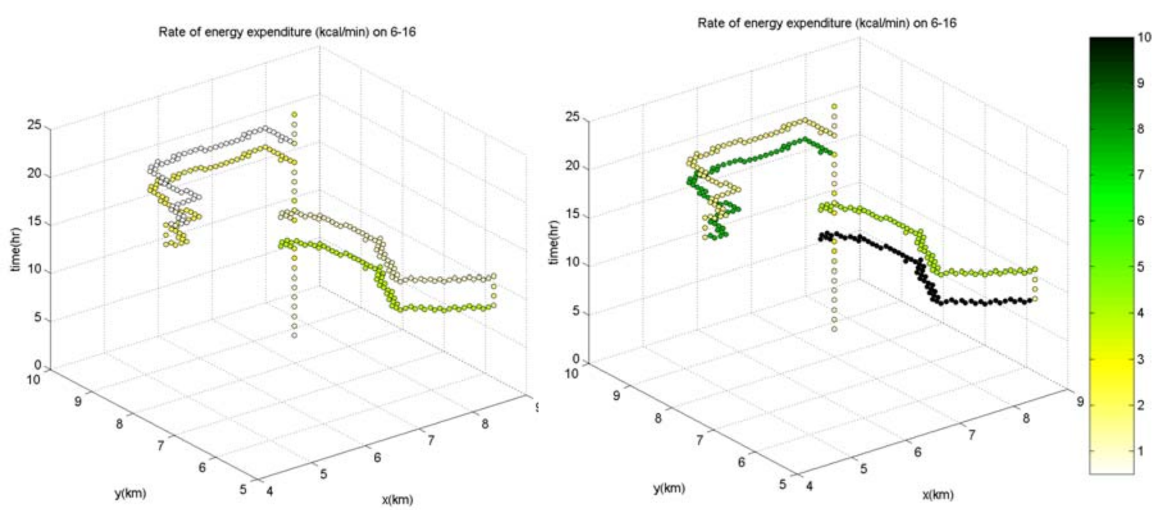

Figure 4-19 Two daily timelines of the rate of energy expenditure for an individual, in which on the right all travels are made driving, and on the left all are bike trips.

To be in keeping with the rest of CHAD METs values, the mean of the driving and other transportation mode distributions, 2.3 METs, is retained rather than assigning the value of 2 corresponding to driving an automobile or light truck in the compendium (riding in a car or bus has a value of 1).

Work activities are differentiated by occupation in CHAD tables, however the data available for EPA region 4 (the "South") does not contain occupation. Therefore "general work" distributions are ascribed to all work activities. Note that recreational activities such as outdoor activities, sports, and playing music, contain age-specific METs distributions in the CHAD tables (for 20, 30 and 40-year olds). Table E-1 in the appendix E furnishes the information on MET factors for each activity type present in BESSTE.

To obtain total energy expenditure associated with an activity Ejt(j), the rate of energy expenditure is multiplied by the duration of the activity considered:

$$Ejt(j)=MET(j)*BM*AD(j) \qquad (kcal/minute),$$

where *AD(j)* is the duration in minutes of the activity taking place at time step *j*.

Applying this process in the BESSTE context of a sequence of activities at different times, Figure 4-19 illustrates two time line graphs of the energy expenditure rate for an individual throughout the day, where on the left hand graph the mode of travel is driving, and on the right biking, for all trips.

4.3.3.2 *Inhalation dose*

The MET factor *MET(j)* picked for each activity at each time step *j* is then used to compute the ventilation rate during that activity and that time step, $V_E(j)$, (also called minute ventilation) and then the inhalation dose *ID(j)* for each pollutant. Algorithms leading to these factors first entail the determination of the average energy expenditure, *EE* (kcal/min), and the oxygen uptake rate VO_2 (liters oxygen/min) for each activity (Johnson 2002):

$$EE(j)=MET(j)*RMR,$$

where *RMR* is the resting metabolic rate of the individual (kcal/min).

$VO_2(j)=ECF*EE(j),$

where ECF is the individual's energy conversion factor (Liters of oxygen/kcal, the volume of oxygen required for the individual to produce one kilocalorie of energy).

Finally, a non-linear relationship links the ventilation rate per unit mass to the oxygen uptake rate per unit mass. The empirical equation reported by Johnson (2002) is as follows:

$Ln(V_E(j)/BM)= a+b*ln(VO_2(j)/BM)+d+e(j),$

where $V_E(j)$ is the ventilation rate for activity j, BM refers to the body mass (kg) of the individual, a and b are constants function of the individual's age and gender, d is a random variable (person-level error) selected for the individual from a normal distribution with mean 0 and standard deviation σ_d, and e(j) is a random term selected for the individual and the activity at that time step from a normal distribution with mean 0 and standard deviation σ_e. Johnson (2002) provides tables of values for a, b, σ_d and σ_e for different age-gender combinations (Table 9.1 in Johnson 2002). In addition, Johnson proposes processes for determining the needed personal factors for the individual.

BM is randomly generated from lognormal distributions that are gender specific but do not vary with age for adults over 18 years of age (Table 9-8 in Johnson 2002).

$RMR=0.166* (a+ b*BM+e),$ (kcal/min)

where e is randomly selected from a normal distribution with mean 0 and standard deviation σ_e, which is given along with a and b for specific gender-age groups in Table 9.11 in Johnson 2002. The factor 0.166 is to convert MJ/day into kcal/min.

ECF is assigned a uniform probability distribution with lower and upper limits equal to 0.20 and 0.21 liters of oxygen/kcal respectively, for all age and gender combinations (pages C16 to C21 in Johnson 2002)

The inhalation dose can then be computed as follows:

$ID(j)=V_E(j)*mP(j)*T(j),$ (μg)

where T(j) is the duration of the activity taking place at time step j, and mP(j) is the concentration of the pollutant considered in the microenvironment where the activity takes place at time j. The microenvironment pollutant concentration is computed as:

$$mP(j) = zP(j) * PEN(j), \qquad (\mu g/L)$$

where *zP(j)* is the ambient pollutant concentration at time step j derived from the pollution modeling, and *PEN(j)* is the penetration factor for the type of microenvironment activity at time *j* takes place in.

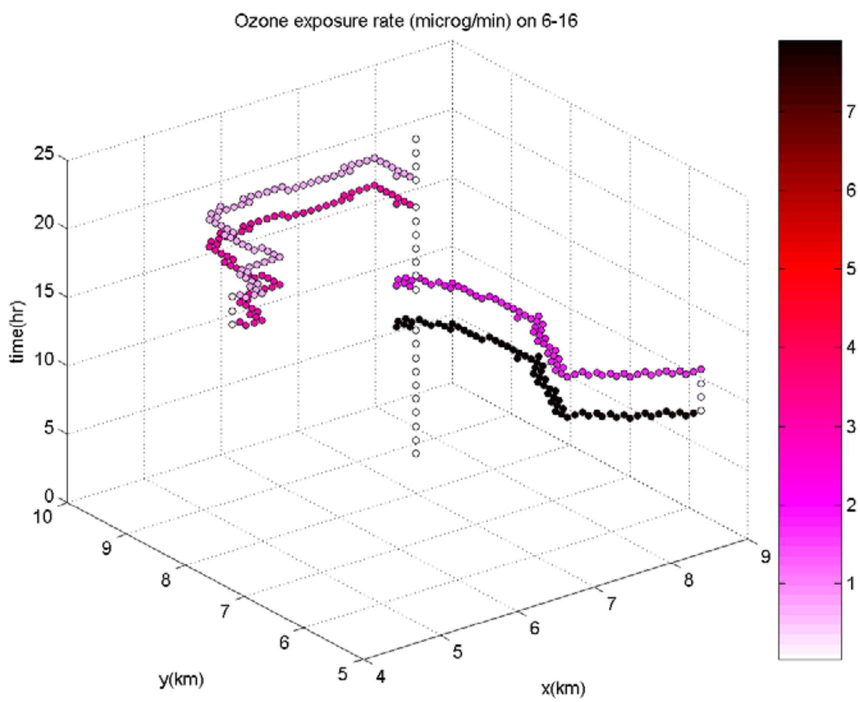

Figure 4-20 Daily timeline of ozone exposure rate for an individual, in which all travels are made biking

Some simple sensitivity analysis was performed to check the influence of the age and gender- specific parameters used for estimating inhalation rates, to ensure the value of this degree of complexity in the model. While there was not so much impact when activities were more arduous (high METs values), the difference was higher at low METs values. The decision was finally to integrate these age and gender-specific parameters since age and gender are also a component relevant in the Rodríguez mode choice model, and may be a relevant factor in the choice of activity pattern, and would likely be relevant in health impact assessment as well. (For different age and gender combinations, basal metabolic rate parameters are from Table 9-11, and regression parameters for the inhalation rate calculations from Table 9-1, in Johnson 2002).

To illustrate the concept of inhalation rates, Figure 4-20 portrays the same individual as in Figure 4-19 of individual daily profiles, for ozone inhalation dose and all trips made biking.

4.3.4 *Simulation*

4.3.4.1 *Monte Carlo simulation structure for full BESSTE model*

The series of relationships presented conceptually and numerically in the two preceding sections are tied together to create a full simulation of an individual's energy expenditure and exposure resulting from changes in the built environment, and then a simulation of the entire population in the study area.

The first component of the simulation is thus to characterize the effects of the built environmental changes on an individual. The suite of models linking the built environment to exposure and energy expenditure (and in the future, to health outcomes) is run for an individual for each built environment scenario. The basic structure of the algorithmic flow of the model is as follows:

i) An individual and associated activity pattern is randomly picked from the CHAD database.

ii) Destination locations are stochastically determined for each change in locations throughout the day, given relative attractiveness of destination choices.

iii) Mode choice is stochastically determined for each trip, given the trip distance and built environment factors.

iv) Total energy expenditure is stochastically determined given probabilistic expressions of the individual's energy expenditures for the different activities throughout the day.

v) Exposure to air pollution (inhalation dose) is stochastically determined given a probabilistic expression of the air pollution field and the above energy expenditures.

vi) Process i) to v) are repeated many times to obtain a probability curve of the outcomes of interest: inhalation dose and energy expenditure.

vii) Steps iii) to vii) are reiterated for a different built environment scenario.

viii) The changes in energy expenditure and in air pollutant inhalation dose due to the changes in the built environment are compared for the individual.

ix) Steps i) to viii) are reiterated for many individuals

Beyond the basic model flow outlined above, several more parameters regarding the timeline of exposure and the defining attributes of the individual, must be elaborated. As mentioned in section 4.1, a year of exposure is chosen for the temporal metric, for a sense of longterm effects and chronic diseases. Thus, each individual is modeled for each day of a whole year. However, CHAD only offers one day of activity for each respondant. Thus, for characterizing an individual within this temporal reference, several CHAD-respondents are combined to form a single BESSTE-individual. It is assumed that people are likely to vary their behaviors by weekend and weekday status, and by season. Therefore a single BESSTE-individual is constituted by picking at random one CHAD respondants within the same age and gender combination bracket from each of the 8 season and weekend-weekday status (hence, 8 CHAD-individuals form 1 BESSTE-individual). The resulting CHAD individual is assigned a home and a work location, as well as individual factors such as weight and inhalation rate personal factors, which do not vary from season to season (and week end to weekday). The age attributed to the BESSTE-individual is the average of the 8 individuals picked. Further, two approaches are tested to characterize the variability of behaviors and exposures for the individual: A) a low variability-scenario in which all activity locations and mode choice are assumed to be invariant within each weekday status-season combination ("the creature of habit"), and B) a high-variability scenario in which locations of each activity and mode choice are allowed to vary everyday. These two scenarios are meant to bound outcome estimates given the unknown variation in people's behaviors in a year. To approximate the Chapel Hill-Carrboro population behaviors, the gender-age bracket categories of individuals are picked from CHAD proportional to the Chapel Hill population composition, according to the 2000 Census. A total of 85 individuals are thus modeled for each variability scenario. The Cervero mode choice model is used for these runs, which are henceforth referred to as the full BESSTE model runs.

4.3.4.2 *Person-day uncertainty simulations*

To assess uncertainty associated with outcomes of each day of activity, a person-day simulation is also performed, in which a day of exposure is modeled 300 times in a MonteCarlo process for a single day of activity. Sixty four individuals are thus simulated, each representing a different age-gender and day status-season combination (within each day status-season bloc the day is picked randomly). The Cervero and the Rodríguez transportation models are employed consecutively in this uncertainty assessment, to gauge the impacts of travel behavior methods. Several air pollution scenarios are tested in this simulation as well (see section 4.3.4.4.).

Each run for a single individual of a day of activity produces an uncertainty distribution for the outcomes of that person-day. For the population, the uncertainty associated with daily measures of pollutant inhalation dose and energy expenditure is assessed by first examining the inverse cumulative distribution across the 64 individuals of different percentiles of the different outcomes. The difference between the 5th, 50th and 95th percentile distributions for each outcome and associated transportation model- built environment combination provides a measure of uncertainty for a daily ouptut. The width of each percentile cdf gives a sense of the variability across the population for these estimates. The difference in the distributions of outcomes corresponding to each built environment scenario are also evaluated for each person-day simulation using a Wilcoxon matched-paired singed-rank one-tailed test to assess impacts of the transformations. Results obtained with both travel models are compared to appraise their influence.

Next, considering more specifically the effect of the built environment, inverse cumulative distributions of the change in outcomes are evaluated. The 5^{th} and 95^{th} percentiles and mean distributions of percent increase in inhalation dose for the two pollutants, and difference in energy expenditure due to active travel are analyzed in a similar way as described above.

4.3.4.3 *Sensitivity analyses*

Sensitivity analyses are performed to assess the relative contributions to the variance in BESSTE outcomes of the different stochastic processes that interplay in BESSTE and of the varying built environment characteristics, as well as to test different forms of capturing relationships characterized in the model. Secondly, effects on the magnitude of average outcomes are considered to evaluate the drivers of results.

The general approach of the contribution to variance sensitivity analyses is to apply the model in a Monte Carlo simulation to a daily activity of an individual, varying solely the features of interest and comparing the mean and variability, measured by the coefficient of variation, of the BESSTE model outcomes. To be able to compare each element under consideration, care is given to save the settings for a set of characteristics that must remain fixed throughout the different model runs. These include all of the following except the factor being tested and other variables necessarily influenced by that change[37]: the individual with associated activity pattern, date of activity day (including ozone day), body weight, resting metabolic rate, stochastic elements associated with ventilation rate simulations, student status, METs factors associated with each activity, location choice, transportation mode choice, land use variables, street pattern scenario. The process is repeated for ten individuals with 200 model runs each, to keep the assessment manageable while still capturing a variety of situations. The various targets of the

[37] For example if travel mode varies, than necessarily the METs factor associated with the travel activity must change as well

sensitivity analysis and the elements allowed to vary for each test are described below and summarized in Table 4-4.

1. **Testing relative contribution of varying elements of the built environment**

   Connectivity – The model is run allowing only the street network to vary, keeping all other stochastic elements fixed. The influence of the street network connectivity is tested separately to see its effect on mode choice solely, and on the combination of location choice followed by mode choice as well. Unfortunately in the Cervero model changes in the network must be applied to all modes indiscriminately, in other words the additional short cuts or paths must be open to motorized travel as well as to pedestrians and cyclists. Thus when testing the change in connectivity using the Cervero model, the only variable that may vary is the distance to the next destination (if trip ends are on a route affected by the change in street patterns). However the relative change in transportation supply for motorized and non-motorized modes is tested using the Rodríguez model.

   Land use – The effect of varying land use variables on individuals' exposure and physical activity outcomes is tested separately for a model run where both locations and transportation mode choice are allowed to vary, and a model run where only mode choice varies. Three land use scenarios are tested: as is, random locations of activities, and the pedestrian-friendly density and mixed use scenario. The random location hypothesis is assessed by actually keeping the same locations as in the status-quo but picking those locations at random instead of using a gravity model (thus facilitating the process of estimating BESSTE final outcomes compared to having to truly create a new set of activity locations and corresponding routes).

   Sidewalks – A change in sidewalk provision from the status-quo to 100% sidewalk is tested considering only a change in transportation mode choice, using only the model.

2. **Testing use of different approaches to characterize relationships**

   Transportation models - The two transportation models (Cervero and Rodríguez) not only reflect different modeling frameworks applied to different sets of data (one national, one local), but they use distinct sets of explanatory variables. Therefore the comparison between outcomes using one model over the other necessarily reflects a comparison of diverse characteristics of the built environment as well. The difference in transportation model is tested for the following scenarios:

i) A fixed built environment scenario

ii) Changes in the connectivity and sidewalk presence, affecting only mode choice and not location choice. This scenario is applied differently for each transportation model since in using the Cervero model the added paths must be opened to all modes, while as in Rodriguez they are mode-specific attributes thus it is implemented here as variations that only affect non-motorized modes. This analysis permits the comparison of an extreme case of using the two different models, since it necessarily mildly impacts mode choice under the Cervero model (only distances for some destinations change), while it allows full variations in the Rodriguez model.

iii) Changes in the land use variables affecting both location choice and mode choice[38]. This analysis allows the comparison of another extreme in choice of transportation models, since it should trigger a much greater variation in outcomes under the Cervero model, and milder changes using the Rodriguez model which will be affected only by changes in distance due to changes in destinations.

iv) Combination of both connectivity and land use changes

Location choice model - Different forms of the location choice model, described in section 4.3.1 are tested. The Cervero model is used for transportation behavior simulation, and the test is performed for the combination of land use and street pattern changes.

[38] Note that it is not interesting to compare the use of transportation model considering only mode choice impacts of changes in the land use variables, since the Rodriguez model does not take into account the effect of land use mix and density on walking and biking, thus would not vary under these land use changes.

3. Assessing the relative contributions of other stochastic processes in BESSTE

METS factors – BESSTE is run for an individual allowing only the METS factors to vary, and keeping all other elements fixed. METs values are picked from the uncertainty distributions associated with each activity, described in section 4.3.3. No effect of changes in the built environment is estimated.

Air pollution – Air pollution estimates are allowed to vary along the uncertainty distribution constructed from the mean and variance outputs of the BME pollution mapping process (otherwise BESSTE uses BME mean estimates as the air pollution estimate).

Table 4-4 Summary of sensitivity analysis targets and procedures

Element tested	1st test variable(s) allowed to vary	2nd test additional variable(s) allowed to vary	3rd test additional variables allowed to vary
Connectivity	Mode choice	Location choice	Travel model
Land use	Mode choice	Location choice	
Sidewalks	Mode choice		
Transportation models	Mode choice	Connectivity + sidewalks	Land use + location
Gravity model	Location + mode choice	Connectivity + land use	
METS factors	METS per activity		
Air pollution	Exposure concentration		

The contribution to variance of each of these elements is assessed by comparing the coefficients of variation (standard deviation divided by the mean) obtained for each individual, and examining the range of these coefficients for the 10 individuals. To gauge the effects of each factor as a driver in the outcomes the mean of the outputs are compared.

Other stochastic processes that are not tested in this 10-individual analysis but vary for each iteration of the full BESSTE model runs include the personal factors that affect inhalation rates: body weight, stochastic terms that intervene in the inhalation rate calculation, resting metabolic rate, and the energy conversion factor. A simple sensitivity analysis is performed on these factors for a synthetic individual, which also serves to measure inhalation dose thresholds of interest. The scenario is descibed in the following section on calculating threshold levels.

4.3.4.4 *Threshold levels*

As mentioned previously, for the inhalation dose a threshold is calculated in reference to the NAAQS standard rather than to an effect, since there are no known thresholds for effect. To calculate inhalation dose used as thresholds, a simulation is run based on an indvidual with a simplified activity experiencing a day where pollutant levels are at the NAAQS standards. The simple activity pattern consists in 10 hours spent in general work activities (METs=3), including 1 outdoors (and the rest indoors), and 14 hours resting (METs=4). Pollutant concentrations are related to NAAQS standards: 10 hours of ozone at 0.08ppm (during the work activity), and the rest at 0.03ppm; all 24 hours at 150µg/m^3 for $PM_{10.}$ A 2000-run Monte Carlo simulation is performed for a female and male respondent between ages 30 and 44, allowing all personal factors to vary at every run. The average from these runs is used as the threshold inhalation values.

Theshold levels used for energy expenditure due to active travel is simply the recommended level of physical activity: 150 kcal/day (on at least five days of the week).

4.3.4.5 *Air pollution scenarios*

High and low air pollution concentration reductions scenarios are applied, to test improvements in air quality (for example due to increased walking and cycling). To simplify the analysis, uniform decreases in ozone and air pollution are applied to the area. The two scenarios tested are a 5% and a 20% decrease in concentrations. These modifications are implemented solely for the person-day uncertainty analysis (see section 4.3.4.2).

5 RESULTS AND DISCUSSION

First results from the full BESSTE model simulation are reported, and then outcomes from the sensitivity analysis. The findings are analyzed then discussed in relation to the decision framework in sections 5.3. Policy and research recommendations ensue.

5.1 Full BESSTE model results

The full BESSTE model, as described in section 4.2.4, simulates a year of exposure for 85 individuals, following two simulation protocols (A and B). Outcomes for each day for each person are estimated only once, however the uncertainty around each daily output is analyzed in the following section and will be discussed jointly later. The graphs rendered in this section thus represent the distrubution across the population of measures of variability in the outcomes for each individual. Throughout this section, graphs will portray in lighter colors (cyan and magenta) simulation B versus darker colors (red and blue) for simulation A, and the status quo built environment (B1) in blue-cyan versus the more pedestrian-friendly scenario (BE2) in red-magenta.

5.1.1 *Variability in inhalation dose and active travel*

Comparisons are made between simulation scenario A (low behavioral variation) and B (high behavioral variation) for the variability across the population of different percentiles of inhalation and active travel outcomes, and for effects of the built environment (BE).

In terms of the variability across the population, distributions are essentially the same for the two simulation approaches for PM and ozone, with slightly higher outputs in simulation B for most of the populations except at the tails. This can be seen in Figures 5-1 to 5-3 which portray the inverse CDFs of several percentile values of inhalation and energy outcomes for the two simulations and the two built environments. To be more specific, the 50th, 95th and 99th percentiles of the variability distribution of each individual are calculated to create for each a variability distribution across the population. High percentiles in the variability of inhalation exposure are shown (50th, 95th and 99th) since the lower intakes are not of concern (unless the low percentiles are high as well). To illustrate, it can be said from looking for example in Figure 5-1 at the 90th population percentile[39] for simulation A and the status-quo built environment (BE1), that 90 percent of the population experiences on half of the days in the year an inhalation dose equal or less than 280 µg/day, and on 95% of days inhalation equal or less than 650µg/day. A general pattern of difference between simulation approach and built environment scenarios are not apparent from these graphs; these differences are discussed later.

For active travel the 50th and 30th percentiles are chosen for display, respectively to get a measure of central tendency and the value of minimum energy expenditure for 70% of the days in a year. Energy expenditure due to active travel is shown to be close to the null for most of the population for these percentiles. For individuals with the highest levels of activity, simulation A produces higher outputs than B.

[39] To read the 90th population percentile value for different variability distributions, look up the values on the y-axis that correspond for each distribution to the x-axis value of 0.9.

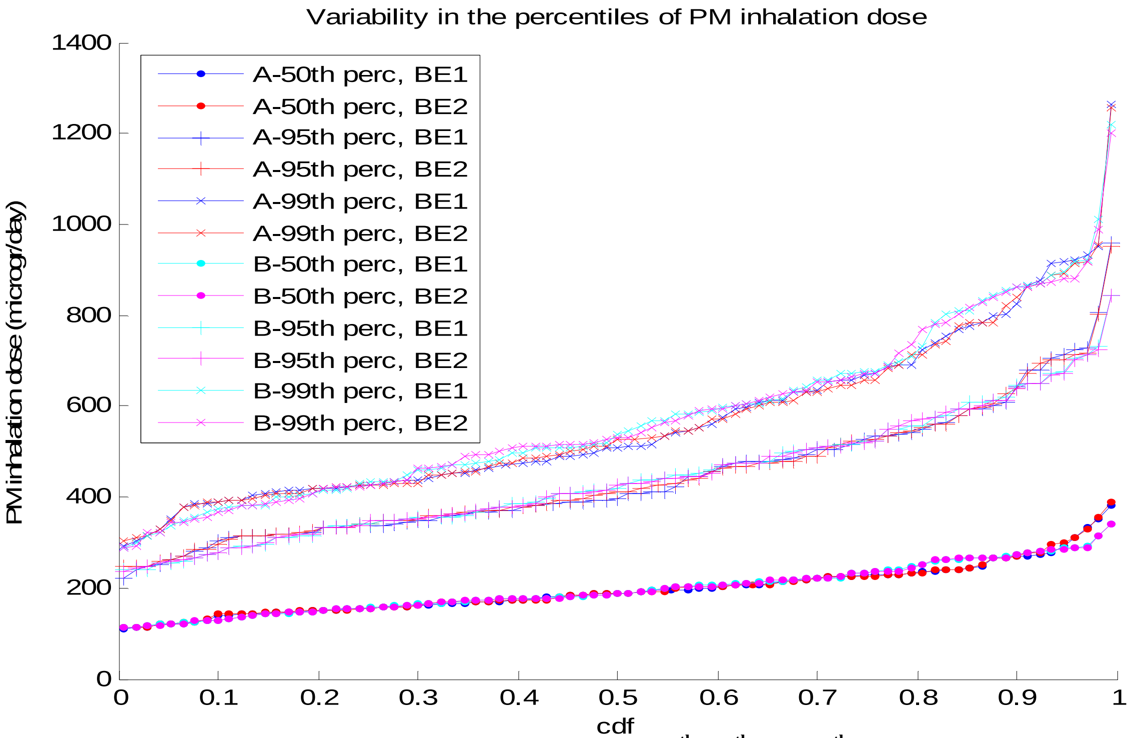

Figure 5-1 Cumulative distribution for the population of 50th, 95th and 99th percentiles of variability in individuals' yearly exposure for daily PM inhalation dose for two built environment scenarios (BE1 is the as-is and BE2 the pedestrian-friendly scenario) and two simulation approaches (A is low-behavioral variability and B high behavioral variability simulation).

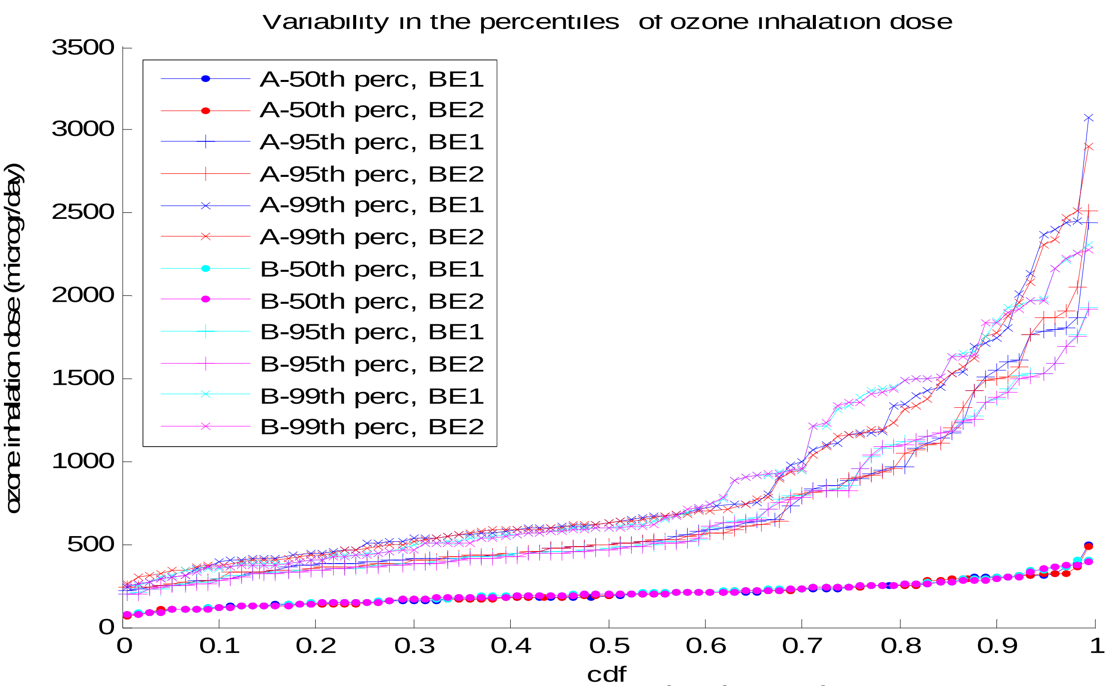

Figure 5-2 Cumulative distribution for the population of 50th, 95th and 99th percentiles of variability in individuals' yearly exposure for daily ozone inhalation dose for two built environment scenarios (BE1 is the as-is and BE2 the pedestrian-friendly scenario) and two simulation approaches (A is low-behavioral variability and B high behavioral variability simulation).

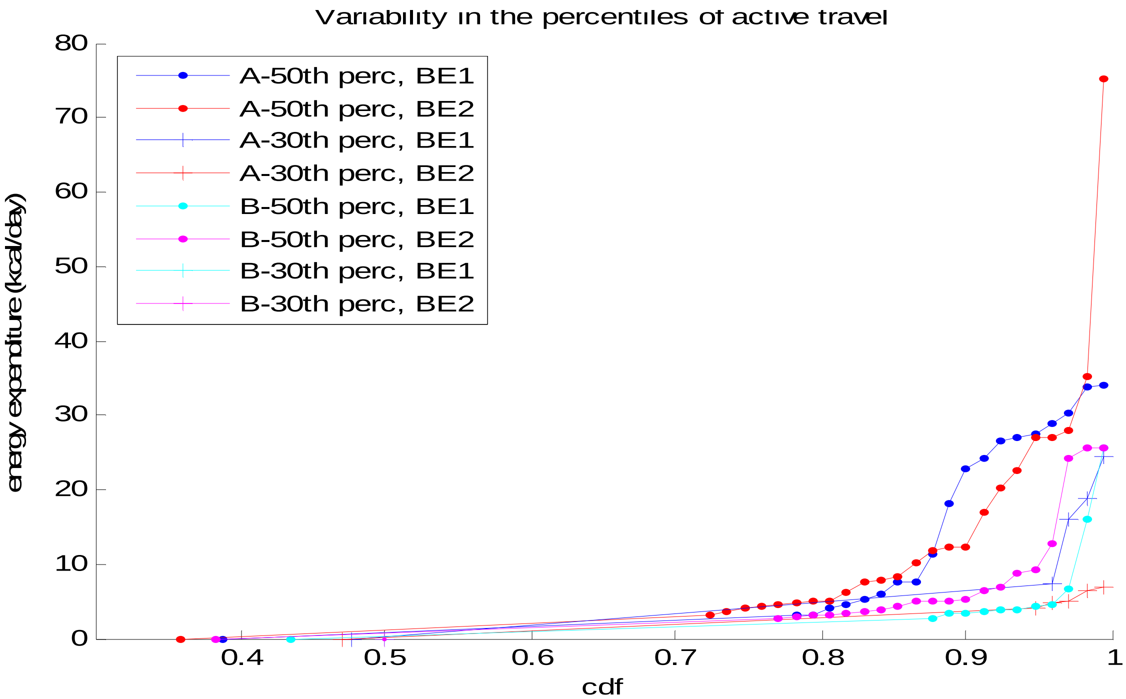

Figure 5-3 Cumulative distribution for the population of 50th and 30th percentiles of variability in individuals' daily energy expenditure due to active travel throughout the year for two built environment scenarios (BE1 is the as-is and BE2 the pedestrian-friendly scenario) and two simulation approaches (A is low-behavioral variability and B high behavioral variability simulation).

5.1.2 *Variability in fraction of days above thresholds*

Variability distributions in the fractions of days above the thresholds are shown in Figure 5-4 for PM_{10} and ozone inhalation dose and Figure 5-5 for active travel. Threshold levels are set at 520µg/m^3 for PM_{10}, 470µg/m^3 for ozone (based on the simplified activity scenario under NAAQS standard threshold conditions described in section 4.3.4.4), and 150Kcal for active travel (recommended level). Patterns are overall similar across BEs and simulation methods, however a more pronounced difference is noted between simulation approaches for ozone and for active travel than for PM_{10}. For PM_{10}, half of the population has around one percent or fewer days above the threshold, and 5% experiences more than 17% of days of high inhalation. High ozone dose days appear on less than 5% of days for half of the population, and more than 30% of days for five percent of modeled individuals. For active travel, in simulation B, contrary to simulation A, all individuals display some active travel throughout the year, but the levels do not reach the more extreme values observed in A. Overall the model finds a very low adherence to healthy levels of physical activity, with the 5 percent most active (in terms of frequency) individuals attaining recommended levels of activity for only 11 to 14% (BE1) or 14 to 25% (BE2) of days for simulation A, and a low 6 to 10% of days for simulation B.

Differences between built environments are small, yet in simulation A the less pedestrian-friendly scenario seems to generate higher values of fraction of days above thresholds for ozone and energy expenditure for most of the population; for PM the lines are more inter-twined.

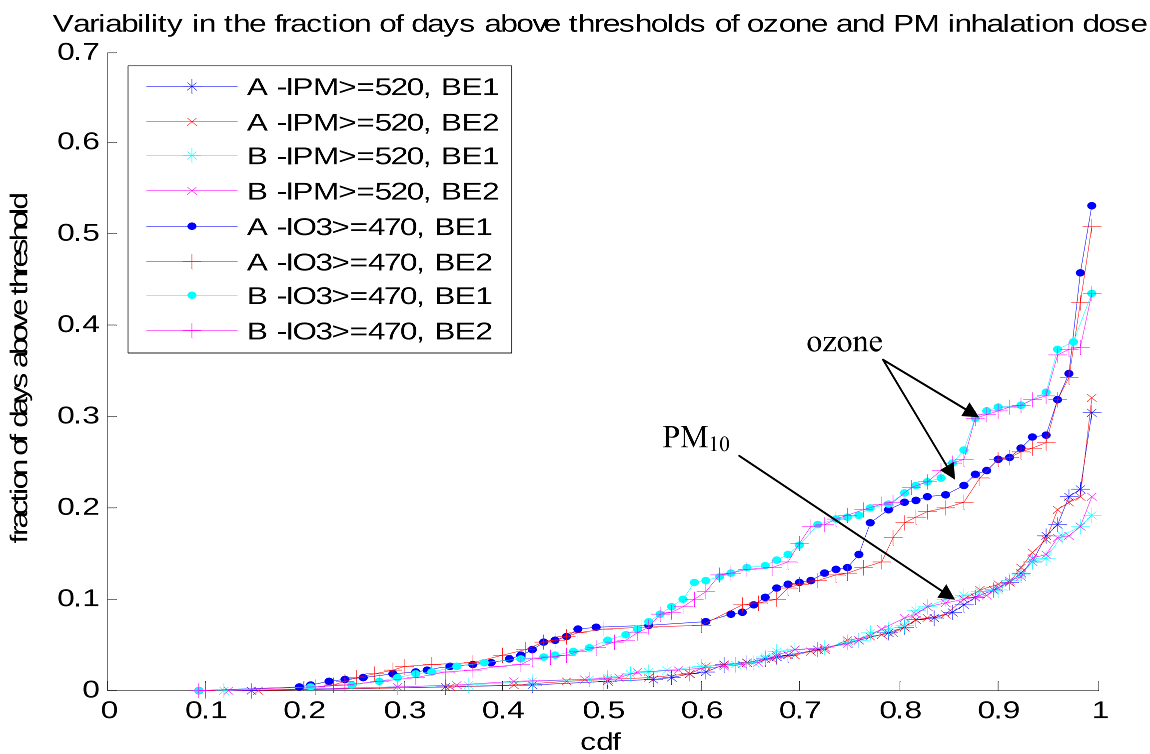

Figure 5-4 Cumulative distribution of fractions of days of inhalation of PM_{10} (IPM) and ozone (IO3) above corresponding thresholds (530 µg/day and 470 µg/day) for two built environment scenarios (BE1 is the as-is and BE2 the pedestrian-friendly scenario) and two simulation approaches (A is low-behavioral variability and B high behavioral variability simulation).

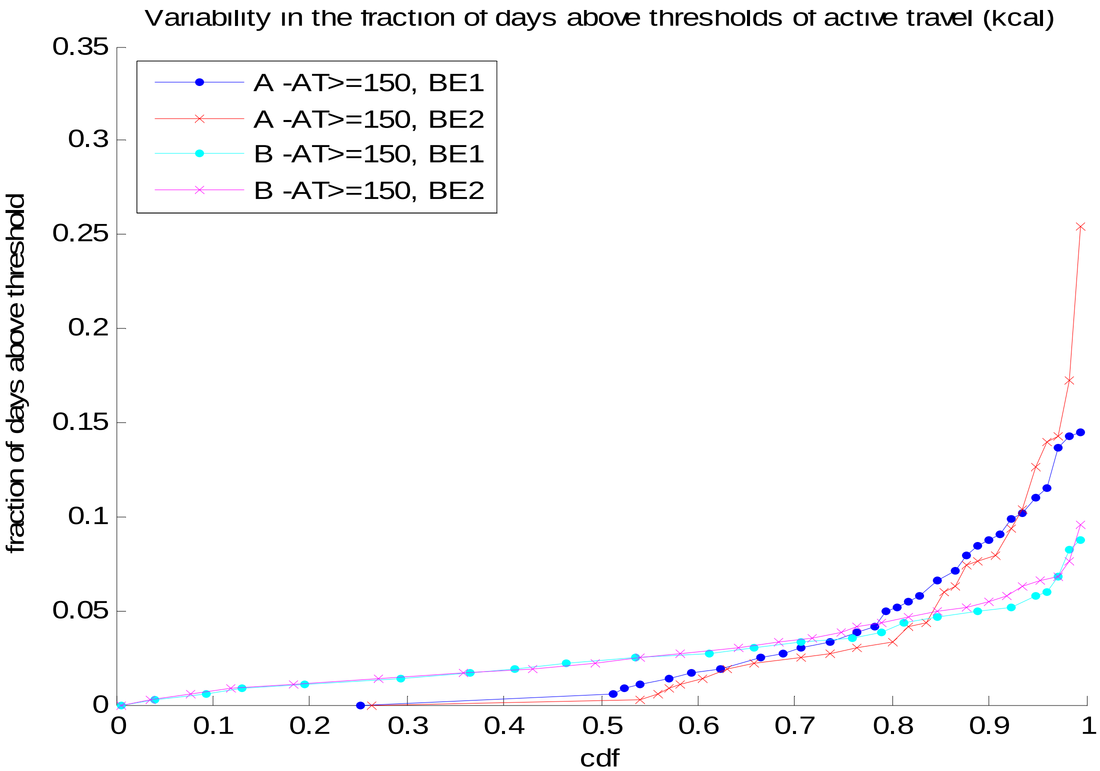

Figure 5-5 Cumulative distribution of fractions of days above energy expenditure due to active travel (AT) thresholds (150Kcal/day) for two built environment scenarios (BE1 is the as-is and BE2 the pedestrian-friendly scenario) and two simulation approaches (A is low-behavioral variability and B high behavioral variability simulation).

5.1.3 *Impacts of the built environment*

To examine specifically the impact of the built environment, metrics employed are the percent change in inhalation dose following community transformations for ozone and PM (Figures 5-6 and 5-7), the difference in energy expenditure due to active travel (Figure 5-8), the percent change in inhalation dose on high intake days (Figure 5-9), and the difference in fraction of days above thresholds (Figure 5-10). The Wilcoxon matched-pairs signed-ranks one-tailed test is applied to test differences in distributions of outcomes for each built environment scenario.

The three graphs of change (percentage changes for inhalation dose, and difference for active travel) in Figures 5-6 to 5-8 display the same schema for the population: all individuals experience both increases and decreases in exposures or activity in approximately an equal numbers of days throughout the year. In terms of the magnitude of change overall, most individuals undergo similar amounts of change in both directions, averaging out at, or close to, zero[40]. However, the days of most extreme changes for ozone and PM exhibit greater increases than decreases: the 5 percent of the population with the greatest decreases in their 5th percentile of their variability in PM inhalation dose reduce intakes by 19 to 44% (simulation A) or 14 to 16% (simulation B), while the 5 percent of the population with the greatest increases in their 95th variability percentile inhale 83 to 173% (simulation A) or 25 to 34 % (simulation B) more pollutant in BE2. For ozone these numbers are: 35 to 49% (A) or 26 to 39% (B) decrease, versus 60 to 178% (A) or 29 to 52% (B) increase. For active travel on the other hand, the magnitude of change in either direction is more homogeneous (especially for simulation B) with slightly higher decreases than increases at the respective tail ends. Overall, in simulation A, individuals experience an increase in energy expenditure due to active travel on 25% of days, another quarter shows reductions in the measure, and the remaining days have equal amounts for each built environment. For simulation B these numbers are 27% raises and 24% reductions.

In terms of differences between simulation approaches, the most noteworthy distinction is for the tail end of the inhalation curves. In PM_{10} exposure, the inverse CDF of percentiles of variability are reasonably well aligned for both simulations, until the 95th percentile curves depart around the 70th population percentile to produce a substantial difference in the 10% population segment with highest exposures. For these individuals, 5% of the days with the greatest changes display between 20 and 35% increases in PM_{10} exposure in the more pedestrian friendly scenario relative to the status quo built environment under simulation A, and between 35 and 175% under B. Similar results are found for ozone, although approach A produces a wider range of variability throughout the population, and begins departing significantly from simulation B around the 80th population percentile (changes for the 10% population segment with highest increases are 25 to 50% raises for simulation B, and 50 to 180% for A). Similarly large changes and differences in

[40] Distributions of mean change are not shown so as not to confuse the graph, but they are closely aligned to the median distribution with slight differences at the tail ends.

changes are not observed for reductions in exposure, but simulation A produces slightly greater decreases than simulation B at that tail end.

One more item of interest regarding changes in behaviors is the difference in actual number of bike and walk trips generated by each built environment scenario (data not shown in figures). The difference in the number of non-motorized trips in a year, ranging across the population from -63 to +126, is positive for 80% of the population, and is above 50 for 15%. On average, each modeled individual increases by 22 trips a year their number of non-motorized trips, according to simulation B[41].

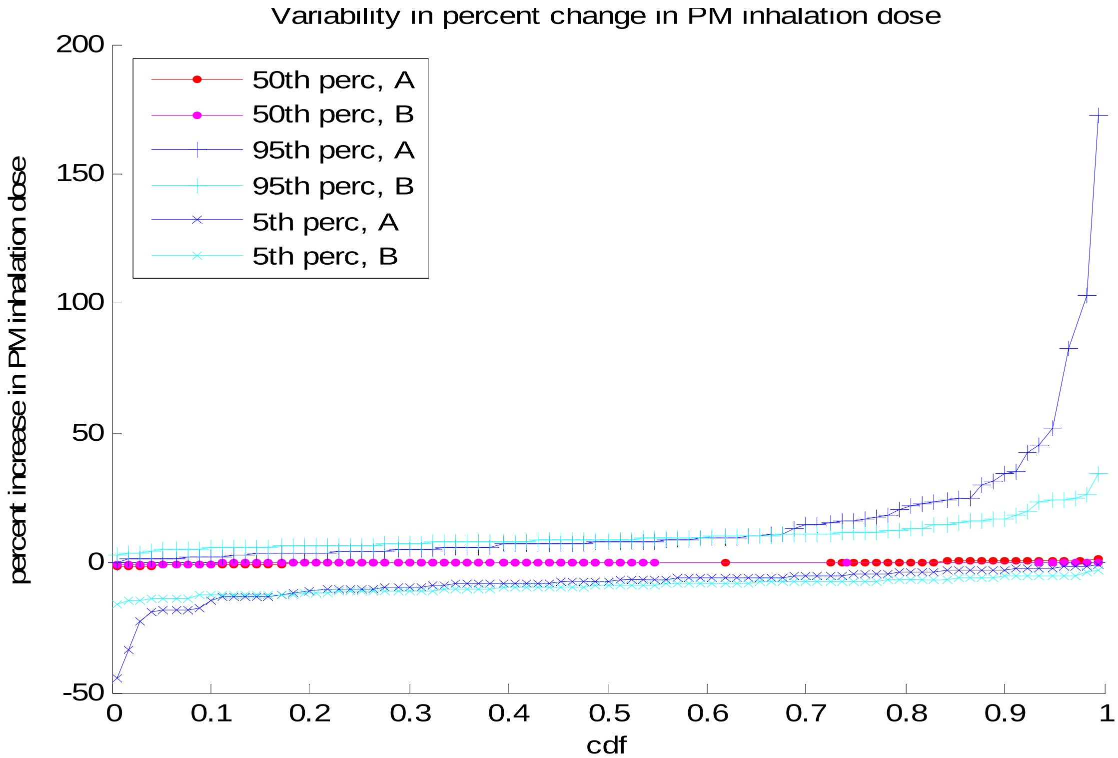

Figure 5-6 Cumulative distribution of percent change in PM inhalation dose following changes in the built environment towards the more pedestrian-friendly design, for 2 simulations approaches (A is the low-behavioral variability and B the high-behavioral variability simulation)

[41] Unfortunately only simulation B can produce these results, because of an error in the simulation A program indexing the number of trips variable.

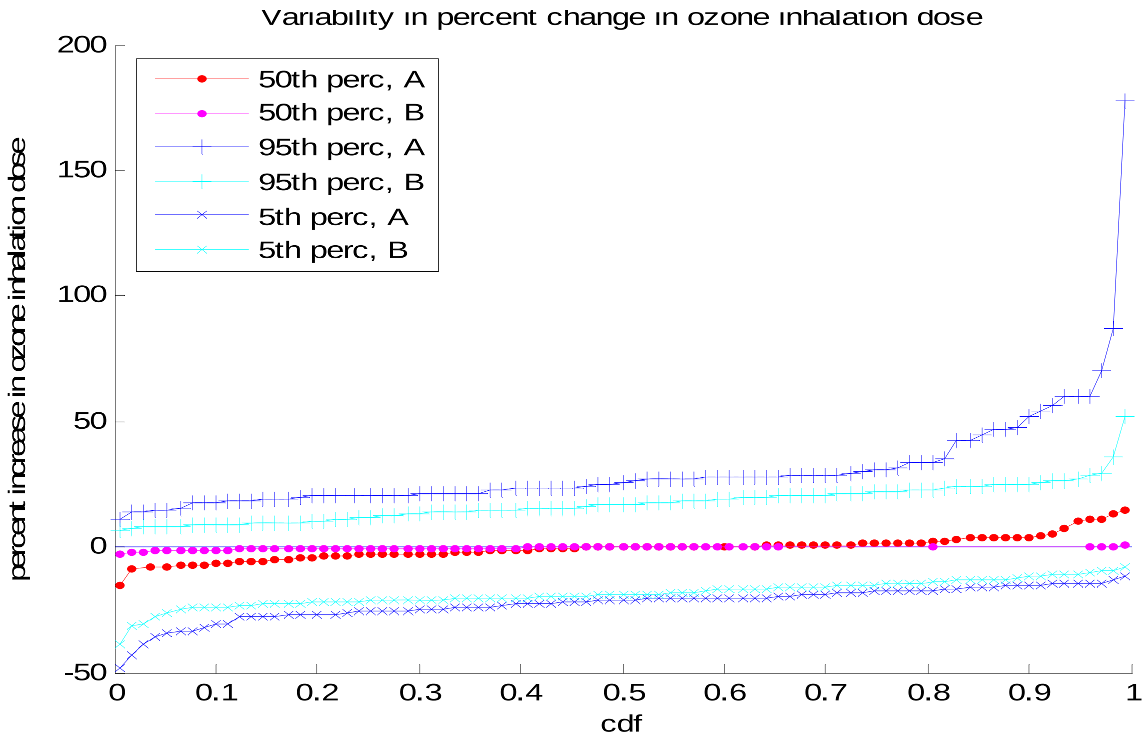

Figure 5-7 Cumulative distribution of percent change in ozone inhalation dose following changes in the built environment towards the more pedestrian-friendly design, for 2 simulations approaches (A is the low-behavioral variability and B the high-behavioral variability simulation)

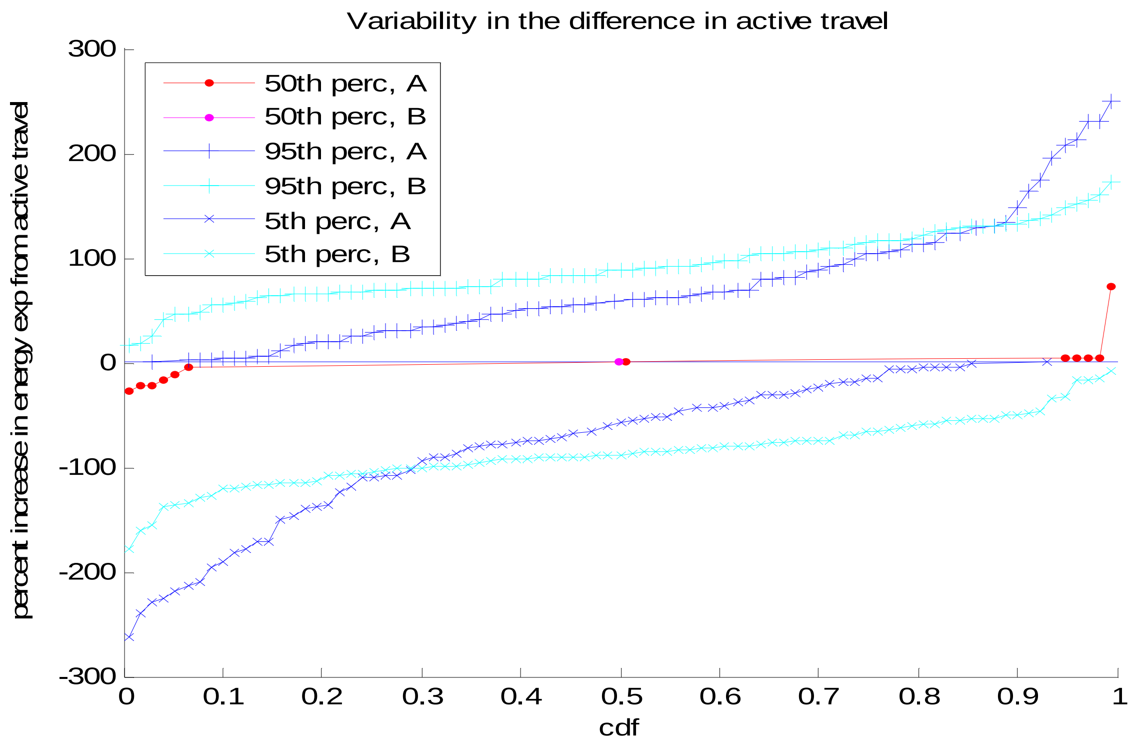

Figure 5-8 Cumulative distribution of the difference in energy expenditure due to active travel following changes in the built environment towards the more pedestrian-friendly design, for the 2 simulations approaches (A is the low-behavioral variability and B the high-behavioral variability simulation)

The results and Figures of percentage change in the outcomes following changes in the built environment towards more pedestrian friendly-design presented above account for all days with no consideration of the actual level of exposure; now special attention is given to the days of highest concern, i.e. where exposures are above the threshold. Figure5-9 shows the CDF of the pollutants intakes change for all days (individuals combined) where both of the built environment scenarios are above the corresponding thresholds for ozone and PM. In 90% of the person-days, individuals experience between a -7% and +10% change in PM inhalation, and between -24% and +29% (A) or -11% and +10% (B) ozone intake.

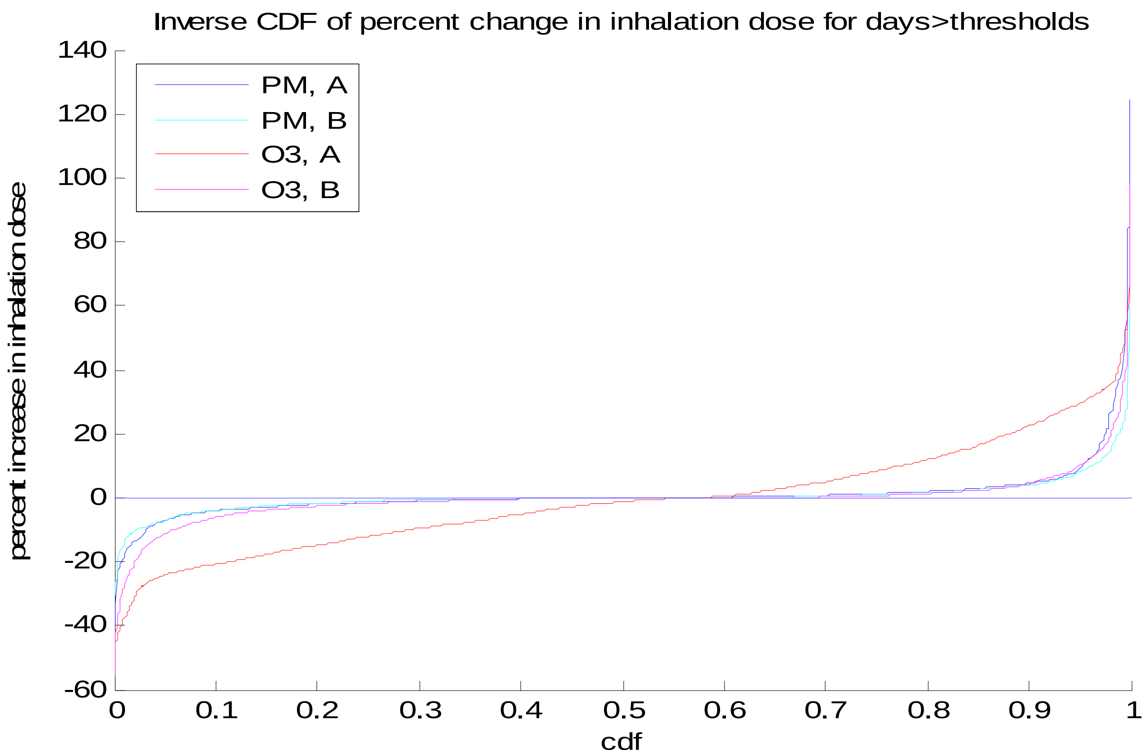

Figure 5-9 Cumulative distribution of percent change in ozone and PM_{10} inhalation dose following changes in the built environment towards more pedestrian friendly design for days above inhalation dose thresholds for all individuals combined and for the 2 simulations approaches (A is the low-behavioral variability and B the high-behavioral variability simulation)

The fraction of days above thresholds provides a measure that can be more specifically related to health effects, in particular to assess chronic effects associated with repeated days above certain levels for an individual. Therefore the change in numbers of days of high exposure or high activity rates, portrayed in Figure 5-10, is another interesting metric to consider in assessing effects of the built environment. As in other graphs of change, differences are equally partitioned between positive and negative shifts, with variations at the tail ends. Simulation A produces greater differences at the tails than simulation B. For PM_{10} inhalation dose, the negative extreme, reaching a 1.9% reduction, is a little larger than the positive one (1.6%), and ozone spans from -16% to +10%. Conversely, a greater positive shift is observed at the extreme for active travel, with a high of 25% increase in energy expenditure compared to the highest decrease of 14% of days.

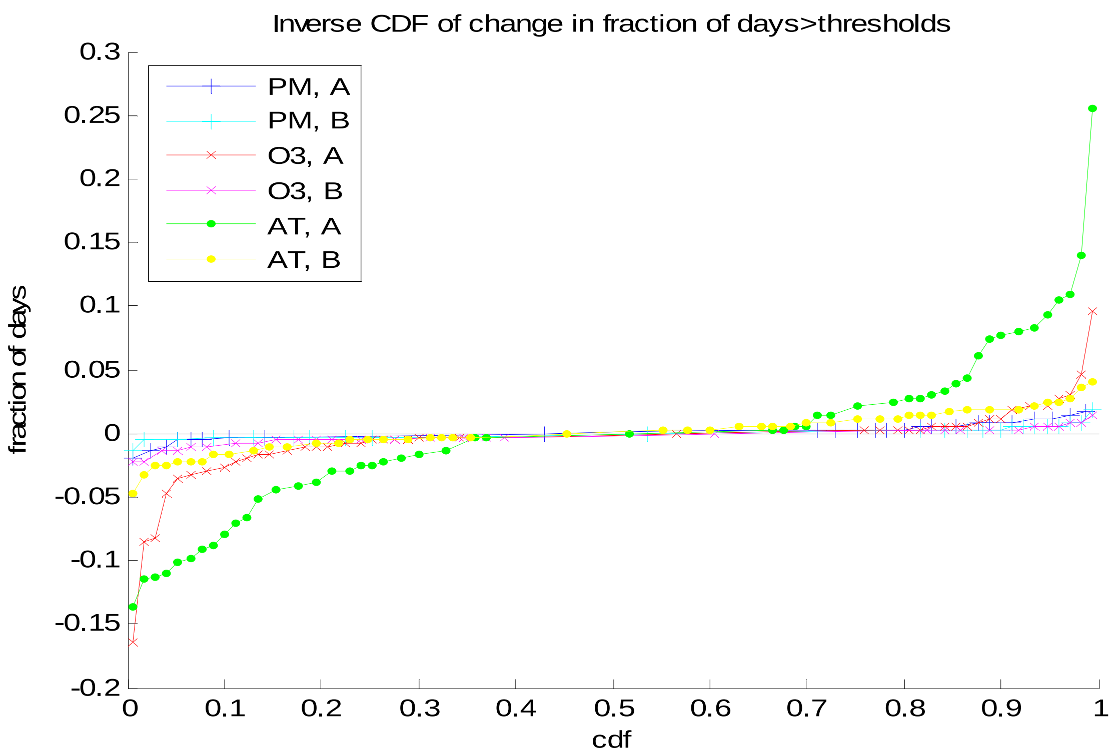

Figure 5-10 Variability across the modeled population of the change in fraction of days above thresholds following BE changes, for PM, O3 and active travel (AT) for the two simulation approaches (A is the low-behavioral variability and B the high-behavioral variability simulation)

Next, statistical tests are performed to determine the significance of change between built environment scenarios. Combining all outputs together and performing a Wilcoxon test (one sided) for both simulations A and B, matched-pairs of ozone and of PM inhalation dose produce a significant number of decreases instead of increases after built environment transformations, with a p-value below 0.00001. On the other hand, significant increases are found for energy expenditure due to active travel for all data combined with a p-value below 10^{-15}, albeit only for simulation B. This test thus suggests that the BE transformation is decreasing exposure but increasing energy expenditure.

Considering the matched pairs of fractions of days above the threshold for all individuals in each built environment, a significant reduction in number of individuals with days above the threshold is also observed for ozone inhalation in both simulation approaches (p-value below 0.03). Yet, for PM_{10} the matched-pair fractions of days above the thresholds increases with community changes in simulation A (but not B), with a p-value for significance of 0.03. No significant changes are found for fractions of days above energy expenditure thesholds in either direction.

Table 5-1 Results of Wilcoxon matched-pairs signed-rank tests for different outcomes for all individuals, and for individuals with days above the corresponding threshold.

	Simulation A (low-var)		**Simulation B (hi-var)**	
Individuals:	**All**	**w/ days >threshold**	**All**	**w/ days >threshold**
% indiv **increase PM**	36	39	6	8
% indiv **increase O3**	28	28	1	1
% indiv **increase active travel**	44	-	32	-
% indiv **decrease PM**	49	53	50	49
% indiv **decrease O3**	41	42	60	59
% indiv **decrease active travel**	39	-	2	-

Looking at each individual separately, as summarized in Table 5-1, the Wilcoxon tests finds more people with significant numbers of days with decreasing inhalation dose than people with increases (for example 49% versus 36% of all individuals for PM inhalation in simulation A). The difference is more drastic in simulation B, with for instance only 1% of individuals increasing ozone inhalation compared to 60% reducing it significantly. However a greater portion of the population experiences a significant increase in days of rising energy expenditure due to active travel than a significant decrease. Because people with higher inhalation dose are of greater concern, changes in individuals who have days above the threshold level (70 to 75% of the population for PM and 80% for ozone) are considered in particular. Results, reported also in Table 5-1, are similar to those for the whole modeled population.

In an attempt to determine whether changes in inhalation dose are linked to shifts in active travel, the joint outcomes are considered. For simulation A, in respectively 72% and 63% of individuals where PM_{10} and ozone inhalation dose increases significantly, energy expenditure due to active travel also increases significantly. Corresponding numbers for simulation B are 40% (PM_{10}) and 100% (ozone only concerns one individual). These numbers indicate that in a majority of cases for simulation A, rising pollutant intake coincides with increases in active travel. A smaller proportion of individuals with decreasing inhaled pollutant are accompanied by reductions in energy expenditure (65% and 55% respectively for PM and ozone in simulation A, 2% for both pollutants in simulation B). To explore further the hypothesis of concomitant changes in active travel and inhalation dose, the correlations between the differences in inhalation intake and the differences in energy expenditure are calculated for each individual: Figure 5-11 shows the resulting inverse CDF for the modeled population, where for the ozone outcome only days during the ozone season are accounted for. All simulation B correlations are significant at the 0.05 probability, and in simulation A, 82% for PM and 75% for ozone. Around 30 to 40% of the modeled population have correlations higher than 0.5 (suggesting a fairly strong correlation) for PM, and two thirds to one quarter for ozone.

The temporal variation of the outcomes is another interesting measure to consider, in particular in proposing policies that could be season-specific if seasonal patterns are present. Figure 5-12 displays in the same graph the temporal pattern of the population 95th percentile of the three outcomes (i.e. each day in the graph plots the 95th percentile from the population distribution of outcomes for that day) for simulation B and BE2. The energy expenditure through active travel outcome was multiplied by 5 to be on a similar scale as the inhalation outputs. The figure illustrates how active travel in the winter days would probably be healthier than in most other days of the year, especially spring and summer, as for similar activity levels inhalation dose is lower on these days.

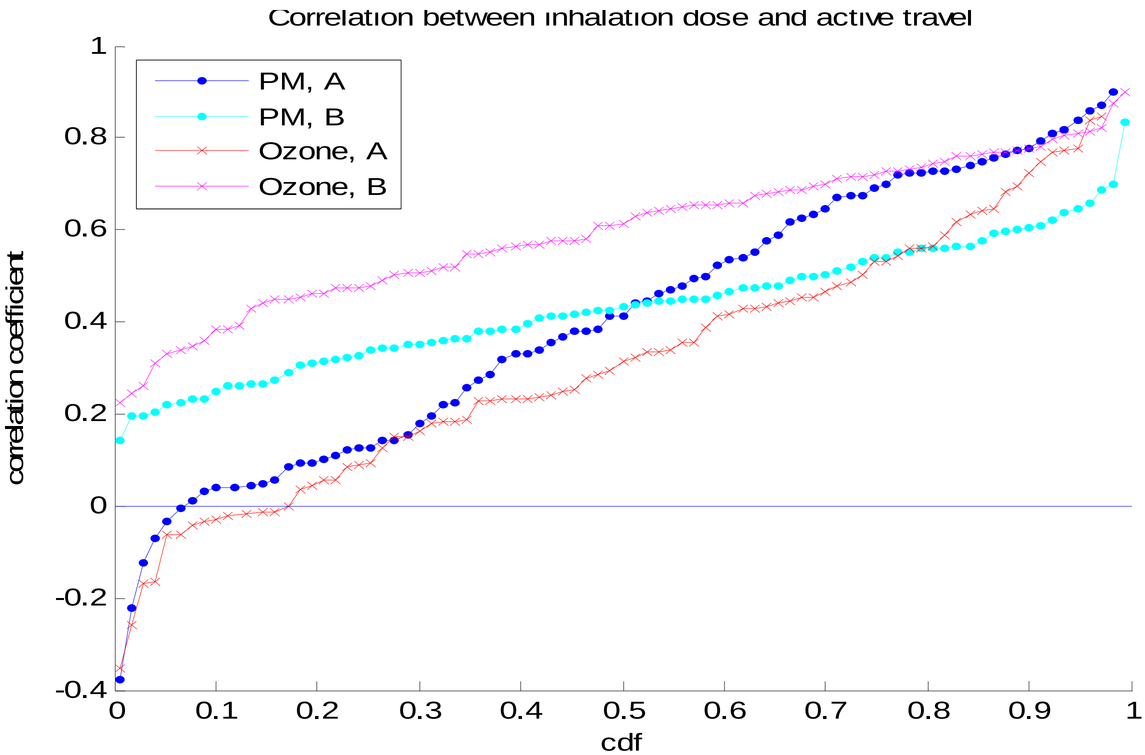

Figure 5-11 CDF across the population of correlations between inhalation dose and energy expenditure due to active travel for the two simulation approaches (A is the low-behavioral variability and B the high-behavioral variability simulation)

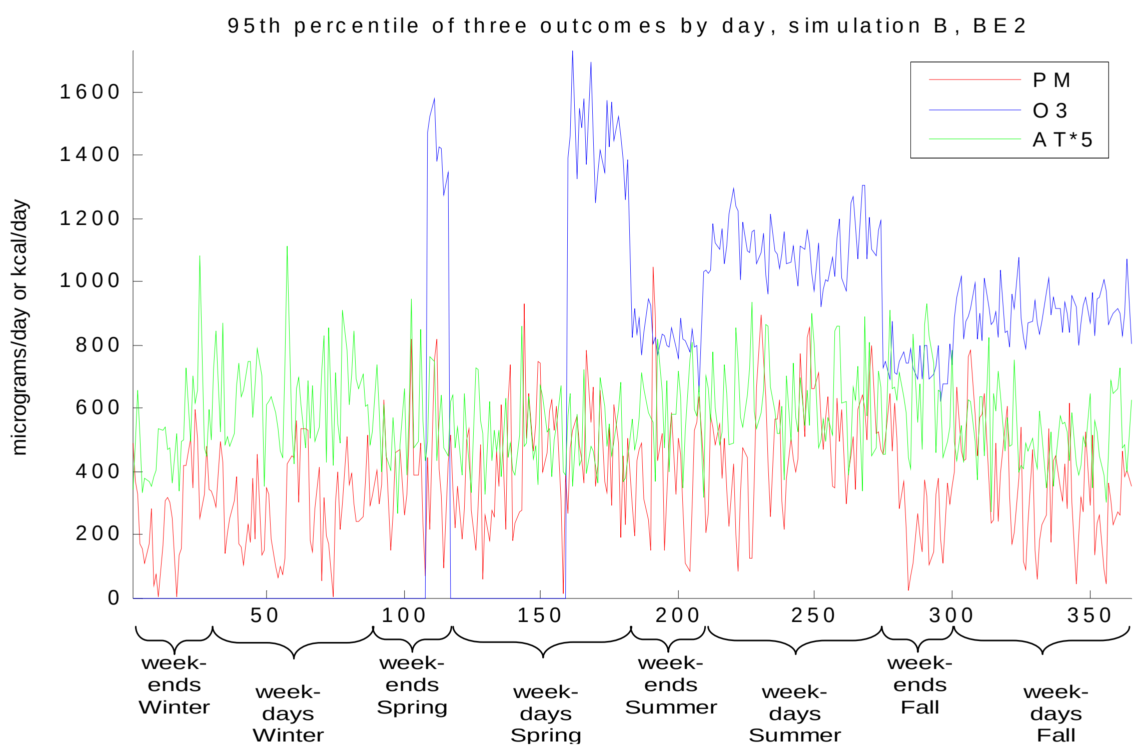

Figure 5-12 Temporal pattern of the 95th percentile of population variation in three outcomes: ozone (O3) and PM10 inhaltion, and energy expenditure due to active travel (AT, multiplied by 5 for scaling)

5.2 Sensitivity analyses – sources of variability and uncertainty

5.2.1 *Drivers of variability: results of sensitivity analyses on 10 individuals with 200 Monte Carlo runs varying different factors.*

In the 10-individual sensitivity analysis, the relative contribution to variance of different model factors are considered by comparing the range of coefficients of variation (CV) obtained for each modeled person[42]. Table 5-2 summarizes results for the METs and air concentrations uncertainty analysis. Table 5-3 describes coefficients of variation for the analyses on mode choice, location choice, and built environment (BE) factors.

With low corresponding coefficients of variation (around 0.05), the uncertainty associated with ozone and with PM_{10} concentrations is shown to have little contribution to the variance in the pollutants' inhalation intakes[43]. The METs uncertainty yields a greater variance in all outputs, with in the case of PM and energy expenditure outcomes, an effect slightly lower but comparable to that of mode choice variation when applying the Rodríguez model (see Table 5.2 for the latter). The upper-end of coefficient of variation associated with METs variation is about double that of pollutant concentration, thus producing less stable results. In the full BESSTE model analysis, the METs uncertainty distributions are kept as part of the Monte Carlo process, while mean air pollution values are chosen instead of generating random estimates from the uncertainty curves.

Table 5-2 Ranges over the 10 sampled individuals of coefficients of variation associated with PM and ozone intake and energy expenditure for variations in METs and air pollution concentrations

	PM intake	Ozone intake	Energy expenditure
METS	0.03 - 0.11	0.04 - 0.11	0.02 - 0.09
Air Pollution	0.01 - 0.06	0.04 - 0.05	-

[42] One of the 10 individuals is taken out in the results presented where mode choice is allowed to vary because the little travel undertaken by that individual made all CV lower bounds equal to 0.

[43] Air concentration uncertainty is not further considered in the analysis (i.e. each full BESSTE run simply takes the mean hourly outputs rather than pick randomly from the uncertainty curve).

The choice of travel behavior model has a considerable impact on variability. As further discussed in (and in agreement with) the next section, the Rodríguez version approximately doubles upper bound coefficients of variation compared to the Cervero model for all three outcomes. The latter produces rather stable results with low variability, with a maximum coefficient of variation of 0.1 for PM_{10} and energy expenditure, and 0.23 for ozone. The variability associated with mode choice variation remains similar in different built environment scenarios (looking at the horizontal progression in the table), however as expected increases when both location choice and mode choice are allowed to vary concomitantly.

The three different location models produce similar coefficients of variation, even though the random choice (no gravity) model could have been expected to produce more erratic results. Compared to runs where only mode choice varies[44], they approximately triple the lower bound (which still remain fairly low) and slightly increase the upper bounds of variation coefficients.

In all cases ozone varies more than the other outcomes, with CV upper bounds two to three times higher than those for PM_{10}. Energy expenditure variability is in all cases slightly lower than the latter. These results indicate that ozone outputs from the BESSTE model will have greater uncertainty than the other outcomes since each daily random pick has a wider range of possibilities than would be the case for PM_{10} and energy expenditure.

Effects of these different factors on the magnitude of the outcomes are also inspected, comparing the mean values obtained under the same scenarios. As can be seen from the results in Table 5-4, as well as from comparing mean outputs for the 10 individuals separately (data not shown), the Cervero model does not trigger any noticeable changes in outputs on average as the BE varies. The Rodríguez model does yield some small changes on average across BEs for PM_{10} and ozone intake, but little for energy expenditure. Most often the full pedestrian-friendly scenario with improvements in connectivity, land use and sidewalks combined, produces the highest increases in outcomes, but this is not always the case. No other individual BE factor

[44] Comparisons are made with the Rodríguez model, since it is the model used in the location choice runs

displays a consistent leading influence. Given the lack of apparent prominent driver in BE factors, to decrease model complexity and increase model run time, only the "full" BE scenario is considered for community transformations in the rest of the BESSTE analysis.

Table 5-3 Ranges ovre the 10 sampled individuals of coefficients of variation associated with PM and ozone intake and energy expenditure for variations in different model inputs: mode choice, location choice, and built environment factors*

		BE1	BE2				
			Connec-tivity	Connect +sidewalk	Landuse	LU+Conn +Sidewlk	Sidewalk
PM_{10} intake							
Mode choice	Cerv	0.01-0.05	0.01-0.06				
	Rod	0.01-0.12	0.01-0.12	0.02-0.12			0.02-0.11
Location & mode choice	Cerv	0.02-0.08	0.02-0.1		0.02-0.1	0.02-0.08	
	Rod	0.03-0.18	0.03-0.12		0.03-0.16	0.03-0.14	
Location choice	Grav	0.03-0.11				0.02-0.08	
	SSGrav	0.02-0.09				0.03-0.1	
	NoGrav	0.03-0.11				0.03-0.09	
Ozone intake							
Mode choice	Cerv	0.01-0.18	0.01-0.22				
	Rod	0.03-.031	0.03-0.32	0.03-0.32			0.03-0.31
Location & mode choice	Cerv	0.04-0.23	0.04-0.23		0.04-0.23	0.04-0.23	
	Rod	0.1-0.43	0.05-0.3		0.12-0.37	0.09-0.32	
Location choice	Grav	0.04-0.19				0.04-0.23	
	SSGrav	0.03-0.24				0.05-0.22	
	NoGrav	0.05-0.23				0.05-0.23	
Energy Expenditure							
Mode choice	Cerv	0-0.04	0-0.05				
	Rod	0.01-0.1	0.01-0.1	0.01-0.1			0.01-0.1
Location & mode choice	Cerv	0-0.05	0-0.05		0-0.05	0.01-0.05	
	Rod	0.02-0.13	0.01-0.1		0.02-0.12	0.01-0.1	
Location choice	Grav	0.01-0.04				0.01-0.05	
	SSGrav	0.01-0.05				0-0.04	
	NoGrav	0.01-0.05				0.01-0.05	

* BE1 and BE2 refer respectively to the first (less pedestrian-friendly) and second (more pedestrian-friendly) built environment scenarios; Cerv and Rod indicate respectively the Cervero and Rodríguez mode choice models; the location choice models Grav, SSGrav and NoGrav are respectively the generic gravity model used in BESSTE, the Sermons and Seredich gravity model, and no gravity model (random choice). The model runs comparing location choice models are performed using the Cervero mode choice model.

One remarkable consistent result from this analysis is the higher values of outputs from the Rodríguez model compared to the Cervero model, especially at the upper bound of ranges in mean changes. Every individual Rodríguez output is at least equal to the corresponding Cervero result, and in most cases is greater, by 5 to 20 percent in general (and up to 50%). The next section examines the difference in travel models further.

Another consistent result is the little effect of the selection of location choice model. If anything, the no-gravity model triggers slightly higher ozone inhalation intakes, but the data is insufficient to establish any relationship (3 of the 5 individuals with a modeled ozone day reveal around 10% higher ozone with the no gravity model compared to regular gravity model).

Table 5-4 Ranges of mean outputs for model runs where different combinations of mode choice, location choice, and built environment factors are allowed to vary

		BE1	BE2				
			Connec-tivity	Connect +sidewalk	Landuse	LU+Conn +Sidewlk	Sidewalk
PM_{10} intake (µg/day)							
Mode choice	Cerv	50-350	50-350				
	Rod	50-380	50-390	50-390			50-380
Location & mode choice	Cerv	50-310	50-310		50-310	50-310	
	Rod	50-340	50-360		50-340	50-370	
Location choice	Grav	50-320				50-320	
	SSGrav	50-320				50-320	
	NoGrav	50-320				50-320	
Ozone intake (µg/day)							
Mode choice	Cerv	100-460	100-460				
	Rod	100-660	100-660	100-700			100-700
Location & mode choice	Cerv	200-490	200-490		200-480	200-490	
	Rod	320-730	320-750		320-730	320-670	
Location choice	Grav	200-500				210-490	
	SSGrav	210-510				210-510	
	NoGrav	220-530				220-540	
Energy Expenditure (kcal/day/10)							
Mode choice	Cerv	170-480	170-480				
	Rod	200-490	200-490	200-490			200-490
Location & mode choice	Cerv	170-430	170-430		170-430	170-430	
	Rod	200-450	200-450		200-450	200-450	
Location choice	Grav	170-430				170-430	
	SSGrav	170-430				170-430	
	NoGrav	170-430				170-430	

* BE1 and BE2 refer respectively to the first (less pedestrian-friendly) and second (more pedestrian-friendly) built environment scenarios; Cerv and Rod indicate respectively the Cervero and Rodríguez mode choice models; the location choice models Grav, SSGrav and NoGrav are respectively the generic gravity model used in BESSTE, the Sermons and Seredich gravity model, and no gravity model (random choice). The model runs comparing location choice models are performed using the Cervero mode choice model.

5.2.2 *Uncertainty in person-day outputs: results of sensitivity analysis of 300 runs of daily outputs for 64 individuals.*

This analysis of 64 individuals is meant to generate uncertainty assessments for person-day outputs, and to compare the Cervero and Rodríguez transportation models in BESSTE. In the figures throughout this section, the blue lines refer to the Cervero model and red lines to Rodríguez; lighter colors (magenta and cyan) depict the more pedestrian-friendly scenario (BE2) and darker lines (blue and red) the status-quo scenario (BE1).

5.2.2.1 *Variability and uncertainty in pollutant inhalation dose and energy expenditure*

For PM_{10} and ozone inhalation dose, the variability in the uncertainty estimates associated with the outputs of each modeled day is fairly wide and is similar across transportation models and built environment scenarios. This can be seen in Figures 5-13 and 5-14, which depict for PM_{10} and ozone respectively the inverse cumulative distribution across the modeled population of the 5th, 50th, and 95th percentiles of uncertainty distribution associated with person-day pollutant intake. To be more explicit, for each person-day 300 run, the 5th, 50th and 95th percentile values of the 300 outputs were calculated, hence representing percentile of uncertainty associated with the person-day outcomes, and then individually ordered to produce the population variability of these percentiles of uncertainty. For example, looking at the 90th population percentile of the PM10 inhalation graph for the Cervero model and BE1, it can be seen that the 5th percentile of uncertainty for 90% of the population is below 340µg/day, the 50th percentile of uncertainty for 90% of the population is below 415µg/day, and the 95th percentile of uncertainty for 90% of the population is below 480µg/day.

The uncertainty associated with the person-day output can be measured for example by coefficients of variation, or by the width between the percentiles of uncertainty distributions.

Visual inspection of the graph shows that for PM_{10} uncertainty associated with each output is narrow compared to the variability across the population. Indeed, the interval between the 5th and 95th uncertainty percentiles for the median person-day represents approximately 15% of the 90% population variability for the median uncertainty distribution for the Cervero model, and 22% for Rodríguez[45]. The coefficient of variation for each person-day simulation varies for both travel models between 0.02 and 1.6 (an outlier), with a mean around 0.1, and for all data combined is 0.5.

The ozone graph shows a wider distribution of variability than ozone, with percentile distributions further apart. For the Cervero model, the width of 5th to 95th uncertainty percentile is approximately equal to 20% of the 90% population variability for the median uncertainty distribution, and up to 35% for Rodríguez. The Cervero coefficients of variation range from 0.05 to 0.23 with an average of 0.12; they are 0.1 to 0.6 for Rodríguez with a mean around 0.21. For all data combined the CV is 0.6.

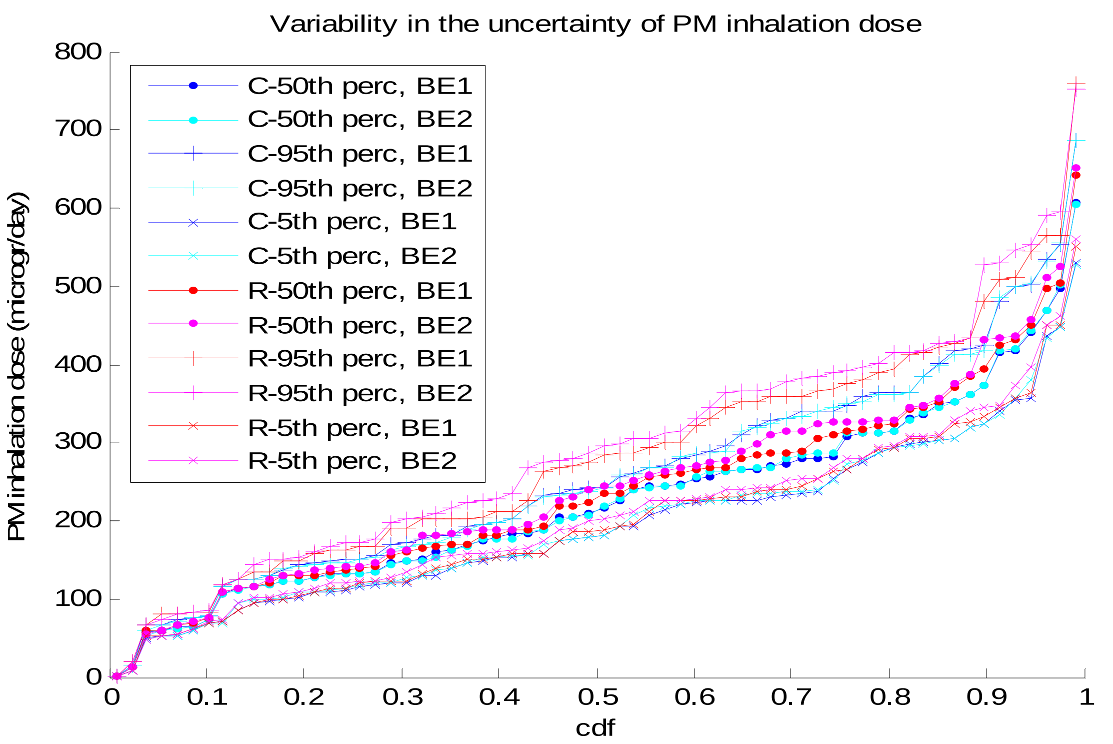

Figure 5-13 Variability across the modeled population in the uncertainty associated with person-day PM_{10} intake, comparing BESSTE using the Cervero ('C', blue and cyan lines) and Rodríguez ('R',

[45] For example, for the Cervero model the variability of the 50th percentile of uncertainty distribution from the 5th to 95th percentile of the population is 390µg/day, and the width of the interval between the 5th and 95th uncertainty percentiles for the midpoint of person-days is 60µg/day, hence 15=60/390*100.

red and magenta lines) models for BE1 (status-quo built environment), BE2 (pedestrian-friendly built environment) and for the 5th, 50th and 95th percentile of uncertainty.**

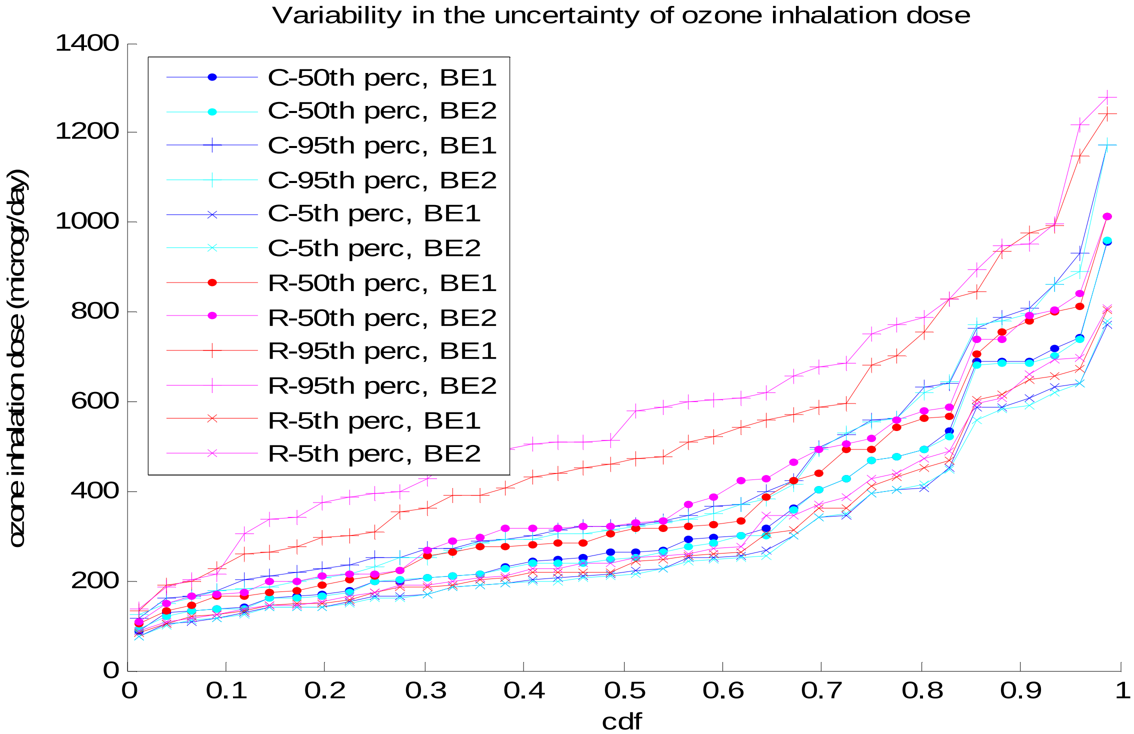

Figure 5-14 Variability across the modeled population in the uncertainty associated with person-day ozone intake, comparing BESSTE using the Cervero ('C', blue and cyan lines) and Rodríguez ('R', red and magenta lines) models for BE1(status-quo built environment), BE2 (pedestrian-friendly built environment) and for the 5th, 50th and 95th percentile of uncertainty.

Outcomes of the energy expenditure due to active travel (Figure 5-15) display greater uncertainty than the pollutant outputs, especially for the Rodríguez model. Indeed, the interval between the distributions of percentiles is wide: the 5th percentile cdf remains at or close to 0 for 55% (BE1) to 65% (BE2) of the modeled population under the Rodríguez model, while the 95th percentile distribution rises steadily, reaching at the midpoint 370 kcal/day (BE1) to 525kcal/day (BE2). In the Cervero model the range between percentiles is narrower, with the midpoint of the 95th percentile distribution attaining around 90kcal/day for both BEs, and the 5th percentile distribution persisting at 0 except for the top 1to 5% of the population. While the median activity level stays close to 0 for the entire population in the Cervero model, achieving at best 43kcal, it already reaches 125kcal for Rodríguez at the midpoint of the population, and surpasses 150kcal for more than 40% of the modeled person-days.

The variability range across the population is comparatively small, going from 0 to 20 or 30 kcal/day for the median energy expenditure for 90% of the population in the Cervero first and second BE scenarios. Thus the midpoint uncertainty range represents 3 to 4 times the median variability range. With the Rodríguez model median variability ranging from 0 to 290 kcal/day (1st BE) and 0 to 570 kcal/day (2nd BE), the midpoint uncertainties are lower comparatively, representing respectively 130% and 90% of the variability for the 1st and 2nd BE scenarios. The coefficients of variation are very high, with a mean of 2.9 for Cervero and 1 for Rodríguez. Combined data produce similar values for CVs.

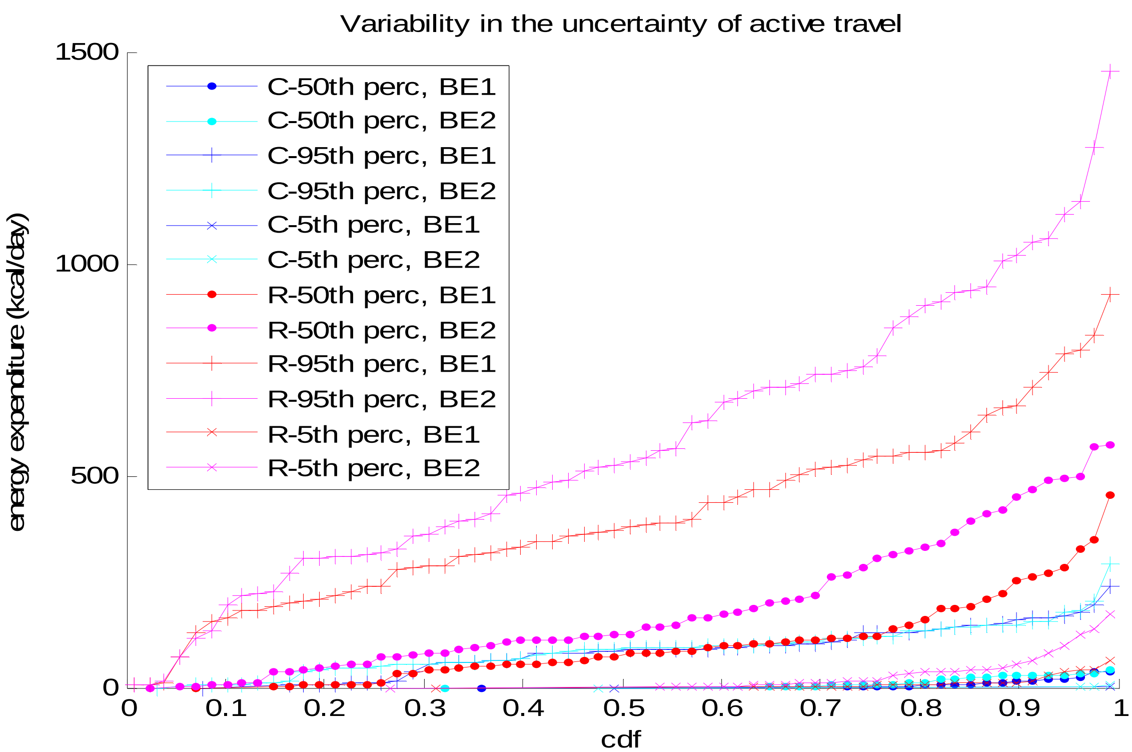

Figure 5-15 Variability across the modeled population in the uncertainty associated with person-day energy expenditure due to active travel, comparing BESSTE using the Cervero transportation model ('C', blue and cyan lines) and using the Rodríguez model ('R', red and magenta lines), for BE1(status-quo built environment), BE2 (pedestrian-friendly built environment) and for the 5th, 50th and 95th percentile of uncertainty.

5.2.2.2 *Impact of the built environment*

Overall, while in the Cervero model both built environment scenarios are fairly well aligned in all outcome distributions, the Rodríguez model shows a noticeable increase in the outputs of the more pedestrian-friendly scenario. The Wilcoxon matched-pairs signed-ranks one-tailed test applied to each person-day simulation output reveals a significant increase in the more pedestrian-friendly built environment scenario for a 0.05 alpha in 17% versus 75% of individuals for the distributions of PM_{10} inhalation dose when using the Cervero compared to the Rodríguez models. For ozone inhalation intake these numbers are 10% and 76% of individuals with significant changes, and 31% and 72% of cases for active travel energy expenditure. Hence, when running BESSTE for a single day, use of the Rodríguez model would about quadruple the likelihood of detecting a significant increase in PM inhalation following the neighborhood transformations, double the chance of finding increases in energy expenditure and multiply by seven chances for an increase in ozone intake.

A Wilcoxon test is applied to compare the use of the two different transportation models, matching the pairs of differences in outcomes for each individual obtained with the Cervero and Rodríguez models respectively (for an alpha of 5% in a one-tail test). Results show a significantly higher distribution of differences when applying the Rodríguez model in approximately three fourths of modeled individuals for the three outcomes (PM_{10}, ozone, active travel).

The uncertainty in the magnitude of changes in outcomes due to transformations in the built environment is also assessed. Figures 5-16 to 5-18 show the inverse cumulative distributions of percentiles of measures of change in the different outcomes: percent increase in inhalation dose for PM_{10} and ozone, and difference in energy expenditure for active travel.

With the Cervero approach, most of the modeled population present no or close to no changes in PM inhalation dose on average. The 95^{th} percentile of change is below 6% for half of the modeled population, but rises rapidly at the tail end with 5% of the population displaying larger than 50% increases. The width between the 5th to 95th percentile distributions remains fairly constant around 13% except at each tail-end where the uncertainty is wider (much wider in the case of increases). The standard deviation varies between 0.2% and 277%, with an average of 10.4%. Using Rodríguez on the other hand, percent increase on average are larger and are present for a larger portion of the population modeled (85%). The 95th percentile of percent change is mostly positive, and half of the population displays higher than 20% increases for that percentile of uncertainty. The difference between the 5th to 95th percentile distributions is around 30% for most of the population, and larger at both ends. The median standard deviation varies between 0.6% and 232%, with a mean of 16%.

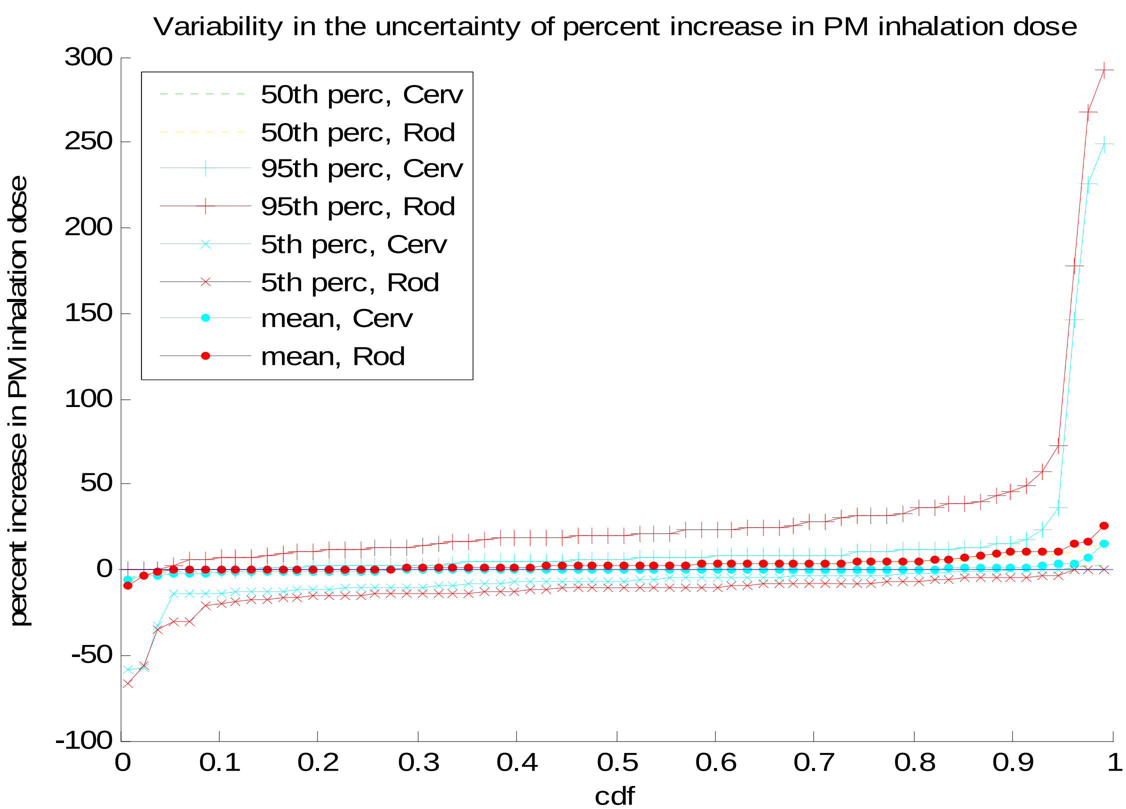

Figure 5-16 Cumulative distribution function across modeled population of percentiles of percent change in PM inhalation dose in the more pedestrian friendly scenario relative to the status-quo built environment, for the two transportation models ('Cerv' is the Cervero model and 'Rod' the Rodríguez model).

In the case of ozone, the Cervero model yields on average more reductions than growths in inhalation intake in the population, although all are close to zero, with the 5th and 95th population percentiles equal to -6% and 3% respectively (median values span from -4% to +1%). In the Rodríguez version however, an average rise in intakes above 3% is observed for two thirds of modeled individuals, including 1/3 above 10%. The 95th percentile of the uncertainty distribution reaches respectively 14% and 44% for the 50th and 95th percentiles of the population for Cervero, and 55 and 130% for Rodríguez. The intervals between the 5th and 95th percentile distributions are larger than for PM, with an average of 32% for the Cervero model, and 87% for the Rodríguez model. The mean standard deviations are 10.3% for Cervero and 26.9% for Rodríguez.

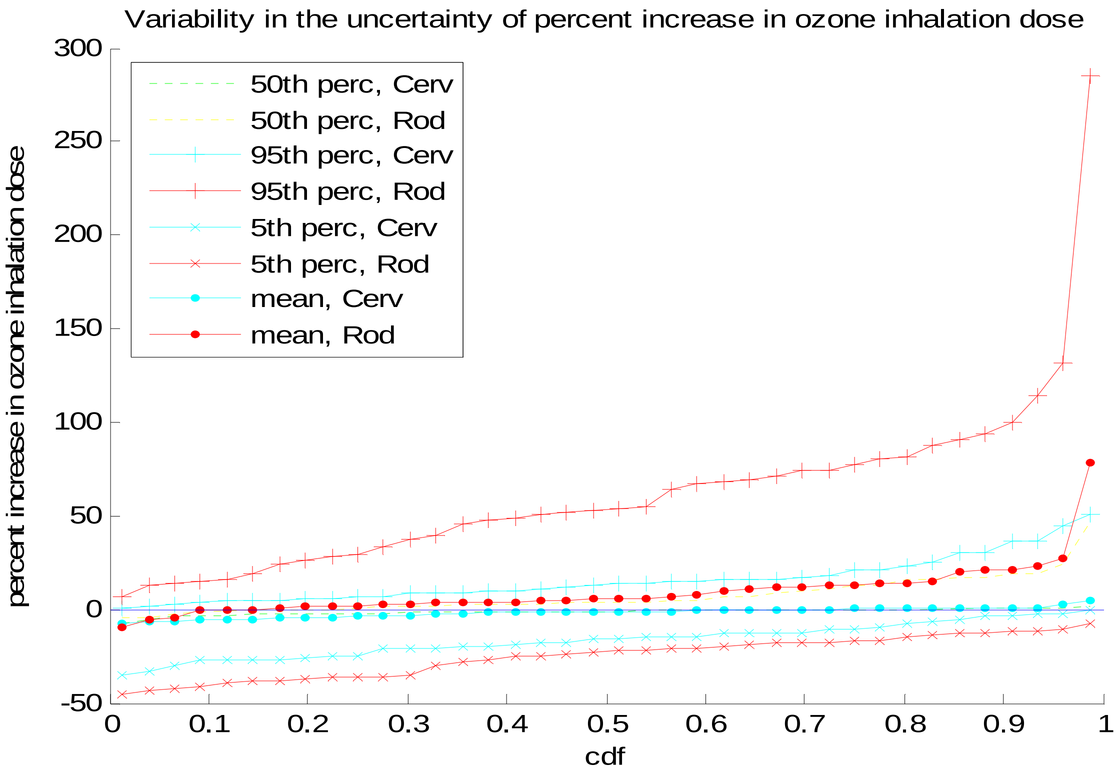

Figure 5-17 Cumulative distribution function across modeled population of percentiles of percent change in ozone inhalation dose in the more pedestrian friendly scenario relative to the status-quo built environment, for the two transportation models ('Cerv' is the Cervero model and 'Rod' the Rodríguez model)

Changes in energy expenditure due to active travel display similar patterns to those of ozone. The Cervero model mean change is negligible, with the 5th and 95th population percentiles equal to -7 and +14 kcal/day. The 95th percentile of the uncertainty distribution barely reaches the recommended activity level (150kcal/day) at the 95th population percentile. With the Rodríguez model on the other hand, almost all of the population exhibits increases in physical activity on average, and even 20% reach an increase by 150kcal/day or more. Eighty five percent of modeled individuals have a 95th percentile of uncertainty in activity increase that attains the recommended level of activity. However the 5th percentile of uncertainty also displays decreases by the recommended amount of activity for 80% of the population. Margins of error are substantial, with the standard deviations varying between 3 and 136 kcal/day with mean 51 kcal/day for Cervero, and between 2 and 523 kcal/day, with mean 231 kcal/day for Rodríguez.

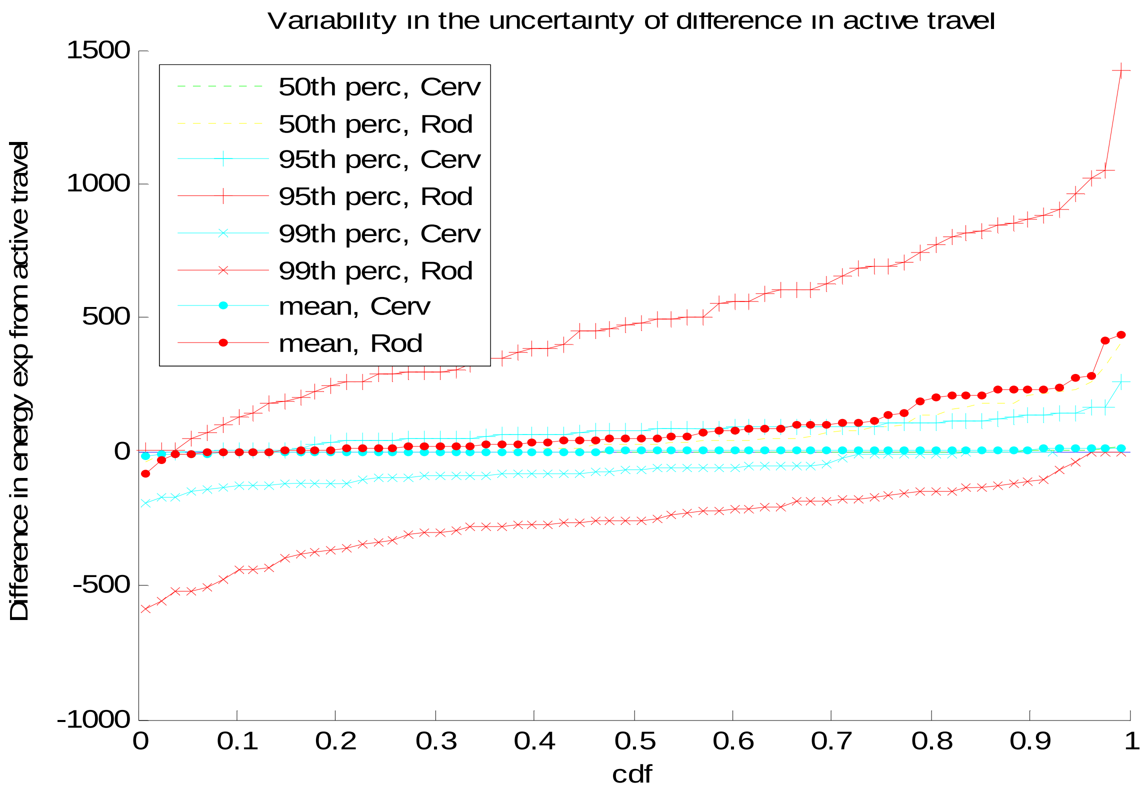

Figure 5-18 Cumulative distribution function across modeled population of percentiles of change in energy expenditure due to active travel in the more pedestrian friendly scenario relative to the status-quo built environment, for the two transportation models ('Cerv' is the Cervero model and 'Rod' the Rodríguez model)

Given this knowledge on uncertainty associated with percent change in PM and ozone inhalation dose respectively, results from the previous section can be revisited. Figure 5-9 in section 5.1.3 depicted the percent change in inhalation dose for days above threshold, and predicted at least a 10% increase in PM inhalation for 5% percent of person-days, and at least 29% (simulation A) or 10% (B) ozone inhalation increase. However, knowing mean standard deviations of 10.4% and 10.3% for the uncertainty associated with percent change in PM_{10} and ozone respectively (Cervero model), it can be said that anything short of a 10.4% change for PM_{10} and 10.3 % change for ozone could be considered within the uncertainty limits indicating no changes for an average 68 % confidence interval. Applying a 95% probability interval (1.96*standard deviation), the model finds that around 2% and 12% of days respectively experience a significant increase in PM10 and ozone (simulation A) inhalation dose. For a 95% probability of a 10% increase in intake, the increase would need to be above 30.2 for ozone (10+1.96*10.3) and above 30.4 for PM_{10} (10+1.96*10.4). A little over 4% of person-days are found to be in this bracket for ozone, and 1.5% for PM_{10}.

5.2.3 *Sensitivity analysis of personal factors, and threshold level*

An analysis on personal factors shows that the variability and uncertainty associated with inhalation factors, such as body weight and resting metabolic rate (see section 4.3.3.), play an overwhelming role in the variability found in the previous section. Figure 5.19 exhibits the inverse cumulative distribution function associated with pollutant inhalation dose for males (blue) and females (red) with the simplified activity pattern described in section 4.3.4.3, allowing only the personal factors to vary. PM_{10} varies for 90% of the population combining males and females by 340µg/day and ozone by 315µg/day[46]. This PM_{10} variability interval length is comparable to the range found for the variability in the median uncertainty output shown in Figures 5.12[47] (410µg/day), indicating that a large part of the variability observed across the population in the latter figure could be due to the personal factors variation. For ozone the interval length of Figure 5.13 is about twice as large as that of the personal factors variation, which still recognizes an important contribution of personal factors. The coefficients of variation associated with these distributions are around 0.2 for both pollutants.

[46] A simulation keeping the body weight fixed produced slightly smaller but similar intervals.

[47] Recall that Figures 5.12 and 5.13 portray the variability of percentiles of uncertainty for the 64 person-days.

Note that this analysis provided the scenario for estimating theshold levels of PM10 and ozone inhalation for conditions reproducing NAAQS standard levels of pollution. The median of the male and female population combined produced daily inhalation doses of 520µg for PM_{10}, and 470 µg for ozone.

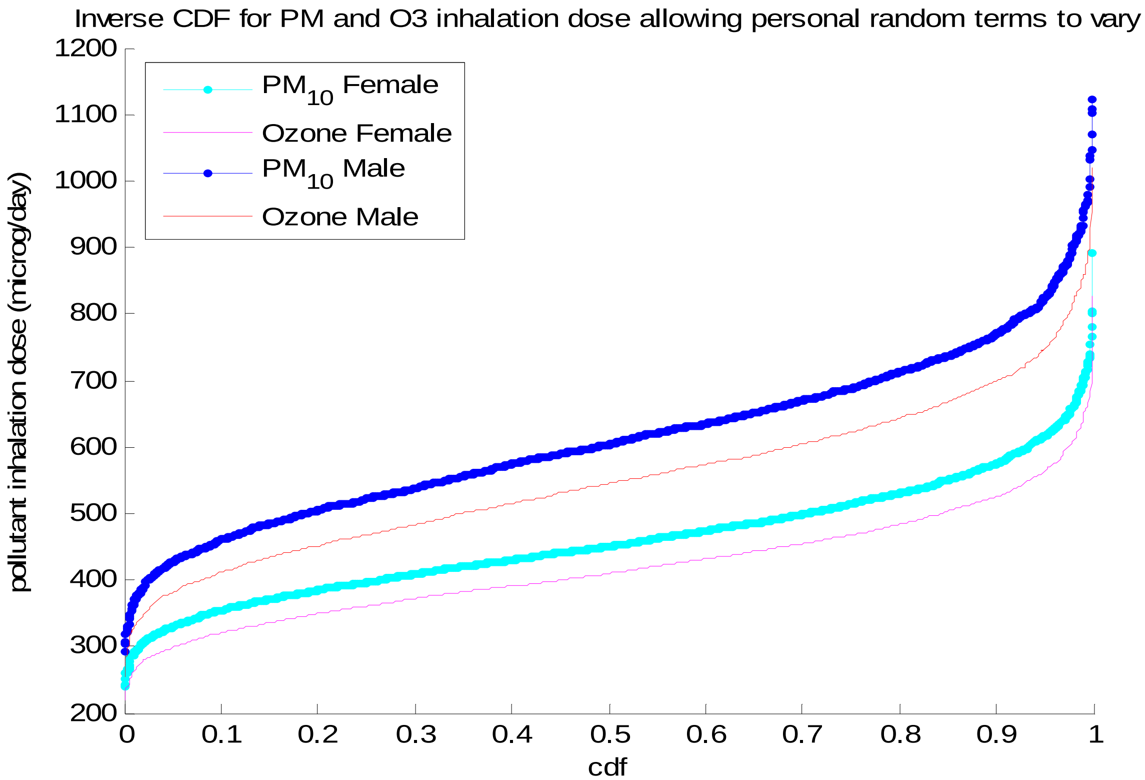

Figure 5-19 Cumulative distribution function of ozone and PM inhalation dose in a simulation where only personal factors vary

5.2.4 *Air pollution scenarios*

Uniform air pollution reductions are applied to the more pedestrian-friendly scenario in the 64 person-day analyses, to account for possible effects of mode shifts (5% reduction), and to examine the result of more ambitious policies (20% reduction). To illustrate, Figures 5-20 and 5-21 show the 20% reduction outcomes for PM and ozone respectively; the 5% reductions graphs look something in between these Figures and Figures 5-16 and 5-17.

With a 5% decrease in air pollution, the Wilcoxon test identifies under the Cervero model a remaining 2% of individuals still having a significant increase in PM inhalation, and none for ozone, in the more pedestrian-friendly design relative to the as-is built environment; in the Rodríguez version, still respectively 16% and 40% of individuals are found to have significant increases in PM and ozone inhalation. The potential air pollution mitigation accompanying the built environment changes does however result in most individuals decreasing inhalation intakes for both travel models. Under the Cervero model, the median change in PM inhalation ranges between -10% and -3%, with an average 5% decrease; the 95th percentile of uncertainty is below zero for half of the population, yet does exceed 100% increases for 4% of the population. Outcomes are similar for ozone, with just a higher proportion of the population with positive 95th percentile values of change. The Rodríguez model yields larger confidence intervals and a greater portion of individuals with median increases in inhalation in the more pedestrian-friendly design: 15% and 40% of the modeled person-days show positive changes for PM and ozone inhalation respectively, reaching 18% increase at the population 95th percentile of ozone, but remaining small for PM. The 95th percentile of change is positive for most of the population for PM, and for all for ozone.

With a 20% reduction in air pollution, the median change in PM inhalation dose under the Cervero model does not exceed -18%. The 95th percentile of intake is above zero only for five percent of the population, yet it still reaches 100% increases for about 4% of the population. Ozone numbers are similar, with a remaining 15% of the population having a positive change in their 95th percentile of uncertainty intake. The Rodríguez model still finds increases in ozone inhalation dose for the median value of exposure for one individual and for 80% of the population in their 95th percentile of exposure. PM median changes are at most an 8% decrease, and 30% of the people have a positive change in their 95th percentile.

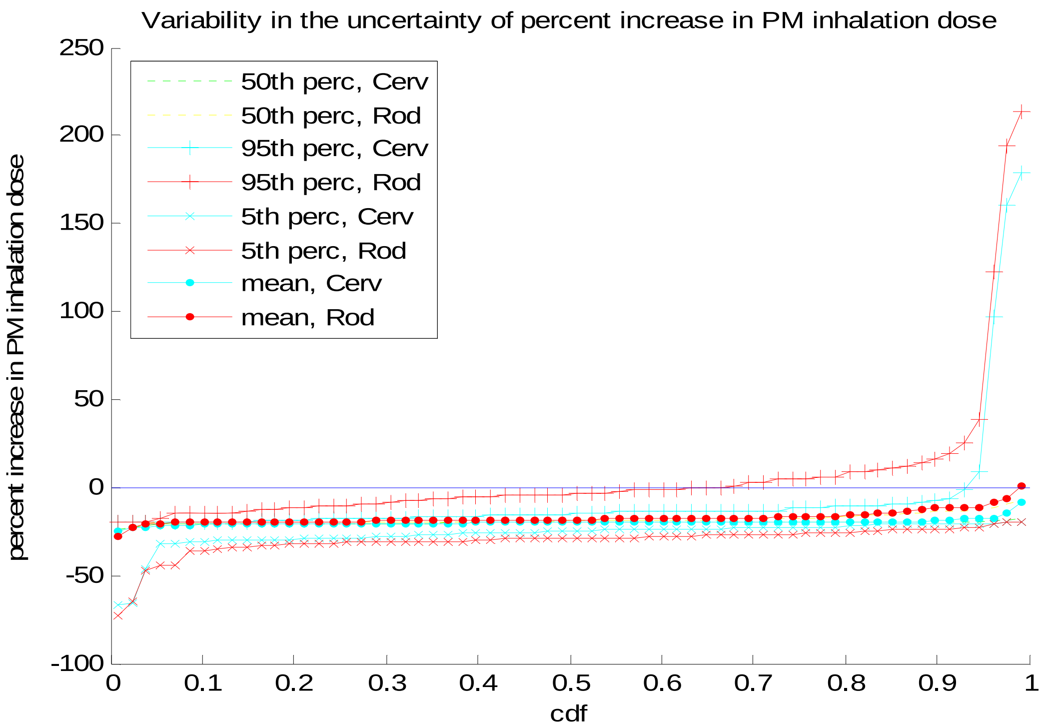

Figure 5-20 Cumulative distribution of percentiles of changes in PM inhalation dose in the more pedestrian-friendly design relative to the stauts-quo built environment, for a scenario in which a 20% uniform reduction in air pollution is applied to the more pedestrian-friendly community.

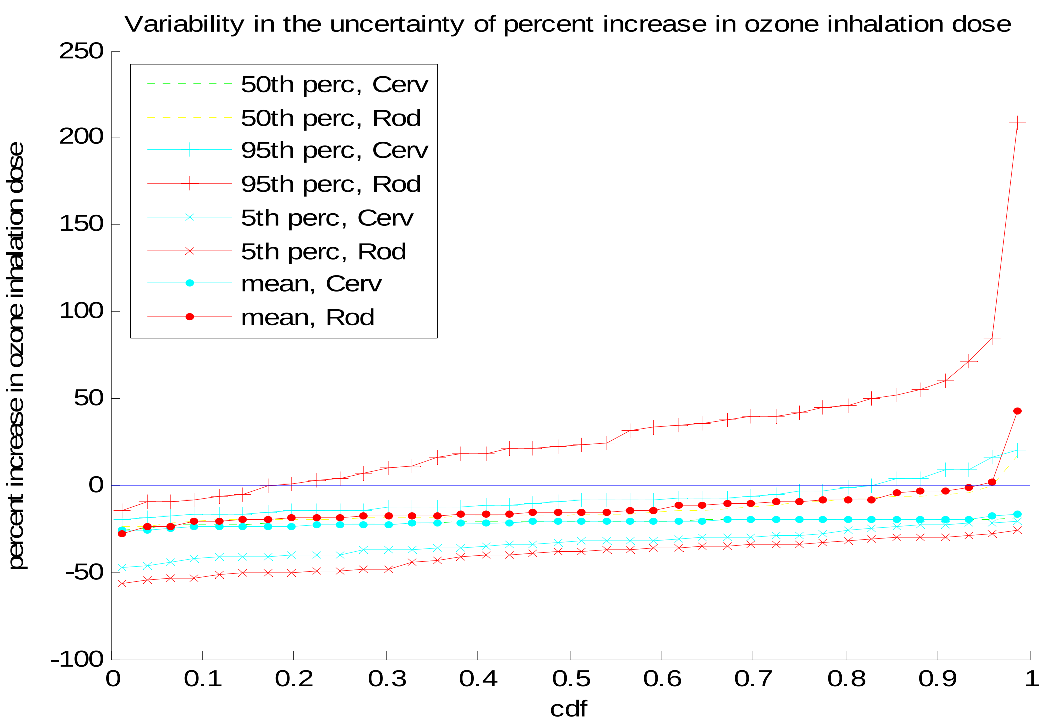

Figure 5-21 Cumulative distribution of percentiles of changes in ozone inhalation dose in the more pedestrian-friendly design relative to the stauts-quo built environment, for a scenario in which a 20% uniform reduction in air pollution is applied to the more pedestrian-friendly community.

5.3 Discussion of results

5.3.1 *Summary and interpretation*

To summarize, the BESSTE simulation shows equivocal results concerning risks and benefits of community transformations. Changes in the built environment produce as many reductions as increases in the exposures and activity measures, and in most days no appreciable difference at all. At first glance this could be interpreted as proof that outcomes are the result of a random process and that the transformations in the built environment are not sufficient to create a pattern of change in inhalation and activity. However several points can be raised as explanations, and are discussed within the context of these results.

The built environment affects travel and mode choice in several ways: 1) the level of comfort or general appeal created by the community design – this is accounted for in the Cervero model through the land use mix and density variables, and 2) the distance between destinations. While the change in distance may be equally or more important as the less tangible "pedestrian feel" of the community in terms of mode choice, it has another effect in terms of activity: it reduces trip length. This means that trips that started out by being non-motorized may still be non-motorized but with less effort to get to the destination, and trips that remain motorized will still benefit from a shorter distance by creating a shorter time period in the more polluted outdoor environment (as modeled in BESSTE). Hence, the pedestrian environment may be 1) generating more walking and biking trips, but in some instances less energy expenditure when trips in the status-quo environment were already in that mode and 2) triggering both higher inhalation dose on days where a mode shift to non-motorized modes is modeled, and also lower intakes when the mode remains motorized but is shortened thus decreasing time spent in the polluted environment.

Therefore, the pattern seemingly random because of similar increases and decreases in outcomes may be in reality the result of these competing mechanisms. This hypothesis is supported by the data in several ways.

First, it was noted that the pedestrian friendly environment generated more walk and bike trips throughout the year for 80% of individuals, with an average of 21 additional walk-bike trips per person. Second, Wilcoxon tests reveal significant changes between scenarios, whether positive or negative, meaning that the outcomes are not the result of chance alone. The test does not account for the magnitude of change, and could be detecting significant changes of very small magnitude, such as would be observed from repeated decreased auto trip lengths. Third, in most cases in simulation A, an increase in active travel accompanies rising inhalation rates, and a fall in active travel is linked to a decrease in inhalation rates. The process in simulation B appears to be more random however, perhaps because the measure considers changes for an entire year, which masks the day-to-day variations that are at play in that simulation. However the measure of correlation between inhalation dose and active travel confirm in both A and B that on a day-to-day bases, these outcomes are positively and significantly linked for a majority of the population. This means that rather than being random, most raises and reductions in inhalation dose are due to similar patterns of active travel. The remaining changes could be in part random, and in part due to shorter vehicular trips. Since most person-days bear no walk and bike trips (a about 65% of days are fully motorized), there is more opportunity for reductions in inhalations to occur because of reduced auto-trip lengths then because of mode shifts.

However, the data does not necessarily lend credit to the hypothesis that reductions in energy expenditure due to active travel could be driven by shorter non-motorized trips. For example, for overall trips in a day, while 66% of days with an increase in energy expenditure due to active travel began with all motorized modes in the first built environment, also 64% of days with decreasing energy ended with all vehicular modes in the 2nd BE. Hence, if most increases in energy expenditure are associated with mode shifts, most reductions are also due to mode shifts, not to shorter trip lengths. These numbers concern all trips in a day combined however, since the model did not keep track of the detailed trip-level data to alleviate model run time. In conclusion, these hypotheses to explain the patterns of behaviors and exposures observed in the BESSTE model merit further exploration, but the data seems to point to a systematic rather than random explanation of observed patterns in the simulation.

Further discussion is required concerning the level of uncertainty associated with the model outputs. No formal integration of uncertainty in daily outputs is undertaken for the full BESSTE simulation of the variability of individual's yearly exposures, although it can be said that the variability analysis also accounts for uncertainty. The person-day analyses revealed that the 68% uncertainty range for each daily inhalation output under the Cervero model for an average individual could vary by about 10% in either direction. More extreme individuals had much wider variations (up to 150% for PM_{10}, up to 23% for ozone). This means that each daily outputs of the year-long simulation could have taken on such varied values instead of the one estimated for it. While BESSTE accounted for this uncertainty to a certain extent by allowing all elements to vary day to day (simulation B) or season-to-season (simulation A) as part of the variability analysis, a more formal integration of the daily output uncertainty could have revealed more extreme individuals with greater risks, or greater benefits.

Another form of uncertainty is the one generated by choice of the travel behavior model employed in BESSTE. Sensitivity analysis suggested that while the choice of location model did not seem to appreciably vary outcomes, the selection of the transportation model did. Certainly employing the Rodríguez model instead of Cervero in the full BESSTE simulation would have yielded different results in the magnitude of inhalation dose and energy expenditure outcomes, as well as in the impacts of the built environment. The person-day analysis indicated higher median outcomes and wider confidence intervals for these outputs under the Rodríguez model. Although the patterns of change resulting from the built environment were similar for Rodríguez and Cervero, both showing increases and decreases in the outcomes, the former model generated a higher proportion of raises than the latter. Yet, greater uncertainty was associated with the Rodríguez model outputs, and effects remained low for most of the population (for example 80% of the person-days modeled had median values change below: 150 kcal/day increase for active travel, 15% increase for ozone and 4% increase for PM inhalation). Hence, it is not sure that the assessment of the built environment impact would have drawn discernibly different results for all of the population. In all likelihood though, individuals at greater risks would have emerged, especially for ozone exposure. Indeed, the Rodríguez model produces greater than 24% increases in median intake for 5% of the population, and up to 79% increase, versus 1% to a maximum of less than 2% rise for Cervero (for PM_{10} the Cervero model generated only slightly lower tail end values for percent increase than the Rodríguez version). Differences in the 95% percentile distribution of uncertainty are even greater, reaching close to a 300% increase in Rodríguez, versus 50% in Cervero. Individuals with greater benefits in terms of physical activity would also be suggested by applying the Rodríguez model, since it predicts increases by the recommended level of activity (150kcal/day) for 20% of the population, versus none for Cervero. Although the much larger uncertainty intervals may shed doubt on finding such increases significant, in comparing 68% confidence intervals it is noteworthy that the 34^{th} percentile of uncertainty distribution stays at or below 0 for all the population for Cervero, and takes off above zero for around 30% of the population for the pollutant inhalation dose, and for more than 20% of the population for the activity measure. Therefore greater positive change is not only predicted by median outputs, but also by 68% confidence intervals. Corroborating these findings, the Wilcoxon test found significant increase in inhalation dose in four times more individuals in the Rodríguez model than in the Cervero model, and in twice as many for the physical activity measure.

The simulation approach and definition of what constitutes and individual is one more source of uncertainty in BESSTE. Although simulations A and B did not create remarkably dissimilar results, one meaningful difference is the effect on extreme levels of inhalation dose, with simulation A producing 50% to 5 times higher increases in inhalation intake than simulation B at the population extremes. The reason for this discrepancy is that simulation B, the "high variability" scenario, results in more averaging out of effects, while simulation A allows repeated measures of more extreme situations to take place. The fact that high variability in the outcomes was observed when varying personal factors, as well as in the person-day analysis and in the full BESSTE run, lends to believe that the simulations would give different results with another set of 85 individuals. Changes however would be expected to be greater in simulation A, again because the approaches "fixes" behaviors more, allowing more radical patterns to emerge. Approach A therefore requires a higher rate of simulation runs to obtain a full picture of potential effects, and generates more uncertain results than B when few individuals are modeled. Besides differences in outcomes found between approaches, questions need to be raised about the appropriateness of the method in representing yearly patterns of activity. Simulation A fixes location and mode choice for periods of around 26 or 66 days (weekend or weekdays in a season), while simulation B varies these choices every day (except for home and work locations). The true individual could be something between A and B, or could also be more extreme than A – i.e. an even greater "creature of habit". In fact, it is likely that some individuals will have the same pattern of activity throughout the year, perhaps only distinguishing weekdays from weekends. Therefore, more extreme cases of change than those produced by simulation A are possible. For example, a conceivable scenario would be that an individual discovers the joys of riding a bicycle after such a thing as a change in the built environment triggers a desire to try it, and then from then on uses it as her means of transportation for all commute trips instead of driving. A simulation approach that allows less variance (one or two CHAD-individuals for a whole year of simulation for example) are likely to trigger more substantial changes of the risk and benefit measures.

Overall, it can be concluded from this discussion on the sources of uncertainty that the full BESSTE simulation produced conservative results, that outcomes can vary considerably according to the travel model chosen especially, but also to the manner in which individuals are defined in the simulation approach. More extreme outcomes can be expected from using for example the Rodríguez travel behavior model, and a simulation approach with less variability in activity patterns within the year. In addition, BESSTE only models active travel, yet research has also shown significantly higher rates of outdoor leisure time activity in pedestrian-oriented environments. Therefore this model only paints one side of the picture, and both more risks and more benefits would be expected from accounting for all kinds of active behaviors associated with community changes.

In light of this discussion, knowing that results are likely to be conservative and hence that extreme cases may not be so implausible, another look at the full BESSTE outcomes is warranted. In the 5% of individuals with the most extreme increases, the change in the built environment may trigger for 18 days of the year minimums of 80% and 60% increases in PM and ozone inhalation respectively, and up to 170% rise in the individual with the greatest change. Although "safe" thresholds have not been determined yet, there are indications that effects are found for levels far below NAAQS standards for both PM_{10} and ozone, so that such increases may be cause for concern at any level of concentration. Moreover, looking specifically at days above the NAAQS-derived thresholds, 5% of person-days are found to experience at least 10% increases in PM_{10} and 29% increase in ozone intake, and up to 130% and 90% increases for PM_{10} and ozone respectively for the most extreme day. In terms of changes in fractions of days above the threshold for an individual, there could be respectively 4 and 10 more days in a year where the 5% of individuals would have PM_{10} and ozone inhalation intakes above the threshold. Again, while these worrisome outcomes are only found in the most extreme cases and hence could be discarded as unlikely to occur, because BESSTE is probably conservative, they are considered plausible and cause for concern in this analysis.

In terms of benefits of the policy, according to this simulation, no one achieves the physical activity recommendations (150kcal of energy expenditure in physical activity on 5 or more days of the week) through active transportation. The number of days above the recommended levels does increase by 10% for 5% of the population, however it decreases by almost the same amount also for 5% of the population. For the most radical changes in 1% of the population at either end of the curve however, days above the threshold rise by 25% while they only decrease by 11%. At best, the most transportation-active individual attains 150kcal/day for only about one quarter of days in a year in the more pedestrian-friendly environment, and just 15% in the as-is environment. It is worth noting however that in the person-day analysis, the difference between the Cervero and Rodríguez models was even more pronounced for active travel than for inhalation outcomes. For example, the latter generated at the population mid-point more than five times the amount energy expenditure for the 95th percentile distributions, and the median distribution mid-point went from 0.6 for Cervero to 125kcal for Rodríguez.

5.3.2 *Decision framework and policy implication*

5.3.2.1 *Random versus systematic effects*

The significance of determining whether effects are random or not is that if an increase in risks can be attributed to a change in the built environment rather than to the erratic behavior of humans (or of the models), than the policy response may be different. If the outcomes were to be truly random and not related to the community changes, then even though some individuals clearly inhale much higher levels of pollutant than others when they follow a particular behavior, two argument can be made for not requiring additional policies to address this disparity. The first is that the same reason why risky behaviors such as improper diet, sedentary lifestyles, or excessive alcohol consumption are poorly or not at all regulated, can be given for not addressing the risk of people who choose, say, to bike on a busy road of their own free will. The second and less cynical argument is that in developing air pollution standards, while not addressing specifically active travels, it can be assumed that the science that informs the policy takes all people and lifestyles into account. For example epidemiology studies look at populations as a whole, which necessarily includes people with varying exposure levels due to their daily routines. Nevertheless, especially with the increasing recognition that a change in lifestyles is becoming necessary for most Americans to address both personal health issues and global problems such as climate change, it can be argued that air pollution standards should be revised to insure proper protection of the most exposed groups.

On the other hand, if the increase in inhalation dose is the result of policy to encourage people to use non-motorized forms of transportation, then a different interpretation is fitting. True, perhaps the same increases and decreases are observed as in the random situation, but the data is conceived differently. Now many of those who decrease their inhalation intakes can be viewed as free riders, because they benefit from shorter distances between destinations to spend less time driving places (hence less time in a more polluted environment), and those who shift modes are both the beneficiaries (because of increased physical activity in particular) and the victims (higher inhalation intakes) of the policy. Because the increased risk is the result of a deliberate policy that puts people in harm's way, despite its good intentions, then the argument can be made that it is incumbent to the policy makers to mitigate the unintended consequences. The policy response portfolio is discussed in the next section.

This BESSTE analysis cannot provide a definitive answer on the question of randomness. However the mechanisms that would explain the increases and decreases in inhalation dose are in part supported by the data, and above all the sensitivity analysis proved that results obtained are conservative. So, while it is recommended that more research be undertaken, the conclusion of this debate is also that developing policies to address unintended consequences is advisable.

5.3.2.2 *Decision framework*

The decision framework outlined in section 4.1 proposed three routes of conduct according to the risk results, the first one requiring action to reduce risk, the second calling for an expansion of programs promoting walking and biking, and the third one asking for more research.

Action path 1 is triggered by the results, on all three accounts of the decision rules. First, the Wilcoxon test found a significant increase in the fraction of days above the PM_{10} threshold in the population following community changes (even if significant decreases were found for ozone). Second, 5% of days of inhalation intakes above the threshold were found to have at least 10% increases in ozone and PM_{10}; however only 1.5% and 4% of person-days for ozone and PM_{10} respectively had a 95% probability of experiencing a 10% increase in intake, applying an average standard deviation on the data. Finally, at least one individual doubles intake rates on 5% of days for both ozone and PM_{10}. However the latter results represent extreme values and are not within any reasonable confidence bounds. Policies for actions to reduce risk are discussed in the following section.

No clear benefits were found according to the decision rule suggested in section 4.1: no-one attained 150kcal/day of energy expenditure through active travel 70% of the year. However, as explained in the previous section, employing another travel model and another simulation approach could trigger very different results. As expressed earlier, finding no clear benefit through this work does not sanction a break on efforts to create more pedestrian-friendly environments. Indeed, the literature has shown the many different facets of health and wellbeing that can be advanced through such policies, including leisure time physical activity in addition to active travel. With an ascertainment of clear benefits however, this work would have concluded with a call for a forceful expansion of neighborhood transformation programs.

One certitude emerges from this work: more research is needed in this area. The level of uncertainty provided by the results is too high to enable a clear answer on whether increased risks would truly be borne by creating more pedestrian-friendly neighborhoods. Although it can be concluded from the preceding discussion that risks are likely to arise, the magnitude of health impacts are not known. A research agenda is proposed in section 5.3.2.4.

5.3.2.3 *Policies*

Section 4.1 on the decision framework stated that the extent of the policy effort required to mitigate unintended consequences should be commensurate to the magnitude of potential detrimental effect. The problem is of course that, as mentioned above, the amount of uncertainty prevents a measure of the extent of increased exposure both in terms of the amount of increased inhalation dose and the proportion of people concerned. The results of the full BESSTE simulation point to particular cases of extreme individuals rather than entire populations at risk. However the Rodríguez model would probably diffuse the risk more in the entire population, as well as create more extremes. Hence a variety of policy approaches are suggested here to address diverse risk outcomes.

The pollution reduction scenarios tested in section 5.1.4. suggested that at least in person-day sensitivity analysis, the 5% uniform reduction would according to the Cervero model eliminate risks of significant increase in inhalation in most of the population except for a remaining PM_{10} peak in 4% of person-days. The 20% reduction yields no more significant increases in the population for a 95% probability, even though the peak is still apparent. The Rodríguez version also finds a drop in person-days at risk, cutting almost by half the number of person-days with significant increases in the 5% reduction, almost eliminating significant increases in the 20% reduction. Hence, 5% and 20% reductions are good targets for a population approach to reduction in risk for two different levels of risk. Other more behavioral policies are suggested to address remaining peaks.

A five percent reduction in local air pollution may be sufficiently addressed by local policies, while a 20% or greater reduction would probably necessitate a more regional involvement. Vehicle emissions are the target of the policies proposed, since they contribute to the majority of urban air pollution for many pollutants, they may be controlled in part by local policies, and roadway exposure is a major concern of this study.

The built environment transformations analyzed in BESSTE to increase walking and biking are themselves means to reduce emissions. They may require a more systematic, forceful, and comprehensive approach than the scenarios portrayed in BESSTE however to achieve significant reductions. Major (and related) policy directions for attaining emissions reductions goals are 1) to prevent dispersed low-density types of development (sprawl), and 2) make the cost of driving comparatively higher than alternative modes (including by making alternatives more appealing). Steps that could be taken by local governments include:

- Change land use codes to promote compact and mixed land uses in the urban core, and to require maximum parking rather than minimum parking for new developments
- Establish a policy of street connectivity, sidewalks and bicycle lanes for any new construction or maintenance work.
- Develop finance mechanisms to promote mixed use properties and infill and brownfield development
- Eliminate or reduce free public parking
- Create incentives/requirements for employers to provide appropriate facilities (e.g. bike parking, showers) and incentives (e.g. parking cash-out) to promote alternative means of transportation, and to offer affordable housing for employees near where they work
- Provide more local transit, and transit-oriented development around transit lines
- Work with adjoining jurisdiction to avoid tax-base competition that leads to poor planning, and to improve transit connectivity
- Develop promotional programs to encourage alternative mode of transportation: bike loan programs, social-marketing campaign
- Provide gathering places downtown
- Enhance the human scale walkable character of streets and neighborhoods

A local action that could have the double benefit of potentially reducing emissions (through non-motorized modes incentives) and also reducing exposure, it to create a network of paths, trails, or linear parks to guide non-motorized traffic through the town but away from vehicular traffic. By being away from the source this could reduce intakes for toxic air pollutants and particulate matter, although it would not necessarily help with ozone.

Were all the policies above rigorously implemented, sizable emissions reductions could be expected locally. Still, an ambitious regional approach could achieve a drop of 20% or more in pollutant concentrations more effectively. This is because changes in regional accessibility have been shown to be a much more important predictor of changes in vehicle miles traveled then local density, diversity or mix (Ewing and Cervero 2001). Much of the same recommendations from the local scale could apply to the regional scale. Examples include: regional cooperation for transit connectivity and transit expansion, transit-oriented development, incentives for brownfield and infill development, open space preservation to guide growth in existing communities, employer incentive programs, etc. In addition the region can choose to implement highway tolls, and prevent highway expansion which promote sprawl by reducing the cost of auto travel.

Finally state and federal governments can also take a share of the responsibility in preventing risks accrued when increasing healthy active lifestyles, especially if physical activity promotion becomes a state or national health priority. The air quality and transportation federal laws and their state implementations can provide all the right incentives for the programs mentioned above. This could be done most obviously through their funding mechanism for transportation infrastructure, also through recognizing more fully the land use-transportation connection in air quality legislation, and providing technical guidance and expertise for better transportation and land use planning. In addition, the states and national governments can implement some pricing strategies more readily than local or regional entities, such as toll roads, road use metering, and fuel pricing. Other programs that can be developed through state incentives in partnership with private entities are location-efficient mortgages, car-sharing programs, and pay at the pump auto insurance. Finally federal government can set more stringent emissions standards, which do not reduce vehicle use (unless it were to make cars much more expensive), but tackle pollution reductions nonetheless.

The above panoply of policies would offer solutions to reduce risks for most of the population. However as BESSTE demonstrated, it is likely that even a 20% reduction could not protect some individuals from high peaks of increased intake. Therefore a different approach is necessary for these extreme individuals. Information and education campaigns could be the most effective way to address these cases, while still helping the general population reduce risks. Such a program could include: creating and distributing maps depicting routes with highest or lowest pollutant concentrations, providing information on hours of pollutant peaks, and publicizing daily air pollution forecasts with recommendations on protective behaviors for groups of different levels of sensitivity. The analysis on the temporal pattern of outcomes (see Figure 5-12) supports a seasonal approach to policy making.

It was mentioned earlier that the policy investment should measure up to the level of risk incurred. However, because uncertainty is high, it is difficult to state at this stage whether more aggressive and ambitious programs are necessary to address increased risks or not. Yet, it is worth noting that all policies to reduce auto-dependency and car use have many more ramifications other than protecting those whose risk is accrued because of active living. Emissions reductions would better protect health-impaired and sensitive groups, would address the problem of climate change, and could bring about all the other health and social benefits reviewed earlier in the dissertation. Hence, opting for far-reaching and audacious policies is a desirable course of events, no matter what the level of risks estimated by BESSTE.

5.3.2.4 *Research agenda*

The greatest driver of uncertainty identified in BESSTE is the choice of transportation models. The two models tested generated significantly different results in increases in the three outcomes for three quarters of the modeled person-days (for an alpha of .05 in the Wilcoxon test). Furthermore, neither of these models was ideal for the purpose of modeling mode choice for all trip purposes, as discussed in the methods section. Hence, more research is needed in mode choice modeling, including non-motorized modes, as a function of built environment variables in a wide variety of settings (trip purpose, geographic location, time of year, etc.).

The other most prominent difference found in BESSTE were results of more extreme individuals as modeled with a low and high behavioral variability approach. To identify individuals most at risk in terms of the repetitiveness of behaviors and to assess better chronic effects, an improved knowledge on modeling the variability of behaviors and on habit-formation is necessary.

Microscale distribution of air pollution also needs further investigation to produce reliable maps. The sensitivity analysis on air pollution concentration uncertainty did not demonstrate a need for accounting for it in BESSTE (the variation of concentrations along uncertainty distributions produced low variability compared to other factors modeled). However the uncertainty estimated for the outputs using the BME method were just provided by variance estimates given hard and soft data inputs, and were not verified for conditions under which they were used. More specifically, the estimates could not be compared with observed values at the small scale at which they were produced. Therefore uncertainty was naturally highly under-estimated. The methods sections discussed pros and cons of different modeling approaches to account for microscale concentrations. It is clear that advancements in this field are needed to produce sound estimates for street-scale concentrations across neighborhoods.

Sensitivity analyses identified personal factors such as body weight, resting metabolic rate, and stochastic factors that intervene in inhalation rate calculations, as having a large impact on the variability of intake estimates. Future work should therefore track these factors carefully, especially to then link the individual's exposures to health outcomes.

Health impacts calculations were pinpointed in the conceptual model discussion as bearing the greatest challenges in this work of linking health status to the built environment. Research is needed to allow the specific inhalation intake of a pollutant to be associated with health outcomes, under conditions of daily living in the general population. This could be done through epidemiologic studies that could follow individuals in their every-day activities to measure exposure precisely. It could also be accomplished through innovative work in epidemiology where respondents' activities would be simulated given known information on their personal characteristics, and perhaps lifestyle habits and home and work locations.

Other health impacts discussed in the conceptual model should be included in future work on integrative models to estimate net health impacts of the built environment. These include health benefits of physical activity and risks of traffic injuries. More broadly than the specific risks and benefit that compete with each other that were explored in the conceptual analysis, it is important for future assessments to at least qualitatively measure other effects of the built environment so as not to paint a biased picture of effects on health and quality of life.

5.4 Conclusion

This work has uncovered the potential for a trade-off of competing risks, accompanied by considerable uncertainty in estimating the risks and benefits, associated with creating more pedestrian-friendly environments. While results are not entirely conclusive, they do show at least in the context of the particular simulations performed here that there can be a significant increase in the number of days above the PM_{10} inhalation threshold overall as individuals spend more time walking and/or biking in communities. They also demonstrate the potential for more than a 10% increase for some individuals in inhalation on high pollution days for both ozone and PM_{10}, and suggest that air pollution inhalation may more than double in some individuals on certain days for both pollutants. The analysis concludes that these estimates are likely to be conservative: a larger portion of the community could in reality be affected, and some individuals could experience greater inhalation increases. The simulation could not demonstrate any significant benefit in terms of individuals reaching the recommended levels of physical activity through active travel alone (i.e. not including recreational walking or biking).

However, it is important to bear in mind that these conclusions are specific to the one community studied and the particular set of transportation models employed..

Caution must be taken in interpreting the results. Beyond the considerations of uncertainty due to the transportation mode choice model and behavioral variability that were assessed in the computational analysis, the model contains many simplifications that were discussed conceptually in Chapter 3 and were not quantitatively addressed in BESSTE. The overall significance of these limitations cannot yet be assessed completely due to a current inability to validate the results with real-life individual activities and exposures that can be compared against the predictions of this analysis. Sources of uncertainty not quantified in BESSTE include:

- Using regional daily activity pattern dataset which may not match daily routines of Chapel Hill and Carrboro residents.
- Using successive gravity and mode choice model rather than a joint location-mode choice model.
- Confining activities within Orange County.
- Testing a single scenario for built environment improvements (choosing top 20% of neighborhoods with the most pedestrian-friendly features and not for example the next 20%).
- Assuming that a change in the built environment will result in a change in behaviors in the same individuals.
- Scaling down air pollution concentration field to street level exposures (100 meter grid).

In addition to these caveats about interpreting the BESSTE results, further caution is necessary to draw conclusions on overall impacts of the built environment. BESSTE specifically looks at the competing risks and benefits of active travel and air pollution exposure, and much more information than this narrow focus would be necessary to provide general conclusions on pedestrian-friendly environments. For example, quantifying exposures to traffic hazards and crime could reveal more important sources of risk. On the other hand, including recreational physical activity in addition to utilitarian non-motorized travel in the model could trigger much greater benefits outcomes than those estimated here. Moreover, as discussed previously, impacts of the built environment go beyond these competing effects, and pedestrian-friendly communities could improve human health and wellbeing in many different ways, including through its impact on: social capital, air and water quality, noise, diet, vector-borne diseases, etc. To understand whether the disparate health impacts of changes in the built environment could be detrimental or beneficial overall, it will be necessary to include these other competing risks and benefits in future analyses, and a unifying measure of health, such as quality-adjusted life years, applied.

Policy recommendations are provided, however, for the specific context of this simulation. Given the amount of uncertainty associated with the results, it is not possible to suggest policies that would match the potential level of risk incurred. Nevertheless, the discussion revealed that despite results showing almost equivalent amounts of increases and decreases in inhalation intake in different segments of the population, the outcomes are unlikely to be the result of random patterns of behavior. This suggests that there may be policies available in communitv design that target those individuals whose health risks appear to be increased in the current study. And in any event, policies that decrease auto-dependency and car-use generate many other benefits, so that ambitious policies leading to such decreases are recommended anyhow.

Pointers for future work were laid out in a research agenda to address the drivers of uncertainty and the gaps in the knowledge that could ensure a reliable estimate of health impacts of neighborhood transformations. It will be essential for future work in this area to consider all risks and benefits before making recommendations, rather than the three measures employed here (energy expenditure, ozone intake and PM intake). Benefits of exercise especially are plentiful in a public health context, and overlooking them could create a biased assessment.

While this work is far from providing definitive answers on net health impacts of creating more pedestrian-friendly neighborhoods, it has the merit of being innovative and proposing for the first time a rigorous quantitative framework for assessment of health risks and benefits of urban design and land use policies. It also makes the case for comprehensive approaches to decision making, by revealing potential unintended consequences of built environment policies. Integrated risk assessment seems to be an appropriate approach for tackling such multi-attribute decision making problems.

APPENDIX A ACTIVITY TYPE CLASSIFICATION

Table A-1 Conversion of PSIC classification to my coding scheme

PSICCOD	PRIMSICDESCR	LocCode
7311-06	Advertising-Newspaper	40
4512-01	Airline Companies	40
6513-03	Apartments	40
8611-02	Associations	40
6021-01	Banks	40
5112-07	Business Forms & Systems (Wholesale)	40
9621-04	City Government-Transportation Programs	40
8641-08	Clubs	40
5211-28	Concrete-Ready Mixed	40
7389-39	Conference Centers	40
8732-01	Educational Research	40
4911-01	Electric Companies	40
1731-01	Electric Contractors	40
3699-02	Electric Equipment-Manufacturers	40
8322-03	Family Planning Information Centers	40
6282-03	Financial Advisory Services	40
9224-04	Fire Departments	40
1521-03	General Contractors	40
1611-03	Grading Contractors	40
5099-05	Importers	40
6411-33	Insurance-Holding Companies	40
6361-01	Insurance-Title	40
5961-02	Internet & Catalog Shopping	40
8732-04	Market Research & Analysis	40
2431-02	Millwork (Manufacturers)	40
2711-01	Newspapers (Publishers)	40
8399-98	Non-Profit Organizations	40
1611-04	Parking Area/Lots Maintenance & Marking	40
2721-98	Periodicals-Publishing & Printing	40
8731-08	Pharmaceutical Research Laboratories	40
9221-04	Police Departments	40
6531-18	Real Estate	40
8732-06	Research Service	40
9221-03	Sheriff	40
6541-02	Title Companies	40
8299-31	Training Programs & Services	40
4213-06	Trucking-Liquid & Dry Bulk	40
7812-11	Video Production & Taping Service	40
4941-02	Water & Sewage	40

	Companies-Utility	
8049-12	Audiologists	41
8011-04	Clinics	41
8021-01	Dentists	41
8099-07	Health Services	41
8082-01	Home Health Service	41
8062-02	Hospitals	41
8063-01	Mental Health Services	41
8331-04	Mental Retardation & Dev Disabled Svcs	41
8051-01	Nursing & Convalescent Homes	41
8011-01	Physicians & Surgeons	41
3841-04	Physicians & Surgeons Equip & Supls-Mfrs	41
8331-02	Rehabilitation Services	41
8059-04	Retirement Communities & Homes	41
8221-08	Schools-Medical	41
8351-04	Child Care Centers-Consultants	42
8299-72	Education Centers	42
8299-29	Educational Service-Business	42
8211-03	Schools	42
8244-01	Schools-Business & Vocational	42
8221-01	Schools-Universities & Colleges Academic	42
8299-09	Tutoring	42
5511-02	Automobile Dealers-New Cars	50
5511-02	Automobile Dealers-New	50

	Cars	
5941-41	Bicycles-Dealers	50
5211-26	Building Materials	50
8661-07	Churches	50
7212-01	Cleaners	50
5311-02	Department Stores	50
5211-38	Home Centers	50
7011-01	Hotels & Motels	50
8742-13	Marketing Programs & Services	50
5112-13	School Supplies (Wholesale)	50
5941-13	Sporting Goods-Retail	50
5411-03	Convenience Stores	51
5411-05	Grocers-Retail	51
5813-01	Bars	52
5812-12	Caterers	52
5812-22	Pizza	52
5812-08	Restaurants	52
9111-04	City Government-Executive Offices	53
8322-29	Community Services	53
9441-03	County Government-Social/Human Resources	53
9121-04	Government Offices-City, Village & Twp	53
8231-09	Libraries-Institutional	53
8231-06	Libraries-Public	53
8412-01	Museums	53
7992-01	Golf Courses-Public	60
7999-51	Parks	60

APPENDIX B LANDUSE CODING

As shown in FigureB-1, land use types were divided into an impractically high number of categories (more than 50) in the study area. The Chapel Hill data contained some broad categories with general description and thus was more manageable: categories were converted to the Cervero variables following the coding scheme described in Table 2.3, after verifying that it seemed to match using my own knowledge of the area and Google earth maps. Several Cervero variable categories can be true for a single land use, therefore the Table only indicates when a category is present (coded as 1), and the zeros (0) are omitted. The Carrboro data seemed more ad-hoc and more difficult to transform systematically. Thus, each land use polygon was verified using the town of Carrboro GIS maps and Google earth maps, and followed a coding scheme in keeping with the one described in Table4-1. Table B-1 describes the coding scheme for each of the detailed land use categories.

Table B-1 Chapel Hill land use data conversion to Cervero variables

CH-Ca LU code	SFd	Sfa	MFmr	MFhr	NR	Groc
Office & Institutional 1, 2 & 3 & Neighborhood Commercial					1	
Residential 1, 3 units/acre & Residential 1A, 2 units/acre	1					
Medium Density Residential, 10 units/acre		1				
Community Commercial					1	1
High Density Residential, 15 units/acre			1			
Residential 2, 4 units/acre	1	1				
Medium Density Residential, 7 units/acre		1	1			
High Density Residential, 15 units/acre			1			
Town Center 2[48]			1	1	1	
High Density Residential, 15 units/acre Conditional Use[49]	1	1	1		1	
High Density Residential, 15 units/acre Conditional Use[50]			1			
Mixed Use, Low Density Residential[51]	1				1	1
Neighborhood Commercial Conditional Use[52]			1		1	1
Office & Institutional 4[53]			1	1	1	

[48] Chapel Hill downtown

[49] Part of Southern Village and Meadowmont

[50] Other neighborhoods

[51] Part of Meadowmont

[52] Part of Southern Village

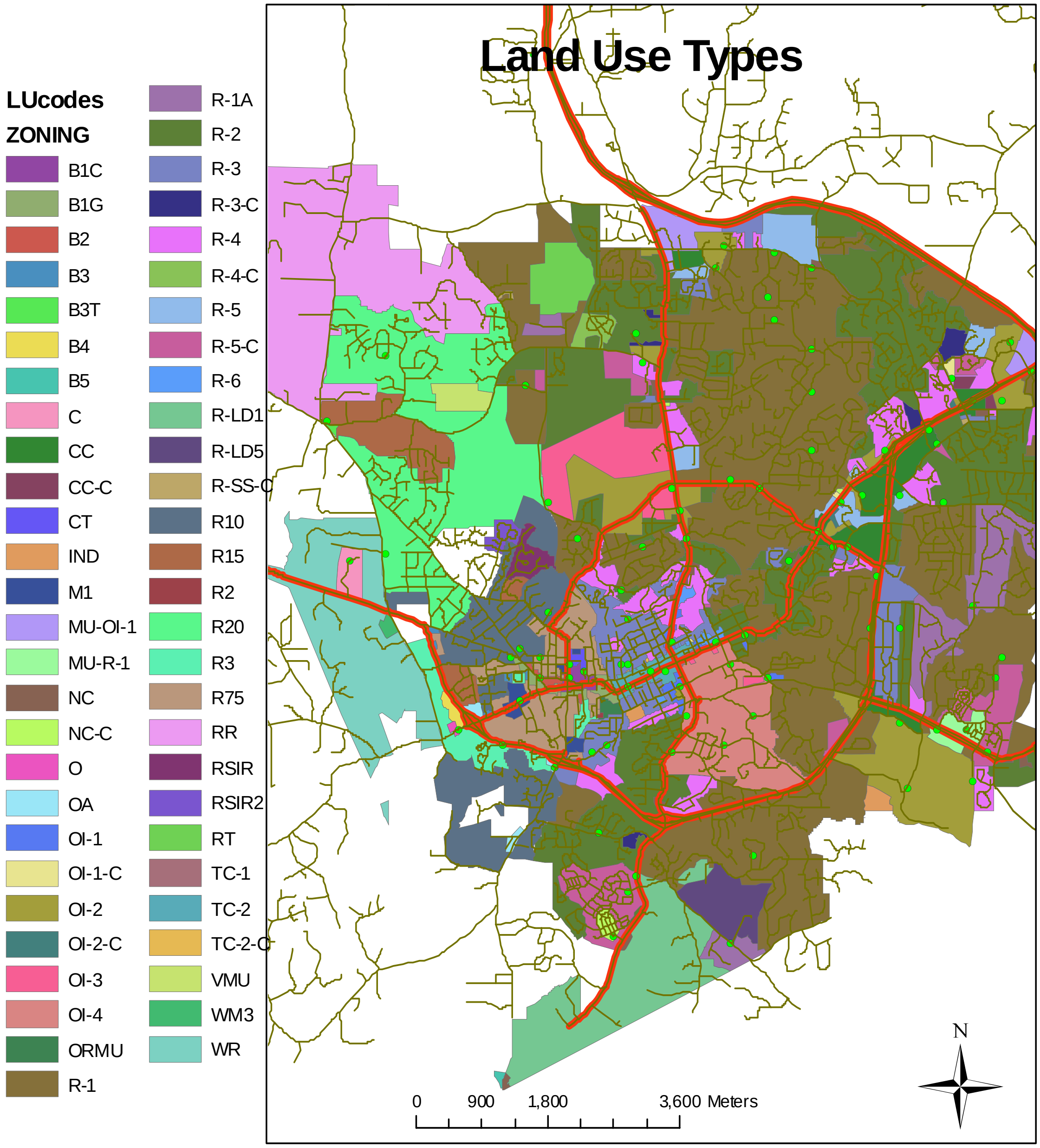

Figure B-22 Land use types in Chapel Hill Carrboro area, used to develop the Cervero variables for the study area. Land use coding scheme associated with categorizations are shown in TableA2 in the appendix.

To then assign the Cervero land use indeces, 300 feet buffers were created around each location and intersected with land use type layer from the towns' planning departments data. Thus for each location all land use types present in the 300 feet buffer is documented, and provides the inputs for appropriately determining the SFd, Sfa, MFmr, MFhr and NR indices. The resulting classification was verified to insure

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[53] Campus (including student and student family housing)

they matched the activity data used in BESSTE (for example in some cases the land use code indicated no non-commercial land uses when in BESSTE non-residential activities were present).

For the grocery store variable, Groc, 1 mile buffers were created around each location. Both crow fly's distance buffers and network distance buffers were considered for this. Locations thus selected as not having grocery stores within a mile are depicted in Figure B-2(pink circle for crow fly's distance, green triangles for network distance). For the purpose of the Cervero variable however, the crow fly's distance was chosen, even though the variable used in Cervero was perhaps more adequately represented by the network distance, since the variable seems to refer to a self-reported presence of grocery stores within a mile and people may think of distances along networks rather than aerially. Yet, it reduces the complexity of the modeling framework to use the crow fly's distance, particularly to test the land use mix scenario separately from the network connectivity scenario (otherwise the Groc variable needs to be re-estimated for separate street network connectivity scenarios).

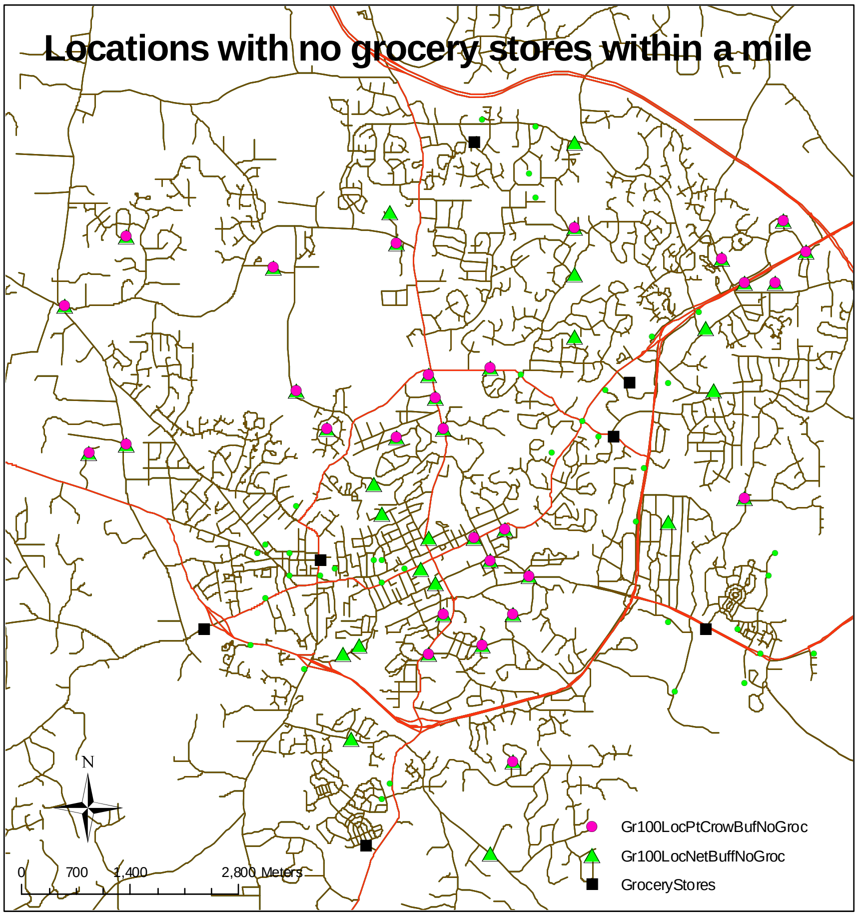

Figure B-23 Locations with no grocery stores within a mile (pink circles: crow fly's distance; green triangles: network distance).

APPENDIX C SCENARIO BUILDING

Figure C-1 shows the gradient of the number of activity per grid cell measure in the study area, exclusing the distant location, Hillsborough.

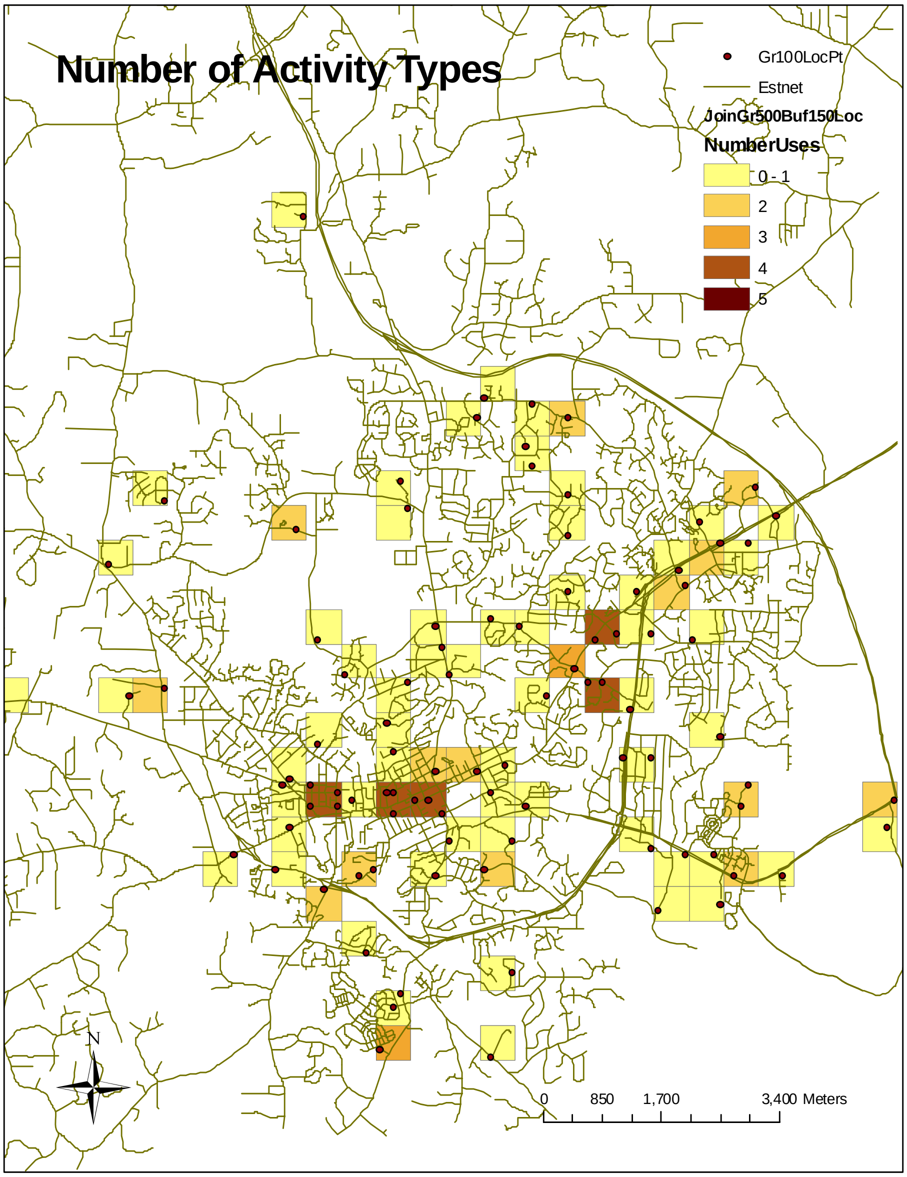

Figure C-1 Number of different activity types in 25 hectare gridblocks, excluding residential land uses.

Table C-1 provides a description of the proposed land use changes in the selected areas. To illustrate the process, a more detailed description is provided for the first few gridblocks, and all the proposed changes are summarized in Table C-2. The number FID refers to the selected 25 hectare gridblock identification (ID) number. The table shows existing number of people (employees or residents) represented by each activity type for each activity gridblock in normal font, and the additional activities identified by the bold characters. The column headings are the abbreviated activity type for which descriptions were provided in Table 4.1.

To then reflect the proposed changes at the 500 meter gridblock level to the 100 meter grid scale (where activity centers are located), simply uses or densities are added on to the existing locations rather than add new 100 grid locations within each 25hectare square. This simplifies the modeling framework as the same routes along the street network can be used in the new scenario as in the previous one.

Table C-1 Description of land use change scenario building process

FID 9 and 34: These 2 gridblocks were selected specifically for increasing population density. In each of these, the population was approximately 1000 people. In the other 19 gridblocks with residential population in the model, the highest population count is approximately 8000, the following two around 4000, then 3000, 2000, and the rest are around 1000. The median population count of the more populated gridblocks (above 2000) is thus 4000 people, and hence it is suggested to quadruple the population in these 2 selected gridblocks to attain this medium density.
FID 14: Contains the following activities: school, grocery store, restaurant/bars, public building. Neighboring grids contain residential population and medical uses, general work, and outdoor recreation. Thus general shopping purposes are add to the gridblock, with the employment count for that activity corresponding to the median of shopping activities in the study are: 250 people.
FID21: General shopping is also added here, but because the purpose is rather for neighborhood commerce (not a central place in study area), a lower end of employment associated with shopping is added: 75 people.
FID 23: General shopping added, with 250 employees. The area is also selected to add more residential density, since it's so central: it is triple from the existing 1023 to 3069.
FID 30: Grocery store added with number of employees corresponding to the median of other grocery stores: 175.
FID 31: Opportunity for outdoor recreation, with 4 uses (because central rather dense location).
FID 33: Selected for grocery shop, 175 employees.
FID 35: General shopping added, associated with median employment for that purpose: 250 people
FID 37: General shopping added, associated with median employment for that purpose: 250 people
FID 51: Grid is surrounded by all activities, so add just mean general work: 240 people
FID 57: General shopping added, associated with median employment for that purpose: 250 people
FID 65: General shopping added, associated with median employment for that purpose: 250 people
FID 71: Grocery store: 175 people
FID 73: Restaurant and bars, mean 175 people
FID 76: Outdoor recreation, 7 activities.

Table C-2 Changes made to selected locations in the more pedestrian-friendly land use scenario: numbers in bold are the additional employment assigned for each activity.

FID	WorkG	Med	School	Shop	Grocer	Rest/bar	PubBul	OutRec	Resid
9	0	0	0	0	0	0	0	0	**4024**
14	0	0	174	**250**	174	224	248	0	0
21	0	74	174	**75**	74	0	0	0	0
23	174	0	1007	**250**	0	372	0	9	**3069**
30	693	4775	0	749	**175**	223	0	0	0
31	74	0	0	0	0	0	74	**4**	0
33	348	0	0	0	**175**	0	0	0	0
34	0	0	0	0	0	0	0	0	**4028**
35	148	0	0	**250**	0	0	74	0	0
37	149	0	0	**250**	75	0	0	0	0
51	**240**	74	74	174	0	0	0	0	0
57	74	174	0	**250**	374	74	0	0	0
65	74	249	0	**250**	0	0	0	0	0
71	74	0	0	0	**175**	74	0	0	0
73	0	74	174	0	0	**175**	0	0	0
76	74	174	0	0	0	0	0	**7**	0

APPENDIX D PROXIMITY TO ROAD FACTOR

Literature on proximity to roads and air pollutant concentration was reviewed to produce quantitative summaries of relationships for particulate matter, as shown in Table D-1. The articles gave the direct relationships in some cases, in others the numbers had to be extrapolated from graphs or otherwise computed. Average and standard deviation proximity factors were then computed for PM10 and PM2.5 as shown in Table D-2. Finally, the factor chosen was 20% increase concentration by the road side, with a standard deviation of 16%, which is the overall average of these factors.

Table D-1 Quantitative summary of proximity to roads literature

Percent higher concentration in traffic sites compared to backround		**Reference**
PM10	16% (street), 37% (motorway)	Roemer and can Wijnen (2001)
PM2.5 and PM10	30%	Janssen et al. (1997)
PM2.5	8%, 12%, 35%	Cyrys et al. (2003)
	17-18%	Hoek et al. (2002)
Percent lower concentration at a distance from the road		
PM10	8-13% (15m)	Monn (1997)
PM2.5 and PM10	No gradient	Roorda-Knape et al. (1998)
PM2.5	5% (50m)	Levy et al. (2003)
	25%(100-150m, wind from the road), 65% (375m, parallel wind)	Hitchins et al. (2000)
High traffic intensity sites compared to low traffic sites		
PM10 and PM2.5	15-20%	Fischer et al. (2000)

Table D-1 Average (and standard deviation) proximity to roads factors

	Average (std)
PM10 only	18.5 (12.8)
PM2.5 only	23.1 (19.4)
PM10 and (PM10 and PM2.5)	17.4 (11.8)
PM2.5 and (PM10 and PM2.5)	20.8 (17.2)
All PM10 and PM2.5	20.3 (15.8)

APPENDIX E METS DISTRIBUTION

Table E-1 METs distribution information

Description	Age	DistType	Mean	Med.	StdDev
Work, general		Triangle	2.9	2.7	1
Breaks		Uniform	1.8	1.8	0.4
General household activities		Triangle	4.7	4.6	1.3
Prepare food		LogNormal	2.6	2.5	0.5
Prepare and clean-up food		Exponential	2.8	2.5	0.9
Indoor chores		Exponential	3.4	3	1.4
Clean-up food		Uniform	2.5	2.5	0.1
Clean house		Exponential	4.1	3.5	1.9
Outdoor chores		Normal	5	5	1
Clean outdoors		Exponential	5.3	4.5	2.7
Care of clothes		Exponential	2.2	2	0.7
Wash clothes		Point Est.	2	2	
Build a fire		Point Est.	2	2	
Repair, general		Normal	4.5	4.5	1.5
Repair of boat		Point Est.	4.5	4.5	
Paint home / room		Exponential	4.9	4.5	1.4
Repair / maintain car		Triangle	3.5	3.4	0.4
Home repairs		Exponential	4.7	4.5	0.7
Other repairs		Uniform	4.5	4.5	1.4
Care of plants		Uniform	3.5	3.5	0.9
Care for pets/animals		Uniform	3.3	3.3	0.1
Other household		Exponential	6.6	5.5	3.6
Child care, general		LogNormal	3.1	3	0.7
Care of baby		Uniform	3.3	3.3	0.1
Care of child		Uniform	3.3	3.3	0.1
Help / teach		Uniform	2.8	2.8	0.1
Talk /read		Uniform	2.8	2.8	0.1
Play indoors		Uniform	2.8	2.8	0.1
Play outdoors		Uniform	4.5	4.5	0.3
Medical care-child		Uniform	3.2	3.2	0.1
Other child care		Uniform	3	3	0.3
Obtain goods and services, general		Triangle	3.8	3.7	0.8
Dry clean		Uniform	3.3	3.3	0.4
Shop / run errands		Triangle	3.7	3.6	0.8
Shop for food		Triangle	3.9	3.8	0.8
Shop for clothes or household goods		Uniform	3.4	3.4	0.6
Run errands		Uniform	3.5	3.5	0.6
Obtain personal care service		Uniform	3.5	3.5	0.6
Obtain medical service		Uniform	3.5	3.5	0.6
Obtain govern't / financial services		Uniform	3.5	3.5	0.6
Obtain car services		Uniform	3.5	3.5	0.6
Other repairs		Uniform	3.5	3.5	0.6
Other services		Uniform	3.5	3.5	0.6
Personal needs and care, general		Uniform	2	2	0.6

Shower, bathe, pers. hygiene		Normal	2	2	0.3
Shower, bathe		Uniform	3	3	0.6
Personal hygiene		Uniform	1.8	1.8	0.4
Medical care		Uniform	1.8	1.8	0.4
Help and care		LogNormal	3.1	3	0.7
Eat		Uniform	1.8	1.8	0.1
Sleep or nap		LogNormal	0.9	0.9	0.1
dress, groom		Point Est.	2.5	2.5	
Other personal needs		Triangle	2	2	0.4
General educ. and pro. training		LogNormal	1.9	1.8	0.7
Attend full-time school		Uniform	2.1	2.1	0.4
Attend day-care		Uniform	2.3	2.3	0.4
Attend K-12		Uniform	2.1	2.1	0.4
Attend college or trade school		Uniform	2	2	0.3
Adult education and special training		Uniform	1.8	1.8	0.2
Attend other classes		Uniform	2.2	2.2	0.5
Do homework		Point Est.	1.8	1.8	
Use library		Uniform	2.3	2.3	0.4
Other education		Uniform	2.8	2.8	0.7
General entertainment / social activities		LogNormal	2.2	2	1.1
Attend sports events		Uniform	2.7	2.7	0.8
Participate in social, political, or religious activities		Uniform	1.7	1.7	0.2
Practice religion		Uniform	1.7	1.7	0.2
Watch movie		Uniform	1.3	1.3	0.2
Attend theater		Uniform	1.7	1.7	0.4
Visit museums		Uniform	2.5	2.5	0.3
Visit		Uniform	1.5	1.5	0.3
Attend a party		LogNormal	3.3	3	1.4
Go to bar / lounge		LogNormal	3.3	3	1.4
Other entertainment / social events		Uniform	3.8	3.8	1.3
Leisure, general	20	LogNormal	5.7	5	3
Leisure, general	30	Normal	5	5	2
Leisure, general	40	Normal	4.5	4.5	1.4
Sports and active leisure	20	LogNormal	5.7	5	3
Sports and active leisure	30	Normal	5	5	2
Sports and active leisure	40	Normal	4.5	4.5	1.4
Participate in sports	20	LogNormal	3.6	3.2	1.9
Participate in sports	30	LogNormal	3.6	3.2	1.9
Participate in sports	40	LogNormal	3.4	3	1.7
Hunting, fishing, hiking	20	Normal	5.6	5.6	2.1
Hunting, fishing, hiking	30	Normal	5.8	5.8	2.4
Hunting, fishing, hiking	40	Normal	4.7	4.7	1.8
Golf	20	Uniform	3.8	3.8	1
Golf	30	Uniform	3.8	3.8	1
Golf	40	Uniform	3.5	3.5	0.9
Bowling / pool / ping pong / pinball		Uniform	3	3	0.6
Yoga		Triangle	3.1	3.2	0.6
Participate in outdoor leisure	20	LogNormal	4.2	3.9	1.5
Participate in outdoor leisure	30	LogNormal	4.2	3.9	1.5
Participate in outdoor leisure	40	Point Est.	3.5	3.5	

Play, unspecified	20	LogNormal	4.2	3.9	1.5
Play, unspecified	30	LogNormal	4.2	3.9	1.5
Play, unspecified	40	Point Est.	3.5	3.5	
Passive, sitting		Uniform	1.5	1.5	0.2
Exercise	20	LogNormal	5.8	5.5	1.8
Exercise	30	Normal	5.7	5.7	1.8
Exercise	40	Normal	4.7	4.7	1.2
Walk, bike, or jog (not in transit)	20	LogNormal	5.8	5.5	1.8
Walk, bike, or jog (not in transit)	30	Normal	5.7	5.7	1.8
Walk, bike, or jog (not in transit)	40	Normal	4.7	4.7	1.2
Create art, music, work on hobbies	20	Normal	5.3	5.3	1.8
Create art, music, work on hobbies	30	Normal	5.2	5.2	1.7
Create art, music, work on hobbies	40	Normal	3.8	3.8	1
Participate in hobbies		Triangle	2.8	2.7	0.8
Create domestic crafts		Triangle	2	1.9	0.4
Create art		Uniform	2.5	2.5	0.3
Perform music / drama / dance	20	Normal	5.3	5.3	1.8
Perform music / drama / dance	30	Normal	5.2	5.2	1.7
Perform music / drama / dance	40	Normal	3.8	3.8	1
Play games		Triangle	3.3	3.2	0.6
Use of computers		Uniform	1.6	1.6	0.2
Recess and physical education		Uniform	5	5	1.7
Other sports and active leisure	20	LogNormal	6.6	5.9	3.2
Other sports and active leisure	30	Normal	6	6	2
Other sports and active leisure	40	Normal	4.8	4.8	1.4
Participate in passive leisure		LogNormal	1.3	1.3	0.3
Watch		Uniform	1.5	1.5	0.2
Watch adult at work		Uniform	0	0	0
Watch someone provide childcare		Uniform	0	0	0
Watch personal care		Uniform	0	0	0
Watch education		Uniform	0	0	0
Watch organizational activities		Uniform	0	0	0
Watch recreation		Uniform	2.7	2.7	0.8
Listen to radio / recorded music / watch T.V.		LogNormal	1.2	1.2	0.4
Listen to radio		Uniform	1.2	1.2	0.1
listen to recorded music		Uniform	1.9	1.9	0.2
Watch TV		Point Est.	1	1	
Read, general		Uniform	1.3	1.3	0.2
Read books		Uniform	1.3	1.3	0.2
Read magazines / not ascertained		Uniform	1.3	1.3	0.2
Read newspaper		Uniform	1.3	1.3	0.2
Converse / write		Uniform	1.4	1.4	0.2
Converse		Uniform	1.4	1.4	0.2
Write for leisure / pleasure / paperwork		Uniform	1.4	1.4	0.2
Think and relax		Uniform	1.2	1.2	0.1
Other passive leisure		Uniform	1.9	1.9	0.2
Other leisure		Uniform	1.5	1.5	0.2
Travel, general		LogNormal	2.3	2	1.3
Travel during work		LogNormal	2.3	2	1.3
Travel to/from work		LogNormal	2.3	2	1.3

Travel for child care	LogNormal	2.3	2	1.3
Travel for goods and services	LogNormal	2.3	2	1.3
Travel for personal care	LogNormal	2.3	2	1.3
Travel for education	LogNormal	2.3	2	1.3
Travel for organ. activity	LogNormal	2.3	2	1.3
Travel for event / social act	LogNormal	2.3	2	1.3
Travel for leisure	LogNormal	2.3	2	1.3
Travel for active leisure	LogNormal	2.3	2	1.3
Travel for passive leisure	LogNormal	2.3	2	1.3
Utilitarian Walk	Normal	3.3		1
Utilitarian Bike	Normal	8		2.5

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