Investigating Daily Effects of Activity Space-based Built Environment Exposures on Physical Activity Behaviors in Hispanic Women during Pregnancy and Early Postpartum

by

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Dedication

To my parents, wife, and furry paws.

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Table of Contents

Dedication ii

Acknowledgements iii

List of Tables viii

List of Figures ix

Abbreviations x

Abstract xi

Chapter 1 Introduction 1

1.1. Disparities of Obesity-Related Outcomes in Hispanic Women 1

1.2. Critical Gaps in Research 2

1.3. Analytical Challenges 4

1.3.1. Daily Mobility in Health and Place Research 4

1.3.2. Uncertain Geographic Context Problem (UGCoP) 5

1.3.3. Within-Person Effects of BE Exposures 6

1.3.4. Moderating Mechanisms in Behavioral Pathways 7

1.4. Mobile Sensing in PA Research 8

1.5. Conceptual Framework and Dissertation Outline 9

Chapter 2 Time-Activity and Daily Mobility Patterns during Pregnancy and Early Postpartum 12

2.1. Related Work 12

2.2. Methods 16

2.2.1. Study Design 16

2.2.2. Data Collection 17

2.2.3. Data processing 18

2.2.4. Statistical Analysis 27

2.3. Results 30
2.3.1. Data Completeness 30
2.3.2. Descriptive Statistics of Covariates 31
2.3.3. Descriptive Statistics for Time-Activity and Daily Mobility Patterns 33
2.3.4. Base GLMM Results 39
2.3.5. Final GLMM Results..42
2.4. Discussion...47
2.4.1. Time-Activity and Mobility Patterns of Pregnant Women 47
2.4.2. Changes in Time-Activity and Mobility Patterns during Pregnancy and Postpartum...49
2.4.3. Additional Predictors of Time-Activity and Mobility Patterns........................50
2.4.4. Implications for Future Studies 51
2.4.5. Study Strengths and Limitations...52
2.5. Conclusions 54
Chapter 3 Assessing Dynamic Daily Exposures to Built-Environment Characteristics during Pregnancy and Early Postpartum using Smartphone Location Data 55
3.1. Related Work...55
3.2. Methods 58
3.2.1. Design and Overview 58
3.2.2. Data Collection..59
3.2.3. Data Processing 60
3.2.4. Statistical Analysis 65
3.3. Results 67
3.3.1. Data Completeness 67
3.3.2. Daily BE Exposure Estimates during Pregnancy and Early Postpartum...............67
3.3.3. Within-person Correlations in Daily BE Exposures across Time 70

3.3.4. Correlations of BE Exposures across methods (Static versus Dynamic) 70

3.3.5. Impact of Daily Mobility on Potential for Exposure Misclassification using the Static Method 71

3.4. Discussion 81

3.4.1. Women's Daily BE Exposures during Pregnancy and Early Postpartum 82

3.4.2. Similarities of Exposure Estimates between Static and Dynamic Methods 83

3.4.3. Exposure Misclassification Introduced by the Static Method to Due to Daily Mobility 85

3.4.4. Study Strengths and Limitations 86

3.5. Conclusions 88

Chapter 4 The Association between Built Environment Characteristics and Physical Activity during Pregnancy and Early Postpartum 89

4.1. Related Work 89

4.2. Methods 92

4.2.1. Study Design and Participants 92

4.2.2. BE Measures 93

4.2.3. PA Outcomes 96

4.2.4. Covariates 97

4.2.5. Statistical Analysis 98

4.3. Results 100

4.3.1. Descriptive Statistics 100

4.3.2. Predictors of Day-Level PA Outcomes in Pregnant Women 103

4.3.3. Moderators of Day-Level Associations between BE and PA 105

4.4. Discussion 111

4.4.1. Day-Level Associations between BE and PA 112

4.4.2. Differences in Day-Level BE-PA Associations by Temporal Factors 113

4.4.3. Differences in Day-Level BE-PA Associations by Individual Sociodemographics and Neighborhood Characteristics 115

4.4.4. Study Strengths and Limitations 117

4.5. Conclusions 119

Chapter 5 Conclusions 121

5.1. Contributions and Connections 121

5.2. Limitations and Directions for Future Studies 125

5.3. Major Takeaways 128

References 130

Appendix A: Confidence flagging algorithm for signal loss scenarios using the Maternal And Developmental Risks from Environmental and Social stressors (MADRES) real-time and personal sampling study Global Positioning System (GPS) data 147

Appendix B: Rules used to classify contexts of stays detected with the Maternal And Developmental Risks from Environmental and Social stressors (MADRES) real-time and personal sampling study Global Positioning System (GPS) data 148

Appendix C: An illustration of the GPS imputation rules based on existing data and home locations detected from context classification. 149

Appendix D: Individual sociodemographics, neighborhood characteristics, and temporal factors included in the study along with their measures and data sources 150

Appendix E: Zero-inflated Generalized Linear Mixed-Effects Model (GLMM) results for changes in time-activity patterns by pregnancy and postpartum period 151

Appendix F: Zero-inflated Generalized Linear Mixed-Effects Model (GLMM) results for changes in daily mobility patterns by pregnancy and postpartum period 152

Appendix G: Sensitivity analyses results of between-subject (BS) and within-subject (WS) effects of built-environment (BE) exposures on day-level moderate-to-vigorous physical activity (MVPA) outcomes 153

Appendix H: Significant interactions between day-level built-environment (BE) exposures and temporal, individual and neighborhood factors in predicting day-level moderate-to-vigorous physical activity (MVPA) outcomes 155

List of Tables

Table 2.1. Descriptive statistics of participant characteristics at baseline (a) and person-day level temporally varying factors by 1st and 3rd trimesters, and 4-6 months postpartum (b). 32

Table 2.2. Summary of total number of visits to multiple spatial contexts and indoor/outdoor microenvironments and total number of pedestrian and vehicular trips made. 34

Table 2.3. Day-level summary of time spent in spatial contexts, indoor/outdoor microenvironments, and number of pedestrian/vehicular trips made. 35

Table 2.4. Zero-inflated Generalized Mixed-Effects Model (GLMM) results for time spent in five non-home spatial contexts adjusted for covariates. 43

Table 2.5. Zero-inflated Generalized Mixed-Effects Model (GLMM) results for time spent in home and non-home contexts and microenvironments adjusted for covariates. 44

Table 2.6. Zero-inflated Generalized Mixed-Effects Model (GLMM) results for time spent in pedestrian and vehicular trips and number of pedestrian and vehicular trips performed adjusted for covariates. 45

Table 3.1. Built-environment (BE) measures, corresponding data sources, resolutions, and processing steps. 64

Table 3.2. Descriptive statistics of daily built-environment (BE) exposure estimates for participants using the route buffer (RB), kernel density estimation (KDE), and residential network buffer (RNB) methods. 68

Table 3.3. Intraclass-Correlation Coefficients (ICCs) of daily exposure estimates derived using the kernel density estimation (KDE) and route buffer (RB) methods. 71

Table 3.4. Pearson correlation coefficients between day-level static versus dynamic exposure estimates for the same built-environment (BE) variable during the 1st and 3rd trimesters and 4-6 months postpartum periods. 72

Table 4.1. Descriptive statistics for physical activity (PA) outcomes, built-environment (BE) predictors, and covariates of the study participants. 102

Table 4.2. Between-subject (BS) and within-subject (WS) effects of exposures to built-environment (BE) characteristics derived using the 250 m kernel density estimation (KDE) and 250 m route buffer (RB) methods on daily moderate-to-vigorous physical activity (MVPA) outcomes. 104

List of Figures

Figure 1.1. The conceptual framework within which topics of this dissertation research are organized. 10

Figure 2.1. Global Positioning System (GPS) pre-processing steps of Maternal And Developmental Risks from Environmental and Social Stressors (MADRES) real-time and personal sampling study GPS data. 19

Figure 2.2. Geoprocessing steps executed to detect stays from Global Positioning System (GPS) data, classify their contexts based on land use, and their indoor/outdoor microenvironments based on building footprints. 23

Figure 2.3. Geoprocessing steps to detect trips and classify their modes based on mean and standard deviation of Global Positioning System (GPS) observations in trips. 26

Figure 2.4. Distributions of top five origin-destination combinations by pedestrian- and vehicle-based trip modes. 40

Figure 2.5. Base Generalized Mixed-Effects Model results of variations in time-activity and daily mobility patterns by 1st and 3rd trimesters of pregnancy and 4-6 months postpartum. 41

Figure 3.1. An illustration of two activity space metrics – route buffer (RB) and kernel density estimation (KDE) applied in this study 61

Figure 3.2. The directions of potential residential network buffer (RNB) exposure misclassifications for built-environment (BE) measures compared to kernel density estimation (KDE) estimates. 73

Figure 4.1. The significant interactions between built-environment (BE) characteristics and temporal factors, individual sociodemographics, and neighborhood characteristics in predicting day-level moderate-to-vigorous physical activity (MVPA) outcomes..........106

Abbreviations

BE	Built Environment
EMA	Ecological Momentary Assessment
GIS	Geographic Information Systems
GLMM	Generalized Linear Mixed-Effects Model
GPS	Global Positioning System
ICC	Intraclass Correlation Coefficient
LMM	Linear Mixed-Effects Model
KDE	Kernel Density Estimation
MADRES	Maternal and Development Risks from Environmental and Social Stressors
MCU	Measured Contextual Unit
MVPA	Moderate-to-Vigorous Physical Activity
NDVI	Normalized Differenced Vegetation Index
PA	Physical Activity
RB	Route Buffer
RNB	Residential Network Buffer
SES	Socio-Economic Status
TAGA	Time-Aligned GPS Accelerometry Dataset
TCU	True Contextual Unit
UGCoP	Uncertain Geographic Context Problem
USC	University of Southern California

Abstract

Increasing rates of maternal obesity during and after pregnancy are associated with numerous short- and long-term health risks and outcomes in women postpartum. Hispanic women of childbearing age have disproportionally high obesity risks and low physical activity (PA) levels compared to non-Hispanic white populations. This dissertation study used 4-day objective, highly resolved smartphone location and accelerometry-assessed activity data collected from 62 Hispanic women of childbearing age in urban Los Angeles, CA, during pregnancy and the early postpartum period to investigate the associations among women's daily mobility patterns (Chapter 2), dynamic built-environment (BE) exposures (Chapter 3), and PA outcomes (Chapter 4). Results of these three empirical case studies revealed exceedingly low parks and open space exposure for this group at their daily activity locations and along travel paths during and after pregnancy, which had negative impacts on their day-to-day PA outcomes. In addition, important modifiers (e.g., late pregnancy, early postpartum, high pre-pregnancy BMI, low neighborhood safety) of women's daily mobility and BE exposures, and their associations with PA outcomes were identified. Lastly, measurement error and bias resulting from applying traditional residential-based measures were evaluated and their implications for uncovering the relationships between BE exposures and PA outcomes were investigated. Future studies should conduct qualitative analyses of the BE features (e.g., parks) in which women's PA were performed, mitigate selective daily mobility bias, and apply real-time surveying techniques such as ecological momentary assessment (EMA) to elucidate psychosocial pathways from BE exposures to PA outcomes. Future PA promotion interventions for pregnant women should target at-risk pregnancy periods and sub-population groups to improve their efficacy, especially for those of low socioeconomic status and specific racial/ethnic minority groups.

Chapter 1 Introduction

Increasing rates of maternal obesity during and after pregnancy are associated with numerous short-term and long-term health risks and outcomes for women postpartum (Algoblan, Alalfi, and Khan 2014; Fan et al. 2013; Fowles, and Sterling 2011; Fraser et al. 2011; Soltani and Fraser 2000; Walker, Walter et al. 2015). Rates of pregnancy-related obesity risks and health outcomes are disproportionally high in Hispanic women (Brawarsky et al. 2005; Chasan-Taber et al. 2008; Headen et al. 2012; Ogden et al. 2016). Research indicates physical activity (PA), a common etiological factor of obesity, is disproportionally low among Hispanic pregnant women (August and Sorkin 2011; Hughes, McDowell, and Brody 2008; Arredondo et al. 2016), which may be explained by women's consistent exposures to the built environment (BE) barriers for PA. This chapter describes the critical gaps and analytical problems in past studies examining the associations between BE exposure and women's PA during and after pregnancy, presents a conceptual framework that aims to tackle these gaps, and further elucidates the impact of BE on PA in women of childbearing age, particularly for those of low-income or in specific racial/ethnic minority groups.

1.1. Disparities of Obesity-Related Outcomes in Hispanic Women

Obesity prevalence is rapidly growing in the US, with the latest 2016 National Health and Nutrition Examination Survey showing 39.8% of US adults were obese (Hales et al. 2018). Obesity rates for US women of childbearing age have doubled over the past 30 years (Ogden et al. 2016). Evidence indicates more than 40% of women gained weight during pregnancy that exceeded recommended levels (Rasmussen, Catalano, and Yaktine 2009). Increasing rates of maternal obesity during and after pregnancy pose serious health concerns for mothers. Higher pre-pregnancy weight and excessive weight gain during pregnancy lead to increased risks of postpartum weight retention (Soltani and Fraser 2000; Walker, Fowles, and Sterling 2011), which can result in long-term health outcomes such as diabetes, cancer, and cardiovascular diseases (Algoblan, Alalfi, and Khan 2014; Fan et al. 2013; Fraser et al. 2011; Walter et al. 2015). Rates of pregnancy-related obesity risks and health outcomes are disproportionally high in Hispanic women. Latest data indicates that 40% of Hispanic women of childbearing age were obese compared to 31% for non-Hispanic white women of this age and 51% of them gained more weight than recommended during pregnancy (Brawarsky et al. 2005; Chasan-Taber et al. 2008; Headen et al. 2012; Ogden et al. 2016). Energy-balance behaviors such as PA and diet are common etiological factors of obesity (Taveras et al. 2010; Singh et al. 2008). Although few existing studies have examined PA in Hispanic women of children bearing age, some evidence indicates Hispanic women overall was less likely to meet the PA guidelines than non-Hispanic white population (August and Sorkin 2011; Hughes, McDowell, and Brody 2008; Arredondo et al. 2016). Understanding drivers of causes of disparities in PA outcomes among minority women is a critical step towards reducing the disproportionate obesity risks borne by these groups.

1.2. Critical Gaps in Research

According to Sallis's socioecological model, exposure to the BE could be linked to obesity-related risks and health outcomes through influencing individual-level energy-balance behaviors (Sallis et al. 2006). BE exposures typically refer to objectively assessed measures of access to destinations (e.g., parks) and features (e.g., street trees) that might influence behaviors, as well as measures characterizing urban form (e.g., walkability) within certain spatial extents (e.g., buffers of home address points) and time periods (e.g., days) (Sallis et al. 2012; Booth, Pinkston, and Poston 2005). For pregnant women, past studies report mixed results of associations between BE features and characteristics and their PA behaviors. For instance, a

Norwegian study showed positive associations between both objectively measured and perceived access to parks and open space in the residential neighborhood and moderate-to-vigorous PA (MVPA) minutes during and after pregnancy (Richardsen et al. 2016). However, similar associations between total green space area within residential census tracts and PA outcomes during pregnancy were not significant in a New Zealand study (Nichani et al. 2016). In addition, past studies indicate associations between BE features and PA outcomes only exist at a specific pre- and postpartum period. For instance, a US study indicates total greenspace area within residential census tracts was positively associated with women's MVPA minutes during the 3rd trimester, while the same study also reports distance from home to transit and PA facilities were negatively associated with MVPA minutes at postpartum periods (Porter et al. 2019). However, there is little research on how the effects of BE on PA behaviors operate during the pre- and postpartum periods. Since PA behaviors of women may be subject to dramatic changes during the pre- and postpartum periods due to growing family and childcare responsibilities (Borodulin, Evenson, and Herring 2009; O'Brien et al. 2017), as well as biophysiological changes, it is important to examine the contributions of various BE features or characteristics to PA among this population and how their associations vary across periods for these populations.

Moreover, besides the disproportionate rates of obesity experienced by Hispanic women of childbearing age, previous studies also show that women from disadvantaged minority and low-income groups are disproportionately exposed to BE barriers that deter PA, including low access to recreational facilities and parks and open space, low quality pedestrian infrastructure such as under-maintained sidewalks, and less aesthetically pleasing streetscapes (Lovasi et al. 2009; Perez, Ruiz, and Berrigan 2019; Sallis et al. 2011; Singh et al. 2008). In addition, past research on low-income populations also indicates how the effects of various BE elements might operate differently among different socioeconomic status (SES) groups. For example, a study on exercise among low-income African American women reports high membership costs of recreational facilities in their neighborhoods as one of the major deterrents for them to utilize such facilities to exercise (Krans and Chang 2011). As a result, research to examine BE features and the characteristics associated with PA behaviors among low-income Hispanic pregnant women can further elucidate the behavioral pathways that link BE exposures to gestational weight gain and postpartum weight retention in this population, and to formulate evidence-based behavioral interventions, policies, and guidelines to combat the high obesity prevalence.

1.3. Analytical Challenges

1.3.1. Daily Mobility in Health and Place Research

In addition to a lack of research on influences of BE exposures on PA behaviors during and after pregnancy, several analytical and inferential problems arise in studies drawing inferences between BE exposures and PA outcomes. The most prominent is the lack of integration of individual daily mobility into exposure assessment. Many of the published studies use the residence-based neighborhood (e.g., radius buffer around the home location or census tract or block group) as the measured contextual unit (MCU) of analysis, in which BE features and characteristics are assessed with arbitrarily defined spatial extents that may or may not be the most relevant or influential for the specific outcome under study (Jankowska, Schipperijn, and Kerr 2015; James et al. 2016). This residence-based approach assumes the effect of BE exposure on health behaviors and outcomes primarily or exclusively operates around the home and ignores areas of contact or exposures that occur outside of the home based on individuals' every day mobility patterns. This may be true if the study population spends most of its time in the home neighborhood; however, empirical evidence suggests otherwise. For instance, several studies (e.g., Evenson et al. 2009; Nethery, Brauer, and Janssen 2009; Ouidir et al. 2015; Zhu et al. 2019) report their participants are highly mobile during data collection periods and spend a large proportion of time at non-home locations. As a result, the residence-based approach might result in exposure misclassification and attenuate or potentially bias effect estimates in subsequent health analyses (Jankowska, Schipperijn, and Kerr 2015; James et al. 2016).

1.3.2. Uncertain Geographic Context Problem (UGCoP)

The lack of integration of daily mobility into BE exposure assessment is part of the uncertain geographic contexts problem (UGCoP) (Robertson and Feick 2018; Kwan 2012). The problem "arises because of the spatial uncertainty (e.g., buffer sizes) in the actual areas that exert contextual influences on the individuals being studied, and the temporal uncertainty of the timing and duration in which individuals experienced these contextual influences" (Kwan 2012). It is also very difficult for any individual study that uses area-based BE contextual variables to explain individual behaviors to fully overcome this problem because the complete and perfect knowledge of “true causally relevant” BE contexts for PA behavior is unknown (Kwan 2012).

The mitigation of UGCoP requires more accurate measurement and estimation the "true causally relevant" geographic context (true contextual unit or TCU) than is accomplished with residence-based approach (Kwan 2012; Matthews and Yang 2013). To achieve this, a growing body of research has delineated MCUs through generating daily activity spaces (i.e., activity locations visited, or paths traversed in their daily lives) and measure BE exposures within activity space-based MCUs (Perchoux, Chaix, and Kestens 2019; Matthews and Yang 2013; Rainham et al. 2010; Sherman et al. 2005). In compared to the residence-based approach, the activity space-based approach is able to improve accuracy of exposure assessment by linking BE exposures and PA outcomes in space and time beyond home contexts (Yi et al. 2019).

Nevertheless, there remains the uncertainty of choices of spatial (e.g., buffer size, kernel bandwidth) and temporal (e.g., time unit, duration of exposures) parameters in delineating the MCU (Smith, Foley, and Panter 2019; Yi et al. 2019). To further mitigate the UGCoP, recent review studies have recommended generation of multiple area-based environment attributes based on several combinations of spatial (e.g., buffer size, kernel bandwidth) and temporal (e.g., hour, day, weekday) parameters for use in sensitivity tests to understand the influence of these choices on obtained exposure-response effect estimates, further shedding light on the "true causally relevant" spatial and temporal extent of the exposure (Lee and Kwan 2019; Yi et al. 2019). Additionally, these reviews have also recommended that future studies consider durations of exposure in assessments of BE (Lee and Kwan 2019; Yi et al. 2019). However, few GPS-based studies have been able to adopt these recommendations to incorporate daily mobility and start to tackle the UGCoP in their analyses.

1.3.3. Within-Person Effects of BE Exposures

In addition to study biases, most often, past studies assessed BE exposures (i.e., greenness) and PA outcomes (i.e., walking minutes) at the person-level (Smith, Foley, and Panter 2019). The person-level analysis offers insights of effects of inter-individual (i.e., between-person) variations in BE exposures on PA outcomes. For example, whether living in a walkable downtown is associated with higher walking activity compared to living in an automobile-dependent suburb. However, repeated measures designs where individuals are assessed at multiple points in time can address questions related to the effects of intra-individual (i.e., within-person or day-to-day) variations in exposures due to the impact of daily mobilities of study participants on outcomes. For instance, whether the variations in exposures to parks and open space within daily activity spaces of individuals are associated with their day-level PA outcomes. Therefore, to provide a more comprehensive understanding on contextual influences of BE on PA behaviors, it is very important to examine the effects of both within and between person variations in exposures to BE features and characteristics on their day-to-day PA outcomes (Dunton 2018). However, very few studies have examined this relationship to date.

1.3.4. Moderating Mechanisms in Behavioral Pathways

Lastly, several studies (e.g., Diez Roux and Mair 2010; Sallis et al. 2009; McNeill, Kreuter, and Subramanian 2006; Perez et al. 2016; and Larsen et al. 2013) have examined the moderating effect of neighborhood social environment (e.g., social cohesion, crime) on relationships between BE and PA behaviors. For instance, a study on Hispanic women shows perceived safety from crime modified the associations between sidewalk conditions and outdoor MVPA minutes (Perez et al. 2016). Nevertheless, most of the studies of this type only examined the residential neighborhood environment and did not investigate possible moderators of the effects of BE exposure on PA behaviors encountered within activity spaces or in non-residential contexts. Moreover, many previous studies have linked temporal factors (e.g., weekdays versus weekend days, pregnancy and postpartum periods) to pregnant women's PA behaviors (Borodulin, Evenson, and Herring 2009; da Silva et al. 2019; Jenum et al. 2013; Renault et al. 2012; Schmidt et al. 2006; Sinclair et al. 2019). For example, a study of 1,482 US women reported that pregnant women's PA decreased over pregnancy periods (Borodulin et al. 2008). Another US study of 688 pregnant women showed how PA rebounded during postpartum periods compared to pregnancy (Borodulin, Evenson, and Herring 2009). Therefore, it is important to understand how these temporal factors can potentially moderate the effect of BE exposures on PA behaviors, especially in low-income, Hispanic health disparity populations.

1.4. Mobile Sensing in PA Research

The recent development of mobile sensing technology such as Global Positioning System (GPS), accelerometry and ecological momentary assessment (EMA) offer new opportunities to collect novel datasets to fill some of aforementioned gaps. Among them, GPS provides users with real-time geo-locations, which can then be imported into Geographic Information Systems (GIS) to generate individual activity spaces (i.e., MCUs) and measure BE exposures within them (Yi et al. 2019). The accelerometer measures the physical acceleration experienced by an object and can be worn by study participants to record their epoch-level steps taken and intensity of PA (Troiano et al. 2008). Lastly, EMA is an intensive survey technique that allows participants to self-report on symptoms, affect, behavior, cognition, and environment contexts close in time to experience (Moskowitz and Young 2006). Mobile phone-based EMA applications can be programmed at a customized daily frequency over study periods to collect both data of self-reported environment contexts and energy-balance behavioral outcomes (Dunton 2017).

Past studies have combined GPS, accelerometry and EMA in answering a variety of questions regarding effects of BE exposures on PA outcomes. To start, epoch-level GPS and accelerometry data can be aligned by timestamps to generate time-aligned GPS accelerometry (TAGA) data so that minute-level relationships between BE and PA behaviors can be examined (Yi et al. 2019). For example, one study used TAGA dataset to study minute-level influences of greenness exposure level on PA outcomes (Almanza et al. 2012). In addition, GPS and accelerometer data can be linked with EMA data by timestamps and aggregated at day- or person-levels to examine effects of BE exposures on daily or personal PA outcomes. For example, a study might generate activity spaces from daily GPS tracks and calculate densities of sport facilities within these spaces to examine associations between daily accessibility to sports facilities and day-level energy expenditure. In addition, the same study might also measure day-level energy expenditures using movement counts from accelerometry (Shrestha et al. 2019). However, no studies on pregnant women have integrated GPS technology with daily movement patterns collected by accelerometry to derive daily activity spaces and assess BE exposures within these activity spaces to examine the effects of BE exposures on PA outcomes.

1.5. Conceptual Framework and Dissertation Outline

This dissertation research aimed to address aforementioned gaps by investigating associations between daily time activity and mobility patterns, BE exposures, and PA behaviors in a group of predominantly low-income Hispanic women of childbearing age, while accounting for potential analytical and inferential errors and biases and considering potential moderation mechanisms in the BE-PA relationship. The topics of this dissertation research are organized within the conceptual framework summarized in Figure 1.1. This framework is adapted from Sallis's socio-ecological model framework that describes the interplay of the BE, PA behavior, and obesity (Sallis et al. 2012). The new model focuses on individual mobility in examining effects of BE exposures on PA outcomes. In this model, women's daily mobility patterns (e.g., time spent at home, daily path areas) at pre- and postpartum periods are hypothesized to be important determinants of their dynamic daily exposures to BE characteristics such as parks and open space access, walkability, which in turn may influence women's PA behaviors (e.g., sports activities, walking to the bus stop) through multiple behavioral pathways (e.g., the visual exposure to a park along the sidewalk, the past experience of visiting a nearby exercise facility).

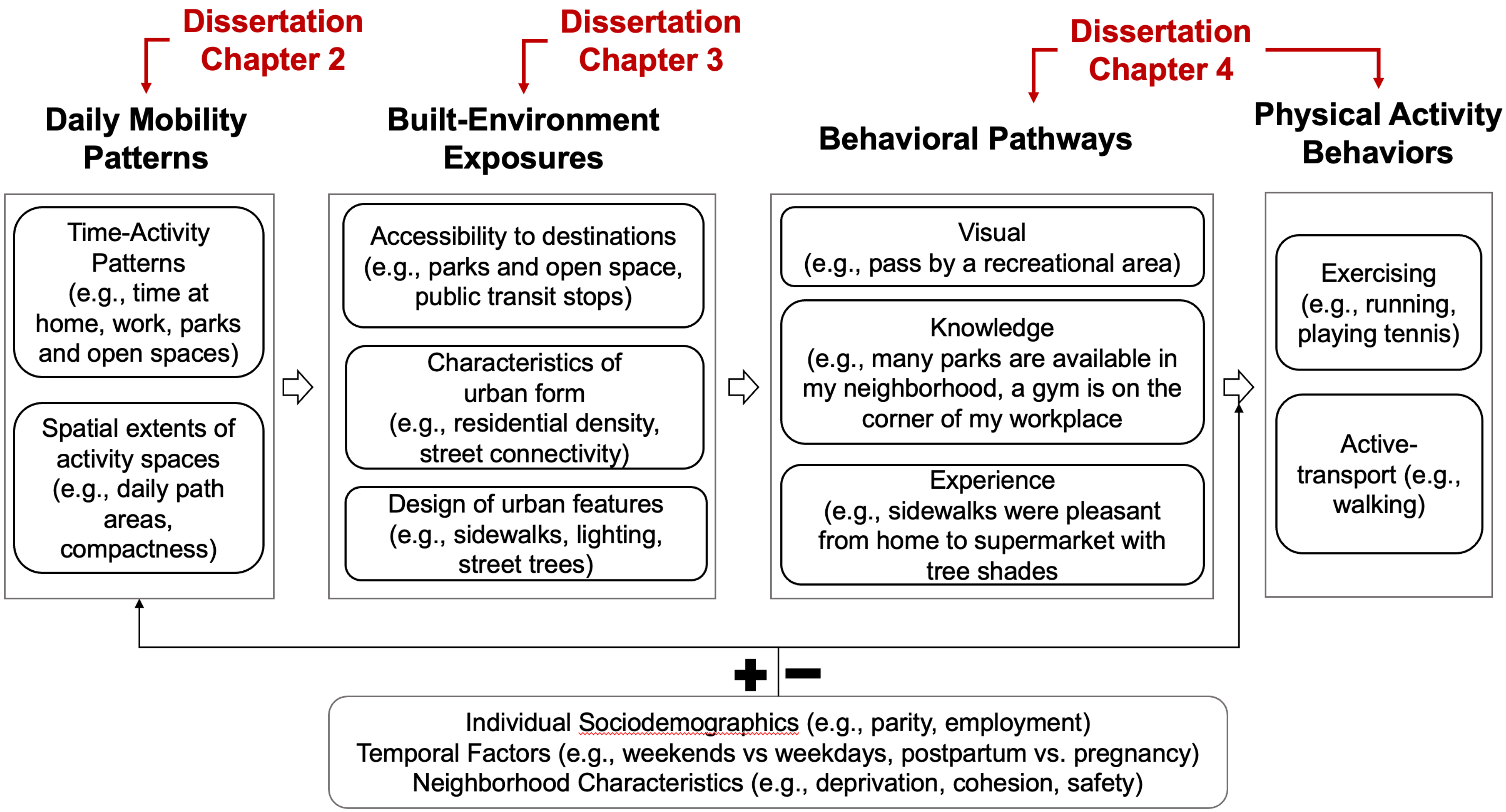


Figure 1.1. The conceptual framework within which topics of this dissertation research are organized.

Building on this conceptual framework, in three sequential parts (i.e., three empirical case studies), this dissertation examines the associations between women's daily time-activity mobility patterns, BE exposures, and PA behaviors during pregnancy and the early postpartum period. Among them, the first study (Chapter 2) tackles the "Daily Mobility Pattern" part of the framework by examining changes in women's daily time-activity and mobility patterns across pregnancy and the postpartum period, and their potential individual and neighborhood level determinants. The second study (Chapter 3) tackles the "Built Environment Exposure" part of the framework by examining women's dynamic daily exposures to BE characteristics derived using activity space methods and evaluated the BE exposure measurement error using static compared to dynamic methods. The third study (Chapter 4) tackles the "Behavioral Pathways" and "Physical Activity Behaviors" parts by examining the associations of dynamic daily BE exposures and PA outcomes and tested potential moderators in these associations. Since all three studies are stand-alone manuscripts, each of these chapters includes an introduction as well as related work, methods, results, discussion, and conclusions. The fifth and final Chapter provides a summary of major findings, the contribution of this work to the current literature and limitations, future research directions, and major takeaways.

Chapter 2 Time-Activity and Daily Mobility Patterns during Pregnancy and Early Postpartum

Pregnant women's daily time-activity and mobility patterns determine their environmental exposures and related health effects (Balakrishnan et al. 2015; Blanchard et al. 2018; Dadvand et al. 2012; Hannam et al. 2013; Nethery, Brauer, and Janssen 2009; Zhu et al. 2019). Most studies ignore these and assess pregnancy exposures using static residential measures exposures (Porter et al. 2019; Nichani et al. 2016; Richardsen et al. 2016). This chapter applied 4-day continuous geo-location monitoring in 62 pregnant Hispanic women during the pregnancy and early post-partum periods to derive their daily time-activity and mobility patterns and examine whether these patterns differed by individual sociodemographics, temporal factors, and neighborhood characteristics.

2.1. Related Work

Chemical and physical environment exposures including air pollution, lack of access to parks and green space, and low walkability, have been associated with poorer health behaviors and increased risk of health problems in pregnant women and their offspring (McEachan et al. 2016; Porter et al. 2019; Leggett et al. 2018). However, prior studies examining the influence of environmental exposures on health behaviors (e.g., PA, diet) and disease outcomes (e.g., asthma, obesity, diabetes) in pregnant women have mainly applied the residence-based assessment approach (i.e., measuring physical environment features and characteristics at or near residences) to estimate individual, personal exposures (Porter et al. 2019; Nichani et al. 2016; Richardsen et al. 2016). This approach assumes outdoor environmental exposures around home residences are surrogates of daily "true causally relevant contexts" (true contextual units or TCUs) that influence behaviors or outcomes of interest (Robertson and Feick 2018). Nonetheless, this assumption has two limitations – it assumes participants always stay within their residential neighborhoods when they might be highly mobile daily or they may change their residential addresses during and after pregnancy, and that all exposures occur in outdoor environments whereas quite often they occur mainly indoors or in transit, resulting in exposure misclassification or measurement error (Kwan 2012; Delmelle et al. 2022).

Indeed, past studies on time-activity and mobility patterns (hereafter referred to as time-activity patterns) of women during pregnancy have validated these concerns (Zhu et al. 2019; Ouidir et al. 2015; Blanchard et al. 2018; Payam Dadvand et al. 2012). For example, a study in Shanghai, China, reported that pregnant women on average spent over a third of their time in work locations within three-day observation periods during the 2nd trimester (Zhu et al. 2019). Another study conducted in France reported a median of almost 12 non-home h/day for pregnant women during a 3-week observation period in the 1st trimester (Ouidir et al. 2015). As a result, the failure to capture or model the non-home contribution to environmental exposures in past studies might lead to under- or over-estimation of exposures and therefore mask their true relationships with health behaviors or outcomes (Yi et al. 2019). Very few studies of pregnant women have incorporated time-activity patterns into environmental exposure assessments largely due to either feasibility or burden-related challenges with tracking or capturing these patterns at high spatiotemporal resolutions in large population-based studies.

Moreover, unlike other populations, pregnant women have increased demands to prepare for childbirth, increased fatigue, difficulty physically moving around, and poor sleep, which might influence or lead to dramatic variations in their time-activity patterns across the pregnancy and postpartum periods (Varshavsky et al. 2020). For example, a Canadian study on time-activity patterns of pregnant women has reported that more time was spent at home during the 3rd trimester of pregnancy compared to the 1st trimester (Nethery, Brauer, and Janssen 2009). Another US study has found that in-vehicle travel times were longer during the early stages compared to later stages of the pregnancy (Wu et al. 2013). While very few studies have examined changes in time-activity patterns of women across pregnancy, to the best of my knowledge, none have extended the investigation to the early postpartum period. Given that the timing of the environmental exposures during these critical windows of time could have different effects on fetal development, early childhood and postpartum maternal health (Porter et al. 2019; Nichani et al. 2016; Richardsen et al. 2016), it is important to better understand time-activity patterns and how they might change over pregnancy and early postpartum periods.

Although limited, a small number of studies have implemented various approaches to collect mobility data for pregnant women and integrate time-activity patterns into exposure assessments. Among them, most have relied on self-reported mobility surveys or diaries (Balakrishnan et al. 2015; Blanchard et al. 2018; Dadvand et al. 2012; Hannam et al. 2013; Nethery, Brauer, and Janssen 2009; Zhu et al. 2019). This approach is relatively cost-efficient with low technical barriers and thus may suit population-based studies with large sample sizes; however, the subjective nature of self-reported survey data also makes the approach prone to recall bias and measurement error. Additionally, it is difficult to collect highly space- and time-resolved data using diaries or surveys. Recently, a growing body of research has started to apply GPS technology to objectively capture the mobility of participants (Ouidir et al. 2015; Nethery, Brauer, and Janssen 2009; Ha et al. 2020). The geolocation coordinates collected from the GPS device can be imported into the GIS software, in which spatial clusters and trip detection algorithms can be applied to derive time-activity (i.e., time spent in specific contexts, and indoor/outdoor microenvironments) and mobility (i.e., modes and durations of trips) patterns of study participants (Thierry, Chaix, and Kestens 2013; Kirby, Delmelle, and Eberth 2017). Also, GPS data and these derived time-activity patterns can be integrated with fine-scale (e.g., 10-s) personal air pollution monitoring or other wearables data to construct highly individualized, contextualized, and space-time resolved exposure models (Ouidir et al. 2015). Finally, activity spaces derived from GPS data can be integrated with other geospatial data layers (e.g., crime, parks and open space, walkability scores) to understand actual exposure to BE (Yi et al. 2019).

To address the above gaps, this study combines GPS technology and geospatial analysis to describe time-activity patterns in a subset of 62 low-income, Hispanic women participating in the Maternal and Development Risks from Environmental and Social Stressors (MADRES) cohort study, during 4-day observation periods in the 1st and 3rd trimesters of pregnancy and at 4 to 6 months postpartum. By analyzing highly time-resolved (i.e., 10-s epoch) GPS data from the customized smartphone app for MADRES study (madresGPS), this study aimed to answer the following questions:

1) What are typical time-activity (i.e., time spent in multiple contexts, and indoor/outdoor microenvironments) and mobility patterns (i.e., trips performed, their duration, and mode) of women during pregnancy and during the early postpartum period?

2) Do daily time-activity and mobility patterns change over time, across pregnancy and early postpartum periods?

3) Do temporal (e.g., weekdays versus weekend days), individual sociodemographic, and residential neighborhood factors explain some of the variation in these patterns?

This study hypothesized that women's time spent at their home residences would increase, and time spent in non-home contexts and in transit would decrease as pregnancy progresses from the 1st to the 3rd trimesters, and such trends may continue into the postpartum period. Moreover, this study hypothesized time-activity and mobility patterns may differ by other temporal, individual sociodemographic, and residential neighborhood factors.

2.2. Methods

2.2.1. Study Design

Data for this study comes from the Real-Time and Personal Sampling sub-study of the MADRES cohort (Bastain et al. 2019). This study uses an intensive longitudinal, observational panel study design and examines the daily effects of environmental exposures and social stressors on maternal pre- and post-partum obesity-related biobehavioral responses (O'Connor et al. 2019). A total of 65 Hispanic, women with lower incomes, were drawn from the larger MADRES prospective cohort study which recruited participants from prenatal care providers in Los Angeles, CA, serving predominantly medically-underserved populations (Bastain et al. 2019). To be eligible for the larger MADRES study, a participant needed to be 18 years old with a singleton pregnancy and be at less than 30 weeks' gestation at time of recruitment. In addition, participants who were HIV positive, had physical, mental, or cognitive disabilities that prevented participation, or were currently incarcerated were excluded from the study. Recruitment of 65 Hispanic women occurred on a rolling basis between 2016 and 2018 from one county hospital prenatal clinic (*N*=16) and one non-profit community health clinic (*N*=49). Additional eligibility criteria for this sub-study are described in further detail in a separate manuscript (O'Connor et al. 2019). The University of Southern California (USC) Institutional Review Board approved all study procedures and participants signed an informed consent before enrolling into the study.

2.2.2. Data Collection

2.2.2.1. GPS Based Location Information

GPS data were continuously collected from participants at 10-s intervals for four days (two weekdays and two weekend days) during the 1st and 3rd trimester of pregnancy and at 4-6 months postpartum (O'Connor et al. 2019). MADRES researchers designed a custom smartphone application (madresGPS app) for Android operating systems to collect highly resolved and encrypted GPS data (O'Connor et al. 2019). Study coordinators configured the application on dedicated study smartphones (Samsung MotoG phone) to gather geographic coordinates and geolocation/motion metadata (O'Connor et al. 2019). The application logged instantaneous GPS location and sensor data every 10 s from the smartphone's multiple built-in location finding features (cell tower triangulation, WiFi networks, and GPS) and motion sensors. Along with the timestamp, metadata such as the number of satellites in use/view, geolocation accuracy, source of GPS, velocity (if GPS source), and network connection status (if network source) were recorded (O'Connor et al. 2019).

2.2.2.2. EMA data

EMA data were self-reported through a commercially available application (MovisensXS app) built for Android operation systems, which was pre-installed on the same study phone used to collect GPS data. The EMA survey was prompted at random times during each five pre-specified sampling windows (i.e., wake-up to 10 a.m.; 11 a.m. to 1 p.m.; 2 p.m. to 4 p.m.; 5 p.m. to 7 p.m., and 8 p.m. to bedtime) within the same four-day time GPS data collection windows during the three study periods (O'Connor et al. 2019). Survey questions included physical and social contexts at the prompt time, current affective and physical feeling states, current perceived stress, and past 2-h exposure to a list of daily stressors. The complete list of EMA survey questions is described in further detail in a separate manuscript (O'Connor et al. 2019).

2.2.2.3. Retrospective surveys and medical record abstraction

Sociodemographic data including maternal height and weight race/ethnicity, enrollment age, education, parity, and country of origin were assessed in prenatal interviewer-administered questionaries with the women. Weight and height were also measured at study visits. Retrospective surveys were completed at various study timepoints to gather residential and occupational histories and assessed psychosocial stressors. Working status was also collected via questionnaires in the 1st trimester, 3rd trimester, and 6 months postpartum and perceived neighborhood cohesion and safety score was gathered in the 2nd trimester (chosen to represent pregnancy) and 6 months postpartum questionnaires. Additionally, residential locations at screening were geocoded and used to generate residential neighborhood characteristics in this work.

2.2.3. Data processing

2.2.3.1. GPS processing

The major processing steps of raw GPS data are described in Figure 2.1. In total, this study collected 6,948,118 GPS observations for 62 of the 65 participants. Raw observations collected outside of the 4-day designated monitoring period (during device set up and return) were dropped ($N_{dropped}$=1,893,013). Then, this study dropped a small number of observations with erroneously logged zero values of latitude and longitude ($N_{dropped}$=28,848). After that, this study devised a logic to drop the least accurate source of geolocation data for every 10-s epoch when two sources of data (GPS/Network) were available as follows. This logic was informed by comparing the time-series of GPS versus network source coordinates in relation to the

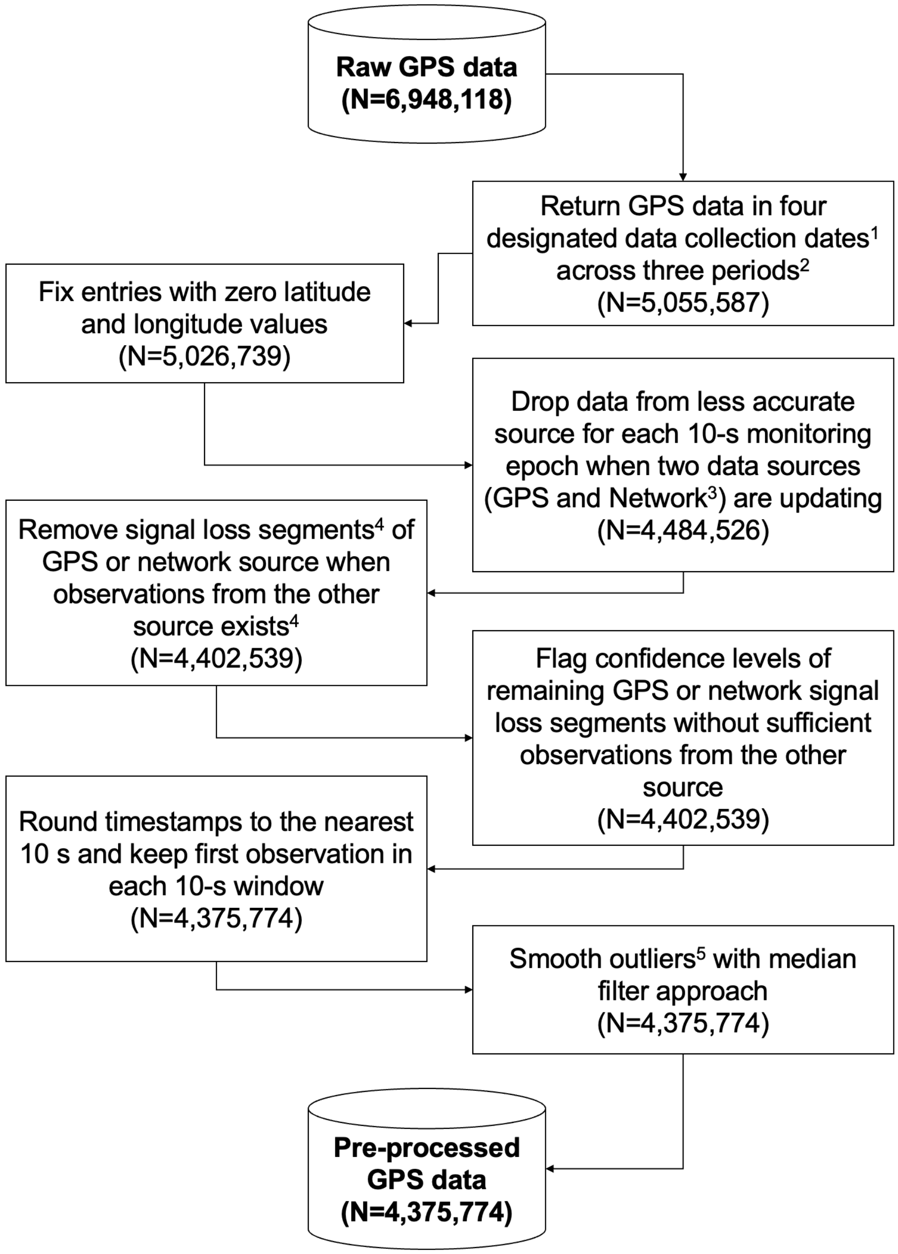


Figure 2.1. Global Positioning System (GPS) pre-processing steps of Maternal And Developmental Risks from Environmental and Social Stressors (MADRES) real-time and personal sampling study GPS data.

[1] Data collection dates included two weekdays and two weekend days.
[2] Three periods were first trimester, third trimester, and four-to-six months postpartum.
[3] Network source included observations recorded by WiFi and cellular networks.
[4] Signal loss scenarios were defined as ≥ 1 min time windows with same timestamps.
[5] Outliers were defined as observations with a distance > 450 m from the median latitude/longitude coordinates (corresponding to the maximum realistically possible distance moved in 10 s based on a speed of 45 m/s or 100 mph) and replaced with the median coordinates within the moving window.

participants' potential movement in space and time. Based on preliminary analyses, the GPS source usually exhibited the fastest update frequency compared to the network especially when individuals were mobile. When individuals appeared to be stationary (i.e., at home), both sources seemed to be frequently updating, but the network source generally exhibited higher accuracy. Of particular note, participants were asked to connect study smartphones to their home WiFi networks, when possible, to complete study-related EMA surveys on the same smartphones, resulting in a high likelihood of phones connecting to home WiFi networks (and thus network source geolocation data being available often when stationary/at home) during this study (averaging 12.8% per observation day). When both GPS and network sources were available, they were examined, and the less accurate source was dropped ($N_{dropped}$=542,213).

In circumstances when the signal from either GPS or network source was lost for ≥1 min (i.e., signal loss scenario), the app was designed to log the latest known position for that source along with the latest update (or confirmation) time, both of which will be repeated and will not change for the duration of time the signal was lost. Once signal loss scenarios were identified (per source of data), the update frequency and positional accuracy of the geolocation data from both sources were compared and the less accurate source was dropped ($N_{dropped}$=81,987). For time windows when either the GPS or network source was updating (real sensor data logging timestamp changed) but the other was not because of signal loss, the connected source was kept. Then, under circumstances when both sources lost signal, the one that indicated no movement (no change in latitude and longitude) from the previous to the next interval of time when signal was available was dropped.

Next, this study rounded timestamps to the nearest 10 s and retained the first observation within a 10-s window ($N_{dropped}$=53,530). This step was performed to allow us to align and integrate GPS data with other simultaneously collected accelerometry and personal air pollution exposure monitoring data (in subsequent, ongoing analyses). In addition, it also ensures roughly similar temporal spacing and density of GPS data per participant to enable between-person comparisons of environmental exposures derived using this GPS data and the kernel density algorithm (Jankowska et al. 2017).

Finally, a moving median filter was applied to remove outliers in windows of approximately 1-min duration (7 observations at a 10-s epoch) to correct extreme outliers that might occasionally be present in the data (Wang, Gao, and Juan 2017). Outliers were defined as observations with a distance >450 m from the median latitude/longitude coordinates (corresponding to the maximum realistically possible distance moved in 10 s based on a speed of 45 m/s or 100 mph) and were replaced with the median coordinates within the moving window. The final processed dataset consisted of 4,375,774 observations across 552 person-days.

Throughout the GPS data processing, this study created flags to indicate data quality or identify records affected by any assumptions or decisions made, which were used to inform sensitivity analyses. For example, this study created day-level GPS data completeness flags (i.e., ≤6 h, ≤10 h, ≤16 h), which were then used to evaluate whether time-activity and daily mobility patterns were sensitive to day-level GPS data completeness. This study also created flags indicating confidence in whether an individual likely stayed at the logged location or moved during signal loss windows (see Appendix A). These flags were based on the plausibility of the distance moved within the window and total duration of the window. More specifically, higher confidence levels were assigned to signal loss windows with shorter duration (e.g., ≤120 min) and more reasonable distances traveled (e.g., ≤45 m/s times the time elapsed between the last known location before signal loss and the new location after signal loss). For analyses in this study, signal loss windows were removed ($N_{dropped}$=523,112) that I either could not make a judgement on (i.e., with no distance/duration data) or had extremely low confidence (e.g., distance traveled >45 m/s times the time elapsed, >120 min in duration) on whether a participant likely remained in the same position when the signal was lost.

2.2.3.2. Stay-trip detection

The processed 10-s GPS data were imported into geographic information system software ArcGIS 10.8 (Esri, 2020) to first identify trips and stays and then classify stays based on their spatial contexts and indoor/outdoor microenvironment. Figure 2.2 describes the steps to process GPS tracks for each person and study period combination (i.e., 4-day GPS tracks were treated as one sequential time-series). In order to identify trips and stays, the "Activity Place Detection Algorithm" ArcGIS toolbox developed by Thierry, Chaix, and Kestens (2013) was used, which builds a kernel density surface (50 m bandwidth or search radius) from GPS points and extracts local maxima from the surface as candidates for classification as stays. In comparison to methods that analyze data points sequentially, the kernel-based method has been shown to have better global performance (i.e., better agreement between number of stops detected versus true stops), higher spatial accuracy (i.e., shorter Euclidean distance between a detected stop and the true stop), and lower sensitivity to bandwidth choices (i.e., 50, 100 m) (Thierry, Chaix, and Kestens 2013). Minimum duration for a stay candidate to become a stay was ≥5 min, and two consecutive stay candidates within proximity to each other needed to be separated by at least a ≥5 min timespan to be kept as separate stays. After stays and their respective start and stop times were detected, GPS points recorded between two consecutive stays were connected into trips (path trajectories) by sequences of timestamp and smoothed (snapped to road networks), and their start and stop times were recorded. This essentially means that stays also act as trip origin

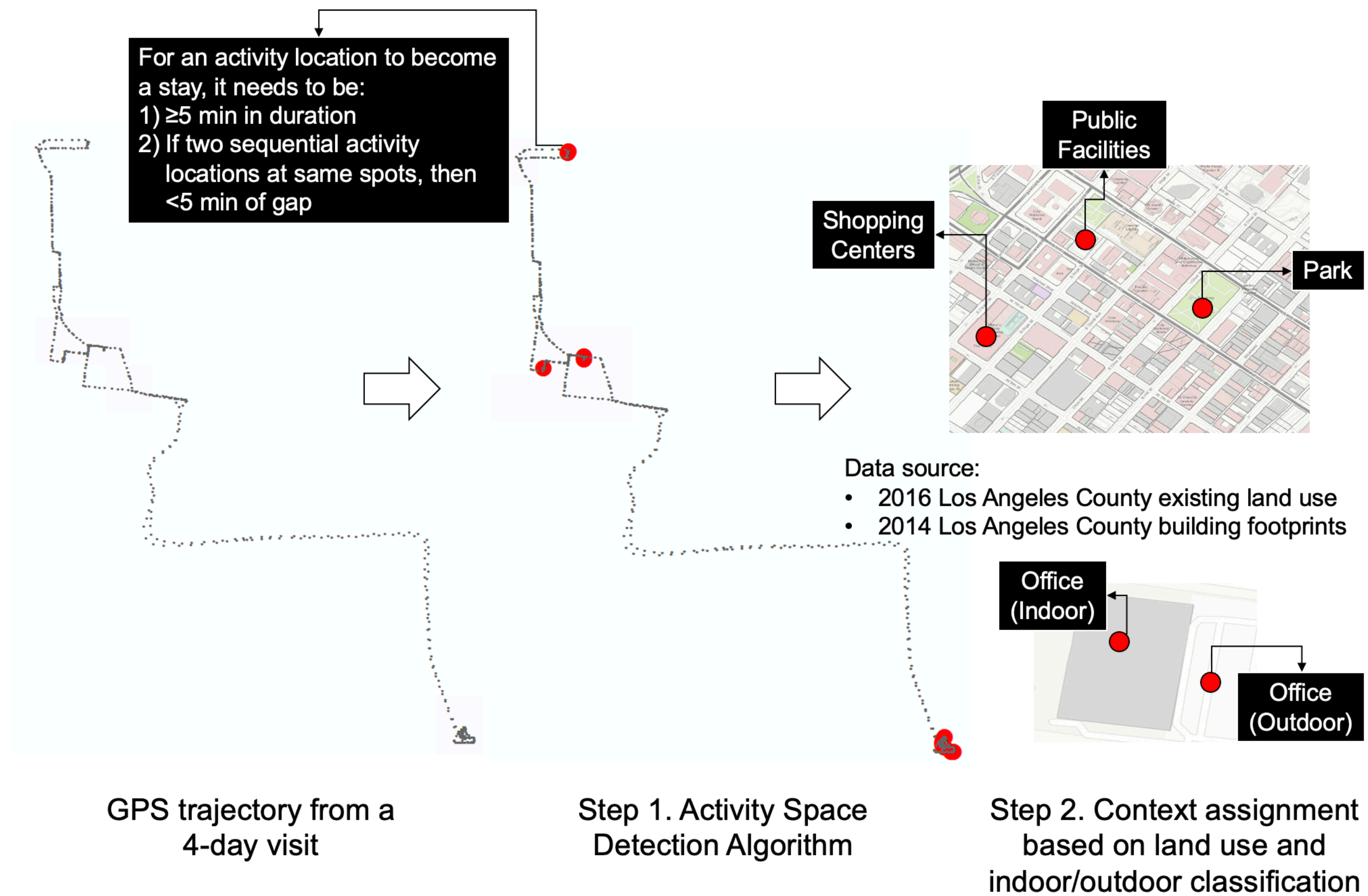


Figure 2.2. Geoprocessing steps executed to detect stays from Global Positioning System (GPS) data, classify their contexts based on land use, and their indoor/outdoor microenvironments based on building footprints.

and destination points when trips occur. A minimum duration of ≥5 min was needed for a loop path trajectory (i.e., one that started and ended at the same location) to be kept as a trip.

2.2.3.3. Context classification of stays

This study next classified the stays (i.e., trip origins and destinations) into one of seven spatial contexts (home residential, non-home residential, commercial and services, parks and open space, schools and public facilities, industrial and office spaces, and other). Spatial parameters and data sources used in context classification are fully documented in Appendix B. The stay with the longest duration in a study period (4-day monitoring period in 1st and 3rd trimesters, and at 4-6 months postpartum) was designated as the residential home context given participants might have changed residence or lived with family or relatives across study periods. Non-home contexts were classified based on their spatial relationships with the Southern California Association of Governments existing land use (2016) data (see Appendix B). A 15 m buffer was applied to existing land use boundaries to account for potential combinations of indoor/outdoor activities within a stay and considering the average width of sidewalks in urban Los Angeles. Additionally, an indoor/outdoor microenvironment was assigned to each stay point by examining its spatial relationship with Los Angeles County building footprints (2014). A 1 m buffer was applied to existing building footprints to account for scenarios when indoor activities occurred mainly in the corners of the building (i.e., corner apartments, stairwells, laundry rooms), resulting in a detected stay point that fell outside the building footprint polygon, which could then be misclassified as outdoor.

2.2.3.4. Missing GPS data imputation using home context

Home residential locations detected via the stay-trip detection algorithm were then used to impute some of the missing records in the processed GPS data. More specifically, participants self-reported their sleep and waking times prior to each study period to help configure suitable timing and frequencies for the EMA survey. This sleep and wake time data was used to divide each four-day study period into day (from waking to sleep time in a data collection day) and night (from sleep time in a data collection day to the waking time on the next day) windows. For night windows, identified visit-level home location was used to impute missing data (if $\geq$ 60 min of GPS logged data that was within $\leq$100 m of the home location). If this rule was not met, the median coordinates logged during the night were used to fill in any remaining missingness that night. If no GPS data was available during the night, then imputation was not attempted. As for day windows, this study filled in missing records with home coordinates when available if the day was identified as a home day (i.e., all EMA survey prompts within the day reported current physical context as either "Home-Indoor" or "Home-Outdoor"). The entire workflow of the missingness imputation process is documented in Appendix C. The imputed GPS records (*N*=306,915) were classified as "home-residential" and merged with processed epoch-level GPS data to produce a final time-activity pattern dataset that records location coordinates and contexts of each stay, its start and stop time, as well as method of classification (i.e., via algorithm or imputation). In addition, flags were created which labelled days with < 6 h of GPS data (post-imputation) as invalid days.

2.2.3.5. Trip mode detection

A trip mode classification algorithm was also applied (Figure 2.3) to classify all trips into either a walking- or vehicle-based mode. Both distance-based trip speed (i.e., sum of Euclidean distances of consecutive GPS records in a trip divided by duration of time elapsed) and total distance traveled (i.e., sum of Euclidean distances of consecutive GPS records in a trip) were considered in the decision-making process. Previous studies have reported a walking speed range

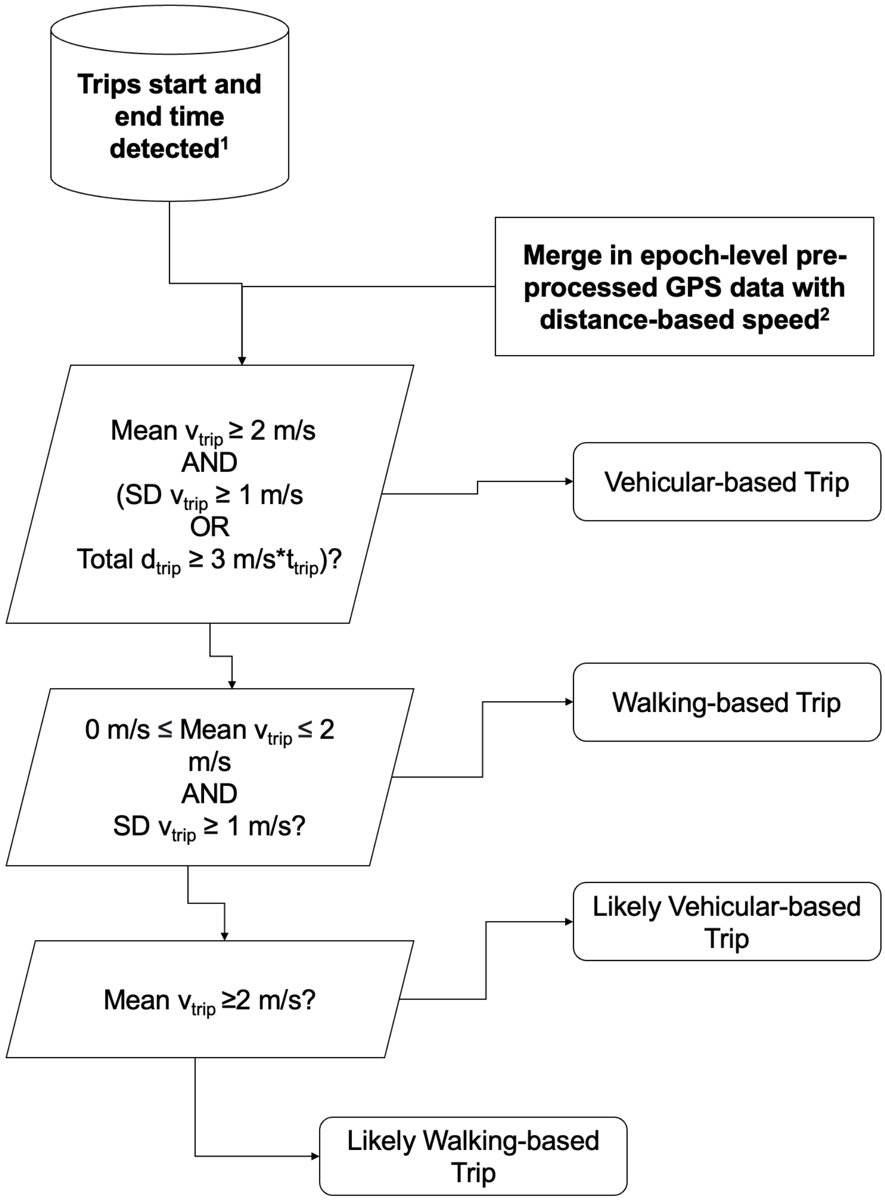


Figure 2.3. Geoprocessing steps to detect trips and classify their modes based on mean and standard deviation of Global Positioning System (GPS) observations in trips.

[1] Trips start time was identified as the end of previous stay and trip end time was identified as the start of the next consecutive stay.
[2] Epoch-level distance-based speed (v_{trip}) was calculated by dividing the Euclidean distance traveled (d_{trip}) between two consecutive epochs with time elapsed (t_{trip}).

of 1.00–1.8 m/s for women during pre- and post-pregnancy periods (Byrne et al. 2011; Gilleard 2013; Loh et al. 2019). In this study, a relatively high threshold of 2 m/s (4.5 mph) was treated as the theoretically possible maximum walking speed for women to account for GPS data noise in areas that might obstruct or interfere with GPS signals (e.g., neighborhoods with multi-level residences or abundant and dense tree canopies). Given similarities in average speed between a true walking scenario and a slow driving one that could occur during Los Angeles rush hours or when passing through areas with frequent traffic lights, a condition was added such that a trip required a standard deviation of speed that was smaller than 1 m/s to be classified as walking-based. This criterion was based on observed patterns in the data showing that walking trips typically have a much smaller standard deviation in speed than slow driving trips comprising sudden acceleration, deceleration, and frequent stops. Furthermore, for a trip to be vehicle-based, it also needed to exceed the maximum possible distance a human can travel via walking (i.e., 3 m/s x trip duration). Lastly, for a limited number of trips (N=99) that exhibited patterns with multiple modes (e.g., walking to the parking lot, driving, riding the metro and walking), the criteria was relaxed and only used the mean speed to determine the primary trip mode (i.e., vehicle-based: ≥2 m/s; walking-based: <2 m/s). For these trips, lower confidence was assigned to their detected trip modes so that they could be excluded for sensitivity analyses purposes.

2.2.4. Statistical Analysis

2.2.4.1. Descriptive analysis

Mean, medians, proportions, or standard deviations for covariates and time-activity and daily mobility outcomes were calculated for the 1st and 3rd trimesters of pregnancy and the 4-6 months postpartum periods. The number of stays were summarized by context and microenvironment and aggregated into day-level time-activity patterns (min/d at each spatial context and within indoor/outdoor microenvironments). Meanwhile, the number of trips were summarized by trip mode and aggregated into day-level mobility patterns (min/d and N/d in trip of vehicular or pedestrian mode). Non-valid days (<6 h of GPS data) were eliminated to reduce potential biases of estimating day-level outcomes.

2.2.4.2. Generalized mixed effects models

To account for the interdependency of the nested data structure in the current study (Level 1-days nested within Level 2-persons), generalized linear mixed-effects models (GLMMs) with participant-level random intercepts were used. Additionally, negative binomial family functions were fitted because outcomes had over-dispersed distributions, which log-transformed the outcome during analyses. Lastly, a zero-inflated portion was added to all models due to the presence of excessive zero values except for the model that examined min/d at home residential context. These zero-inflated models estimated a participant's probability of having zero min/d at a given context (not visiting the context) or at a given trip mode (not performing the trip).

2.2.4.3. Model building strategy

For each outcome, GLMM models were first fitted to test whether the derived time-activity and mobility patterns changed over time during pregnancy and postpartum (hereinafter referred to as the Base GLMM model). Then, individual sociodemographic, neighborhood, and additional temporal factors were further included to explore whether these factors can further explain these time-activity and mobility patterns. This was accomplished by first entering all other covariates to construct the fully-adjusted model if the univariate analysis (one covariate at a time) reported a $p<.1$ (hereinafter referred to as the Fully-adjusted GLMM model). Lastly, covariates with reduced explanatory power (i.e., p-value became $>.05$ in the fully adjusted model) were dropped in the final model to ensure model parsimony (hereinafter referred to as the Final GLMM model). Following the recommended practice, covariates were kept the same for the count and zero parts of each zero-inflated GLMM (Brooks et al. 2017). Additionally, the day-level total GPS data collection hours were always included as a covariate to adjust for the varying amount of GPS data collected possibly due to individual device wearing behaviors or other factors.

2.2.4.4. Model covariate selection

A list of temporal factors, individual-level sociodemographic, and neighborhood-level characteristics were included as covariates in the models. Past studies have associated these covariates with time-activity patterns of pregnant women (e.g., Abatzoglou 2013; Blanchard et al. 2018; P. Dadvand et al. 2012; Hannam et al. 2013; Nethery, Brauer, and Janssen 2009; Nethery et al. 2008; Wu et al. 2013; Zhu et al. 2019). Temporal factors included weekend versus weekday (weekend=1), daily average temperature in degrees Celsius, and study period (1st trimester, 3rd trimester [reference group], and 4-6 months postpartum). The 3rd trimester was chosen as the reference group since most prior pregnancy studies examining the relationship between environmental exposures and maternal or birth outcomes usually characterize environmental exposure based on location at a single point in time late in pregnancy or at delivery (Porter et al. 2019; Banay et al. 2017; Pennington et al. 2017). Since the 3rd trimester is closest to infant delivery, this study contrasted changes in time-activity and mobility patterns over time relative to this commonly used assumption. Individual sociodemographic characteristics from MADRES questionnaires were included, including age, education (less than or equal to high school diploma), marital status (married/living together, single/divorced/separated/widowed, or declined to answer/missing response), birth country (foreign- versus US-born), parity (first born versus second or greater birth) as well as employment status at each period. Body Mass Index (BMI) categories were also calculated (recoded as normal versus overweight/obese) based on height and weight measured during pre-natal visits. Additionally, individual-level neighborhood cohesion and safety scores were included from questionnaires administered during pregnancy and postpartum (Sampson, Raudenbush, and Earls 1997). Neighborhood characteristics were assigned to participants' residences based on the 2010 census block group boundary within which their home residences were situated. These included the National Walkability Index Score from the Environmental Protection Agency (EPA) EnviroAtlas and the Deprivation Index Score from the Neighborhood Atlas (Kind and Buckingham 2018; Pickard et al. 2015). A full list of covariates measures and corresponding data sources is documented in Appendix D.

2.2.4.5. Sensitivity analysis

Finally, sensitivity analyses were run by excluding days with <10 h or <16 h of GPS data to examine the influence of GPS completeness on observed associations, and by replacing study periods with binary (pregnancy versus postpartum) and continuous time (continuous week from conception to post-birth) variables, and by testing non-linear (quadratic) terms. The R 4.0.2 (R Core Team, 2020) and *glmmTMB* package (version 1.0.2.1) were used for generalized mixed-effects modeling (Brooks et al. 2017). Exponentiated effect estimates which are interpreted on a multiplicative scale were reported for all models. Reversed odds ratios (i.e., odds to accumulate any minutes at a given time activity or mobility pattern outcome) of zero-inflated models were calculated for easier interpretation.

2.3. Results

2.3.1. Data Completeness

A total of 65 participants were initially enrolled in the study, of which 62 provided at least one valid GPS observation day (≥6 h of data) across three study periods. Within these 62 participants, 35 had at least one valid day in all three study periods; 17 in two of the three periods; and 10 in one of the three periods. The final analytical sample comprised a total of 552 valid days of GPS data from 62 participants across the 1^{st} (*N*=205 person-days) and 3^{rd} trimesters (*N*=180 person-days) of pregnancy and 4–6 months postpartum (*N*=167 person-days). Each participant provided an average of 8.9 (*SD*=3.00; *Range*: 3.00-12.00) valid GPS days across the three periods. The average number of hours of GPS observations collected on valid days was 21.7 h (*SD*= 5.00; *Range:* 6.2-24.00). The average number of hours was highest in the 3^{rd} trimester (*Mean*=22.3h; *SD*=4.4; *Range:* 6.5-24.00) followed by the 4-6 months postpartum period (*Mean*=21.8h; *SD*=4.7; *Range:* 7.00-24.00) and the 1^{st} trimester (*Mean*=21.1; *SD*=5.6; *Range:* 6.2-24.00). Almost half of the valid person-days (49.3%) were weekend days across the three periods.

2.3.2. Descriptive Statistics of Covariates

Descriptive statistics for the participant- and day-level covariates are shown in Tables 2.1. Participants' mean age at study entry was 29 years (*SD=6.1*; *Range:* 18-45). All the participants were Hispanic, and more than half were born outside of the US (53.2%). About one-third (32.3%) had some college or above education, and 80.6% were either married or living together with their partners at study entry. One in three (36.4%) was employed during the 1^{st} trimester compared to 39.6% during the 3^{rd} trimester, and 19.6% at 4-6 months postpartum. At recruitment, 25.8% were pregnant with their first child, 74.2% were overweight or obese according to their pre-pregnancy BMI. The recruited participants lived in neighborhoods with an average walkability index score of 14.4 (*SD*=2.00, *Range:* 9.3-19; on 1-20 scale; where 1=least walkable) and average deprivation index score of 6.5 (*SD*=1.7, *Range:* 2.00-9.00; on 1-10 scale; where 1=least deprived). The average neighborhood safety and cohesion score (on 1-5 scale;

where 1=least safe and cohesive) self-reported by women was 3.1 (*SD*=.7, *Range:* 1.00-4.4) at the 1st and 3rd (*SD*=.7; *Range:* 1.00-5.00) trimesters, and 3.3 (*SD*=.9, *Range:* 1.4-4.8) at 4-6 months postpartum.

Table 2.1. Descriptive statistics of participant characteristics at baseline (a) and person-day level temporally varying factors by 1st and 3rd trimesters, and 4-6 months postpartum (b).

(a) Baseline statistics	
	Overall (*N*=62 Participants)
Age at consent (years)	
Mean (SD)	29 (6.1)
Median [Min, Max]	28 [18, 45]
Education	
High school or less	42 (67.7%)
Some college/Graduate	20 (32.3%)
Marital status	
Married/Living together	50 (80.6%)
Single/Divorced/Separated/Widowed	10 (16.1%)
Missing	2 (3.2%)
Acculturation	
US-Born Hispanic	29 (46.8%)
Foreign-Born Hispanic	33 (53.2%)
Maternal parity	
First-born	16 (25.8%)
Already had child	46 (74.2%)
Pre-pregnancy BMI category	
Normal	16 (25.8%)
Overweight/Obesity	46 (74.2%)
Neighborhood Walkability Score	
Mean (SD)	14.4 (2.00)
Median [Min, Max]	14 [9.3, 19]
Neighborhood Deprivation Score	
Mean (SD)	6.5(1.7)
Median [Min, Max]	7.00 [2.00, 9.00]
Missing	2 (3.2%)

Table 2.1. (Cont.)

(b) Temporally varying statistics				
	1st Trimester (*N*=205 person-days)	**3rd Trimester (*N*=180 person-days)**	**4-6 Months Postpartum (*N*=167 person-days)**	**Overall (*N*=552 person-days)**
Valid GPS observation (h/day)				
Mean (SD)	21 (5.6)	22 (4.4)	22 (4.7)	22 (5.00)
Median [Min, Max]	24 [6.2, 24]	24 [6.5, 24]	24 [7.00, 24]	24 [6.2, 24]
Average Daily Temperature (°C)				
Mean (SD)	21 (4.2)	21 (4.4)	19 (4.4)	20 (4.4)
Median [Min, Max]	21 [8.00, 31]	21 [9.00, 31]	20 [5.2, 28]	20 [5.2, 31]
Missing	19 (9.3%)	0 (0%)	0 (0%)	19 (3.4%)
Type of day				
Weekday	104 (50.7%)	91 (50.6%)	85 (50.9%)	280 (50.7%)
Weekend	101 (49.3%)	89 (49.4%)	82 (49.1%)	272 (49.3%)
	1st Trimester (*N*=55 Participants)	**3rd Trimester (*N*=48 Participants)**	**4-6 Months Postpartum (*N*=46 Participants)**	**Overall (*N*=149 Participants)**
Employment status				
Unemployed	35 (63.6%)	28 (58.3%)	29 (63.0%)	92 (61.7%)
Employed	20 (36.4%)	19 (39.6%)	9 (19.6%)	48 (32.2%)
Missing	0 (0%)	1 (2.1%)	8 (17.4%)	9 (6.0%)
Neighborhood Cohesion and Safety Score				
Mean (SD)	3.1 (.7)	3.1 (.7)	3.3 (.9)	3.1 (.8)
Median [Min, Max]	3.00 [1.00, 4.4]	3.1 [1.00, 5.00]	3.2 [1.4, 4.8]	3.0 [1.00, 5.00]
Missing	3 (5.5%)	0 (0%)	8 (17.4%)	11 (7.4%)

Note: BMI = Body Mass Index, GPS = Global Positioning System. SD = Standard deviation.

2.3.3. Descriptive Statistics for Time-Activity and Daily Mobility Patterns

2.3.3.1. Time-Activity Patterns

The descriptive statistics for derived time-activity patterns (N stays and min/day by context and indoor/outdoor microenvironment) are shown in Tables 2.2 and 2.3. Overall, 2,621 stays were detected from 552 valid GPS person-days across three study periods (Table 2.2). The

Table 2.2. Summary of total number of visits to multiple spatial contexts and indoor/outdoor microenvironments and total number of pedestrian and vehicular trips made.

	1st Trimester (N_{stay}=947; N_{trip}=682)	**3rd Trimester (N_{Stay}=914; N_{trip}=692)**	**4-6 Months Postpartum (N_{Stay}=760; N_{Trip}=551)**	**Overall (N_{Stay}=2,621; N_{Trip}=1,925)**
	N(%)	**N(%)**	**N(%)**	**N(%)**
Spatial contexts				
Home residential	412 (43.5%)	363 (39.7%)	337 (44.3%)	1,112 (42.4%)
Non-home residential	64 (6.8%)	60 (6.6%)	79 (10.4%)	203 (7.7%)
Commercial and Services	281 (29.7%)	283 (31.0%)	193 (25.4%)	757 (28.9%)
Industrial and Office Spaces	84 (8.9%)	105 (11.5%)	64 (8.4%)	253 (9.7%)
Schools and Public Facilities	52 (5.5%)	61 (6.7%)	57 (7.5%)	170 (6.5%)
Parks and Open Spaces	22 (2.3%)	17 (1.9%)	12 (1.6%)	51 (1.9%)
Other	32 (3.4%)	25 (2.7%)	18 (2.4%)	75 (2.9%)
Indoor/outdoor microenvironment				
Home Indoor	363 (38.3%)	336 (36.8%)	302 (39.7%)	1,001 (38.2%)
Non-Home Indoor	220 (23.2%)	253 (27.7%)	168 (22.1%)	641 (24.5%)
Home Outdoor	49 (5.2%)	27 (3.0%)	35 (4.6%)	111 (4.2%)
Non-Home Outdoor	291 (30.7%)	288 (31.5%)	230 (30.3%)	809 (30.9%)
Out of Los Angeles County	24 (2.5%)	10 (1.1%)	25 (3.3%)	59 (2.3%)
Trip modes				
Pedestrian trips	175 (25.7%)	185 (26.7%)	120 (21.8%)	480 (24.9%)
Vehicular trips	507 (74.3%)	507 (73.3%)	431 (78.2%)	1,445 (75.1%)

Table 2.3. Day-level summary of time spent in spatial contexts, indoor/outdoor microenvironments, and number of pedestrian/vehicular trips made.

	1st Trimester (N=205 person-days)	3rd Trimester (N=180 person-days)	4-6 Months Postpartum (N=167 person-days)	Overall (N=552 person-days)
Spatial Contexts				
Home Residential (h/day)				
Mean (SD)	16.8 (6.6)	17.5 (6.6)	17.6 (6.3)	17.3 (6.6)
Median [Min, Max]	18.8 [0, 24.00]	19.5 [0, 24.00]	19.4 [0, 24.00]	19.2 [0, 24.00]
Missing	2 (1.0%)	0 (0%)	1 (.6%)	3 (.5%)
All Non-Home Contexts (min/day)				
Mean (SD)	205 (324)	219 (328)	190 (295)	205 (316)
Median [Min, Max]	58.00 [0, 1440]	81.4 [0, 1440]	73.2 [0, 1440]	73.2 [0, 1440]
Non-Home Residential (min/day)				
Mean (SD)	51.9 (158)	40.8 (139)	68.7 (164)	53.1 (154)
Median [Min, Max]	0 [0, 1260]	0 [0, 1040]	0 [0, 831]	0 [0, 1260]
Missing	46 (22.4%)	26 (14.4%)	34 (20.4%)	106 (19.2%)
Commercial and Services (min/day)				
Mean (SD)	68.2 (109)	84.2 (134)	47.7 (68.9)	67.4 (109)
Median [Min, Max]	16.2 [0, 561]	22.2 [0, 619]	9.50 [0, 349]	16.2 [0, 619]
Missing	40 (19.5%)	25 (13.9%)	28 (16.8%)	93 (16.8%)
Schools and Public Facilities (min/day)				
Mean (SD)	21.1 (71.8)	26.2 (70.8)	23.4 (66.1)	23.6 (69.7)
Median [Min, Max]	0 [0, 480]	0 [0, 517]	0 [0, 521]	0 [0, 521]
Missing	49 (23.9%)	25 (13.9%)	32 (19.2%)	106 (19.2%)

Table 2.3. (Cont.)

	1st Trimester (N=205 person-days)	**3rd Trimester (N=180 person-days)**	**4-6 Months Postpartum (N=167 person-days)**	**Overall (N=552 person-days)**
Industrial and Office Spaces (min/day)				
Mean (SD)	103 (304)	93.2 (269)	72.5 (241)	90.4 (274)
Median [Min, Max]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]
Missing	44 (21.5%)	25 (13.9%)	29 (17.4%)	98 (17.8%)
Parks and Open Spaces (min/day)				
Mean (SD)	11.8 (55.9)	5.57 (30.1)	8.86 (55.4)	8.73 (48.3)
Median [Min, Max]	0 [0, 384]	0 [0, 275]	0 [0, 517]	0 [0, 517]
Missing	53 (25.9%)	29 (16.1%)	36 (21.6%)	118 (21.4%)
Indoor/outdoor microenvironment				
Home Outdoor (min/day)				
Mean (SD)	150 (389)	129 (389)	138 (391)	139 (389)
Median [Min, Max]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]	0 [0, 1440]
Missing	49 (23.9%)	26 (14.4%)	37 (22.2%)	112 (20.3%)
Non-Home Outdoor (min/day)				
Mean (SD)	109 (248)	117 (272)	112 (253)	113 (257)
Median [Min, Max]	15.5 [0, 1440]	12.00 [0, 1440]	12.00 [0, 1440]	12.3 [0, 1440]
Missing	40 (19.5%)	23 (12.8%)	24 (14.4%)	87 (15.8%)
Daily Mobility				
Trip (min/day)				
Mean (SD)	60.2 (73.3)	66.6 (69.4)	64.7 (76.6)	63.7 (73.00)
Median [Min, Max]	40.00 [0, 387]	49.6 [0, 363]	37.8 [0, 351]	44.2 [0, 387]

Table 2.3. (Cont.)

	1st Trimester (N=205 person-days)	**3rd Trimester (N=180 person-days)**	**4-6 Months Postpartum (N=167 person-days)**	**Overall (N=552 person-days)**
Pedestrian-based Trip (min/day)				
Mean (SD)	16.2 (30.8)	17.9 (31.7)	14.9 (29.8)	16.4 (30.8)
Median [Min, Max]	0 [0, 205]	0 [0, 186]	0 [0, 166]	0 [0, 205]
Missing	45 (22.0%)	23 (12.8%)	30 (18.0%)	98 (17.8%)
Vehicular-based Trip (min/day)				
Mean (SD)	57.3 (67.6)	58.1 (63.7)	60.9 (72.00)	58.7 (67.6)
Median [Min, Max]	36.3 [0, 372]	41.6 [0, 356]	35.3 [0, 351]	39.3 [0, 372]
Missing	35 (17.1%)	22 (12.2%)	23 (13.8%)	80 (14.5%)
Trip (N/day)				
Mean (SD)	3.33 (3.86)	3.84 (3.97)	3.30 (3.61)	3.49 (3.82)
Median [Min, Max]	2.00 [0, 18.00]	3.00 [0, 17.00]	2.00 [0, 16.00]	2.00 [0, 18.00]
Pedestrian-based Trip (N/day)				
Mean (SD)	1.09 (1.97)	1.18 (1.75)	.876 (1.37)	1.06 (1.73)
Median [Min, Max]	0 [0, 13.00]	0 [0, 8.00]	0 [0, 6.00]	0 [0, 13.00]
Missing	45 (22.0%)	23 (12.8%)	30 (18.0%)	98 (17.8%)
Vehicular-based Trip (N/day)				
Mean (SD)	2.98 (2.97)	3.21 (3.32)	2.99 (3.31)	3.06 (3.19)
Median [Min, Max]	2.00 [0, 12.00]	2.00 [0, 15.00]	2.00 [0, 15.00]	2.00 [0, 15.00]
Missing	35 (17.1%)	22 (12.2%)	23 (13.8%)	80 (14.5%)

Notes: SD = Standard Deviation.

1st trimester (*N*=947 stays) had larger numbers of different stays detected compared to the 3rd trimester (*N*=914 stays) and 4-6 months postpartum (*N*=760 stays). Among all stays, 42.4% (*N*=1,112) were at home, with an average duration of 17.3 h/day (*SD*=6.6 h/day). Commercial and services locations were the most popular destinations (28.9% of all stays; *N*=757 stays; *Mean*=1.1 h/day; *SD*=1.8 h/day) among all non-home contexts, followed by non-home residential locations, industrial and office spaces, and schools and public facilities, each of which constituted 5~10% of all stays (Table 2.2). Lastly, women in this panel study rarely visited parks and open space (1.9% of all stays; *N*=51 stays; *Mean*=8.73 min/day; *SD*=48.3 min/day).

In terms of descriptive trends across the three study periods, the number of visits to industrial and office spaces, and to commercial and services locations increased from the 1st trimester to the 3rd trimester but decreased at 4-6 months postpartum. However, women's visits to non-home residential places increased at 4-6 months postpartum compared to the 3rd trimester (10.4 versus 6.6% of all stays). Additionally, women's visits to parks and open space showed a decreasing trend from the 1st to the 3rd trimester of pregnancy and onto the 4-6 months postpartum (2.3, 1.9, and 1.6%, respectively of all stays in these time periods). Approximately one in three (35.1%) of stays detected across the three study periods occurred in outdoor microenvironments including locations outside of the home (e.g., porch, lawns, sidewalks) (4.2% of all stays; *Mean*=2.1 h/day; *SD*=3.4 h/d) and at non-home outdoor locations (e.g., parks, sports venues, sidewalks) (30.9% of all stays; *Mean*=1.9 h/day;*SD*=4.3 h/day). Overall, the 3rd trimester had the lowest fraction of stays (39.8%) at home (both indoor and outdoor) and the highest fraction of stays (27.7%) at non-home indoor microenvironments (Table 2.3).

2.3.3.2. Daily Mobility Patterns

The summary statistics for derived mobility patterns (N and min/d for trips, and N/d by trip mode) are reproduced in Tables 2.2 and 2.3. Overall, participants took 1,925 trips over the duration of the study spread across 552 person-days, one in four of these trips (24.9%) was pedestrian-based (*N*=489; *Mean*=16.4 min; *SD*=30.8 min). The number of trips made varied slightly between the 1^{st} and 3^{rd} trimesters (*N*=682 versus *N*=692) and decreased at 4-6 months postpartum (*N*=551). This pattern was replicated across all trip modes.

Figure 2.4 shows the most popular trip origins and destinations by mode and purpose. For pedestrian-based trips (*N*=489), around 1 in 5 (21.7%, *N*=103) were between different commercial and services locations, followed by walking within the same commercial and services locations (14.5%; *N*=71). For vehicle-based trips (*N*=1445), about 2 in 5 (37.8%; *N*=546) were between home and commercial and services locations, followed by commuting between different commercial and services locations (18.5%; *N*=268) and between home and non-home residential locations (9.0%, *N*=130).

2.3.4. Base GLMM Results

The base GLMM results examining whether day-level time-activity and mobility patterns varied across the three study periods are illustrated in Figure 2.5. The odds of visiting commercial and services locations were 58% lower at 4-6 months postpartum compared to the 3^{rd} trimester (*OR*=.42, *95%CI*: .23–.76) (Figure 2.5). No other stay contexts (in terms of frequency or duration of time spent within them) were significantly different across the three time periods. These results did not change in sensitivity analyses using days with ≥10 h or ≥16 h of GPS data, binary (pregnancy versus postpartum) and continuous (week number from conception to post-birth) time. variables, and non-linear (quadratic) time terms. Moreover, the

39

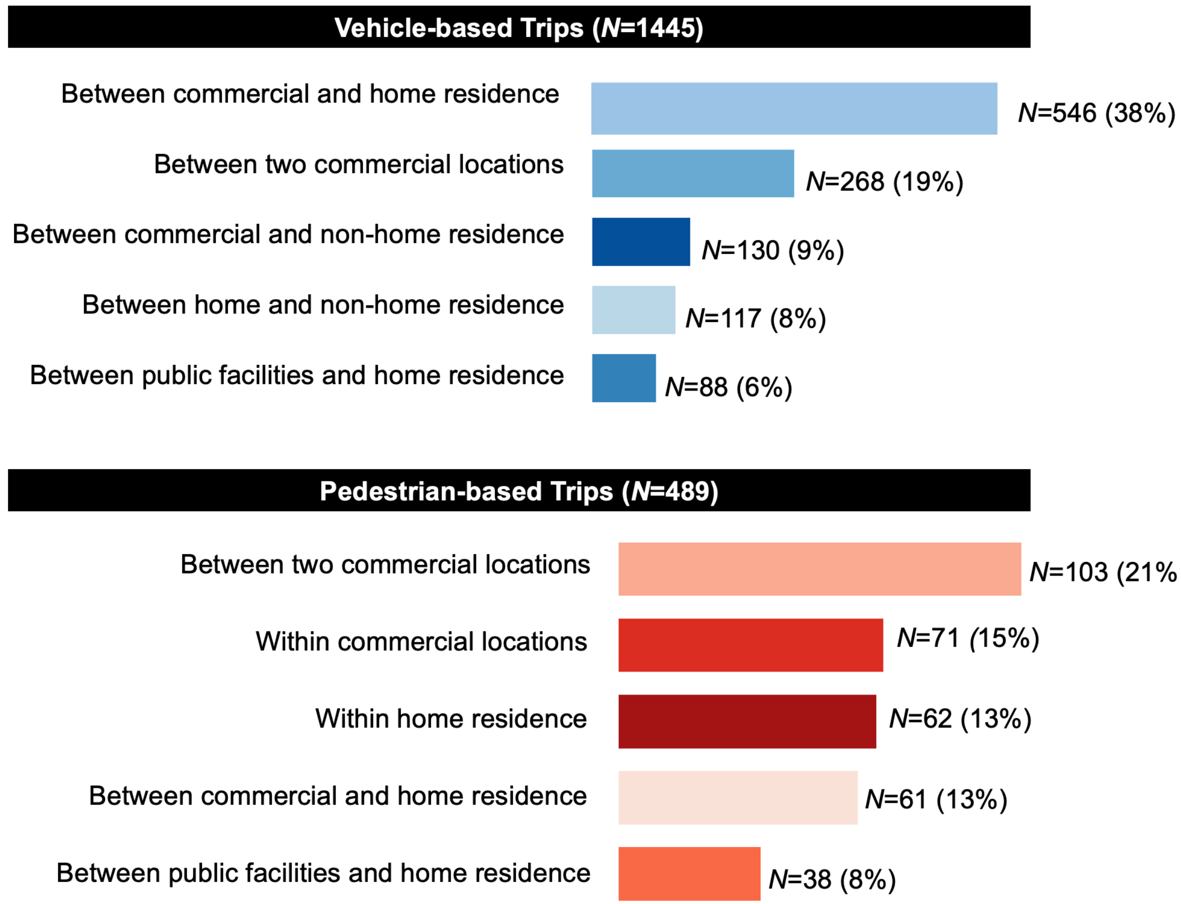


Figure 2.4. Distributions of top five origin-destination combinations by pedestrian- and vehicle-based trip modes.

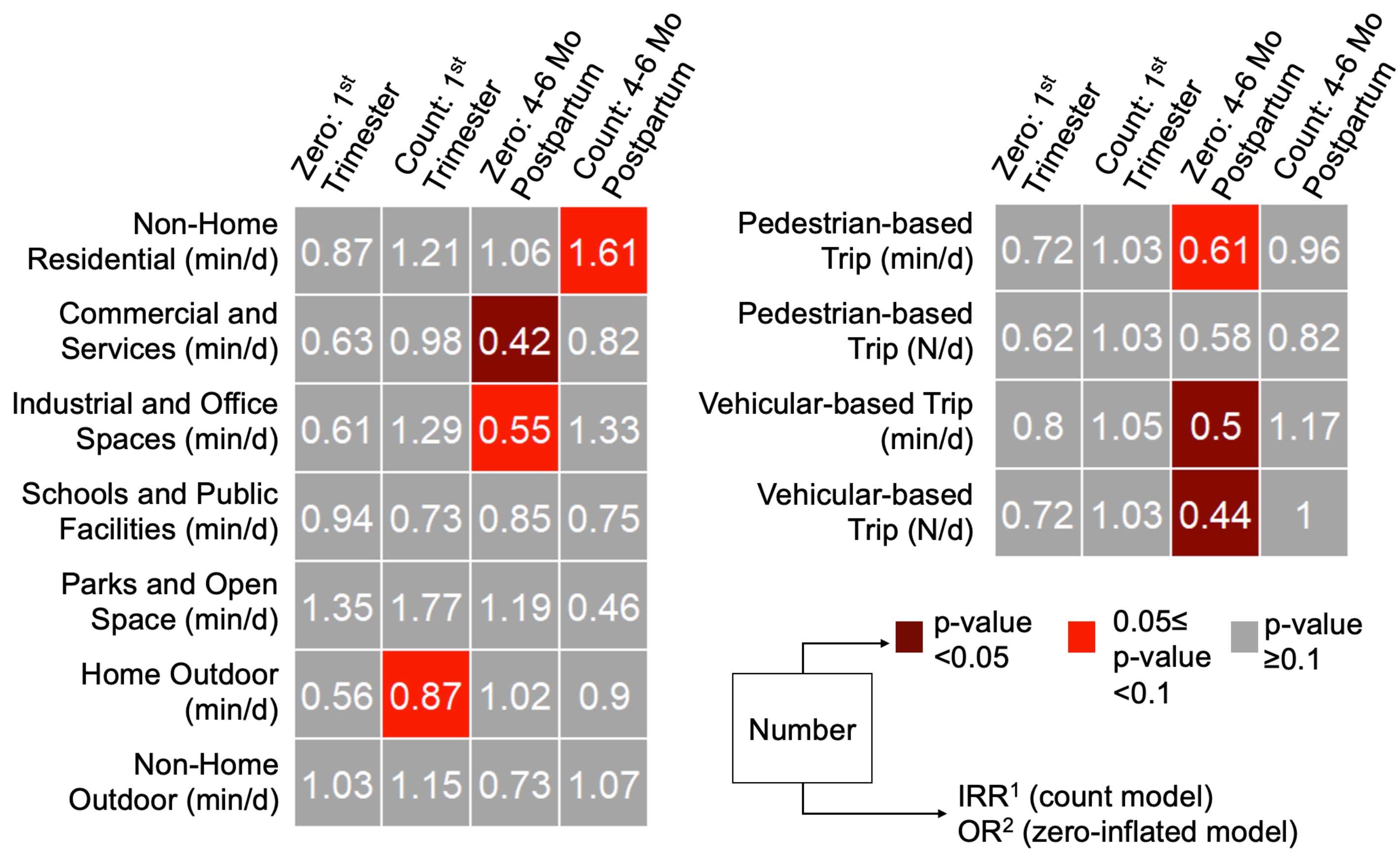


Figure 2.5. Base Generalized Mixed-Effects Model results of variations in time-activity and daily mobility patterns by 1st and 3rd trimesters of pregnancy and 4-6 months postpartum.

Note: IRR = Incidence Rate Ratio. OR = Odds Ratio.

[1] IRR can be interpreted as: if mothers visit a particular context or perform trips with a particular mode, their min/d spent increase (if IRR>1) or decrease (if IRR<1), compared to the reference time point (i.e., 3rd trimester).

[2] OR can be interpreted as: mothers in a time point decrease (if OR<1) or increase (if OR>1) the odds of visiting a particular context or performing trips with a particular mode, compared to the reference time point (i.e., 3rd trimester).

odds of staying outdoors and time spent outdoors did not vary significantly across the three study periods (Figure 2.5). Lastly, in terms of mobility patterns, the odds of taking a vehicular trip were 56% lower at 4-6 months postpartum compared to the 3rd trimester at the day level (*OR*=.44, *95%CI*: .21–.92) (Figure 2.5). These results did not change in sensitivity analyses restricting trips to those with ≥ 5% of epoch-level GPS data within trip segments detected. The odds of performing any trips overall or in pedestrian-mode did not vary by study period in these base models using min/d spent in trips or N/d trips taken. The full model results of base GLMM can be found in Appendices E and F.

2.3.5. Final GLMM Results

2.3.5.1. Three Study Periods

The results of the final GLMM exploring whether individual sociodemographic, neighborhood, and other temporal factors such as weekdays vs weekend days additionally explained the women's time-activity and daily mobility patterns are summarized in Tables 2.4, 2.5, and 2.6. All significant results found in the base models examining variation over time remained in the fully adjusted models for odds of taking commercial and services locations, and for odds of performing any vehicle-based trip). Additionally, the final GLMM results showed that when women visited non-home residential locations in the 4-6 months postpartum period, their mean min/day spent there increased by 83% (*Incidence Rate Ratio or IRR*=1.83, *95%CI*: 1.03-3.25) compared to when they visited this same context in the 3rd trimester (see Table 2.4).

2.3.5.2. Weekdays versus Weekends

Other temporally varying factors including weekdays versus weekend days and daily temperature were not significantly associated with duration of time (min/day) spent at the home

Table 2.4. Zero-inflated Generalized Mixed-Effects Model (GLMM) results for time spent in five non-home spatial contexts adjusted for covariates.

Predictors	**Non-Home Residential (min/d)**	**Commercial and Services (min/d)**	**Industrial and Office Spaces (min/d)**	**Schools and Public Facilities (min/d)**	**Parks and Open Spaces (min/d)**
Count Model			***Incidence Rate Ratio (95%CI)***		
Period: 1st Trimester	1.14 (.65 – 1.98)	1.01 (.79 – 1.30)	1.37 (.89 – 2.10)	.81 (.49 – 1.34)	1.07 (.37 – 3.11)
Period: 4-6 Months Postpartum	1.83 * (1.03 – 3.25)	.88 (.66 – 1.17)	1.51 (.96 – 2.36)	.91 (.56 – 1.46)	.45 (.16 – 1.31)
Valid GPS observation (h/day)	1.01 (.94 – 1.09)	1.07 ** (1.02 – 1.13)	1.03 (.97 – 1.09)	1.05 (.96 – 1.15)	.95 (.80 – 1.13)
Type of day: Weekend	1.64 * (1.05 – 2.56)				3.02 ** (1.32 – 6.92)
Average air temperature (°C)	1.04 (.99 – 1.10)				
Maternal parity: Already had child		.63 ** (.46 – .86)			
Employment status: Employed		1.43 ** (1.11 – 1.85)	2.01 * (1.06 – 3.79)	2.25 *** (1.40 – 3.64)	
Maternal age at consent		.99 (.97 – 1.01)			
Neighborhood safety and cohesion score		.83 * (.71 – .97)			
Zero-Inflated Model			***Odds Ratio (95%CI)***		
Period: 1st Trimester	.95 (.53 – 1.79)	.60 (.33 – 1.09)	.63 (.34 – 1.18)	.88 (.45 – 1.72)	1.35 (.50 – 3.85)
Period: 4-6 Months Postpartum	1.05 (.59 – 2.00)	.37 ** (.19 – .72)	.63 (.32 – 1.27)	.96 (.48 – 1.96)	1.2 (.40 – 3.70)
Valid GPS observation (hay/day)	.34 * (.12 – .97)	.28 * (.10 – .85)	.20 (.04 – 1.01)	.14 ** (.03 – .59)	.22 (.02 – 2.70)
Type of day: Weekend	.74 (.45 – 1.22)				1.37 (.59 – 3.23)
Average air temperature (°C)	1.00 (1.00 – 1.06)				
Maternal parity: Already had child		.53 (.18 – 1.59)			
Employment status: Employed		.62 (.29 – 1.33)	2.33 * (1.11 – 5.00)	.61 (.28 – 1.35)	
Maternal age at consent		1.10 * (1.01 – 1.19)			
Neighborhood safety and cohesion score		1.16 (.77 – 1.82)			

*p<.05. **p<.01. ***p<.001. Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation.

Note: BMI = Body Mass Index. GPS = Global Positioning System.

Table 2.5. Zero-inflated Generalized Mixed-Effects Model (GLMM) results for time spent in home and non-home contexts and microenvironments adjusted for covariates.

Predictors	**Home Residence (h/day)**	**Home Residence Excluding Sleep Hours (min/day)**	**Home Residence Outdoor (min/day)**	**All Non-Home Contexts (min/day)**	**All Non-Home Contexts Outdoor (min/day)**
Count Model			***Incidence Rate Ratio (95%CI)***		
Period: 1st Trimester	.98 (.93 – 1.05)	.95 (.85 – 1.06)	.87 (.74 – 1.02)	1.18 (.94 – 1.47)	1.15 (.84 – 1.57)
Period: 4-6 Months Postpartum	1.00 (.93 – 1.07)	1.01 (.90 – 1.13)	.90 (.75 – 1.10)	1.08 (.86 – 1.36)	1.07 (.78 – 1.47)
Valid GPS observation (h/day)	1.06 *** (1.05 – 1.07)	1.15 *** (1.13 – 1.17)	1.06 *** (1.04 – 1.08)	1.05 ** (1.01 – 1.08)	1.03 (.98 – 1.07)
Employment status: Employed	.92 (.84 – 1.01)			1.48 ** (1.10 – 1.99)	
Type of day: Weekend				1.06 (.89 – 1.27)	
Maternal age at consent				1.00 (.97 – 1.02)	.99 (.95 – 1.03)
Zero-Inflated Model			***Odds Ratio (95%CI)***		
Period: 1st Trimester		1.14 (.4 – 3.23)	.56 (.15 – 2.13)	.71 (.42 – 1.22)	1.05 (.62 – 1.82)
Period: 4-6 Months Postpartum		1.49 (.53 – 4.35)	1.02 (.21 – 5.00)	.83 (.45 – 1.54)	.72 (.42 – 1.27)
Valid GPS observation (h/day)		1.92 *** (1.67 – 2.38)	.20 (.02 – 1.85)	1.19 *** (1.15 – 1.25)	.23 * (.07 – .79)
Employment status: Employed				.59 * (.38 – .93)	
Type of day: Weekend				1.89 (1.00 – 3.70)	
Maternal age at consent				1.10 ** (1.11 – 1.18)	1.10 ** (1.11 – 1.16)

*p<.05. **p<.01. ***p<.001. Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation. Zero-inflated model was not applied to home residence related outcomes given that extremely rare cases of having zero min/day spent at home residence.

Note: GPS = Global Positioning System.

Table 2.6. Zero-inflated Generalized Mixed-Effects Model (GLMM) results for time spent in pedestrian and vehicular trips and number of pedestrian and vehicular trips performed adjusted for covariates.

Predictors	All Trip (min/d)	Pedestrian-based Trip (min/d)	Vehicular-based Trip (min/d)	All Trip (N/d)	Pedestrian-based Trip (N/d)	Vehicular-based Trip (N/d)
Count Model			***Incidence Rate Ratio (95%CI)***			
Period: 1st Trimester	1.03 (.86 – 1.24)	1.03 (.75 – 1.41)	1.05 (.86 – 1.28)	1.00 (.85 – 1.18)	1.04 (.73 – 1.47)	1.04 (.88 – 1.23)
Period: 4-6 Months Postpartum	1.04 (.87 – 1.25)	.96 (.69 – 1.32)	1.17 (.95 – 1.43)	.90 (.76 – 1.06)	.86 (.59 – 1.25)	1.00 (.84 – 1.20)
Valid GPS observation (h/day)	1.05 *** (1.02 – 1.08)	1.02 (.97 – 1.08)	1.05 ** (1.02 – 1.09)	1.04 ** (1.01 – 1.07)	.97 (.92 – 1.03)	1.05 ** (1.02 – 1.08)
Type of day: Weekend	.96 (.83 – 1.11)			.93 (.82 – 1.06)		
Maternal age at consent	1.01 (.99 – 1.03)	.99 (.96 – 1.02)	1.01 (.99 – 1.03)	1.03 * (1.00 – 1.05)		1.02 (1.00 – 1.04)
Education: Some college/Graduate	1.08 (.86 – 1.36)		1.05 (.82 – 1.35)			1.13 (.87 – 1.48)
Neighborhood deprivation score					1.12 * (1.01 – 1.25)	
Neighborhood safety and cohesion score						.86 * (.76 – .97)
Zero-Inflated Model			***Odds Ratio (95%CI)***			
Period: 1st Trimester	.76 (.45 – 1.27)	.74 (.43 – 1.25)	.79 (.45 – 1.41)	.75 (.42 – 1.37)	.51 (.21 – 1.27)	.71 (.37 – 1.43)
Period: 4-6 Months Postpartum	.78 (.45 – 1.35)	.6 (.34 – 1.03)	.5 * (.28 – .92)	.79 (.42 – 1.49)	.48 (.18 – 1.28)	.53 (.24 – 1.18)
Valid GPS observation (h/day)	1.18 *** (1.11 – 1.23)	.2 * (.05 – .86)	.36 * (.14 – .94)	1.18 *** (1.11 – 1.23)	.21 (.03 – 1.82)	.31 (.08 – 1.18)
Type of day: Weekend	.54 ** (.36 – .82)			.53 * (.33 – .87)		
Maternal age at consent	1.08 ** (1.01 – 1.14)	1.06 * (1.01 – 1.11)	1.10 ** (1.11 – 1.18)	1.06 * (1.01 – 1.14)		1.09 * (1.01 – 1.16)
Education: Some college/Graduate	2.13 * (1.11 – 4.35)		3.33 ** (1.43 – 7.69)			3.33 * (1.25 – 9.09)
Neighborhood deprivation score					.74 (.56 – 1.01)	
Neighborhood cohesion and safety score						1.3 (.83 – 2.13)

*p<.05. **p<.01. ***p<.001. Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation.

Note: GPS = Global Positioning System.

residence (when participants were there). Results remained unchanged in sensitivity analyses excluding days with <10 h or <16 h of GPS observations, or self-reported sleeping hours. As for non-home contexts, when women visited non-home residential locations or parks and open spaces during weekend days, they spent 64% (*IRR*=1.64, *95%CI:* 1.05-2.56) and 202% (*IRR*=3.02, *95%CI:* 1.32-6.92) more min/day at each context, respectively, as compared to weekdays. Additionally, during weekend days, the odds (*OR*=.48; *95%CI:* .35–.82) of accumulating any minutes in trips decreased by 52%.

2.3.5.3. Individual Sociodemographic and Residential Neighborhood Characteristics

Other than weekdays vs weekend days, individual sociodemographic and residential neighborhood characteristics, including employment status, maternal education, and self-reported neighborhood cohesion and safety scores, were also significantly associated with time-activity (Table 2.4) and mobility (Table 2.6) patterns. Specifically, those employed spent on average 48% more min/d (*IRR*=1.48, *95%CI*: 1.10-1.99) when they visited non-home contexts and had 133% higher odds (*OR*=2.33, *95%CI*: 1.10-5.00) of visiting industrial and office spaces compared to non-employed counterparts. In addition, women who already had at least one child (*IRR*=.65; *95%CI:* .45-.93) spent 35% fewer min/day visiting commercial and services locations compared to women experiencing their first pregnancy.

In terms of mobility patterns, maternal education was significantly associated with longer duration of time spent in trips when they were taken. Specifically, women with post high school education had 223% greater odds (*OR*=3.33, *95%CI:* 1.41-7.69) of accumulating minutes on vehicle-based trips and 113% greater odds (*OR*=2.13, *95%CI:* 1.05-4.35) of accumulating minutes on all trips regardless of mode (Table 2.6) compared to women with high school diploma and below. Moreover, women living in safer neighborhoods (based on reported safety and cohesion score) took 14% fewer vehicle-based trips per day (*IRR*=.86; *95%CI:* .76-.97) overall.

2.4. Discussion

The overarching goal of this analysis was to examine how dynamic time-activity and mobility patterns vary for both the pregnant woman and the fetus, and how these might differ across levels of personal, socioeconomic, or neighborhood level disadvantage. In this work, a data processing and analysis pipeline was developed for highly resolved GPS data in a panel study of Hispanic pregnant women who were continuously monitored for 4 days during each of the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum. This study identified stays and trips and classified their spatial and indoor/outdoor microenvironmental contexts (for stays) and modes (for trips). Then whether time-activity and mobility patterns varied over time during pregnancy and the early postpartum period, and by individual sociodemographic, residential neighborhood, and other temporal factors were tested. This work also highlights the inadequacy of assuming individuals are stationary when assessing environmental exposures during pregnancy and their effects on maternal and child health.

2.4.1. Time-Activity and Mobility Patterns of Pregnant Women

To start, this study found that participants on average spent nearly 70% (17.3 h/day) of their time at their home residences during pregnancy and the early postpartum period, which matches several studies examining the time-activity and mobility patterns of pregnant women (Nethery, Brauer, and Janssen 2009; Ouidir et al. 2015; Wu et al. 2013). For instance, Nethery, Brauer, and Janssen (2009) reported a cohort of Canadian pregnant women spent 16.2 h/day at/near home during pregnancy while Zhu et al. (2019) reported a cohort of Chinese pregnant women spent 15 h/day at/near home. Moreover, although the finding of this study - this group of

Hispanic women rarely visited parks and open space could not be directly compared to other pregnancy studies among Hispanic women in the US, they indicate a potential public health concern since multiple studies have shown that exposure to greenness is associated with lower exposure to environmental hazards and decreased risk of adverse pregnancy outcomes (Dadvand et al. 2012; McEachan et al. 2016; Zhan et al. 2020). Past studies have indicated that minority and low SES populations have lower parks and open space availability (e.g., no park within walking distance) and quality (e.g., crime, lack of maintenance), which might help explain the low utilization of parks and open space in the cohort of this study. Consistently, because urban Los Angeles has limited parks and green infrastructure in general and higher quality parks and open space occur in the more expensive areas of the city, the low-income participants in this study may have had less access to parks and open space (Sister, Wolch, and Wilson 2010; Wolch, Wilson, and Fehrenbach 2005). The next study (Chapter 3) used GIS to measure greenness exposure and parks and open space access in participants' residential neighborhoods, as well as interactions with individual health characteristics, to further understand the consequences that flow from this state-of-affairs.

The daily mobility patterns of participants in this study differed from results reported by Wu et al. (2013) in the other GPS-based Southern California study that also examined mobility patterns of pregnant women (Wu et al. 2013). Specifically, participants of this study spent 1.7 times more min/day on average in vehicle-based trips compared to the prior study. However, Wu et al. (2013) study participants were from different counties with a more diverse racial and ethnic composition and wider SES range compared to this study that focused on predominantly low income, Hispanic participants from Central, East, and South Los Angeles. A study by MacLeod et al. (2018) found low-income, pregnant women in another urban cohort in Los Angeles reported significantly more time in vehicle-based trips in a cross-sectional survey, which might explain this discrepancy since low SES groups may have longer commuting times and make more frequent use of public transit than higher SES groups.

2.4.2. Changes in Time-Activity and Mobility Patterns during Pregnancy and Postpartum

Longitudinally, this study did not find women's time spent at home differed significantly across pregnancy and early postpartum. This finding differs from the results of other studies examining time-activity patterns of women across pregnancy (Nethery, Brauer, and Janssen 2009; Zhu et al. 2019). Nethery et al. (2009) reported that increasing weeks of pregnancy until the 3rd trimester were associated with increased time spent at home in a sample of 62 pregnant women living in Vancouver, BC, Canada. The authors hypothesized this might be due to the decrease in PA in later trimesters of pregnancy. However, this study focused on a group of Hispanic women that were primarily low SES. Consequently, they might not be able to afford or have time to engage in leisure activities due to increased home or work responsibilities (Kakinami et al. 2018).

In terms of time spent in non-home contexts, this study found women's odds of visiting commercial and services locations decreased at 4-6 months postpartum compared to the 3rd trimester of pregnancy. This change may be explained by increasing stays at home residence due to childcare responsibilities or the fact that women permanently or temporarily left their jobs at these times since the employment rate dropped from 39.6 to 19.6% between the 3rd trimester and the 4-6 months postpartum. This study did not find any difference between women's time spent in commercial and services locations between the 1st and 3rd trimesters. However, a similar study in Shanghai, China reported women's time spent working decreased by two hours in the 3rd trimester compared to the 1st trimester (Zhu et al. 2019). This study was able to disentangle whether the purpose of visiting commercial and service locations was for work or fulfilling daily life needs such as visiting hospitals, schools, and supermarkets, which might explain why results of this study differed from the Shanghai study above.

Regarding daily mobility patterns, my finding of no meaningful changes in time spent in vehicle- or pedestrian-based trips between the 1^{st} and 3^{rd} trimesters of pregnancy adds to the mixed results reported in the literature. Results of this study were consistent with the study by Nethery et al. (2009) that reported no longitudinal changes in time spent in transit across the 1^{st}, $2^{nd,}$ and 3^{rd} trimesters of pregnancy, but inconsistent with Zhu et al. (2019) who reported pregnant women's time spent in vehicles increased between the 1^{st} and 3^{rd} trimester. However, the latter study was located in Shanghai, China, a city with an urban planning system that heavily incorporates pedestrian-oriented street networks and public transit systems in contrast to the Los Angeles metropolitan area, which may result in different travel behaviors. Until now, there are few studies that have examined daily mobility patterns of pregnant women, and more are needed to understand how mobility patterns change across pregnancy and postpartum periods.

2.4.3. Additional Predictors of Time-Activity and Mobility Patterns

Findings of this study that pregnant women's time-activity and daily mobility patterns vary with additional temporal, individual sociodemographic, and residential neighborhood factors suggest that there may be highly variable patterns even among a primarily low-income, Hispanic population. This study found that those who were employed spent more time at industrial and office spaces during the week and more time at parks and open spaces during weekends. Participants with higher educational attainment were more likely to take vehicle-based trips, a fact that was consistent with study results of Wu et al. (2013). This study also found that women living in safer neighborhoods performed fewer vehicle-based trips daily, which might be explained by their inclination to take more walking trips given safer streets, although it did not find a statistically significant relationship between neighborhood safety and numbers and durations of pedestrian-based trips.

2.4.4. Implications for Future Studies

This study found pregnant and early postpartum women spent a substantial portion of their time at indoor locations and took several trips per day – approximately a quarter of which were pedestrian trips to visit a variety of destinations. These patterns also differed over the course of the pregnancy and the postpartum period. Findings of this study have important implications for future studies that aim to investigate the association between environmental exposures of pregnant women and maternal or child health outcomes. The residential-based approach used by most studies in the past may under- or over-estimate physical, built, and social environment exposures of interest (e.g., $PM_{2.5}$, green space, crime). Consequently, the true relationships between environmental exposures and targeted health behaviors (i.e., PA) and outcomes (i.e., respiratory diseases) may be masked, especially when investigating acute or short-term dose-response relationships (e.g., daily, weekly, monthly). In addition, the variations in time-activity patterns across pregnancy and postpartum periods suggest the need for more longitudinal studies to complement cross-sectional studies.

Kwan (2018) argues that spatial and temporal mismatches and uncertainties make it difficult to clarify the influence of contextual variables on health behaviors or outcomes. Given the need to prepare for childbirth, infant care, and other responsibilities during pregnancy and early postpartum, women's day-to-day time-activity and daily mobility patterns may vary more than those of the general population (Varshavsky et al. 2020). As a result, future studies should move from "snapshot" to activity space-based approaches to assess the environmental exposures of pregnant women (Yi et al. 2019). Mobile sensing technologies, such as GPS, can provide fine-grained mobility trajectories that can be used to assess environmental exposures that reflect time-activity patterns. As a result, these technologies can reduce the uncertainties in contextual exposures (i.e., the disparities between the true contextual and measured contextual units) (Chaix 2018; Matthews and Yang 2013; Robertson and Feick 2018). Lastly, this study found that pregnant and early postpartum women's time-activity and mobility patterns varied across weekend days versus weekdays, employment status, education attainment, and neighborhood cohesion and safety, which suggest that these might be important modifiers to account for in future exposure studies.

2.4.5. Study Strengths and Limitations

To the best of my knowledge, this is the first study that examines time-activity and daily mobility patterns of pregnant women across the pregnancy and early postpartum periods. A major strength is the application of GPS to repeatedly collect highly resolved geospatial location data across the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum. As a result, this study overcame recall biases inherent in self-reported time-activity or mobility surveys and provided insights into longitudinal changes in these patterns. Additionally, the study applies a kernel density-based algorithm to classify stay contexts and trip modes, achieving higher accuracy and better sensitivity than the point-by-point classification approach. Compared to computationally intensive methods, this study's GPS processing and stay/trip detection workflow may offer a lower technical difficulty threshold for future studies that aim at utilizing mobile-phone collected location-tracking data to generate time-activity patterns. Furthermore, this study collected and used highly time-resolved (10-s epoch) GPS data to detect stays and trips and classified spatial context, indoor/outdoor microenvironments, and trip modes in GIS. These fine-grained data and advanced GIS analytical tools helped us to examine the time-activity and mobility patterns during pregnancy and early postpartum at various temporal spacings. The longitudinal design used for this study allowed us to examine both the variations in time-activity patterns between women and the day-to-day variations for each woman.

This study also has a few limitations. First, the GPS data collected by this study had some missingness. To mitigate its impacts on analyses, this study made efforts to impute GPS data using existing information and re-run the analysis with stricter thresholds of daily observation hours or excluding data collected during sleep hours. Results of this study remained largely unchanged. Additionally, missing data did not demonstrate diurnal patterns (i.e., it was roughly invariant throughout the day). However, there are other factors that may still potentially affect outcomes of this study. For instance, missingness patterns of GPS data may be correlated with spatial contexts (e.g., tall buildings, trees) that could obstruct receiver signals. Second, although this study tackled signal loss issue by flagging signal loss scenarios with confidence levels and excluded those with extremely low confidence, it still could not be sure that the locations recorded by the device during signal loss matched the true location. Third, this study could not distinguish a trip to and from work locations from other trips, which might inform the interpretation of results of time-activity patterns for certain respondents and the types of contexts in play. Fourth, this study had a relatively small sample size and only collected 4-day GPS data in two weekdays and two weekend days during each study period. Thus, the time-activity and mobility patterns detected from samples of this study may not capture some less frequent activities that occur on a weekly basis or on other days of the week, such as grocery shopping. Lastly, this study focused on a health disparity group of low-income, Hispanic women, a population that has been understudied and disproportionally exposed to various environmental hazards. Thus, this study's results may not generalize to pregnant women in other regions or SES or racial/ethnic groups; nevertheless, they shed light on an important population, and they may pave the way for future studies to examine pregnant women's environmental exposures within their everyday activity spaces.

2.5. Conclusions

Pregnancy and early postpartum are critical periods for women's health, and this study have shown that time-activity and mobility patterns of women will likely vary over this journey for many women. Time-activity and mobility patterns can also be used to directly determine environmental exposures that may affect both short- and long-term maternal and infant health outcomes. Therefore, future studies examining the impacts of environmental or contextual exposures on maternal or fetal health should consider the dynamics of these patterns because they may directly influence exposure measurement error and the ability to detect meaningful relationships.

Chapter 3 Assessing Dynamic Daily Exposures to Built-Environment Characteristics during Pregnancy and Early Postpartum using Smartphone Location Data

Emerging research has associated BE characteristics (e.g., park access, walkability) with maternal and infant health during and after pregnancy (Porter et al. 2019; Thomson, Goodman, and Landry 2019; McEachan et al. 2016; Boll et al. 2020; Liao et al. 2019; Anabitarte et al. 2020; Torres Toda et al. 2020). However, most studies have measured the BE exposure via static methods (i.e., residential location at one timepoint during pregnancy). These static methods may not capture pregnant women's dynamic daily exposure encountered in activity spaces across the pregnancy and postpartum periods. This chapter evaluates BE exposure measurement error using static versus dynamic daily exposures using 552-days of smartphone location data from 62 Hispanic pregnant women during the 1st and 3rd trimesters, and at 4-6 months postpartum.

3.1. Related Work

The impact of the BE on pregnant women's health has attracted considerable attention over the past decade. Past research has associated exposure to BE characteristics such as shorter distance to parks and public transit stops and higher neighborhood walkability with greater PA outcomes in pregnant women (Porter et al. 2019; Thomson, Goodman, and Landry 2019). Additionally, studies have shown that greater exposure to urban nature (e.g., visual access, proximity, coverage) decreases pregnant women's stress levels and depressive symptoms (McEachan et al. 2016; Boll et al. 2020). Furthermore, studies have linked higher levels of greenness exposure and park coverage to decreased maternal glucose levels, attenuated risks of gestational diabetes mellitus and weight gain, and higher infant birthweight (Liao et al. 2019; Anabitarte et al. 2020; Torres Toda et al. 2020).

However, most studies assess prenatal BE exposure at a single point in time and at the residential neighborhood level (i.e., in a circular buffer around the home location as determined by an address obtained at time of birth) (Banay et al. 2017). This "static" approach has several major limitations. Spatially, relying on residential address at a single point late in the pregnancy ignores residential mobility (or moving) across pregnancy and postpartum (Bell and Belanger 2012; Chen et al. 2010; Hodgson et al. 2015). Also, static methods do not capture women's dynamic BE exposures occurring outside the home in their activity spaces (e.g., walking trips, errands, other visited locations) which can also influence their health outcomes (Matthews and Yang 2013; Perez, Ruiz, and Berrigan 2019). Moreover, it does not consider changes in activities and behaviors as pregnancy progresses over time and into the postpartum period. These could dramatically vary due to preparations for childbirth, difficulty of physically moving around and increased fatigue later in pregnancy, and childcare responsibilities after birth (Varshavsky et al. 2020). Further, within a particular period (e.g., 3rd trimester), day-to-day changes in BE exposure could result from household, occupational, and recreational activities (e.g., grocery shopping, commuting to work) which differ by days of the week. As a result, assessing exposures using static approaches may fail to capture the "true causally relevant" BE characteristics that exert contextual influence on pregnant women's and infants' health and could introduce exposure measurement error and potential bias (Robertson and Feick 2018; Yi et al. 2019).

Increasingly, studies are starting to apply "dynamic" exposure assessment approaches (i.e., matching dynamic human movement with environmental features) to derive BE exposures (Zenk et al. 2011, 2018; Chaix et al. 2012, Jankowska et al. 2021). In these studies, highly resolved (e.g., every few seconds) GPS monitoring data are usually collected, based upon which individual activity spaces are constructed (e.g., activity locations one visits and paths one travels) and integrated with BE layers (e.g., parks polygons, street centerlines) in GIS software to measure individual's dynamic exposures at high spatiotemporal resolutions (e.g., total areas of parks in daily path areas) (Zenk et al. 2011; Yi et al. 2019). Consequently, these dynamic approaches may improve exposure assessment in pregnancy studies compared to residential-based static approaches since they incorporate information about where and when individuals spend their time. However, very few studies have been able to assess dynamic BE exposures during pregnancy and postpartum on a large number of participants given the potentially higher burden of collecting personal, highly resolved geolocation data. Therefore, to understand whether quantified BE exposures and observed health relationships are sensitive to the choice of measurement method, it is important to evaluate the similarity (i.e., correlation) between static and dynamic exposure estimates. To date, few studies have tackled this topic, and none have focused on pregnant women to our knowledge. (Jankowska et al. 2017; Zhao, Kwan, and Zhou 2018).

In addition, there are several examples of health studies where static residential estimates are used to classify individuals into BE exposure groups (e.g., representing high- and low-walkable neighborhoods using top and bottom quartiles of the residential walkability index score) (Van Dyck et al. 2010; Carlson et al. 2015). Especially for pregnancy studies, comparing dynamic exposure estimates to the typically used static residential approach might shed light on the potential for exposure measurement error and how this varies over time (e.g., pregnancy vs. postpartum) and human mobility patterns (i.e., spatial extent of human movement footprints).

To fill these gaps, this study collected 4-day smartphone location data from a group of Hispanic, predominantly low-income women during the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum, and characterized their daily dynamic and static BE exposures in this critical life stage. The potential for exposure measurement error was then examined in relying on daily, static BE exposures (using the 3rd trimester residential location) compared to dynamic exposures within activity spaces in this environmental health disparities subpopulation in Los Angeles, CA. This study has the three following aims:

1) To describe pregnant women's dynamic daily BE exposure patterns during the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum;
2) To assess correlations between various static and dynamic BE exposure measures; and
3) To evaluate the potential extent and drivers of exposure measurement error in static vs. dynamic BE exposure measures.

3.2. Methods

3.2.1. Design and Overview

Data for this study comes from the Real-Time and Personal Sampling sub-study of the MADRES Center. This study uses an intensive longitudinal, observational panel study design and examines the daily effects of environmental exposures and social stressors on maternal pre- and post-partum obesity-related biobehavioral responses. A total of 65 Hispanic, predominantly lower income mothers were drawn from the larger MADRES prospective cohort study between 2016-2018. Participants were recruited from prenatal care providers serving predominantly medically-underserved populations in Los Angeles, California, including two non-profit community health clinics, one county hospital prenatal clinic, one private obstetrics and gynecology practice, and through self-referral from community meetings and local advertisements (O'Connor et al. 2019). To be eligible for this sub-study, a participant needed to be >18 years old with a singleton pregnancy and be at less than 30 weeks' gestation at time of recruitment. In addition, participants who were HIV positive, had physical, mental, or cognitive disabilities that prevented participation, or were currently incarcerated were excluded from the study (O'Connor et al. 2019). The USC Institutional Review Board approved all study procedures, and participants signed an informed consent before enrolling into the study.

3.2.2. Data Collection

3.2.2.1. Geolocation using GPS

This study continuously collected GPS data from 65 study participants at 10-s intervals for four days (two weekdays and two weekend days) during the 1st and 3rd trimester and at 4-6 months postpartum. To enable collecting highly resolved and encrypted GPS data collection, MADRES researchers designed a custom smartphone application (madresGPS app) for Android operating systems. The application on dedicated study smartphones (Samsung MotoG phone) were configured by study coordinators to record geographic coordinates and geolocation/motion metadata, which logged instantaneous GPS location and sensor data every 10 s from the smartphone's multiple built-in location finding features (cell tower triangulation, Wi-Fi networks, and GPS) and motion sensors (O'Connor et al. 2019). Along with the timestamp, the application recorded metadata such as the number of satellites in use/view, geolocation accuracy, source of GPS, velocity (if GPS source), and network connection status (if network source) (O'Connor et al. 2019).

3.2.2.2. Ecological Momentary Assessment (EMA)

Participants self-reported physical context information in EMA surveys delivered through the MovisensXS application (Android), which was pre-installed on the same study phone used to collect GPS data. EMA surveys were designed to prompt at random times during each five pre-specified sampling windows (i.e., wake-up to 10 a.m.; 11 a.m.to 1 p.m.; 2 p.m.to 4 p.m.; 5 p.m.to

7 p.m., and 8 p.m.to bedtime) within the same four-day GPS data collection windows during the three study periods. O'Connor et al. (2019) describes the EMA survey questions in more detail.

3.2.3. Data Processing

3.2.3.1. GPS Data Analysis

The 10-s epoch GPS geolocation data was processed using a custom algorithm I developed and described in detail in Chapter 2 using SAS version 9.4 (SAS Institute Inc). Missing geolocation data was then imputed when participants were very likely to be at their home location during the day- or night-time. At night, typical sleep and wake time windows were used along with location before and during to determine whether participants were likely to be home and to fill in any gaps in the GPS data. During the day, confirmed EMA reports of being at "Home-Indoor" or "Home-Outdoor" all day were used to fill in gaps with the home location. Flags were then created for days with <6 hours of GPS data (post-imputation) as invalid days, after considering missing data patterns.

3.2.3.2. Exposure Assessment

<u>Constructing Activity Spaces</u>

Daily activity spaces were constructed for each participant based on their geolocation trajectories via the route buffer (RB) and kernel density estimation (KDE) methods (Figure 3.1) using ArcGIS Pro 10.7.1 (Esri, 2021). The two methods complement one another and capture pregnant women's daily exposure to BE characteristics, including those along women's daily travel paths (via RB) and around activity locations where they spent the most time (via KDE).

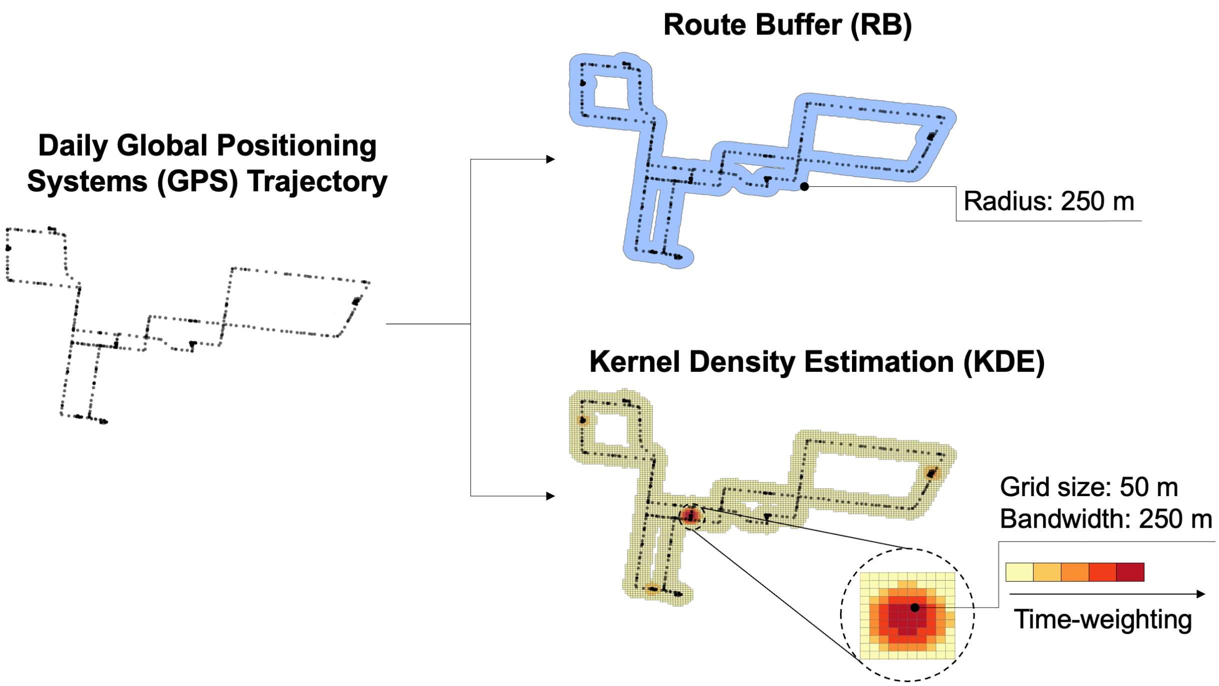


Figure 3.1. An illustration of two activity space metrics – route buffer (RB) and kernel density estimation (KDE) applied in this study

To construct buffers along routes, consecutive GPS points were joined into lines and buffered using a 250 m radius. This distance corresponds to the depth of several blocks in urban Los Angeles, CA. It was selected to approximate two hypothetical mechanisms on how BE characteristics could potentially influence health behaviors and outcomes, including viewshed (i.e., seeing a park when walking on a street) and awareness (i.e., knowing a recreational facility is located nearby) (Yi et al. 2019). Additionally, the geographical area of these route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

Additionally, the KDE approach was applied to generate time-weighted activity grids using 50 by 50 m cells with a bandwidth of 250 m (to match the RB radius). Each grid was assigned a normalized time weight (range from 0 to 1) based on percentage of stay duration within a given day, with total weights adding up to 1.

Defining Residential Neighborhoods

To assess residential neighborhood exposures using the "static" approach, the home location was first determined based on where participants spent the most time in their 3rd trimester. This location was selected as most similar to the typically used approach in pregnancy studies (i.e., assessing exposure based on residential address provided on birth certificates or questionnaires after delivery and assuming it represents the entire prenatal period). Briefly, KDE was applied to identify the longest duration stay during the 3rd trimester as the home location, which was then used to derive 800 m residential network buffers (RNB) via the Service Area Analysis tool and StreetMap Premium product in ArcGIS Pro 10.7.1 (Esri, 2021). The network buffer better captures the area to which a pregnant woman could realistically travel from the home residence as compared to a circular buffer (James et al. 2014). An 800 m radius, which corresponds to a 5-10-minute walk, is recommended for populations with relatively restricted mobility (James et al. 2014; Frank et al. 2017). Additionally, a sensitivity analysis was performed using a larger radius (e.g., 1,600 m) and the resulting BE exposure estimates differed only slightly, so we chose to report 800m results only.

Assessing Built Environment Exposures

Eight BE measures were derived using the RNB, RB, and KDE methods, respectively. These included greenness (3 measures), park and public transit access (3 measures), street connectivity (1 measure), and walkability (1 measure) as follows: mean Normalized Difference Vegetation Index (NDVI; ranges from -1 to 1 with higher value represents higher greenness; the NDVI dataset was date-matched to corresponding residential buffers and activity spaces when calculating mean NDVI), percent green space along walkable roads, and percent tree cover along walkable roads, distance to the nearest park entrance, distance to the nearest public transit stop, total area of parks and open space, pedestrian-oriented intersection density, and walkability index score (ranges from 1 to 20 where higher scores represent more walkable), all of which have been reported by previous studies to be associated with various human activities and health outcomes, particularly among pregnant women (Banay et al. 2017; Besser and Dannenberg 2005, Jiang et al. 2016; Pickard et al. 2015; Porter et al. 2019; Pretty et al. 2005; Tsai, Davis, and Jackson 2019; Saelens et al. 2014). All BE measures, corresponding data sources, resolution, and processing steps and interpretation are shown in Table 3.1.

RNB and RB exposures were calculated by summarizing values of the respective BE measures (e.g., mean NDVI, total areas of parks and open space) within boundaries of corresponding spatial units (i.e., 800 m residential network buffer, 250 m route buffer). KDE exposures were calculated by weighting grid-based values of the respective BE measures with time spent (e.g., multiplying walkability index score value of the grid by percentage of time spent to produce weighted walkability scores per grid, then taking the sum of weighted scores across all grids). Exposures were calculated using Eq 3.1 for the RNB or RB methods and Eq 3.2 for the KDE methods as follows:

$$Exposure_{RNB/RB} = \sum_{n=1}^{n} (\%Area_n * BEC_n) \qquad \text{Eq 3.1}$$

$$Exposure_{KDE} = \sum_{n=1}^{n} (\%Area_n * BEC_n * TW_n) \qquad \text{Eq 3.2}$$

Table 3.1. Built-environment (BE) measures, corresponding data sources, resolutions, and processing steps.

Measures	Data Sources	Data Resolutions	Processing Steps and Interpretation
Mean NDVI (range from -1 to 1)	NASA MODIS 16-Day L3 Global product[1]	250 x 250 m raster grids	The mean Normalized Difference Vegetation Index (NDVI) was used to represent overall vegetation levels within respective spatial units (i.e., residential neighborhood, activity space). NDVI values range from -1 to 1, with negative values corresponding to areas with water surfaces, 0-.2 representing barren surfaces, .2-.5 representing sparse vegetation, and >.5 representing dense vegetation.
Percent green space along walkable roads (%)	EPA EnviroAtlas Community Data	Census block groups	Green space areas were derived by combining areas of multiple land cover classes including water, trees and forest, grass and herbaceous cover, shrubs, agriculture, orchards, and woody and emergent wetlands. Sidewalk areas were derived by buffering NAVTEQ roads with a speed limit less than 55 miles per h (potentially walkable roads) by a width of 25 m on each side. The measure then was calculated by intersecting tree cover and sidewalk areas per city block.
Percent tree cover along walkable roads (%)	EPA EnviroAtlas Community Data	Census block groups	Tree cover areas were derived by combining areas of three land cover classes - trees, forests, and woody wetlands. Sidewalk areas were derived by buffering NAVTEQ roads with a speed limit less than 55 miles per h (potentially walkable roads) by a width of 8.5 m on each side. This measure then was calculated by intersecting tree cover and sidewalk areas per city block.
Distance to the nearest park entrance (m)	EPA EnviroAtlas Community Data	Buffer zones	This measure was derived by delineating approximate walking areas from a park entrance at any given location within the EnviroAtlas community boundary (i.e., Los Angeles County).
Total parks and open space coverage (km^2)	California Protected Areas Database	Parks and open space polygons	This measure included 1) National/state/regional parks, forests, preserves, and wildlife areas; 2) large and small urban parks that are mainly open space (as opposed to recreational facility structures); 3) land trust preserves; and 4) Special district open space lands (watersheds, recreational areas, etc.) and other types of open space.
Distance to the nearest public transit stop (m)	EPA Smart Location Database	Census block groups	This measure was derived by measuring the minimum walking distance in meters between the 2010 population-weighted census block groups (CBG) centroid (as used by SLD version 2.0) to the nearest transit stop of any route type.

Table 3.1 (Cont.)

Measures	Data Sources	Data Resolutions	Processing Steps and Interpretation
Pedestrian-oriented intersection density (m)	EPA Smart Location Database	Census block groups	This measure was derived based on an analysis of NAVTEQ 2011 Streets data. All 3-way intersections were weighted by .6667 since they reduced street connectivity compared to intersections with 4 or more legs.
Walkability index score (range from 1 to 20)	EPA Smart Location Database	Census block groups	A composite index score combining household and employment density, street intersection density, and distance to nearest transit stops. This measure represent different BE characteristics that are known to be supportive of walking. The index scores range from 1 to 20, with higher values representing better walkability.

[1] The MODIS NDVI dataset was date-matched to corresponding activity spaces when calculating mean NDVI.

Note: NASA = National Aeronautics and Space Administration. MODIS = Moderate Resolution Imaging Spectroradiometer. EPA = Environmental Protection Agency.

where BEC_n is the exposure estimate for a BE measure in the nth spatial unit (e.g., census block group, grid) that intersects the RNB, RB, or KDE; $Area_n$ is the percentage of the area in the nth spatial unit that falls within the RNB, RN, or KDE; and TW_n is the normalized time weights (range from 0 to 1) of the nth grid.

3.2.4. Statistical Analysis

Descriptive statistics were calculated for static (i.e., RNB) and dynamic (i.e., RB and KDE) BE exposures, respectively. Additionally, intraclass correlation coefficients (ICC) were calculated to estimate the proportion of day-to-day variability in the dynamic exposures that was between-participant (i.e., ICC%) compared to within-participant (i.e., 1-ICC%). Two-level (days nested within participants) linear mixed-effects random intercept only models were used to calculate the ICCs for the 8 dynamic BE measures. ICC value cut-offs of .40 and .75 were selected to indicate weak (ICC<.40), moderate (.40≤ICC<.75), or strong (ICC≥.75) within-person correlations (Zenk et al. 2018). Analyses were conducted in *R 4.0.2* (R Foundation for Statistical Computing, 2021) using the *lme4* package (version 27.1) (Bates et al. 2015).

Pearson's correlation coefficients were used to examine similarity of BE exposures assessed using static versus dynamic methods (e.g., correlation between RNB and KDE mean NDVI), given the approximately normal distributions of BE measures. Moreover, Pearson correlation coefficients were calculated by study period (i.e., 1st trimester, 3rd trimester, and 4-6 months postpartum) to investigate how well dynamic estimates correlate with static 3rd trimester estimates as an indication of potential for measurement error in relying solely on the latter.

Furthermore, daily BE exposures were classified into four groups (quartiles) using KDE as the most dynamic method that is spatiotemporally matched to human movement and the percent of "misclassified" days that were assigned to a different group using the static RNB method was calculated as an indication of potential for exposure measurement error in the latter approach. For example, if the KDE method classifies a day into the highest exposure (4th quartile) group but the RNB method classifies it into lower exposure groups (1st, 2^{nd,} or 3rd quartile), it was labelled as a misclassified day. Sankey diagrams were then used to illustrate these relationships, where arrows represent flows from quartiles of KDE exposures (left, assumed "true" daily varying exposure) to quartiles of RNB exposure (right, static exposure), and the thickness of the lines flowing from left to right (representing percent of days) indicates the potential for exposure misclassification. In this study, whether potential exposure misclassification was sensitive to daily mobility was investigated by creating the same Sankey diagrams for low, medium, and high mobility days. Analyses were conducted in *R 4.0.2* (R Foundation for Statistical Computing, 2021) and Sankey diagrams were created using the *ggalluvial* package (version 0.12.3) (Brunson 2020).

3.3. Results

3.3.1. Data Completeness

Across three study periods, 62 out of 65 participants who were initially enrolled in the study provided at least one valid GPS observation day (≥6 hours of data). Thirty-five out of 62 participants had at least one valid day in all three study periods; 17 out of 62 in two of the three periods; and 10 out of 62 in just one of the three periods. The final analytical sample of this study comprised a total of 552 valid person-days of GPS data from 62 participants, with 205 person-days during the 1st trimester, 180 person-days during the 3rd trimester, and 167 person-days at 4–6 months postpartum. An average of 8.9 valid GPS days (*SD*=3.00; *Range*: 3.00-12.00) were provided by participants across the three periods. On average, 21.7 hours (*SD*= 5.00; *Range:* 6.2-24.00) of GPS observations were collected on valid days. The number of hours was highest in the 3rd trimester (*Mean*=22.3 hours; *SD*=4.4; *Range:* 6.5-24.00) followed by the 4-6 months postpartum period (*Mean*=21.8 hours; *SD*=4.7; *Range:* 7.00-24.00) and then the 1st trimester (*Mean*=21.1 hours; *SD*=5.6; *Range:* 6.2-24.00). Almost half of the valid person-days (49.3%) were weekend days across the three periods.

3.3.2. Daily BE Exposure Estimates during Pregnancy and Early Postpartum

Descriptive statistics for daily BE exposure estimates derived by the RNB, RB, and KDE methods are shown in Table 3.2. The median geographic extent was 2.49 km^2 (*IQR*=11.20), which is equivalent in coverage to several city blocks (.5 to 1 mile long) in urban Los Angeles, CA. Depending upon the BE measure, exposure estimates can greatly vary across the three methods. In addition, the exposure estimates derived by the KDE method had the largest variability (i.e., IQR values) among the three methods.

Table 3.2. Descriptive statistics of daily built-environment (BE) exposure estimates for participants using the route buffer (RB), kernel density estimation (KDE), and residential network buffer (RNB) methods.

	N=552 person-days from 62 participants					
Variables	**Mean**	**SD**	**Median**	**IQR**	**Min**	**Max**
Geographic extent (km^2)						
RB 250 m	7.96	11.94	2.49	11.20	.20	91.91
Normalized Difference Vegetation Index (NDVI) (range from -1 to 1)						
RB 250 m	.18	.05	.18	.06	.06	.41
KDE 250 m	.18	.05	.17	.06	.08	.41
RNB 800 m	.18	.05	.18	.07	.10	.38
% Green space along walkable routes						
RB 250 m	23.30	5.87	22.76	6.77	6.61	46.76
KDE 250 m	23.28	8.30	21.87	10.32	1.70	46.27
RNB 800 m	23.04	5.97	22.40	7.10	12.14	45.70
% Tree cover along walkable routes						
RB 250 m	21.45	5.51	20.75	6.03	6.32	44.78
KDE 250 m	22.58	8.16	21.99	10.77	1.74	50.37
RNB 800 m	21.72	5.75	20.57	6.06	10.68	45.63
Distance to the nearest park entrance (m)						
RB 250 m	877.97	397.02	791.82	421.93	294.97	2409.52
KDE 250 m	812.31	455.44	668.94	411.95	51.67	2342.11
RNB 800 m	789.29	414.09	660.04	302.91	400.38	2387.07
Total parks and open space area (km^2)						
RB 250 m	243.53	608.87	15.50	146.21	.00	4817.38
KDE 250 m	.03	.10	.00	.01	.00	.93
RNB 800 m	9.67	15.65	2.84	11.44	.00	77.68
Distance to the nearest public transit (m)						
RB 250 m	280.02	103.27	275.38	144.08	1.94	532.25
KDE 250 m	284.95	123.13	282.97	177.60	.03	1041.17
RNB 800 m	268.94	105.79	265.49	135.86	81.28	645.76
Pedestrian-oriented intersection density (# per mi^2)						
RB 250 m	47.90	33.35	42.27	26.55	2.20	190.79
KDE 250 m	51.81	40.78	41.73	38.92	.24	240.01
RNB 800 m	57.60	44.70	46.76	32.24	3.00	222.66
Walkability index score (range from 1 to 20)						
RB 250 m	14.93	1.50	14.96	2.02	10.29	18.43
KDE 250 m	14.84	1.72	14.92	2.59	10.09	18.08
RNB 800 m	14.94	1.43	15.17	1.89	11.59	18.11

In terms of KDE-based activity space neighborhood greenness, women on average were exposed to an NDVI value (range from -1 to 1) of .18 (*SD*=.05). This indicates their daily activity locations, on average, had barren surfaces or very sparse vegetation. In addition, the KDE-measured percent of green space and tree cover along walkable roads at their daily activity locations on average was 23.3% (*SD*=8.3) and 22.6% (*SD*=8.2), respectively. Both numbers were lower than the Los Angeles County average of 32.4% (% of green space along all walkable roads of Los Angeles County) and 28.1% (% of tree cover along all walkable roads of Los Angeles County). Mean exposure estimates of all greenness measures varied slightly for the same measure across the RNB, RB, and KDE methods.

Turning next to park access, women's KDE-measured mean daily distance from their daily activity locations to the nearest park entrance was 812 m (*SD*=455; corresponding to a 15-20-minute walk). The estimates differed slightly with the RB or RNB approaches. The total estimated exposures to parks and open space area; however, varied tremendously. Women were exposed to an average of only 0.03 km^2 parks and open space per day (about the size of a tiny neighborhood park in urban Los Angeles) using KDE, which was on average < 0.5% of exposure to parks and open space areas using RB and RNB. Women's KDE-measured mean distance to the nearest public transit stop at daily activity locations was 285 m (*SD*=123; corresponding to <5-min walk).

Lastly, regarding street connectivity and walkability, the KDE-measured mean number of pedestrian-oriented street intersections at daily activity locations women visited was about 52 intersections per square mile (*SD*=41), and the mean walkability index score was 14.8 (*SD*=1.72; range from 1 to 20). These numbers were 34.7% and 1.5 scores higher than the LA County average, respectively. Exposure estimates of these two measures varied slightly across the three methods.

3.3.3. Within-person Correlations in Daily BE Exposures across Time

ICCs for KDE- and RB-derived day-level exposure estimates are presented in Table 3.3. ICC represents the within-person correlation between (day-level) exposure estimates for each BE variable. In other words, the higher the ICC value is, the larger portion of the variance in day-level BE exposure would be explained by between-person (person-level) differences.

According to Table 3, most BE exposures demonstrated strong within-person correlations (ICC>.75), which can be interpreted as >75% of differences in day-level exposures for a specific BE variable were driven by between-person differences. However, an exception was the Total Park and Open Space Area variable, which showed weak (ICC_{RB}=.13) to moderate (ICC_{RB}=.49) within-person correlations. Lastly, for each BE variable, its exposures derived using the RB method had overall lower ICC values than the KDE method (e.g., $ICC_{KDE\text{-}NDVI} > ICC_{RB\text{-}NDVI}$), suggesting weaker within-person correlations for RB-based day-level estimates.

3.3.4. Correlations of BE Exposures across methods (Static versus Dynamic)

Pearson correlation coefficients between exposure estimates of the same BE measure derived by static versus dynamic methods (e.g., RNB-based mean NDVI versus KDE-based mean NDVI) are summarized in Table 3.4. In general, stronger positive correlations were found between RNB and KDE exposure estimate pairs than between RNB and RB pairs. Moreover, the strength of correlations varied substantially by BE measure.

Specifically, RNB estimates of total area of parks and open space were weakly positively correlated (r=.31, p<.01) with KDE estimates. The RNB and KDE exposure estimates for % green space and % tree cover along walkable roads were moderately positively correlated (r=.52,

Table 3.3. Intraclass-Correlation Coefficients (ICCs) of daily exposure estimates derived using the kernel density estimation (KDE) and route buffer (RB) methods.

Variables	**ICC (KDE)**	**ICC (RB)**
Normalized Difference Vegetation Index (NDVI; range from -1 to 1)	.79	.62
% Green space along walkable roads	.82	.56
% Tree cover along walkable roads	.87	.60
Total parks and open space area (km^2)	.49	.13
Distance to the nearest park entrance (m)	.91	.63
Distance to the nearest public transit stop (m)	.76	.61
Pedestrian-oriented intersection density (# per mi^2)	.90	.74
Walkability index score (range from 1 to 20)	.88	.64

Note: ICC value cut-offs of .40 and .75 were selected to indicate weak (ICC<.40), moderate (.40≤ICC<.75), or strong (ICC≥0.75) within-person correlations.

$P<.01$ and $r=.55$, $p<.01$, respectively). Lastly, the exposure estimates derived by RNB and KDE for the remainder of BE measures were strongly positively correlated ($r>.7$, $p<.01$). The correlation coefficients between RNB and KDE exposure estimates decreased slightly at 4-6 months postpartum and decreased substantially during the 1st trimester compared to the 3rd trimester (Table 3.4). This same pattern is manifested in the distance to the nearest public transit stop measure ($r=.61$ between RNB versus KDE during the 1st trimester compared to $r=.82$ between RNB versus KDE during the 3rd trimester).

3.3.5. Impact of Daily Mobility on Potential for Exposure Misclassification using the Static Method

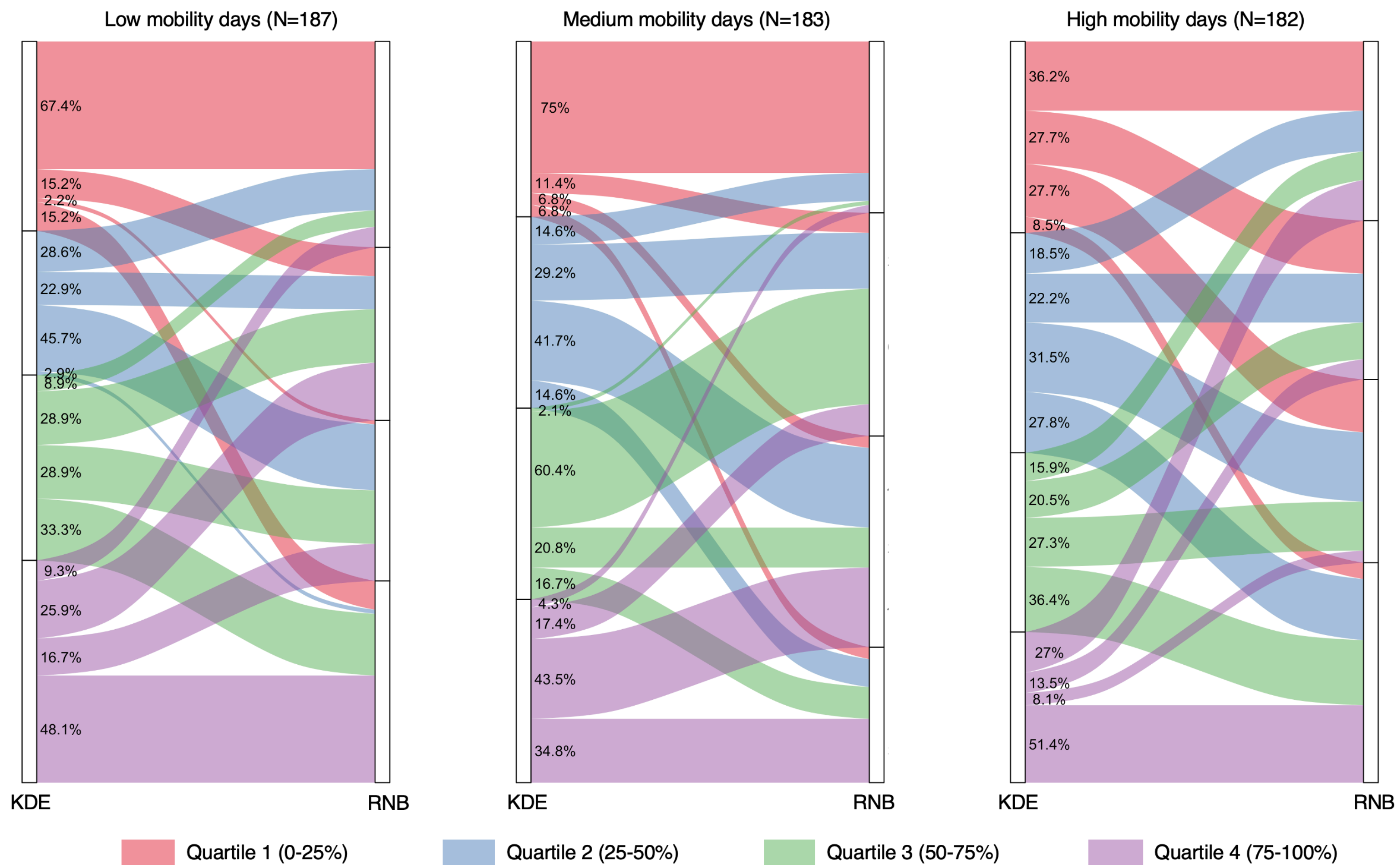
Impact of daily mobility (i.e., low, medium, and high mobility days) on potential exposure misclassification using the “static” RNB method (at single 3rd trimester residential location) as compared to “dynamic” KDE method (at a daily level based on GPS tracks) is shown in Figures 3.2a-h.

Table 3.4. Pearson correlation coefficients between day-level static versus dynamic exposure estimates for the same built-environment (BE) variable during the 1st and 3rd trimesters and 4-6 months postpartum periods.

BE Variable Pairs	**Pearson *r***			
	Overall (N=552 person-days)	The 1st trimester (N=205 person-days)	The 3rd trimester (N=180 person-days)	4-6 months postpartum (N=167 person-days)
Normalized Difference Vegetation Index (NDVI; range from -1 to 1)				
RNB ~ KDE	.82*	.84*	.71*	.88*
RNB ~ RB	.73*	.78*	.58*	.78*
% Green space along walkable routes				
RNB ~ KDE	.52*	.45*	.57*	.56*
RNB ~ RB	.61*	.56*	.63*	.64*
% Tree cover along walkable routes				
RNB ~ KDE	.55*	.48*	.62*	.59*
RNB ~ RB	.67*	.66*	.69*	.67*
Distance to the nearest park entrance (m)				
RNB ~ KDE	.89*	.9*	.9*	.88*
RNB ~ RB	.75*	.81*	.74*	.71*
Total parks and open spaces areas (km^2)				
RNB ~ KDE	.31*	.29*	.4*	.3*
RNB ~ RB	-.04	-.02	.01	-.11
Distance to the nearest public transit stop (m)				
RNB ~ KDE	.74*	.61*	.82*	.85*
RNB ~ RB	.65*	.66*	.58*	.72*
Pedestrian-oriented intersection density (# per mi^2)				
RNB ~ KDE	.79*	.81*	.79*	.76*
RNB ~ RB	.69*	.63*	.7*	.73*
Walkability index score (range from 1-20)				
RNB ~ KDE	.84*	.83*	.86*	.83*
RNB ~ RB	.73*	.72*	.72*	.75*

*p<.01.

Note: KDE = Kernel Density Estimation. RB = Route Buffer. RNB = Residential Network Buffer.



(a) % green space along walkable routes

Figure 3.2. The extent and direction of daily exposure misclassification using third trimester residential network buffer (RNB) exposures for built-environment (BE) measures compared to trimester-specific kernel density estimation (KDE) estimates.

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

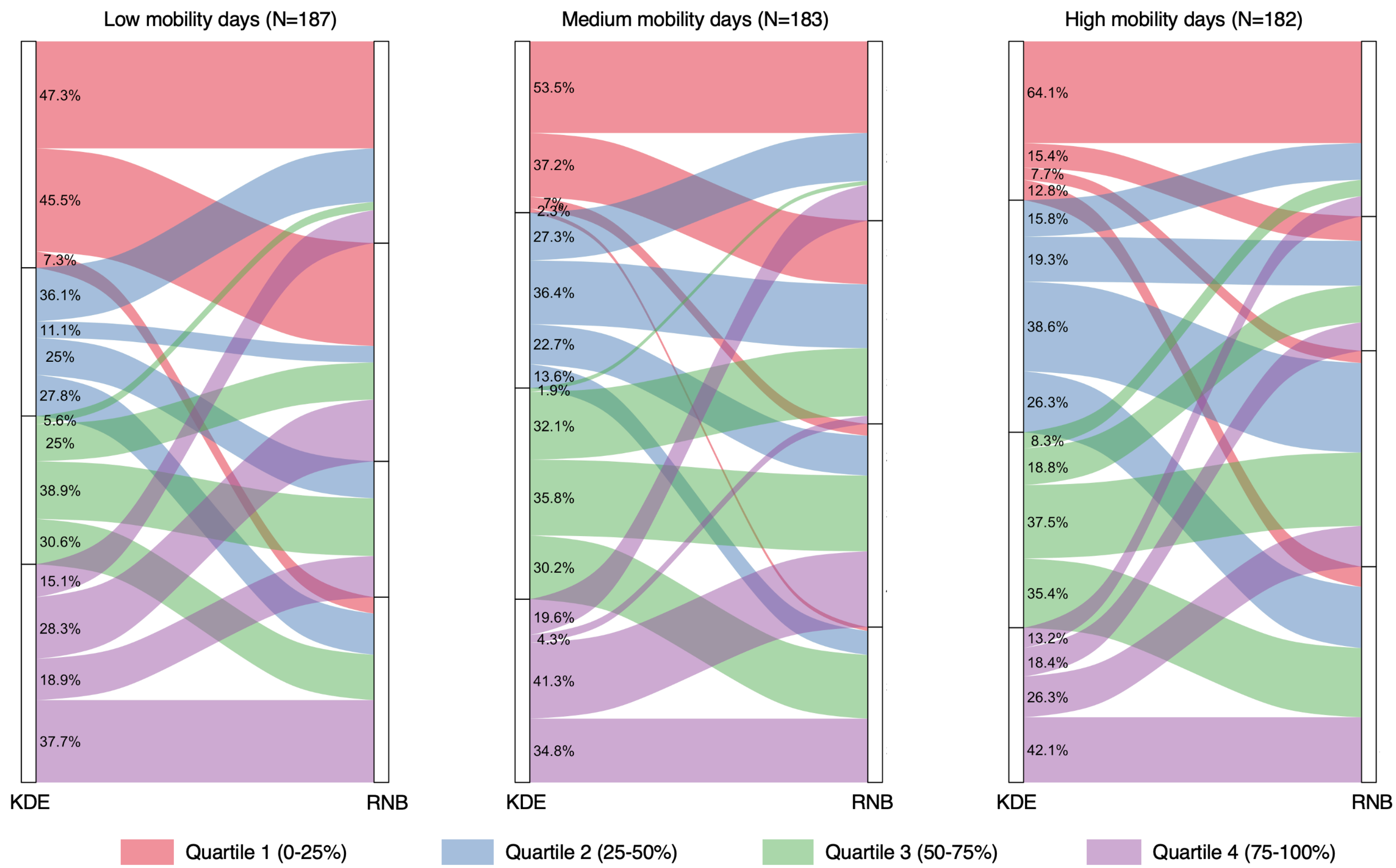


Figure 3.2. (b) % tree cover along walkable routes

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

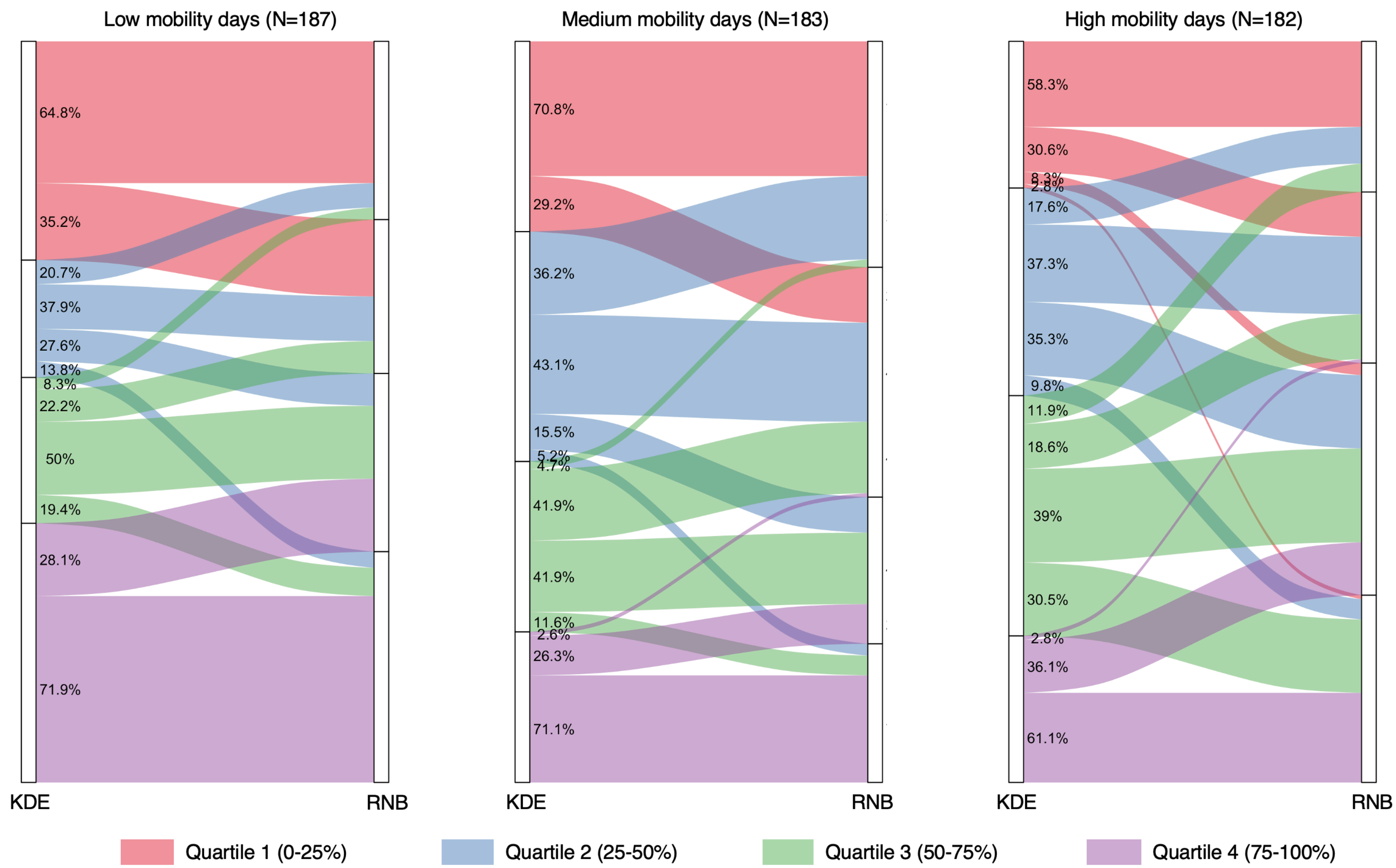


Figure 3.2. (c) Normalized Difference Vegetation Index (NDVI; ranges from -1 to 1)

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

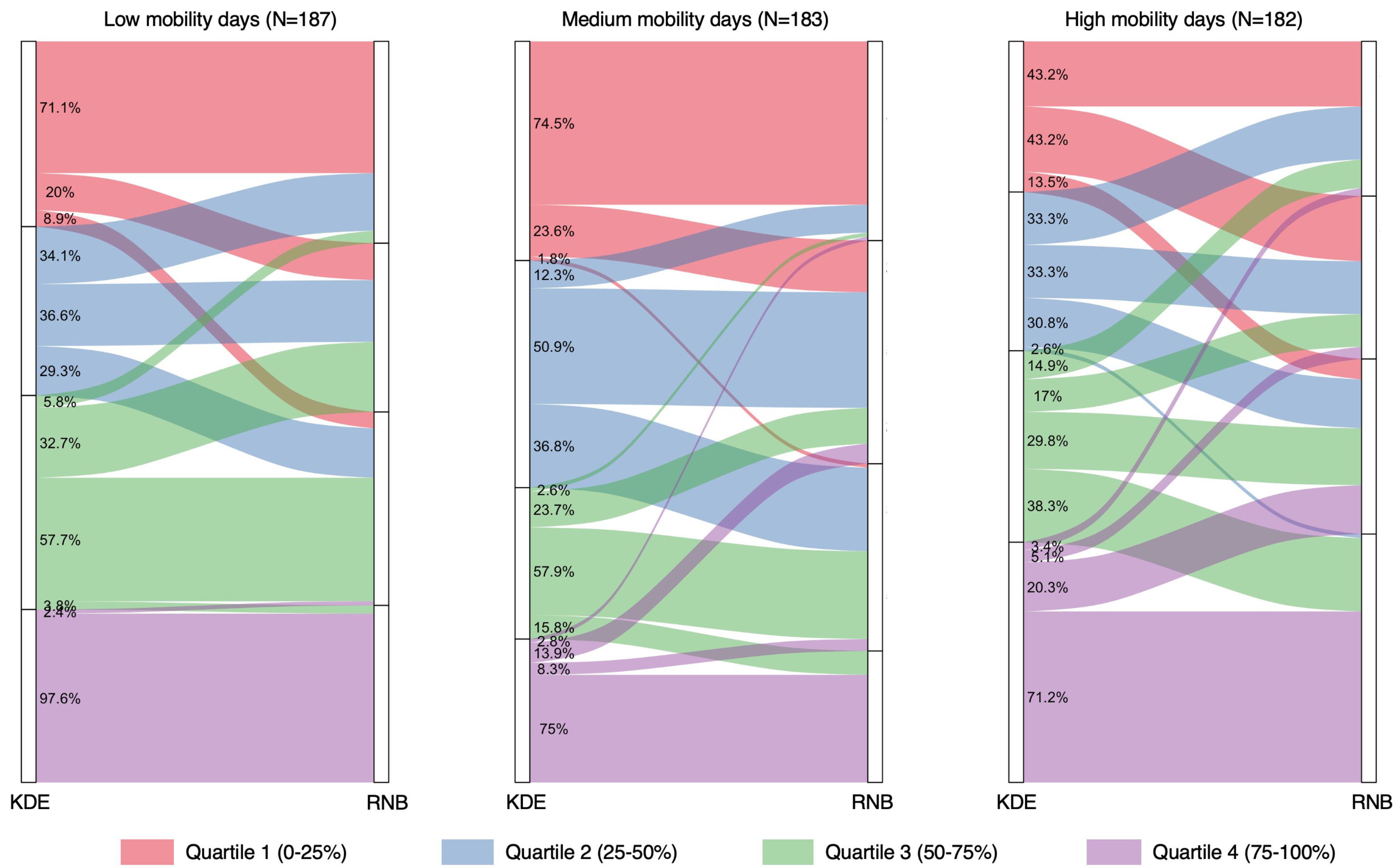


Figure 3.2. (d) Distance to the nearest park entrance (in m)

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

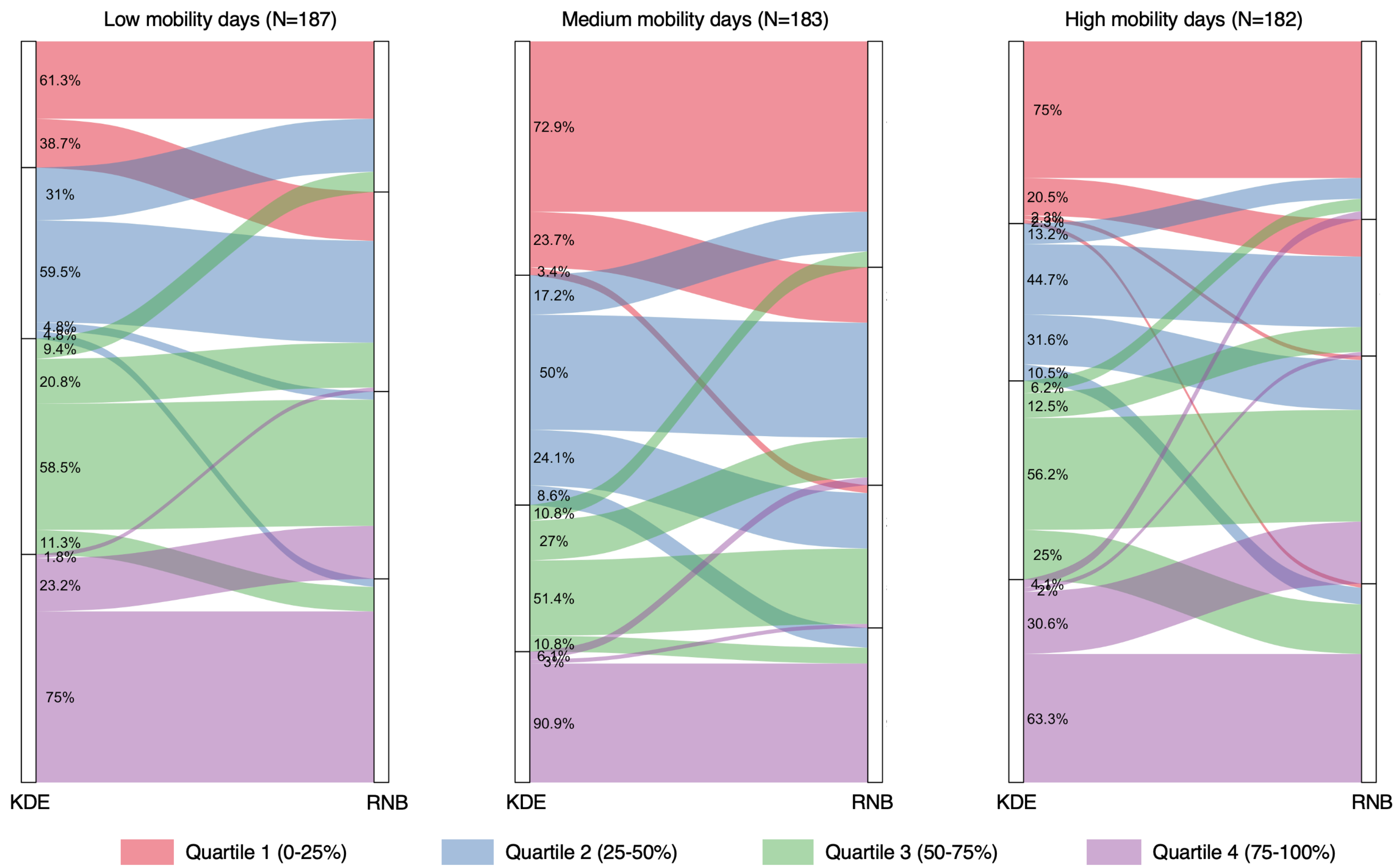


Figure 3.2. (e) Distance to the nearest public transit stop (in m)

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

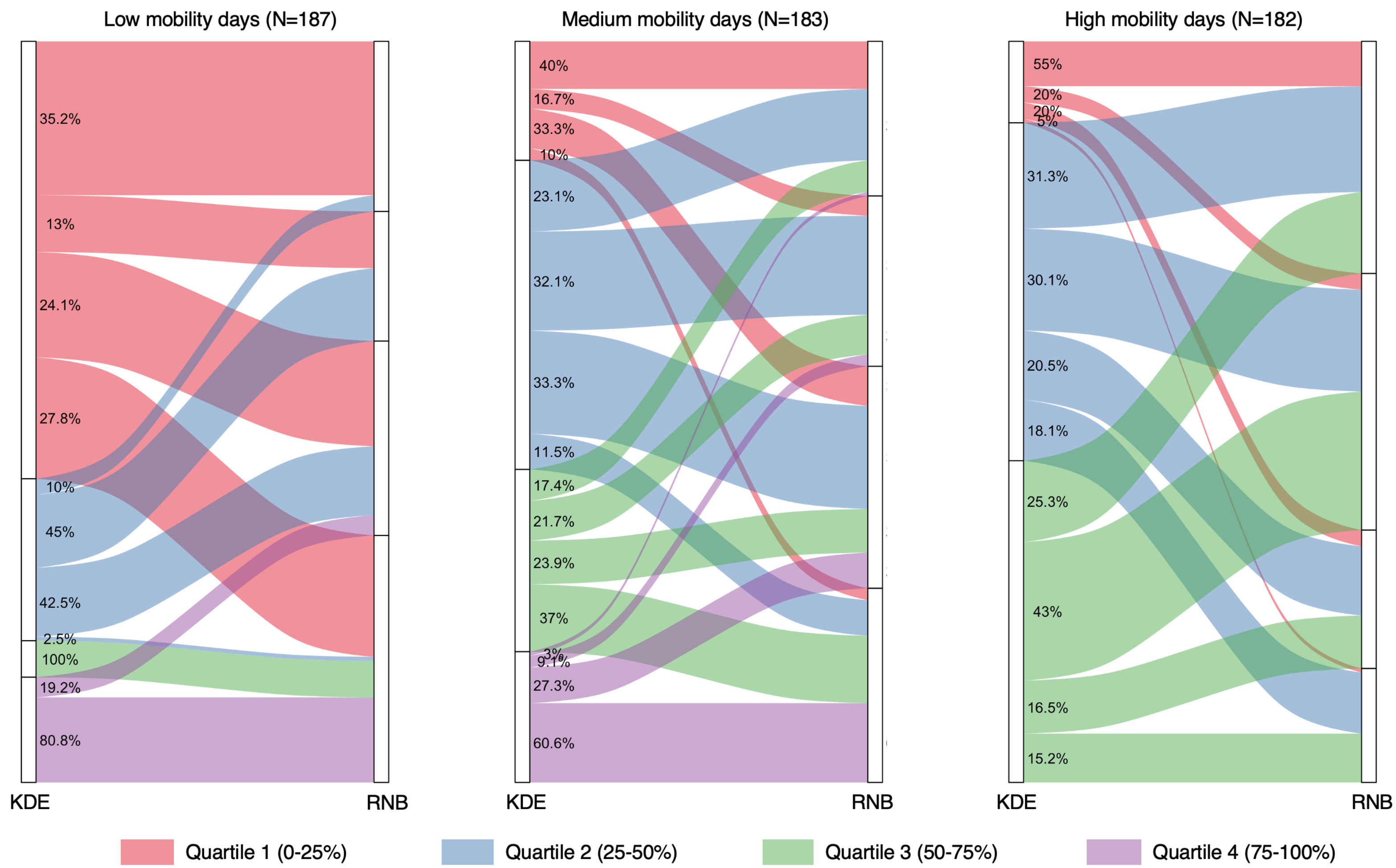


Figure 3.2. (f) Total area of parks and open space (in km^2)

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

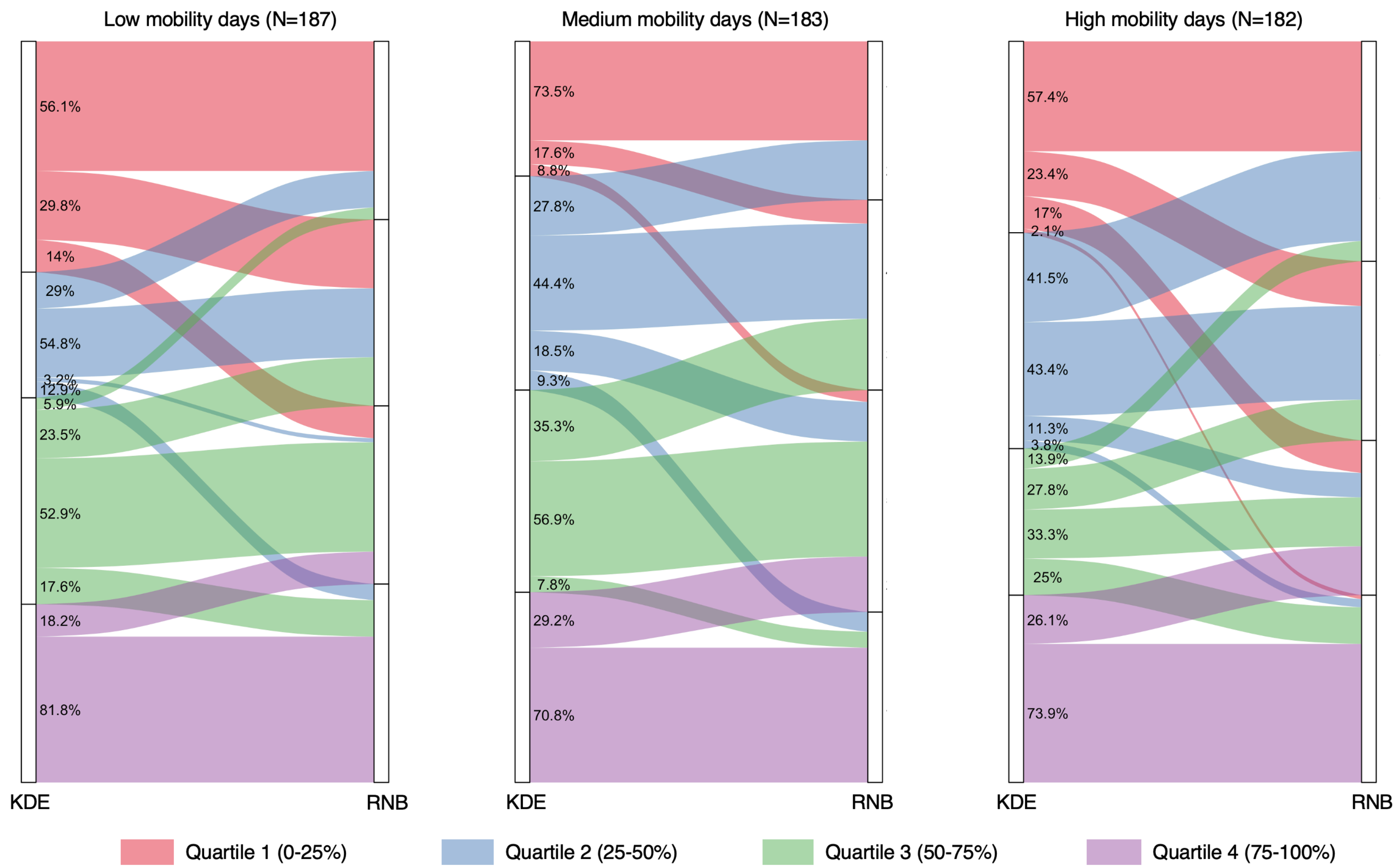


Figure 3.2. (g) Pedestrian-oriented intersection density (per mi^2)

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

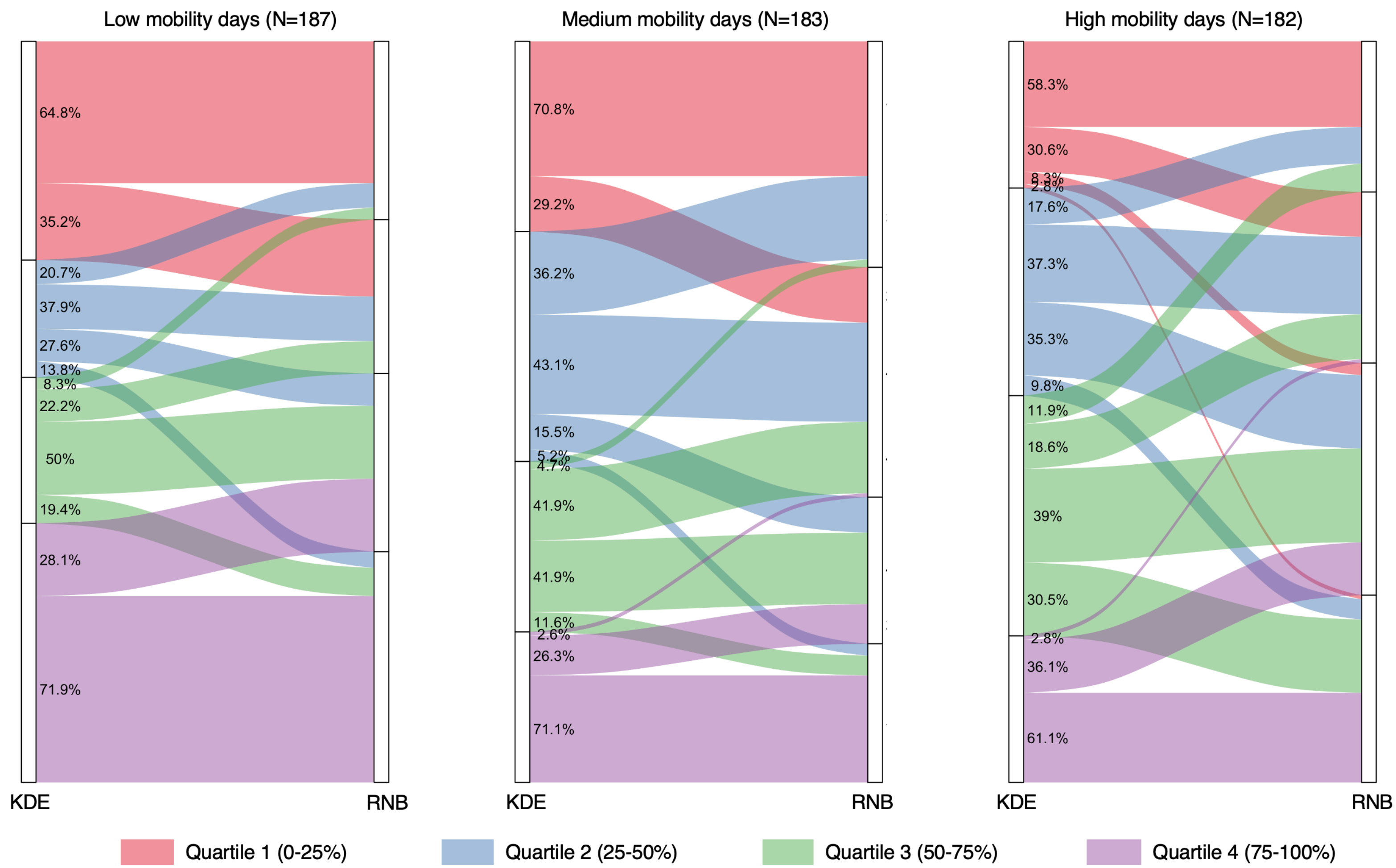


Figure 3.2. (h) Walkability index score (ranges from 1 to 20)

Note: The geographical area of route buffers was calculated to represent spatial extent of daily mobility and classified into low, medium, and high mobility days based on tertiles.

According to these figures, impact of daily mobility on potential exposure misclassification was observed across all BE measures when relying on the 3rd trimester RNB method vs the dynamic KDE method, so that misclassification was largest in high mobility days. This was manifested for measures such as NDVI, distance to nearest park entrance, distance to public transit stop, and total area of parks and open space (Figures 3.2c, 3.2d, 3.2e, and 3.2f). However, this result was less consistent for percent green space along walkable roads, pedestrian-oriented intersection density, and walkability index score measures (Figures 3.2a, 3.2g, and 3.2h) and reversed for mean percent tree cover along walkable roads measure (Figure 3.2b).

Notably, in the highest exposure group (4th quartile) of high mobility days, 49.6% and 57.9% of person-days were misclassified into different groups by the RNB method for % green space along walkable roads and % tree cover along walkable roads measures (Figures 3.2a and 3.2b). The percent of misclassification ranged from 25-35% for the highest exposure group in the remainder of BE measures.

3.4. Discussion

In this study, daily dynamic exposure to BE characteristics during the 1st and 3rd trimesters and at 4-6 months postpartum was described by analyzing highly resolved smartphone location data collected from a sample of 62 Hispanic pregnant women (across 552 observation days) in Los Angeles, CA. Additionally, a critical yet unaddressed research question was answered – how similar were pregnant women's BE exposure derived by the residential-based static method applied by previous studies, to GPS-based dynamic exposure in their daily activity spaces? This study's results have important implications for future studies interested in the association between the BE exposure and maternal and infant health, especially in lower SES and racial/ethnic minority groups. The implications of findings are discussed below.

3.4.1. Women's Daily BE Exposures during Pregnancy and Early Postpartum

Women in our sample were found to have daily activity spaces that were equivalent to several city blocks in Los Angeles (LA). Past studies have found lower SES groups have lower levels of mobility in LA compared to higher SES groups, which may explain the overall small daily spatial footprints in our predominantly low-income sample in this largely sprawling city (Kim and Kwan 2021; Giuliano 2005). Kim and Kwan (2021) found low income and female groups in Los Angeles had lower levels of daily mobility and were often "trapped" in their residential neighborhoods which have disproportionally high exposures to environmental hazards (e.g., traffic, air pollution). Therefore, the low mobility of the MADRES sample indicates residential BE exposure may have greater influences on their activities and health during pregnancy and early postpartum than their high SES counterparts, contrary to my original hypothesis.

In this study, multiple measures were applied to capture different aspects of the greenness exposure, including park coverage and proximity, vegetations levels (i.e., NDVI value), and % green space and tree cover along walkable roads. Results showed women in this sample were found to be typically exposed to daily activity spaces featuring very low to low vegetation levels and minimal parks and open space. Wolch, Wilson, and Fehrenbach (2005) report low-SES areas and neighborhoods dominated by Latinos in Los Angeles have dramatically lower levels of park coverage compared to White-dominated areas, which may explain the overall low greenness exposure in this sample given the greater role of residential exposures in women's total exposures. Interestingly, the women in sample of this study had convenient access to parks in their daily activity spaces (i.e., the nearest park was on average only a 5-10 min walk), which did not lead to actual park use (Chapter 2 found they had very low visits to parks and open space). It is possible that women in the study sample have individual preferences to visit certain parks, which may or may not be the nearest park (Kaczynski and Mowen 2011). Moreover, park quality, amenities, and safety may be more important factors than distance to the closest park to determine park use behaviors, especially for low SES groups (Kaczynski, Potwarka, and Saelens 2008).

The women were exposed to activity spaces with very high proximity to public transit (typically <5-min walk to the nearest public transit stop) and higher than Los Angeles County average street connectivity and walkability. These findings indicate women overall may be exposed to a BE which better facilitates utilitarian walking (e.g., visits to corner groceries) and active transport (e.g., walking to transit stops) than recreational activities (e.g., exercise in a park). Nevertheless, the health impacts of daily exposures to high density areas as identified in this sample should be further examined since previous research has also reported that urban areas with concentrated activities may yield both health benefits and costs such as exposure to high levels of air pollution (Marshall, Brauer, and Frank 2009).

3.4.2. Similarities of Exposure Estimates between Static and Dynamic Methods

Overall, the results showed that the correlations between the static and KDE estimates were higher than those between the static and RB estimates. This is not surprising given the KDE method weights exposure based on the duration of the stay (i.e., time-weighted spatial averaging) and women on average spent a significant amount of time at home locations according to the results reported in Chapter 2, whereas the RB method is time-insensitive (i.e., spatial averaging) and weights the home location similarly to any other visited location. Despite the difference in correlations between the static and the two dynamic methods, one method may be better at measuring some BE characteristics than the other. For instance, KDE may be better at capturing exposure that is time-sensitive in terms of the related health effects. For example, driving through a park may have minimal impact on women's activities, compared to an encounter with an urban park during a leisure walk.

However, among all BE characteristics measured, this study found stronger correlations between the static RNB and dynamic KDE estimates for those measures that required summaries within administrative boundaries (e.g., census block group level walkability) or raster surfaces (e.g., 250 m x 250 m NDVI grids) types of data inputs. For measures that relied on distinct features in space like lines (e.g., % tree cover along a street segment) or polygons (e.g., area of parks and open space), correlations were only low to moderate. This finding is in line with a previous study which also reported similarities in exposure estimates across different methods differed by data input types, with a focus on dynamic methods (Jankowska et al. 2021).

Across the two pregnancy and the early postpartum periods, the results showed that the correlations of exposure estimates further decreased during the 1st trimester and at 4-6 months postpartum compared to the 3rd trimester. This may be partially caused by the residential mobility (10 of 62 women changed their place of residence during these periods). Additionally, this decrease may also be explained by changes in time-activity and mobility patterns across the three study periods, since women in this study spent less time at commercial and service locations and performed more vehicular trips during the 3rd trimester, according to the results presented in Chapter 2.

Lastly, the ICC analysis results indicated most of variance in exposure estimates for a BE measure were due to between-participant differences (i.e., differences in person-mean exposure estimates). This finding suggests that the static method may introduce larger exposure measurement errors when the research goal is to examine the day or within-day level association between the BE and maternal and infant health outcomes, compared to the person level.

3.4.3. Exposure Misclassification Introduced by the Static Method to Due to Daily Mobility

This study's results showed exposure misclassification could potentially occur if the static methods were relied on to estimate exposure levels, especially for days when individuals are highly mobile. Exposure measurement error or misclassification can weaken statistical power to detect associations and potentially bias observed risk estimates in health studies (Zeger et al. 2000). This concern is warranted by recent studies which have increasingly reported mixed results on associations between neighborhood green space and pregnant women's activities and health outcomes (Anabitarte et al. 2020; Banay et al. 2017; Nichani et al. 2016; Porter et al. 2019).

Despite the overall dependence of exposure misclassification on daily mobility, the evidence for measures of street-level greenness exposure, street intersection density, and neighborhood walkability was less consistent. It may be that these measures have very low variability in women's usual daily activity spaces. As a result, even if more activity locations were visited during high mobility days, the exposure estimates around these locations would only slightly differ from static estimates. This lack of variability may be further amplified by the fact that women in our sample had relatively small daily spatial footprints (a few urban blocks in LA, CA) and as a result, the differences in values between BE data in adjacent spatial units (e.g., walkability index score of US census block groups) would be further reduced.

3.4.4. Study Strengths and Limitations

To the best of my knowledge, this is the first study that examines GPS-based dynamic exposures to BE characteristics of pregnant women across the pregnancy and early postpartum periods. A major strength is the estimation of daily exposure to neighborhood BE characteristics by repeatedly collecting highly resolved smartphone location data across the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum. Consequently, this work overcame the recall biases inherent in self-reported BE exposures and provides insights into longitudinal changes in these exposures. Additionally, the longitudinal design used for this study allows the examination of both the variations in BE exposures between the pregnant women and the day-to-day variations for each woman, which previous studies applying the static method could not do. Moreover, the study applies both spatial averaging (RB) and time-weighted spatial averaging (KDE) methods to capture women's actual exposures to BE characteristics in daily activity spaces. As a result, the exposure estimates reported in this chapter may have less error than those derived by the static approach. Lastly, this study is among the first to examine similarities and differences between BE exposure derived by static and dynamic methods and, to the best of my knowledge, the first one that focuses on pregnant women (Zhao, Kwan, and Zhou 2018; Jankowska et al. 2021). The findings of low correlations between static and KDE neighborhood greenness measures have important implications for future studies examining the association between prenatal neighborhood greenness and maternal and infant health outcomes.

This study also has a few limitations. First, the GPS data that was collected has some missingness. To mitigate its impacts on analyses, an effort was made to impute GPS data using existing information and ruled out the existence of diurnal patterns for the remaining missing segments (it was roughly invariant throughout the day). Despite these efforts, there are other factors that may still potentially bias this study's exposure measurements. For instance, missingness patterns of GPS data may be correlated with spatial context (e.g., tall buildings, trees) that could obstruct receiver signals. As a result, BE characteristics (e.g., proximity to public transit stops) in these spatial contexts may not be captured.

Second, this study was subject to the uncertain geographic context problem (UGCoP), which refers to the uncertainties of environmental contexts that influence health behaviors and outcomes (Kwan 2012). Although the GPS-based dynamic method as applied in this study tackles UGCoP better than the static method by reducing the spatial mismatch between exposure and outcomes, it is limited in addressing other potential methodological issues such as the choice of spatial parameters (e.g., buffer sizes). In this study, a 250 m buffer was used to construct activity spaces given this distance considers multiple pathways on how the BE influences maternal activities and health. In addition, the correlation analyses were run a second time using exposure estimates derived with a 100 m buffer. Study results were largely unchanged and thus not reported.

Third, exposure estimates derived by GPS-based methods were aggregated to the day level and daily exposures were computed as the averaged time-weighted exposure value within activity spaces. Other temporal unit (e.g., trip-level, minute-level) can be chosen if future studies are interested in finer grain within-day relationships between BE exposures and health behaviors. For example, one can examine the greenness exposures within a time window (e.g., 30-minute) preceding a walking episode to better understand the time-lagged effects of the greenness exposure on physical activity behaviors. Also, the BE datasets applied in this study to derive exposure estimates may be limited in variability, given the used aggregation method to produce them (e.g., distance to the nearest public transit stop was calculated as the minimum walking distance in meters between the 2010 population-weighted CBG centroid). Consequently, this may in turn decrease the variability of BE exposure estimates derived and thereby reduce their statistical power to detect meaningful associations with health behaviors and outcomes of interest.

Lastly, this work focused on a health disparity group of low-income, Hispanic women, a population that has been understudied and disproportionally exposed to various environmental hazards. Thus, the results may not be generalized to pregnant women in other regions or SES groups; nevertheless, they shed light on an important population, and they may pave the way for future studies to examine women's BE exposures and health outcomes during pregnancy and postpartum.

3.5. Conclusions

Pregnancy and early postpartum are critical periods of exposure, and this study has shown that BE exposures will likely vary over this journey for many days, with potential implications on both short- and long-term maternal and child health. More importantly, this study have demonstrated that the residential-based static methods commonly used in prior studies can introduce exposure measurement error, the extent of which differs by type of BE measure studied. Therefore, future studies examining the impacts of the BE on maternal and infant health should consider the spatiotemporal movement patterns of the pregnant women in exposure measurements as they will directly influence the ability to detect meaningful relationships.

Chapter 4 The Association between Built Environment Characteristics and Physical Activity during Pregnancy and Early Postpartum

An increasing number of studies has examined the relationship of residential BE characteristics to pregnant women's PA (Kershaw et al. 2021; Nichani et al. 2016; Porter et al. 2019; Richardsen et al. 2016). Yet, very little work has been done to understand this relationship at day-level using GPS-based dynamic BE exposures. Applying 4-day smartphone location and accelerometry-assessed movement data collected from a group of Hispanic, predominantly low-income pregnant women during the 1st and 3rd trimesters, and at 4-6 months postpartum. This chapter examines the effects of women's daily GPS-based greenness, parks and open space, and walkability exposures on their day-level MVPA outcomes.

4.1. Related Work

Pregnancy PA is an important risk factor for short- and long-term maternal and infant health outcomes. Past studies have associated physical inactivity with increased gestational weight gain and health conditions including diabetes, heart diseases, and stress and anxiety (Currie et al. 2014; Daley et al. 2007; Evenson et al. 2014). Evidence indicates Hispanic women had disproportionally high rates in pregnancy-related obesity risk and health outcomes and were overall less likely to meet the PA guidelines during pregnancy than non-Hispanic white population (Brawarsky et al. 2005; Chasan-Taber et al. 2008; Evenson and Wen 2010; Headen et al. 2012). Understanding the drivers of PA behaviors among Hispanic women is a critical step towards reducing disproportionate obesity risks and health consequences borne by this group.

Increasingly, studies have begun to examine the impact of the BE on pregnant women's PA. In this realm, studies have reported positive relationships of neighborhood greenness, parks and open space, street connectivity, and walkability on women's PA outcomes during pregnancy and postpartum (Kershaw et al. 2021; Nichani et al. 2016; Porter et al. 2019; Richardsen et al. 2016). In addition, the evidence indicates that presence of sidewalks and access to parks and recreational facilities are associated with higher PA outcomes among Hispanic adults in the US (Cronan et al. 2008; Fields et al. 2013; Larsen et al. 2013; Mama et al. 2015). Nevertheless, to the best of my knowledge, no studies have focuses on the relationship between BE and PA during pregnancy in Hispanic and low-income women groups.

Moreover, most aforementioned studies relied on one residential location and time point to estimate exposures to BE characteristics (most inferred from addresses provided on birth certificates or questionnaires after delivery). This "static" method does not capture women's dynamic exposure to BE characteristics in non-home activity spaces (non-home activity locations, walking trips) and day-to-day changes in BE exposure resulting from household, occupational, and recreational activities (e.g., grocery shopping, commuting to work, visiting a park), and ignores residential mobility and dramatic variations in activities across the pregnancy and postpartum periods (Matthews and Yang 2013; Perez, Ruiz, and Berrigan 2019; Varshavsky et al. 2020). As a result of these limits, studies applying the static method may fail to capture the "true causally relevant" (Robertson and Feick 2018) BE characteristics that exert contextual influences on pregnant women's PA and bias study results. Few studies have examined the day-level BE-PA associations in pregnant women.

Furthermore, temporal, individual, and neighborhood factors may modify the associations between day-level BE-PA associations in pregnant women. Some studies have reported positive associations between individual sociodemographic measures such as being employed, single parity, and low body mass index (BMI) and women's PA during pregnancy and postpartum (Borodulin, Evenson, and Herring 2009; Hausenblas et al. 2011; Redmond, Dong, and Frazier

2015; Wit et al. 2015). Evidence provided by two studies also suggests that neighborhood social environment characteristics such as perceived safety and cohesion have positive effects on PA outcomes during pregnancy (Evenson et al. 2009; Perez et al. 2016). In addition, many studies have reported pregnant women's PA behaviors differed by weekdays versus weekends, and pregnancy and postpartum periods (Berntsen et al. 2014; Borodulin, Evenson, and Herring 2009; da Silva et al. 2019; Jenum et al. 2013; Schmidt et al. 2006; Sinclair et al. 2019). As a result, examining the interactive effects of dynamic BE exposures and these potential moderators may help to understand the important nuances (i.e., at when, for pregnant women of what sociodemographic characteristics) in its associations with day-to-day PA behaviors. Yet, in this arena, studies remain very limited.

To fill the three aforementioned gaps, the study described in this chapter applied smartphone GPS and accelerometry data collected from a group of Hispanic, predominantly low-income women from MADRES personal and real-time data sampling study to answer the following research questions:

1. Are women's daily exposure to BE characteristics associated with their day-level PA outcomes during the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum?
2. Do the BE exposure measurement methods applied (i.e., static and dynamic) influence the detection of the day-level associations between BE exposures and PA outcomes?
3. Do the day-level associations between BE exposures and PA outcomes, if any, differ by temporal factors, individual sociodemographic, and neighborhood characteristics?

This study hypothesized that the study population would have higher day-level PA outcomes during days when the women were exposed to areas with higher greenness, better park access, and higher walkability. Additionally, this study explored whether the detection of the day-level associations between PA outcomes and BE exposures are influenced by the residential versus activity space methods applied to derive these exposures. Lastly, this study explored whether the day-level associations between BE exposures and PA outcomes are moderated by the pregnancy and postpartum periods, weekdays versus weekend days, maternal parity, pre-pregnancy BMI categories, women's employment status, and neighborhood deprivation, cohesion, and safety.

4.2. Methods

4.2.1. Study Design and Participants

The data used for this study comes from the Real-Time and Personal Sampling sub-study conducted in the USC MADRES Center. This study uses an intensive longitudinal, observational panel study design and examines the daily effects of environmental exposures and social stressors on maternal pre- and post-partum obesity-related biobehavioral responses. A total of 65 Hispanic, predominantly lower income mothers were drawn from the larger MADRES prospective cohort study, which recruited participants from prenatal care providers serving predominantly medically-underserved populations in Los Angeles, California, including two non-profit community health clinics, one county hospital prenatal clinic, one private obstetrics and gynecology practice, and through self-referral from community meetings and local advertisements (O'Connor et al. 2019). To be eligible for this sub-study, a participant needed to be >18 years old with a singleton pregnancy and be at less than 30 weeks' gestation at time of recruitment. In addition, participants who were HIV positive, had physical, mental, or cognitive disabilities that prevented participation, or were currently incarcerated were excluded from the study (O'Connor et al. 2019). Recruitment of 65 women occurred on a rolling basis between 2016 and 2018 and is described in further detail in O'Connor et al. (2019). The USC Institutional

Review Board approved all study procedures and participants signed an informed consent before enrolling into the study.

4.2.2. BE Measures

4.2.2.1. Location Information using GPS

GPS data were continuously collected from 65 study participants at 10-s intervals for four days (two weekdays and two weekend days) during the 1st and 3rd trimester and at 4-6 months postpartum. To enable collecting highly resolved and encrypted GPS data collection, MADRES researchers designed a custom smartphone application (madresGPS app) for Android operating systems. Study coordinators configured the application on dedicated study smartphones (Samsung MotoG phone) to record geographic coordinates and geolocation/motion metadata (O'Connor et al. 2019). The application logged instantaneous GPS location and sensor data every 10 s from the smartphone's multiple built-in location finding features (cell tower triangulation, Wi-Fi networks, and GPS) and motion sensors. Along with the timestamp, the application recorded metadata such as the number of satellites in use/view, geolocation accuracy, source of GPS, velocity (if GPS source), and network connection status (if network source).

The 10-s epoch GPS location data was processed using a customized algorithm in SAS version 9.4 (SAS Institute Inc). The algorithm subsets GPS data to the 4-day designated monitoring period (during device set up and return), selects better quality data from one of the two GPS data sources (GPS/network), smooths extreme outliers, and aggregates data at the 10-s level. Missing GPS data was imputed using a customized imputation algorithm that identified participants' time periods at home during nighttime using sleep and waking times they self-reported prior to each study period to help the technology team configure suitable timing and frequencies for the EMA survey (O'Connor et al. 2019). The time periods spent at home were identified when participants reported a home day (i.e., all EMA survey prompts within the day reported physical context as either “Home-Indoor” or “Home-outdoor”). The entire workflow of the missingness imputation process is discussed in Chapter 2. After GPS processing and imputation, flags were created which labelled days with <6 hours of GPS data (post-imputation) as invalid days, after considering missing data patterns.

4.2.2.2. Delineation of Contextual Units

<u>Activity Space Metrics</u>

The processed and imputed GPS data was separated into person-day levels and daily activity spaces were constructed via both the RB and KDE methods (see Figure 3.1 in Chapter 3) using ArcGIS Pro 10.7.1 (Esri, 2021). The two methods complement one another and capture pregnant women’s daily exposure to BE characteristics along women’s daily travel paths (via RB) and around activity locations where they spent most of their time (via KDE).

To construct RBs, consecutive GPS points were joined into lines and buffered using a 250 m radius. This distance corresponds to several blocks in urban Los Angeles and was selected to approximate two hypothetical mechanisms on how BE characteristics could potentially influence health behaviors and outcomes (Yi et al. 2019): the viewshed (e.g., seeing a park when walking on a street) and their awareness (e.g., knowing a recreational facility is located nearby). Additionally, 250 m RBs were calculated and classified into three categories (low mobility: <33%, medium mobility: 33-66%, high mobility: >66% of sizes) to represent participants’ mobility during a given day.

Additionally, a KDE approach was applied to generate time-weighted activity grids using 50 by 50 m cells with a bandwidth of 250 m (to match the RB radius). Each grid was assigned a normalized time weight (range from 0 to 1) based on the percentage of time staying put on a given day, with total weights adding up to 1.

Home Residential Neighborhood

To identify residential locations, a kernel-based stay-trip detection algorithm was applied to 4-day GPS data (per combinations of participants and three study periods) to identify activity locations visited and total time spent at each location (Thierry, Chaix, and Kestens 2013). For this study, the women's activity location with the longest stay duration during the 3rd trimester was assigned as the residential location. This location was selected as most similar to one that was used in a typical approach (i.e., assessed exposures based on addresses provided on birth certificates or questionnaires after delivery and assumed these exposures represent the entire prenatal period). Details of the stay-trip detection and home identification were documented in Chapters 2 and 3, respectively.

The identified 3rd trimester residential locations were then used to derive 800 m RNBs via the Service Area Analysis tool in ArcGIS Pro 10.7.1 (Esri, 2021). The network buffer better captures the area to which a pregnant woman could realistically travel from the home residence. A 800 m radius, which corresponds to a 5-10-min walk, is recommended for populations with relatively restricted mobility (James et al. 2014; Frank et al. 2017). Additionally, a sensitivity analysis was performed using a larger radius (e.g., 1,600 m) and the resulting BE exposure estimates differed only slightly.

4.2.2.3. BE Measures

Four BE measures capturing daily exposures to neighborhood greenness, parks and open space, and walkability were derived using the KDE, RB, and RNB methods, respectively. These measures included percent green space along walkable roads, distance to the nearest park entrance, parks and open space exposure, and walkability index score, all of which have been reported by previous studies to be associated with various human activities and health outcomes, particularly among pregnant women (Banay et al. 2017; Besser and Dannenberg 2005; Jiang et al. 2016; Pickard et al. 2015; Porter et al. 2019; Pretty et al. 2005; Tsai, Davis, and Jackson 2019; Saelens et al. 2014;). All aforementioned BE measures along with data source, resolution, and processing steps and interpretation are summarized in Table 3.1 in the previous chapter.

RNB and RB exposures were calculated by summarizing values of the respective BE measures (e.g., mean NDVI, total areas of parks and open space) within the boundaries of the corresponding spatial units (i.e., 800 m residential network buffer, 250 m route buffer). KDE exposures were calculated by weighting grid-based values of the respective BE measures with time spent (e.g., multiplying walkability index score value of the grid by percentage of time spent). Exposures were calculated using Eq. 3.1 for the RNB or RB methods and using Eq. 3.2 for the KDE methods, as illustrated in Chapter 3.

4.2.3. PA Outcomes

A wGT3X-BT ActiGraph accelerometer was used to measure women's PA during pregnancy and early postpartum. Women were instructed to wear the accelerometer for four consecutive days (two weekdays and two weekend days) during each study period. The accelerometer was attached with an adjustable belt and worn all the time on the right hip except when sleeping, bathing/showering, or swimming (O'Connor et al. 2019). Body movement data were collected by the accelerometer in activity count units for each 10-s epoch. Non-wear times were defined as >60 continuous min of zero activity counts and non-valid days were defined as <10 h of wearing time (Troiano et al. 2008), both of which were removed from the analyses. To be consistent with national surveillance data, MVPA, an intensity of PA that is sufficient to reduce the risk of many adverse health outcomes (Piercy et al. 2018), was identified using the Freedson prediction equation above four metabolic equivalents of task (i.e., activities that accumulate metabolic rate ≥4 times of the resting metabolism, such as brisk walking, based on the Freedson prediction equation; Troiano et al. 2008; Bell et al. 2013; Harrison et al. 2011). Day-level PA outcome variable was created by summing total number of 10-s MVPA epochs occurred within an observation day and converted to a unit of minutes.

4.2.4. Covariates

Individual sociodemographics included enrollment age, education (recoded as some college or graduate degrees versus high school diploma or less), and maternal parity (recoded as first born versus second or greater birth), which were assessed in prenatal interviewer-administered questionaries with the women (Bastain et al. 2019). Body Mass Index (BMI) categories (recoded as normal versus overweight versus obese) were also calculated based on height and weight measured during pre-natal visits, according to Center for Disease Control and Prevention guidelines (Bastain et al. 2019). Working status was collected via questionnaire during the 1st and 3rd trimester, and at 6 months postpartum (Bastain et al. 2019). Participants self-reported neighborhood cohesion and safety scores in questionnaires at the 2nd trimester (chosen to represent pregnancy) and for 6 months postpartum (Sampson, Raudenbush, and Earls 1997), and the Areal Deprivation Index Score from the Neighborhood Atlas dataset produced by the University of Wisconsin-Madison was used to represent neighborhood-level SES of participants (Kind and Buckingham 2018). The score was assigned to participants' residences based on the 2010 census block group in which their home residences were situated. Temporal factors included weekend versus weekday (weekend=1), daily average temperature in degrees Celsius, and study period (the 1st and 3rd trimester and 4-6 months postpartum). Daily accelerometer wear time was also included to adjust for individual device-wearing behaviors. A full list of covariates measures and corresponding data sources is provided in Appendix D.

4.2.5. Statistical Analysis

4.2.5.1. Analytical Samples

A total of 651 accelerometer-measurement days of PA were recorded by the 62 women. Among them, 210 non-valid days with <10 h of wear time were removed. Examination of predictors of non-valid day analyses showed that weekend days were more likely to be non-valid days; all other covariates did not predict valid versus non-valid days. Moreover, 94 data collection days were removed due to lack of daily BE measures data. These efforts resulted in a final data analysis sample of 350 days ($N_{Participant}$=55).

4.2.5.2. Linear Mixed-Effects Models (LMMs)

To account for the interdependency of the nested data structure in the current study (Level 1-days nested within Level 2-participants), LMMs with participant-level random intercepts were applied. To test the necessity of a multi-level model (i.e., within-participant clustering of day-level MVPA outcomes), ICCs was estimated using a LMM with only random intercepts (no covariates). Results indicate 41% (ICC=.41) of variation in the day-level MVPA minutes was between-participant and 59% was within-participant. This result justifies the use of a multilevel model (Bates et al. 2015).

4.2.5.3. Model Building Strategy and Covariates

All four BE measures were person-mean centered to disentangle the between-subject (person-level) and within-subject (day-level) effects (Curran and Bauer, 2011). Since the total parks and open space exposure variable contains a large proportion of zeros (about one third across all observation days), it was recoded into a binary variable (1=had any parks and open space exposure in an observation day or 0 = no exposure). Additionally, the day-level MVPA outcome variable was log-transformed to ensure normality since the variable showed a right-skewed distribution. For each set of four BE measures derived using two activity space methods (250 m KDE, 250 m RB), LMMs were fitted to test person- and day-level effects of each BE measure on day-level MVPA minutes.

All models were adjusted for women's baseline age, education, pregnancy and postpartum periods, and daily wear time. In addition, additional covariates were tested in separate univariate models and included in the final model if they reached a significance level of <.1. These additional covariates included maternal parity, employment status, pre-pregnancy BMI categories, daily averaged temperature (both linear and quadratic terms were tested to account for its potential non-linear relationships with daily PA outcomes), weekdays versus weekends, neighborhood safety and cohesion score, and neighborhood deprivation index score.

Moreover, two-way interaction terms between day-level BE measures and aforementioned temporal factors, individual sociodemographics, and neighborhood covariates were entered separately into LMMs to test whether they moderated the associations between BE measures and day-level MVPA minutes. For each significant interaction ($p<.05$), predicted trajectories for MVPA min/d related to BE measures at a specific value of moderator (all categories if categorical; -1SD, mean, +1SD if continuous) were estimated and visualized, with the slope estimated and its statistical significance tested (i.e., whether an estimated slope of the day-level MVPA on a specific BE measure at a specific moderator value is different from zero).

4.2.5.4. Sensitivity Analyses

Models were also run for sensitivity analyses by using BE measures derived using smaller buffers for two activity space methods (100 m RB, 100 m KDE) and the RNB method (800 m and 1,600 m RNB). In addition, three-level LMMs with random intercepts at person- and period-levels were run as sensitivity analyses to test whether the random effects of pregnancy and early postpartum periods would confound the associations between BE exposures and PA outcomes found in two-level LMMs. The R 4.0.2 (R Core Team, 2020) and *lme4* package (version 1.1-27.1) were used for LMM (Bates et al. 2015), and the *interaction* package (version 1.1.5) was used for simple slope analyses. Since the outcome variable was log-transformed, exponentiated effect estimates interpreted on a multiplicative scale were reported for all models.

4.3. Results

4.3.1. Descriptive Statistics

The descriptive statistics for PA outcomes, BE predictors, and covariates of the study participants are summarized in Table 4.1. Participants' mean age at study entry was 29.00 years (*SD*=6.1; *range*:18.3-45.4). All the participants were Hispanic. Over one-third (34.6%) had some college or above education. 36.2% were employed during the 1st trimester compared to 39.00% during the 3rd trimester, and 21.2% at 4-6 months postpartum. At recruitment, 29.1% were pregnant with their first child, 72.7% were overweight or obese according to their reported pre-pregnancy BMI. The recruited participants lived in neighborhoods with an average deprivation index score (on a 1 to 10 scale; where 1=least deprived) of 6.3 (*SD*=1.8, *Range*:2.00-9.00). The average neighborhood safety and cohesion score (on a 1 to 5 scale; where 1=least safe and cohesive) self-reported by women was 3.00 (*SD*=.69, *Range*:1.00-4.4) during the 1st trimester, 3.1 during the 3rd trimester (*SD*=.81; *Range*:1.2-4.7), and 3.3 (*SD*=.9, *Range*:1.4-4.8) at 4-6 months postpartum.

The average MVPA min/d across all three study periods were 30.7 (*SD*=22.4), which was higher (*p*=.71) during the 3rd trimester (32.00 min/d; *SD*=20.4) than during the 1st trimester (30.8 min/d; *SD*=23.5) and at 4-6 months postpartum (29.5 min/d; *SD*=23.1). Less than half of the data collection days were on weekends (45.4%), which had lower (*p*<.01) day-level MVPA (26.8 min/d; *SD*=19.6) compared to weekdays (34.2 min/d; *SD*=24.2). The mean average daily temperature in Celsius was 19.92 °C (*SD*=4.4; *Range*:5.2-31.4).

In terms of neighborhood greenness, women were exposed to walkable road networks with an average 23.3% green space coverage at daily activity locations visited (*SD*=8.3), which was lower than the Los Angeles County average of 32.4% (mean percent green space along all walkable roads in the County). The exposure estimates of the greenness exposure measure varied slightly using the RB method. As for parks and open space access, women's mean distance from any point in the daily activity spaces to the nearest park entrance was 791 m (*SD*=399; corresponding to 15-20-minute walk). The estimates differed slightly with the RB method. Additionally, women were exposed to parks and open space in activity spaces in approximately three out of every four observation days (73.4%; 257 out of 350 days), according to the KDE method. This percentage was slightly smaller if measured by the RB method. Lastly, regarding walkability, the mean walkability index score was 15.00 (*SD*=1.7), which was 1.5 units higher than the Los Angeles County average. The walkability exposure estimates differed slightly between the two activity space methods.

Table 4.1. Descriptive statistics for physical activity (PA) outcomes, built-environment (BE) predictors, and covariates of the study participants.

	Overall (N=55 participants, N=350 person-days)	1st Trimester (N=47 participants, N=133 person-days)	3rd Trimester (N=41 participants, N=106 person-days)	4-6 Months Postpartum (N=38 participants, N=112 person-days)
Variable	**Mean(SD) or n(%)**			
Outcome				
Day-level MVPA minutes	30.73 (22.45)	30.76 (23.48)	31.99 (20.44)	29.48 (23.13)
Predictors				
% Green space along walkable roads				
RB	23.21 (5.87)	23.73 (5.38)	23.26 (5.91)	22.54 (6.37)
KDE	23.30 (8.27)	24.06 (8.47)	22.80 (7.65)	22.88 (8.58)
Days with parks and open space exposure (yes/no)				
RB	254 (72.6%)	97 (72.9%)	81 (76.4%)	76 (68.5%)
KDE	257 (73.4%)	99 (74.4%)	82 (77.4%)	76 (68.5%)
Distance to the nearest park entrance (in m)				
RB	868.03 (342.07)	826.44 (323.96)	873.76 (328.80)	912.38 (371.49)
KDE	790.80 (398.47)	748.10 (346.55)	807.72 (424.17)	825.79 (429.16)
Walkability index score (range from 1 to 20)				
RB	15.09 (1.39)	15.05 (1.54)	15.24 (1.24)	14.98 (1.35)
KDE	15.01 (1.68)	14.99 (1.78)	15.12 (1.58)	14.95 (1.64)
Covariates				
Age	29.04 (6.14)	-	-	-
Education				
High school or less	36 (65.45%)	-	-	-
Some college/Graduate	19 (34.55%)	-	-	-
Parity				
Second or greater birth	39 (70.91%)	-	-	-
First-born	16 (29.09%)	-	-	-
Pre-pregnancy BMI categories				
Normal	15 (27.27%)	-	-	-
Overweight/Obesity	40 (72.73%)	-	-	-
Employment status [a]				
Unemployed	–	30 (63.83%)	25 (60.98%)	26 (78.79%)
Employed	–	17 (36.17%)	16 (39.02%)	7 (21.21%)
Missing	–	0	0	5

Table 4.1. (Cont.)

	Overall (N=55 participants, N=350 person-days)	1st Trimester (N=47 participants, N=133 person-days)	3rd Trimester (N=41 participants, N=106 person-days)	4-6 Months Postpartum (N=38 participants, N=112 person-days)
Variable	**Mean(SD) or n(%)**			
Neighborhood cohesion and safety score (range from 1 to 5) [a]	–	3.02 (.69)	3.07 (.77)	3.28 (.86)
Missing	–	1	0	5
Neighborhood deprivation index (range from 1 to 10)	6.34 (1.78)			
Missing	2			
Daily accelerometer wearing hours	13.79 (2.63)	13.32 (1.82)	14.19 (3.03)	13.96 (2.95)
Type of day				
Weekday	191 (54.57%)	76 (57.14%)	60 (56.60%)	55 (49.55%)
Weekend	159 (45.43%)	57 (42.86%)	46 (43.40%)	56 (50.45%)
Average daily temperature (°C)	19.92 (4.40)	20.37 (4.36)	20.41 (4.28)	18.95 (4.45)
Missing	9	9	0	0

[a] Summary statistic not available since the employment status variable is measured at each study period.

Note: KDE = Kernel Density Estimation. RB = route buffer.

4.3.2. Predictors of Day-Level PA Outcomes in Pregnant Women

LMM results examining within-subject (day-level) associations between BE measures derived using the 250 m KDE and RB methods and women's day-level MVPA minutes are shown in Table 4.2. In both models, results showed that women engaged in more MVPA on weekdays versus weekend days. In addition, women engaged in more MVPA on days with higher averaged daily air temperatures and this relationship was linear. Education attainment was also associated with women's MVPA min/d so that women who had college or graduate degrees engaged in less MVPA compared to those who had high school or less education.

Table 4.2. Between-subject (BS) and within-subject (WS) effects of exposures to built-environment (BE) characteristics derived using the 250 m kernel density estimation (KDE) and 250 m route buffer (RB) methods on daily moderate-to-vigorous physical activity (MVPA) outcomes.

	Daily MVPA minutes(log-transformed)	
	250 m KDE model	*250 RB model*
Predictors	*Estimates (95%CI)1*	
(Intercept)	8.00*** (3.23 – 19.79)	8.62*** (3.43 – 21.66)
% Green space along walkable roads (BS)	1.01 (.99 – 1.03)	1.03 (1.00 – 1.06)
Distance to the nearest park entrance (BS)	1.01 (.98 – 1.05)	1.04 (1.00 – 1.10)
Walkability index score (BS)	1.05 (.97 – 1.14)	1.18* (1.04 – 1.33)
Daily parks and open space exposure (BS)	1.64 (1.00 – 2.70)	1.47 (.92 – 2.34)
% Green space along walkable roads (WS)	1.00 (.98 – 1.02)	1.01 (.99 – 1.03)
Distance to the nearest park entrance (WS)	1.00 (.94 – 1.05)	.99 (.96 – 1.02)
Walkability index score (WS)	1.01 (.89 – 1.15)	1.02 (.94 – 1.12)
Daily parks and open space exposure (WS)2	1.21* (1.01 – 1.46)	1.22* (1.02 – 1.47)
Maternal age	.99 (.97 – 1.01)	.99 (.96 – 1.01)
Education: Some college/Graduate	.68** (.52 – .89)	.66** (.50 – .88)
Pre-pregnancy BMI category: Overweight	.93 (.69 – 1.25)	.95 (.72 – 1.27)
Pre-pregnancy BMI category: Obesity	.69* (.51 – .92)	.66** (.50 – .87)
Average daily temperature (°C)	1.02* (1.00 – 1.04)	1.02* (1.00 – 1.04)
Type of day: Weekend	.81** (.71 – .93)	.80** (.70 – .92)
The 3rd trimester day	.96 (.81 – 1.13)	.95 (.80 – 1.12)
4-6 months postpartum day	.90 (.75 – 1.08)	.91 (.76 – 1.08)
Neighborhood cohesion and safety score (range from 1 to 5)	1.02 (.91 – 1.14)	1.03 (.92 – 1.15)
Daily accelerometry wearing hours	1.09*** (1.06 – 1.13)	1.09*** (1.06 – 1.13)

* p<.05 ** p<.01 *** p<.001

1 Exponentiated effect estimates interpreting on a multiplicative scale were reported for all models
2 The binary variable was not person-mean centered for the ease of interpretation. The person-mean centered versions of the variable were also tested, and results remained invariant.

After controlling for all covariates, results showed (see Table 4.2 – 250 m KDE model) that the women engaged in more MVPA min/d (b=1.21; *95%*CI:1.01-1.46; p<.05) on days they were exposed to parks and open space in their activity spaces. This result did not change in the

250 m RB model (see Table 4.2). In addition, women who were exposed to activity spaces with higher walkability score, on average compared to other women, engaged in more MVPA min/d (b=1.18; *95%CI*:1.04-1.33; p<.05) in the 250 m RB model. Associations were not detected between other BE variables and women's day-level MVPA outcomes.

Sensitivity analyses that applied BE variables derived using the 100 m KDE and RB, and 800 m and 1,600 m RNB methods were conducted. These results are summarized in Appendix G. In all models, both positive associations between daily parks and open space exposure and MVPA min/d and between daily walkability index score and MVPA min/d were no longer significant, although the associations still approached statistical significance (p<.1) in the 100 m KDE and 100 m RB models. In addition, the associations between BE measures derived using the 250 m KDE and RB and MVPA min/d via three-level LMMs with random intercepts at person- and period-level (i.e., 1st and 3rd trimesters and 4-6 months postpartum) were also tested, and the aforementioned significant results on positive associations between daily parks and open space exposures and MVPA min/d did not change.

4.3.3. Moderators of Day-Level Associations between BE and PA

The LMM results after adding two-way interactions between within-subject (day-level) BE measures and a list of temporal factors, individual sociodemographics, and neighborhood characteristics are visualized in Figure 4.1 and presented in table form in Appendix H. The simple slope analysis results for each significant interaction term are summarized in Table 4.3 as well. Overall, these results show the associations between daily BE exposures and MVPA min/d differed by weekdays versus weekends, late pregnancy versus two other periods, early postpartum versus two other periods, the average daily temperature, maternal parity numbers,

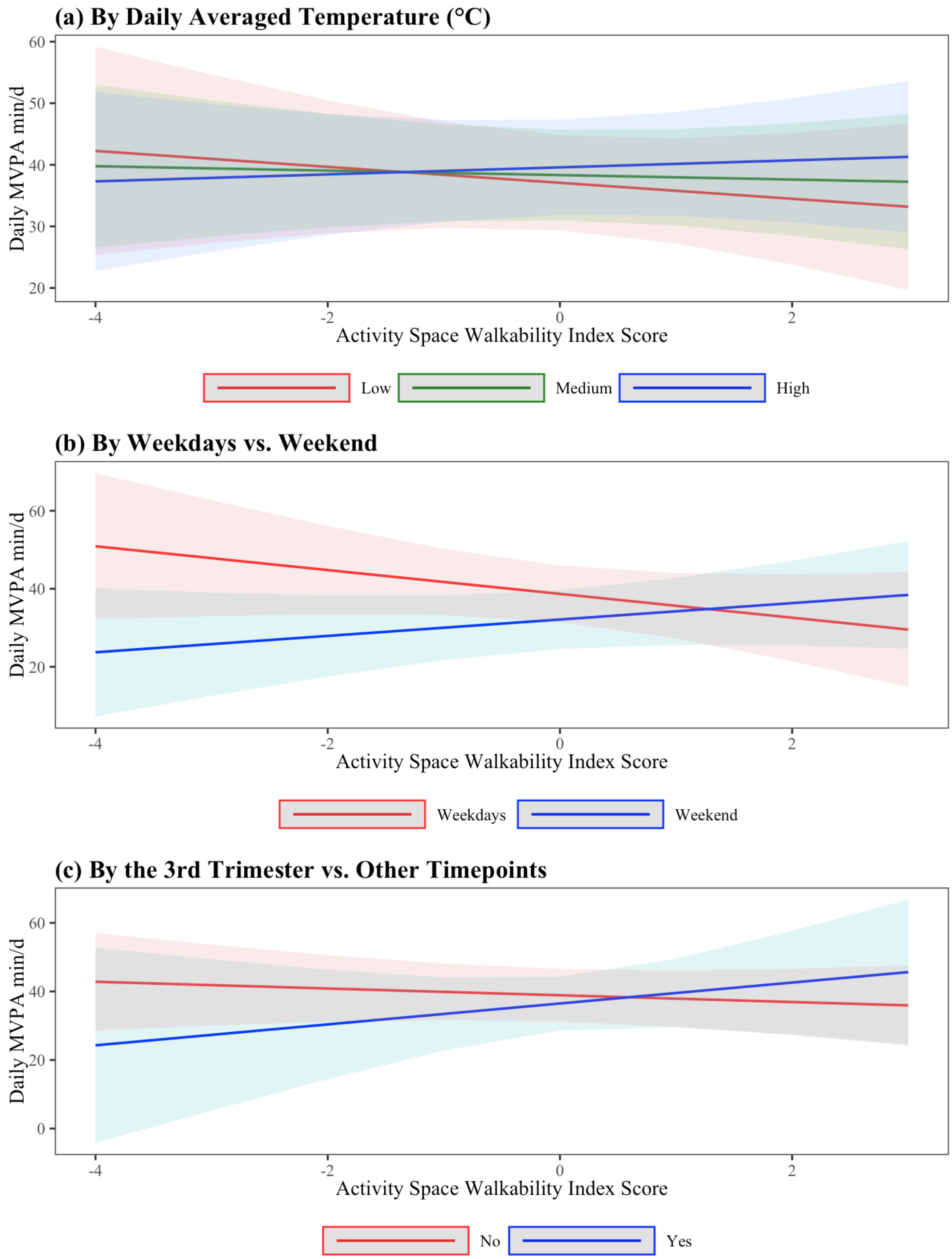
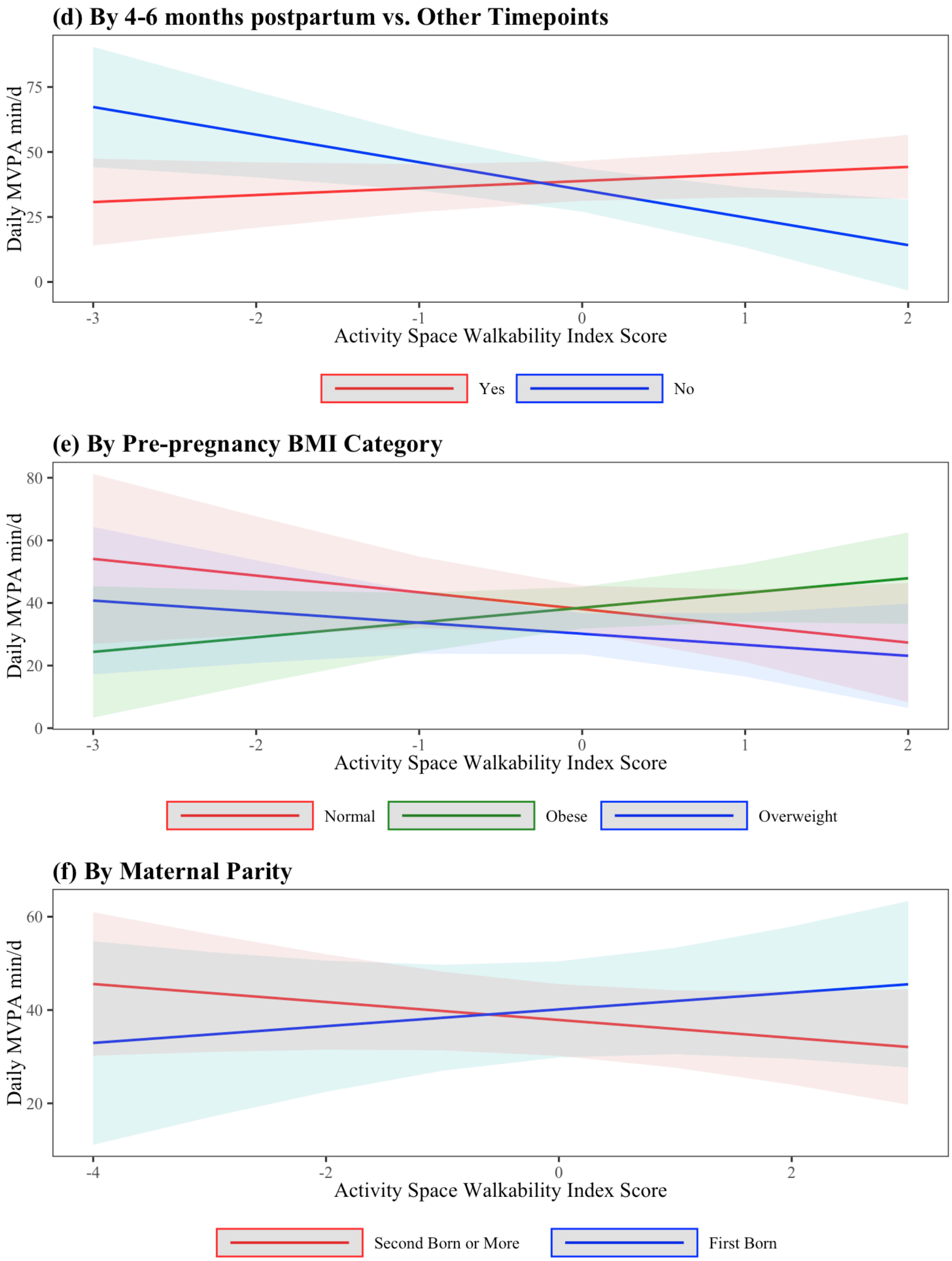


Figure 4.1. The significant interactions between built-environment (BE) characteristics and temporal factors, individual sociodemographics, and neighborhood characteristics in predicting day-level moderate-to-vigorous physical activity (MVPA) outcomes.

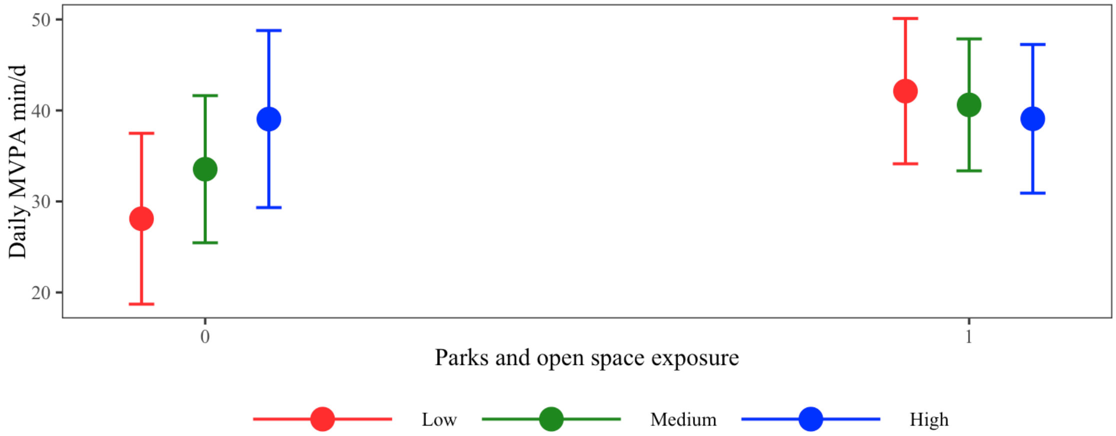
Note: Timepoints include the 1st trimester, the 3rd trimester, and 4-6 months postpartum.



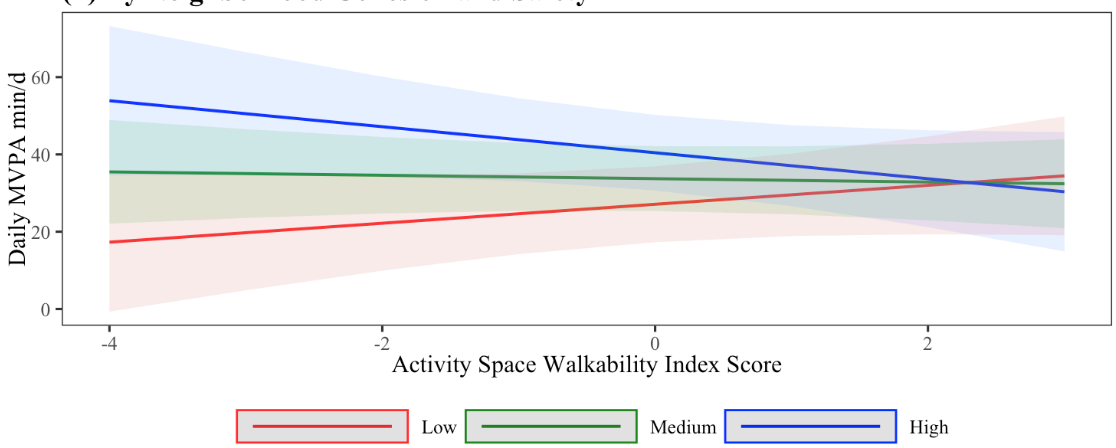
Figures 4.1. (Cont.)

Note: Timepoints include the 1st trimester, the 3rd trimester, and 4-6 months postpartum.

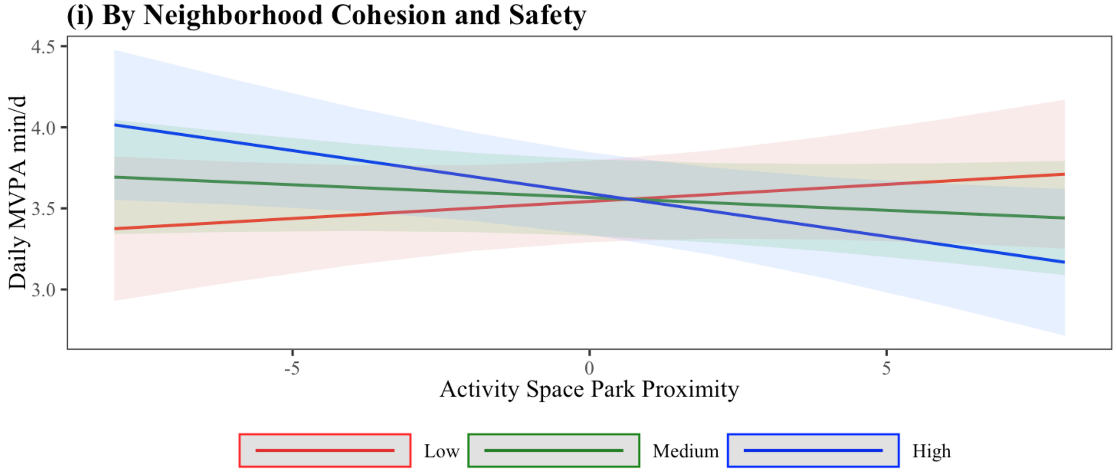
(g) By Neighborhood Cohesion and Safety



(h) By Neighborhood Cohesion and Safety



(i) By Neighborhood Cohesion and Safety



Figures 4.1. (Cont.)

Note: Three Timepoints = the 1st trimester, the 3rd trimester, and 4-6 months postpartum.

Table 4.3. Simple slope analyses results for significant two-way interactions between built-environment (BE) exposures and temporal, individual, and neighborhood moderators in predicting daily moderate-to-vigorous physical activity (MVPA) outcomes.

Interaction Terms	**Estimates (95%CI)**
Activity space walkability x Daily averaged temperature (°C)	
Daily averaged temperature: Low (-1SD)	.93 (.82-1.04)
Daily averaged temperature: Medium (Mean)	1.01 (.93-1.11)
Daily averaged temperature: High (+1SD)	1.11 (1.00-1.23)*
Activity space walkability x Weekends	
Weekend days	1.14 (1.01-1.28)*
Weekdays	.91 (.79-1.04)
Activity space walkability x The 3rd trimester	
The 3rd trimester days	.96 (.93-1.00)
Non 3rd trimester days	1.06 (.99-1.14)
Activity space walkability x 4-6 months postpartum	
The 4-6 months postpartum days	1.12 (.95-1.31)
The 4-6 months postpartum days	.81 (.63-1.03)
Activity space walkability x Pre-pregnancy Body Mass Index (BMI) category	
Pre-pregnancy BMI category: Overweight	.99 (.77-1.27)
Pre-pregnancy BMI category: Obese	1.26 (1.02-1.56)*
Pre-pregnancy BMI category: Normal	.85 (.64-1.13)
Activity space walkability x Maternal parity	
Maternal parity: 1st born	1.18 (1.01-1.38)*
Maternal parity: 2nd or greater birth	.95 (.86-1.06)
Activity space park exposure x Neighborhood safety and cohesion	
Neighborhood cohesion and safety: Low (-1SD)	1.56 (1.20-2.03)***
Neighborhood cohesion and safety: Medium (Mean)	1.27 (1.05-1.52)*
Neighborhood cohesion and safety: High (+1SD)	1.03 (.81-1.30)
Activity space walkability x Neighborhood safety and cohesion	
Neighborhood cohesion and safety: Low (-1SD)	1.16 (1.03-1.32)*
Neighborhood cohesion and safety: Medium (Mean)	1.02 (.94-1.11)
Neighborhood cohesion and safety: High (+1SD)	.89 (.78-1.02)
Activity space park proximity x Neighborhood safety and cohesion	
Neighborhood cohesion and safety: Low (-1SD)	1.02 (.97-1.07)
Neighborhood cohesion and safety: Medium (Mean)	.98 (.95-1.02)
Neighborhood cohesion and safety: High (+1SD)	.95 (.90-.99)*

* p<.05 ** p<.01 *** p<.001

Note: CI = Confidence Interval

pre-pregnancy BMI categories, and participant-reported neighborhood cohesion and safety scores.

In terms of temporal factors, Figures 4.1a-b show that the effects of activity space walkability on women's MVPA min/d differed by the daily averaged temperature (b=1.02; *95%C*I:1.01 – 1.04; p<.01) and weekdays versus weekends (b=1.25; *95%CI*: 1.04-1.51; p<.05). The simple slope analysis results (Table 4.3) show that women engaged in more MVPA when they were exposed to activity spaces with higher walkability index score than usual in weekends (b=1.11; *95%CI*: 1.00-1.23; p<.05) and warmer days (b=1.14; *95%CI*: 1.01-1.28; p<.05). Moreover, Figures 4.1c-d show how the effects of activity space park proximity on women's MVPA differed by the 3rd trimester versus two other time points (b=1.10; *95%CI*:1.01-1.20; p<.05) and the effects of activity space walkability on women's MVPA differed by 4-6 months postpartum versus two other time points (b=.72; *95%CI*:.54-.97; p<.05). However, none of the predicted slope values for each stratum reported in Table 4.3 was significant.

Turning next to individual sociodemographics, the effects of activity space walkability on women's MVPA differed by the first born versus second or greater birth (b=1.23; *95%CI*:1.02-1.49; p<.05), so that the women who had given birth to their first child engaged in more MVPA (b=1.18; *95%CI:*1.01-1.38, p<.05; see Figure 4.1f and Table 4.3) on days when they were exposed to activity spaces with higher walkability. Additionally, the effects of activity space walkability (b=1.49; *95%CI*:1.04-2.12; p<.05) on women's MVPA differed with pre-pregnancy BMI categories. According to Figure 4.1e and Table 4.3., Women who were obese engaged in more MVPA on days when they were exposed to activity spaces with higher walkability index scores (b=1.26; *95%CI*:1.02-1.56; p<.05) than usual.

Lastly, the results show that neighborhood cohesion and safety moderated the effects of BE measures on women's MVPA for measures including park proximity, park coverage, and walkability. The predicted trajectories for MVPA min/d related to each measure were stratified by -1SD, mean, and +1SD of neighborhood cohesion and safety score (see Figures 4.1g-i), but the positive associations between women's daily BE exposure and MVPA were only significant among low neighborhood cohesion and safety score groups. For example (see Figure 4.1h), women who reported their neighborhoods as less safe engaged in more MVPA (b=1.16; *95%CI*:1.03-1.32; p<.05) on days when they were exposed to activity spaces with higher walkability index scores than usual. Similar interpretations can be made for interaction effects as visualized in Figures 4.1g and 4.1i.

4.4. Discussion

This study used highly resolved smartphone location data collected from a sample of 55 pregnant Hispanic women in urban Los Angeles to measure their dynamic daily exposures to BE characteristics during the 1st and 3rd trimesters and at 4-6 months postpartum and examined relationships of these exposure measures to women's day-level accelerometer-assessed PA. This study also examined whether the static versus activity space exposure measurement methods applied influence the statistical power in detecting the day-level associations between BE exposures and PA outcomes. Lastly, the study explored the interactive effects of BE measures applied and the temporal-, and individual- and neighborhood-level moderators in predicting day-level PA outcomes. The results provided evidence of within-day (day-level) associations between BE exposures and women's PA outcomes during and after pregnancy, particularly for those of low SES or racial/ethnic minority groups. Finally, by applying GPS-based BE exposure assessment methods, this study was able to reduce the potential spatial misclassification biases associated with prior studies, which measured BE exposures at residential locations at a single point in time (usually near giving birth). The significance of these results is discussed in more detail below.

4.4.1. Day-Level Associations between BE and PA

The positive daily association found between 250 m activity space-based (both KDE and RB) parks and open space exposure and pregnant women' PA outcomes can be added to prior studies reporting mixed results. For example, Nichani et al. (2016) found the residential green space exposure was not associated with PA during pregnancy, while Richardsen et al. (2016) reported women who lived in neighborhoods with good access to recreational areas accumulated more MVPA compared to women who had limited access. In sensitivity analyses of this study, residential parks and open space exposure derived using the 800 m and 1,600 m residential (RNB) methods were not associated with women's day-level MVPA outcomes during pregnancy and early postpartum. Thus, the discrepancy in results observed in different studies might be attributed to the static, residential-based green space exposure assessment approaches used both studies because these approaches might not capture women's exposure in non-residential locations and therefore biased the study results.

Additionally, daily associations between activity space parks and open space exposure and pregnant women's MVPA were not found for models that applied 100 m KDE and RB BE measures. This suggests that the results are sensitive to the choice of activity space configuration parameters (i.e., buffer sizes). The choice of 100 m to represent the viewshed exposure along daily movement paths and the null association suggest roadside exposure alone did not influence pregnant women's PA behaviors. In this realm, Kwan (2012) points to the existence of uncertain geographic context problem (UGCoP) in health studies, which refers to the uncertainties of contextual exposures that exert influences on health behaviors or outcomes. Among the few studies that explored this issue, Laatikainen et al. (2018) studied 844 adults in Finland and found the association between BE exposure and their mental health and wellbeing differed by activity space method applied. In a study of 403 adults in Guangzhou, China, Zhao et al. (2018) demonstrated that the associations between the BE and obesity were significantly influenced by seven activity space definitions. This study further demonstrates the presence of UCGoP in associations between the relationships of BE exposures and PA outcomes.

Moreover, given the multilevel modeling approach applied, the positive association found in the study (i.e., days with parks and open space exposure were associated with more daily MVPA) should be interpreted as the effect of women's day-to-day variations in parks and open space exposure compared to their usual exposure on their daily PA outcomes. This is different from the large population-based studies (Nichani et al. 2016; Richardsen et al. 2016; Porter et al. 2019) which focused on examining the influences of population-level differences in residential neighborhood park exposure (e.g., women with park access versus those without) on pregnant women's PA outcomes. The evidence on the day-level relationship between BE exposure and PA outcomes of pregnant women is still limited, future studies need to continue exploring this relationship at the day-, within-day- or minute- level to further elucidate the different ways in which the temporality of environmental exposures might influence women's PA behaviors during and after pregnancy.

4.4.2. Differences in Day-Level BE-PA Associations by Temporal Factors

This study also found that weekdays versus weekend days, and the pregnancy and early postpartum periods moderated the day-level association between BE exposures and MVPA outcomes in pregnant women. In terms of pregnancy and postpartum periods, the day-level effects of activity space walkability on women's MVPA differed by postpartum (i.e., 4-6 months postpartum) versus pregnancy, although predicted slopes for both periods were insignificant. According to the interaction plot, a trending positive association between daily activity space walkability and day-level MVPA was found during pregnancy periods. This finding was consistent with Porter et al. (2019), in which authors found the residential neighborhood walkability assessed by the environmental audit tool was associated with both overall and recreational PA during pregnancy. Moreover, the results reported in this chapter demonstrate the importance of having access to a walkable environment at non-home locations or along daily paths to promote pregnant women' PA behaviors.

However, these results also show an inverse association between walkability and women's MVPA at 4-6 months postpartum, which was contrary to the original hypothesis specified for this study and the results of the aforementioned prior study. The walkability measure used in this chapter was directly adopted from the walkability index score created by the US Environmental Protection Agency (EPA), which includes components such as street intersection density and distance to the nearest public transit stop (Pickard et al. 2015). As a result, the walkability measure used in this chapter may be better at predicting the utilitarian type of PA than the recreational type. The result in Chapter 2 also reported that women in the MADRES sample performed less pedestrian-based trips at 4-6 months postpartum. As a result, the utilitarian PA in the MADRES sample may have significantly decreased at the postpartum period and consequently attenuated the predictive powers of that walkability measure that was used here.

Interestingly, in another interaction analysis that compared the effects of activity space walkability on women's MVPA at the late pregnancy (3rd trimester) versus two other timepoints, the results showed positive associations between walkability and MVPA that was nearly significant during the 3rd trimester. This finding, together with the non-significant relationship between walkability and MVPA across two pregnancy trimesters reported in the prior paragraph, suggests activity space walkability may be especially critical for pregnant women to maintain PA during late pregnancy, when they tend to feel less comfortable being active in outdoor recreational places and have mobility (Evenson et al. 2009).

The positive association reported between weekend activity space walkability and women's MVPA may be due to women having more time and opportunities (e.g., family activities, events) to facilitate PA during weekend days (Evenson et al. 2004), which results in higher PA on these days. In addition, the finding that the positive association between activity space walkability and PA only existed during warmer days suggested BE itself, as a part of the physical environment, may not influence pregnant women's PA alone, and therefore it is important to incorporate other time-varying physical environment factors such as weather and air pollution in the efforts of disentangling the influences of multiple environmental contextual factors on women's PA during pregnancy and postpartum.

4.4.3. Differences in Day-Level BE-PA Associations by Individual Sociodemographics and Neighborhood Characteristics

The day-level association between BE exposure and women's MVPA also differed by maternal parity number, pre-pregnancy BMI category, and women's self-reported neighborhood cohesion and safety score. When it comes to daily activity space walkability, the results showed that its positive association with day-level MVPA was limited to those women who had given birth to their first child. It may be that women who had two or more children were involved in more care-giving activities than those who had their 1st born; as a result, their PA behaviors may be less susceptible to changes in BE characteristics (Borodulin, Evenson, and Herring 2009).

Additionally, Melzer et al. (2010) in a descriptive study reported a larger proportion of primiparous women were engaged in >30 min per day of MVPA than multiparous women, although the differences were not significant. Together, these factors may explain the null association between exposure to high walkability areas and PA outcomes among women who had two or more children in the current study.

Additionally, the results in this study indicated that the associations between activity space walkability and daily MVPA were different for obese women versus normal weight groups, but not different for overweight women versus normal weight groups. Specially, exposures to activity spaces with higher walkability were associated with significantly higher day-level MVPA in obese women during pregnancy and early postpartum. A longitudinal study reported women who were obese before pregnancy had the largest decreases in PA during early pregnancy compared to one-year prior (Fell et al. 2009). In addition, a qualitative study that interviewed 14 overweight and obese pregnant women in UK reported the lack of sidewalks in local neighborhoods were one of the major obstacles for their PA behaviors (Weir et al. 2010). Together, these results suggest walkability as a BE feature could mitigate the negative impacts of being obese on women's PA outcomes during pregnancy and postpartum.

Moreover, the women's self-reported neighborhood safety and cohesion score modified the positive effects of park proximity, exposure, and walkability on women's PA outcomes. Specifically, all these relationships were only significant for women who lived in less safe and cohesive neighborhoods. Prior studies have reported a negative relationship between neighborhood safety and pregnant women's PA (Evenson et al. 2009; Laraia et al. 2007). Therefore, it may be that the exposure to favorable BE features around non-home activity locations and along travel routes create additional PA opportunities for those who were not active in their own neighborhoods given the safety concerns.

4.4.4. Study Strengths and Limitations

To the best of my knowledge, this is the first study that examines GPS-based dynamic exposures to BE characteristics and accelerometry-based PA in women during the pregnancy and early postpartum periods. A major strength is the estimation of GPS-derived activity space exposure to greenness, parks and open space, and walkability, and the objective assessment of PA outcomes by repeatedly collecting highly resolved smartphone location and accelerometry data across the 1st and 3rd trimesters of pregnancy and at 4-6 months postpartum. Consequently, the work overcame recall biases inherent in self-reported BE exposures and PA outcomes and provided insights into longitudinal changes in both exposures and outcomes. Additionally, the longitudinal design used for this study allows us to examine both the between-subject effects (variations in BE exposures between pregnant women) and the within-subject effects (day-to-day variations within women) of exposure to BE characteristics on pregnant women's PA outcomes. The work reported in this chapter also applies spatial averaging (RB) and time-weighted spatial averaging (KDE) methods to capture women's activity space exposures to BE characteristics and study the relationships of these dynamic exposure to pregnant women's PA outcomes. As a result, this study was expected to reduce the spatial misclassification between BE exposures and PA outcomes and thereby mitigate the UGCoP, a common issue in residential-based studies. Finally, this study is among the first to examine the effects of person- and day-level BE exposure and its interactions with temporal factors, individual sociodemographics, and neighborhood characteristics in predicting PA outcomes of pregnant women, and, to the best of my knowledge, the first one to focus on a low-income Hispanic population. The findings of a positive association between parks and open space exposures and walkability in daily activity spaces and women's PA outcomes, as well as the moderating roles of weekdays versus weekends, pregnancy and postpartum periods, average daily temperature, maternal parity, pre-pregnancy BMI, and neighborhood cohesion and safety, can provide further guidance on formulating effective PA promotion strategies for pregnant women such as targeting at at-risk groups or days to improve maternal and infant health outcomes after pregnancy, particularly among understudied health disparity populations.

This study also has a few limitations. First, in addition to the GPS missingness issue and its potential influences on BE exposures that was discussed in Chapter 3, the accelerometry data also had missingness issues (211 of 655 data collection days were invalid according to the ≥10 h of wearing threshold. To reduce the potential biases this may bring on the study results (i.e., missing not at random), individual and temporal covariates (e.g., weekend days) that significantly predicted the day-level validity of accelerometry data were controlled in the final statistical models, and the main results did not change. Despite this effort, there may exist other unknown factors that may also influence the day-level validity of accelerometry data and thereby bias the study results. Second, this study was unable to differentiate recreational PA (e.g., leisure walks in a park) from utilitarian PA (e.g., commuting walks to workplaces or for grocery shopping) using the accelerometer data collected. Without fully separating these two types of PA, the mismatch between the BE exposure and PA outcome may still occur, as different BE characteristics may be more related to a specific type of PA (Jankowska, Schipperijn, and Kerr 2015; Sallis et al. 2012).

Third, due to the cross-sectional nature of analyses in this study and the lack of information in the decision-making processes of individual PA scenarios, the results may be subject to selective daily mobility bias, which refers to the circumstance that one is unsure whether an exposure (e.g., saw a park) led to women's PA activity (e.g., a walking session) or the exposure (e.g., a park visit) is in fact part of a pre-planned activity (e.g., a family outdoor activity session). Future studies may mitigate this bias by excluding anchor points (places which people organize their daily activities such as home, work, grocery stores) from environmental exposure measurement so that the effects of novel exposures on behaviors can be uncovered (Chaix 2013). Third, this study did not measure the quality of parks and open space, which has been associated with park use behaviors of predominantly Hispanic communities and thus may mediate or moderate the associations explored in this study (Dolash et al., 2015). Future studies are recommended to measure other aspects of parks and open space accessibility measures (e.g., amenities, accessibility, maintenance) and examine how these additional measures influence pregnant women's PA behaviors.

Lastly, this study focused on a health disparity group of low-income, Hispanic women, a population that has been understudied and has disproportionally low PA outcomes compared to non-Hispanic white population. Thus, the study results may not be generalized to pregnant women in other regions or SES or racial/ethnic groups; nevertheless, it does shed light on BE-PA relationships in an important population, and it may pave the way for future studies to continue exploring this important relationship during pregnancy and postpartum.

4.5. Conclusions

Pregnancy and early postpartum are critical periods for women's health. This study has shown that daily exposure to parks and open space, and walkable environments may affect women's PA outcomes during pregnancy and early postpartum, which in turn would affect both short- and long-term maternal and infant health outcomes. More importantly, this study has demonstrated that the choice of exposure assessment method may greatly influence the ability to detect meaningful relationship between BE exposures and PA outcomes in pregnant women. Consequently, future studies examining the impact of BE on pregnant women's PA should consider their spatiotemporal movement patterns when measuring their daily exposures to BE characteristics, in order to reduce the spatial mismatch between exposures and outcomes. Lastly, this study found that the BE-PA relationships were stronger on weekends, during late pregnancy, and for those in low SES neighborhoods, which provided further guidance in formulating effective PA promotion strategies for increasing women's PA across pregnancy and postpartum and decreasing PA-related health risks and outcomes.

Chapter 5 Conclusions

Maternal obesity during and after pregnancy is a major risk factor for mothers' short- and long-term health outcomes such as diabetes, cancer, and cardiovascular diseases. Hispanic women of childbearing age have disproportionally high obesity risks and low PA levels in compared to non-Hispanic white population. In this dissertation research, through three dissertation studies, I examined daily mobility patterns (Chapter 2), dynamic BE exposures (Chapter 3), and the associations between BE exposures and PA outcomes (Chapter 4) in a group of predominantly Hispanic low-income women of childbearing age. Results of these studies further elucidate the influences of women's daily mobility and BE exposures on PA behaviors in this understudied health disparity population.

The three dissertation studies have important implications for future studies that intend to examine the environmental contextual influences on women's PA behaviors during and after pregnancy, especially women of low SES and specific racial/ethnic groups. The first two sections of this chapter discuss this work's main contributions to the existing literature and some directions for future research. The last section summarizes major takeaways from this work.

5.1. Contributions and Connections

To start, this research contributes to the existing literature through its appliance of cutting-edge exposure assessment methods. Leveraging highly resolved geolocation and accelerometry-assessed movement data from the MADRES real-time data collection and sampling study, this research was able to derive dynamic BE exposures through the application of advanced geospatial analytical methods such as KDE-based spatiotemporal clustering detection. These exposure metrics weighted the exposure values based on the duration a woman spent in each daily activity location and for each trip (time-weighted spatial averaging approach).

Consequently, it overcame the spatial misclassification bias in prior residential-based studies (as demonstrated by the correlation analysis results in Chapter 3) and captured the “true contextual unit” better than traditional activity space methods such as RB, which ignores temporal information. To my best knowledge, this is the first study that measures women’s dynamic daily exposures to BE characteristics using highly resolved smartphone location data, and the study results demonstrate the merit of incorporating spatiotemporal movement patterns into the environmental exposure assessment to reduce measurement error.

With the application of both residential- and activity space-based exposure assessment methods, this dissertation study had a unique opportunity to investigate and mitigate important analytical problems that exist in studies that examine the effects of area-based environmental contextual variables on individual behaviors or outcomes, especially UCGoP. In Chapter 4, I examined the robustness of associations between daily exposure to greenness, parks and open space, and walkability and women’s day-level PA outcomes through applying BE exposure measures derived using the residential (RNB), spatial averaging (RB) and time-weighted spatial averaging (KDE) methods (with two different buffer sizes for each method). I found the association between park exposure and women’s PA outcomes only existed in measures derived using two activity space methods with 250 m buffers. This shows how the configuration choices embedded in different exposure measurement methods can greatly influence the model strength in detecting meaningful BE-PA relationships. This study, to my best of knowledge, is the first study that evaluates the magnitude of UGCoP in environmental contextual influences on PA outcomes. The three studies in this dissertation augment limited existing studies (Zhao, Kwan, and Zhou 2018; Delmelle et al. 2022; Laatikainen, Hasanzadeh, and Kyttä 2018) in showcasing the sensitivity of study results to the geospatial methods that are applied in emerging activity space-based neighborhood health studies.

Moreover, to my best knowledge, this dissertation is one of a handful of that has applied highly resolved smartphone geolocation and accelerometry-assessed movement data to examine the associations between daily mobility patterns, BE exposures, and PA outcomes in pregnant women, and the first one that focuses on low income, Hispanic women of childbearing age. Through three dissertation studies, I found pregnant women in my sample overall made few daily visits to parks and open space (chapter 2) and had little exposure to parks and open space in their daily activity spaces (Chapter 3), and these findings did not differ by pregnancy and early postpartum periods. The latter of the two studies therefore provides further evidence for the existence of an “ethno-racial” disparity in parks and green space access found by previous studies which either examined largely Hispanic communities in Los Angeles or Hispanic pregnant women in other US cities (Byrne 2012; Borodulin, Evenson, and Herring 2009; Derose et al. 2015).

Furthermore, my finding of positive effects of activity space parks and open space exposure on women’s PA outcomes during and after pregnancy (Chapter 4) provides a silver lining and suggests a path forward for improving PA promotion strategies for pregnant women of low SES and specific ethnic/racial minority groups. Specifically, the negative impact of low park access in these women’s residential neighborhoods on their PA may be offset by increasing women’s awareness of and visits to parks and open space close to their frequently visited non-home activity locations (e.g., workplaces, grocery stores). As a result, future PA interventions for pregnant women’s PA should take their daily non-home parks and open space exposure into consideration to improve its efficacy, particularly if these interventions were targeting women of low SES or specific racial/ethnic minority groups.

Lastly, my study also found women's trip behaviors, daily exposures to urban form characteristics (e.g., walkability), and influences of urban form exposures on their PA outcomes to greatly vary by pregnancy and postpartum periods, and levels of neighborhood safety and cohesion. For example, women decreased their time spent at commercial and service locations and reduced the total number of vehicular-based trips at 4-6 months postpartum (Chapter 2). In the same chapter, lower neighborhood cohesion and safety score was associated with increased vehicular trips across pregnancy and postpartum. In examining the day-level effects of BE exposures on PA outcomes, I found activity space walkability was only positively associated with women's PA during the late pregnancy period and for women who reported their neighborhoods as less safe (Chapter 4). Consequently, this research complements two prior residential-based studies in demonstrating the pregnancy and early postpartum period may be a critical modifier in the relationships of BE exposures to women's PA outcomes (Porter et al. 2019; Richardsen et al. 2016). In addition, this research adds to the previous evidence by showing the importance of providing access to walkable environments for women of low SES and specific racial/ethnic minority groups in their daily activity spaces to increase their PA outcomes (Perez, Ruiz, and Berrigan 2019). Moreover, this dissertation research was able to examine day-level influences of BE exposure on pregnant women's PA outcomes during and after pregnancy by disentangling between-subject (person-level) and within-subject (day-level) effects, which provides novel insights on the BE-PA association at a fine temporal granularity.

5.2. Limitations and Directions for Future Studies

Despite the aforementioned merits, this research is limited in terms of its data, methods, analytical approaches, and generalizability. To start, the missingness in GPS and accelerometry data applied in this dissertation research may be a concern. I made multiple efforts to mitigate the potential impact of missingness on study outcomes. These efforts included imputing missing GPS data using participant-reported sleep/wake time and EMA-reported physical context (Chapter 2), exploring diurnal patterns of GPS data missingness (Chapter 2), performing sensitivity analyses using different cut-offs for labeling valid GPS and accelerometry observation days (Chapter 2, 3, and 4), and controlling variables (e.g., weekdays versus weekend days) that predicted invalid days (Chapter 4). However, other unaccounted data missingness scenarios may exist and possibly bias study results. For instance, the missingness of GPS data may be correlated with spatial context (e.g., tall buildings, trees) that could obstruct receiver signals. As a result, BE characteristics (e.g., proximity to public transit stops) in these spatial contexts were not captured and therefore day-level exposure results may be under- or over-estimated. Future studies are recommended to compare different advanced missing data imputation approaches, evaluate their imputation rates and accuracies, and chose the one that achieves the highest accuracies for their specific setting (Barnett and Onnela 2020).

Further, given GPS and accelerometry data were collected using separate devices, the missingness from one or both data may greatly reduce the sample sizes and powers for the statistical models to detect associations between BE exposure and PA outcomes. Increasingly, studies have advocated an “all-in-one” approach such as applying Smartphones or Smartwatches to simultaneously collect geolocation and movement data as well as other self-reported psychosocial variables such as stress and affect (Straczkiewicz, James, and Onnela 2021; Gal et al. 2018). This approach may be more promising in reducing the rates of data missingness than studies applying multiple sensors, although at a potential cost of data accuracy (Piccinini, Martinelli, and Carbonaro 2020).

Besides the data missingness issue, more research is needed to continue improving the activity space-based exposure measurement method applied in this research. For example, the influences of environmental contextual factors on PA behaviors may vary by locations (home versus workplace), time of the day (daytime versus evening), and days of the week (weekdays versus weekends) (Kwan 2018; Koohsari et al. 2016). As a result, an adaptive buffer size approach which derives minute-level BE exposures based on buffer sizes corresponding to time of the day, weekdays versus weekend, and trip modes may be utilized to better capture BE exposures for women during and after pregnancy, given their drastic changes in time-activity and mobility patterns as shown in Chapter 2. In addition, recognizing traditional BE data (e.g., NDVI) is limited in capturing the pedestrian's interactions with green features on the streets, in this research, additional greenness measures such as % green space and tree cover along walkable roads were derived to better capture these interactions. However, both measures still could not capture other crucial street design features such as crosswalks, lighting fixtures, and sidewalk maintenance that were associated with walking behaviors (Yin et al. 2015). Emerging studies have started to extract street-level BE features from Google Street View products via deep learning techniques (Yin et al. 2015; Yin 2017). Future studies should explore these novel approaches and strive to incorporate them when examining the influences of BE exposures on pregnant women's PA behaviors.

Besides its limitations in data and exposure assessment methods, this dissertation study remains subject to the selective daily mobility bias. This bias refers to the fact that an unmeasured factor may have causal effects on both exposures and outcomes (Chaix et al. 2012; 2013). For instance, a pregnant woman with a good knowledge of benefits of exercise may choose to visit a park to exercise. In this case, the measured effect of park access on her exercise outcomes will be spurious since they are both caused by her motivations to exercise. To mitigate the selective daily mobility bias, future studies should apply more advanced methods such as excluding locations where PA occurred from the exposure assessment or only measuring the exposure at or around anchor points (e.g., key locations where one organizes life activities such as home, work, and neighborhood grocery store), which can be extracted over longer periods (e.g., 12-months) of geolocation monitoring (Chaix et al. 2013; Perchoux et al. 2015, Zenk et al. 2018). These methods should be explored by future studies aim to examine the association between GPS-based BE exposure and women's PA behaviors across pregnancy and postpartum.

Furthermore, the analyses in this research are still cross-sectional in nature, which limit the opportunities to infer causal relationships. Numerous studies have associated BE characteristics with PA outcomes, but the behavioral mechanisms from BE exposure to PA outcomes remain largely unknown (Travert, Annerstedt, and Daivadanam 2019). In this realm, future studies should consider applying context-sensitive (e.g., during or after a PA episode, during a walking session in the park) EMA survey tools to collect psychosocial information (e.g., perceived safety, stress, motivation, mood) as events unfold so that the connection between objectively-measured and perceived BE exposures and these psychosocial variables in determining PA behaviors can be further examined (Dunton 2018; Huang et al. 2016).

Finally, when conducting this dissertation study, I leveraged the GPS and accelerometry data collected by the MADRES real-time and personal sampling study. This study focused on understanding the causes of excessive weight gain and retention such as environmental exposure and social stressors among low-income Hispanic women to reduce the disproportionate burden of disease they bear; as a result, it only enrolled Hispanic women to limit between-group racial/ethnic differences in its design. Due to this unique study design, results of this dissertation study may not be generalized to pregnant women in other regions or SES or racial/ethnic group. However, given Hispanic and low-income women of childbearing age as a group forms a large and understudied group that has been disproportionally exposed to various environmental hazards, my explorations of associations between daily mobility, BE exposures, and PA outcomes may help to guide future studies for this important health disparity population or potentially other populations of similar sociodemographic characteristics.

5.3. Major Takeaways

In conclusion, this dissertation study used highly resolved smartphone location and accelerometry-assessed activity data collected from 62 Hispanic women of childbearing age in urban Los Angeles, CA, during pregnancy and the early postpartum period to investigate the associations among women's daily mobility patterns (Chapter 2), dynamic built-environment (BE) exposures (Chapter 3), and PA outcomes (Chapter 4). The results of three empirical case studies revealed an exceedingly low parks and open space exposure for this group at their daily activity locations and along travel paths during and after pregnancy, which were associated with women's lower day-to-day PA outcomes. In addition, important modifiers (e.g., late pregnancy, early postpartum, high pre-pregnancy BMI, low neighborhood safety) of women's daily mobility, BE exposures, and their associations with PA outcomes were identified. Lastly, the second and third studies evaluated measurement error and bias resulting from applying traditional residential-based measures were evaluated and their implications on uncovering the relationships between BE exposures and PA outcomes were investigated. Future studies are suggested to perform qualitative analyses of the BE features (e.g., parks) in which women's PA was performed, mitigate selective daily mobility bias, and apply real-time surveying techniques such as EMA to elucidate psychosocial pathways from BE exposures to PA outcomes. Future PA promotion interventions for pregnancy women are recommended to target at-risk pregnancy and postpartum periods and sociodemographic groups to improve their efficacy, especially for those of low socioeconomic status and specific racial/ethnic minority groups.

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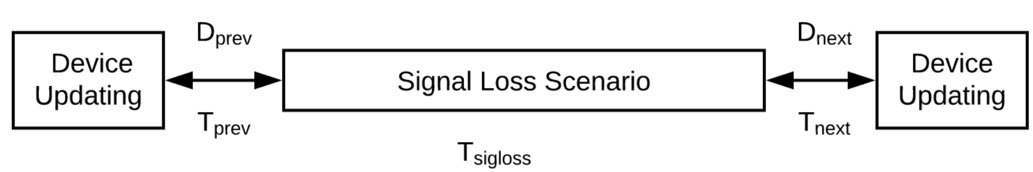
Appendix A: Confidence flagging algorithm for signal loss scenarios using the Maternal And Developmental Risks from Environmental and Social stressors (MADRES) real-time and personal sampling study Global Positioning System (GPS) data

Levels of Confidence	Criteria	Observations (N)
Extremely High	$D_{prev} \leq 1$ m AND $D_{next} \leq 1$ m	5,246
Very High	$D_{next} \leq 45$ m/s* T_{next} AND $T_{next} \leq 30$ min	23,935
High	$D_{next} \leq 45$ m/s* T_{next} AND $30 < T_{next} \leq 120$ min	23,335
Medium	$D_{next} > 45$ m/s* T_{next} AND $D_{next} \leq 45$ m/s* $(T_{next} + T_{sigloss})$ AND $T_{next} \leq 120$ min	1,558
Low	[$D_{next} > 45$ m/s*T_{next} AND $D_{next} \leq 45$ m/s*$(T_{next} + T_{sigloss})$ AND $T_{next} > 120$ min] OR [$D_{next} > 45$ m/s* T_{next} AND $D_{next} > 45$ m/s* $(T_{next} + T_{sigloss})$]	139,784
No Information	No distance/duration data available	383,338



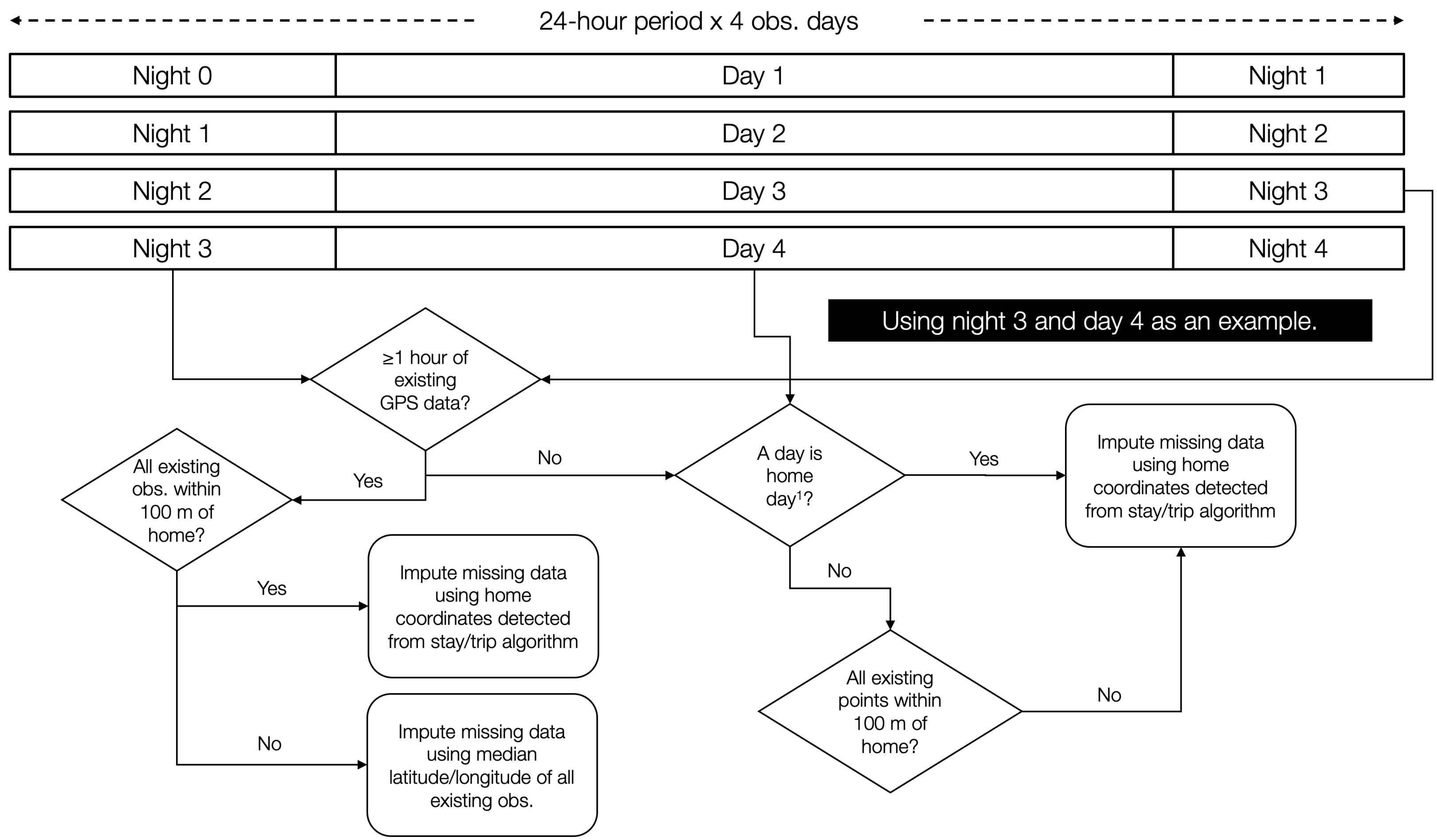
Note: D = distance. T = Time. N = 577,196 observations where signal was lost. Signal loss scenarios = segments with signals from either GPS or network source that are lost for ≥1min.

Appendix B: Rules used to classify contexts of stays detected with the Maternal And Developmental Risks from Environmental and Social stressors (MADRES) real-time and personal sampling study Global Positioning System (GPS) data

Spatial Contexts	Rules
Home residential[1]	Longest stay of the corresponding pregnancy/postpartum period (≥2 h)
Non-home residential	If a stay was assigned one of the following 2016 Southern California Association of Governments (SCAG) land use codes: single-family residential, multi-family residential, mobile homes and trailer parks, mixed residential, and rural residential[2]
Commercial and services	If a stay was assigned the following 2016 SCAG land use codes: general office, commercial and services, industrial land uses[2]
Parks and open space	If a stay was assigned the following 2016 SCAG land use code: "open space and recreation"
Schools and public facilities	If a stay was assigned the following 2016 SCAG land use codes: "Facilities," "Education."
Other	If a stay was assigned a 2016 SCAG land use code besides the above mentioned codes or did not get a 2016 SCAG land use code assigned.
Indoor/Outdoor Locations	**Rules**
Home indoor	If a stay was classified as home residential and fell inside the 1 m buffer of the nearest 2014 Los Angeles County building footprint polygon[3]
Home outdoor	If a stay was classified as home residential and fell outside the 1 m buffer of the nearest 2014 Los Angeles County building footprint polygon[3]
Non-home indoor	If a stay was classified as one of non-home contexts and fell inside the 1 m buffer of the nearest 2014 Los Angeles County building footprint polygon[3]
Non-home outdoor	If a stay was classified as one of non-home contexts and fell outside the 1 m buffer of the nearest 2014 Los Angeles County building footprint polygon[3]
Out of Los Angeles County	If a stay was out of Los Angeles County, its indoor/outdoor status was not classified since building footprints Geographic Information System (GIS) data were unavailable.

[1] The "home residential" context was assigned at the last step, which was defined as the longest stay (a minimum of 2 h) detected within a pregnancy/postpartum period regardless of prior-assigned contexts.
[2] An existing land use was assigned to a stay if the stay point fell within the 15 m buffer of land use parcel boundaries.
[3] 1 m rather than the exact boundary was chosen to account for scenarios when indoor activities occurred mainly on corners of the building, resulting in a stay that fell outside the building footprint polygon and was misclassified as outdoor.

Appendix C: An illustration of the GPS imputation rules based on existing data and home locations detected from context classification.



[1] Home day is defined as the day during which mothers answered home (indoor) / home (outdoor) in the physical context question in all four or five survey prompts.

Note: GPS = Global Positioning System. Obs. = Observations.

Appendix D: Individual sociodemographics, neighborhood characteristics, and temporal factors included in the study along with their measures and data sources

Categories	List	Measure	Source
Individual Sociodemographic	Age	Continuous	MADRES maternal demographics data
	Education		
	Marriage	Living together/married versus others	
	Acculturation	US born versus Foreign born	
	Parity	0 versus >1 child	
	Employment status	Employed versus unemployed	MADRES 1st trimester, 3rd trimester, and 6-month questionnaires
	Safety and cohesion score	Neighborhood cohesion scale (on a scale of 1 to 5 with higher score indicates better cohesion) developed by Sampson (1997)	MADRES 2nd trimester and 6-month questionnaires
Neighborhood characteristics	National Walkability Index score	On a scale of 1 to 20 with higher indicates more walkable neighborhoods	EPA EnviroAtlas
	Area Deprivation Index score	Ranking relatively to other neighborhoods within state of California from domains of income, education, employment, and housing quality (in a scale of 1 to 10 with higher means more disadvantaged)	2018 Area Deprivation Index from Neighborhood Atlas®, University of Wisconsin-Madison
Temporal factors	Universal age[1]	Continuous ages calculated from pre- to post-birth, with zero indicates fetus delivery date	MADRES questionnaires
	Pregnancy/postpartum periods	1st trimester, 3rd trimester, 4-6 month postpartum	MADRES questionnaires
	Weekends	1 = weekend days	Derived from GPS timestamp

[1] Universal age is calculated as a continuous variable (starting from conception till end of monitoring period) as an alternative to pregnancy/postpartum periods for sensitivity analysis purposes.

Appendix E: Zero-inflated Generalized Linear Mixed-Effects Model (GLMM) results for changes in time-activity patterns by pregnancy and postpartum period

Predictors	Non-Home Residential (min/day)	Commercial and Services (min/day)	Industrial and Office Spaces (min/day)	Schools and Public Facilities (min/day)	Parks and Open Spaces (min/day)	Home Residence Outdoor (min/day)	All Non-Home Contexts Outdoor (min/day)
Count Model				*Incidence Rate Ratio (95%CI)*			
Period: 1st Trimester	1.21 (.69-2.12)	.98 (.75-1.28)	1.29 (.85-1.97)	.73 (.43-1.24)	1.77 (.65-4.81)	.87 (.74-1.02)	1.15 (.85-1.58)
Period: 4-6 Months Postpartum	1.61 (.92-2.84)	.82 (.62-1.09)	1.33 (.87-2.02)	.75 (.44-1.28)	.46 (.12-1.78)	.9 (.75-1.1)	1.07 (.78-1.47)
Valid GPS observation (h/d)	1.01 (.94-1.08)	1.08 ** (1.03-1.13)	1.03 (.98-1.08)	1.02 (.93-1.11)	.95 (.78-1.15)	1.06 *** (1.04-1.08)	1.03 (.98-1.07)
Zero-Inflated Model				*Odds Ratio (95%CI)*			
Period: 1st Trimester	.87 (1.63-.46)	.63 (1.12-.36)	.61 (1.14-.33)	.94 (1.79-.5)	1.35 (3.82-.48)	.56 (2.13-.15)	1.03 (1.79-.59)
Period: 4-6 Months Postpartum	1.06 (1.98-.57)	.42 ** (.77-.23)	.55 (1.05-.29)	.85 (1.65-.44)	1.19 (3.63-.39)	1.02 (4.91-.21)	.73 (1.29-.42)
Valid GPS observation (h/d)	.3 * (.82-.11)	.29 * (.83-.1)	.18 * (.94-.03)	.15 ** (.52-.04)	.23 (2.65-.02)	.2 (1.84-.02)	.23 * (.81-.07)

*p<.05. **p<.01. ***p<.001. Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation.

Note: GPS = Global Positioning System.

Appendix F: Zero-inflated Generalized Linear Mixed-Effects Model (GLMM) results for changes in daily mobility patterns by pregnancy and postpartum period

Predictors	**Pedestrian-based Trip (min/d)**	**Vehicular-based Trip (min/d)**	**Pedestrian-based Trip (N/d)**	**Vehicular-based Trip (N/d)**
Count Model		***Incidence Rate Ratio (95%CI)***		
Period: 1st Trimester	1.03 (.75-1.42)	1.05 (.86-1.28)	1.03 (.72-1.47)	1.03 (.87-1.23)
Period: 4-6 Months Postpartum	.96 (.69-1.32)	1.17 (.95-1.44)	.82 (.56-1.2)	1 (.84-1.19)
Valid GPS observation (h/d)	1.02 (.97-1.08)	1.05 ** (1.02-1.09)	.97 (.92-1.03)	1.04 * (1.01-1.07)
Zero-Inflated Model		***Odds Ratio (95%CI)***		
Period: 1st Trimester	.72 (1.23-.43)	.8 (1.45-.45)	.62 (1.43-.26)	.72 (1.46-.35)
Period: 4-6 Months Postpartum	.61 (1.05-.35)	.5 * (.93-.27)	.58 (1.45-.24)	.44 * (.92-.21)
Valid GPS observation (h/d)	.21 * (.86-.05)	.35 * (.92-.13)	.21 (1.55-.03)	.28 (1.11-.07)

*p<.05. **p<.01. ***p<.001. Exponentiated parameter estimates are shown. Reversed odds ratio (i.e., odds for an outcome to be non-zero) of zero-inflated models were calculated for easier interpretation.

Note: GPS = Global Positioning System.

Appendix G: Sensitivity analyses results of between-subject (BS) and within-subject (WS) effects of built-environment (BE) exposures on day-level moderate-to-vigorous physical activity (MVPA) outcomes

	MVPA min/d			
	100 m KDE model	*100 RB model*	*800 m RNB model*	*1,600 m RNB model*
Predictors	*Estimates (95%CI)*			
(Intercept)	4.43 * (1.08 – 18.22)	4.07 * (1.01 – 16.29)	1.19 (.14 – 9.93)	.50 (.04 – 6.23)
% Green space along walkable roads (BS)	1.00 (.99 – 1.02)	1.01 (.98 – 1.05)	1.01 (.98 – 1.03)	1.01 (.98 – 1.03)
Distance to the nearest park entrance (BS)	1.01 (.96 – 1.05)	1.04 (.97 – 1.12)	1.00 (1.00 – 1.00)	1.00 (1.00 – 1.00)
Walkability index score (BS)	1.03 (.95 – 1.12)	1.14 (.99 – 1.31)	1.07 (.98 – 1.17)	1.12 (1.00 – 1.25)
Daily parks and open space exposure (BS)	1.41 (.85 – 2.32)	1.51 (.92 – 2.48)	1.13 (.79 – 1.60)	
% Green space along walkable roads (WS)	.99 (.98 – 1.01)	1.01 (.99 – 1.03)		
Distance to the nearest park entrance (WS)	.99 (.94 – 1.05)	.99 (.96 – 1.02)		
Walkability index score (WS)	1.00 (.88 – 1.13)	1.02 (.94 – 1.11)		
Daily parks and open space exposure (WS)	1.14 (.97 – 1.36)	1.17 (.99 – 1.38)		
Maternal age	1.00 (.97 – 1.03)	1.00 (.97 – 1.03)	1.00 (.97 – 1.03)	1.00 (.97 – 1.03)
Education: Some college/Graduate	.69 * (.49 – .97)	.70 * (.50 – .97)	.73 * (.54 – .99)	.75 (.55 – 1.01)
Parity: First-born	1.21 (.85 – 1.74)	1.21 (.86 – 1.72)	1.24 (.85 – 1.79)	1.22 (.86 – 1.75)

Employment status: Employed	1.03 (.82 – 1.28)	1.02 (.82 – 1.27)	1.06 (.85 – 1.32)	1.07 (.86 – 1.33)
Pre-pregnancy BMI category: Overweight/Obesity	.77 (.56 – 1.04)	.75 (.56 – 1.01)	.78 (.58 – 1.06)	.79 (.59 – 1.06)
Average daily temperature (°C)	1.02 * (1.00 – 1.04)	1.02 * (1.00 – 1.04)	1.02 * (1.00 – 1.04)	1.02 * (1.00 – 1.04)
Type of day: Weekend	.81 ** (.70 – .93)	.80 ** (.70 – .92)	.80 ** (.70 – .92)	.80 ** (.70 – .92)
The 3rd trimester day	.95 (.79 – 1.13)	.94 (.79 – 1.12)	.95 (.80 – 1.13)	.95 (.80 – 1.14)
4-6 months postpartum day	.89 (.74 – 1.07)	.90 (.75 – 1.08)	.89 (.74 – 1.07)	.89 (.74 – 1.07)
Neighborhood cohesion and safety score (range from 1 to 5)	1.04 (.92 – 1.17)	1.03 (.91 – 1.16)	1.04 (.92 – 1.17)	1.04 (.92 – 1.17)
Neighborhood deprivation index (range from 1 to 10)	1.02 (.94 – 1.12)	1.05 (.96 – 1.14)	1.01 (.93 – 1.10)	1.02 (.95 – 1.11)
Daily accelerometry wearing hours	1.09 *** (1.06 – 1.13)	1.09 *** (1.06 – 1.13)	1.10 *** (1.06 – 1.13)	1.10 *** (1.07 – 1.13)
Total valid accelerometry collection days	1.01 (.96 – 1.06)	1.01 (.97 – 1.06)	1.01 (.97 – 1.06)	1.01 (.97 – 1.06)

* $p<.05$ ** $p<.01$ *** $p<.001$. Estimates were exponentiated for the ease of interpretation.

Note: KDE = Kernel Density Estimation. RB = Route Buffer. RNB = Residential Network Buffer.

Appendix H: Significant interactions between day-level built-environment (BE) exposures and temporal, individual and neighborhood factors in predicting day-level moderate-to-vigorous physical activity (MVPA) outcomes

	MVPA min/d						
	250 m KDE x 4-6 months postpartum	*250 m KDE x Pre-pregnancy BMI*	*250 m KDE x Neighborhood safety*	*250 m RB Average daily temperature*	*250 m RB x Weekend days*	*250 m RB x the 3rd trimester*	*250 m RB x First-born*
Predictors	*Estimates (95%CI)*						
(Intercept)	7.10 *** (2.85 – 17.69)	8.72 *** (3.42 – 22.25)	4.40 ** (1.54 – 12.58)	6.83 *** (2.41 – 19.33)	8.76 *** (3.46 – 22.15)	9.45 *** (3.71 – 24.05)	8.70 *** (3.15 – 24.05)
% Green space along walkable roads (BS)	1.01 (.99 – 1.03)	1.01 (.99 – 1.03)	1.01 (.99 – 1.03)	1.03 (1.00 – 1.06)	1.03 (1.00 – 1.06)	1.03 (1.00 – 1.06)	1.03 (1.00 – 1.06)
Distance to the nearest park entrance (BS)	1.01 (.98 – 1.05)	1.01 (.98 – 1.05)	1.02 (.98 – 1.05)	1.04 (.99 – 1.10)	1.04 (.99 – 1.09)	1.05 (1.00 – 1.10)	1.04 (1.00 – 1.10)
Walkability index score (BS)	1.05 (.97 – 1.14)	1.05 (.97 – 1.14)	1.05 (.97 – 1.14)	1.18 * (1.04 – 1.35)	1.17 * (1.03 – 1.32)	1.20 ** (1.05 – 1.36)	1.18 * (1.04 – 1.34)
Daily parks and open space exposure (BS)	1.62 (.98 – 2.67)	1.66 * (1.01 – 2.74)	1.57 (.95 – 2.59)	1.50 (.93 – 2.40)	1.55 (.97 – 2.48)	1.46 (.91 – 2.33)	1.46 (.91 – 2.34)
% Green space along walkable roads (WS)	1.00 (.98 – 1.03)	1.03 (.99 – 1.06)	1.07 (1.00 – 1.15)	1.04 (.95 – 1.13)	1.00 (.97 – 1.03)	1.01 (.99 – 1.04)	1.00 (.98 – 1.02)
Distance to the nearest park entrance (WS)	1.00 (.93 – 1.07)	1.08 (.92 – 1.27)	1.02 (.78 – 1.35)	.92 (.80 – 1.05)	.98 (.93 – 1.03)	.96 (.93 – 1.00)	.97 (.93 – 1.01)
Walkability index score (WS)	1.12 (.95 – 1.31)	.85 (.64 – 1.13)	1.03 (.58 – 1.84)	.68 * (.49 – .94)	.91 (.79 – 1.04)	.99 (.90 – 1.09)	.95 (.86 – 1.06)
Daily parks and open space exposure (WS)	1.30 * (1.05 – 1.62)	1.09 (.75 – 1.58)	2.72 ** (1.30 – 5.66)	1.63 (.82 – 3.22)	1.23 (.98 – 1.55)	1.21 (.98 – 1.49)	1.23 * (1.00 – 1.50)
4-6 months postpartum	1.05 (.77 – 1.44)	.94 (.79 – 1.13)	.93 (.78 – 1.11)	.89 (.75 – 1.06)	.91 (.76 – 1.09)	.91 (.76 – 1.08)	.90 (.75 – 1.07)
Average daily temperature(°C)	1.02 * (1.00 – 1.04)	1.01 (1.00 – 1.03)	1.02 * (1.00 – 1.04)	1.03 * (1.01 – 1.06)	1.02 * (1.00 – 1.04)	1.02 * (1.00 – 1.04)	1.02 * (1.00 – 1.04)

	MVPA min/d						
	250 m KDE x 4-6 months postpartum	*250 m KDE x Pre-pregnancy BMI*	*250 m KDE x Neighborhood safety*	*250 m RB Average daily temperature*	*250 m RB x Weekend days*	*250 m RB x the 3rd trimester*	*250 m RB x First-born*
Predictors	*Estimates (95%CI)*						
Type of day: Weekend	.81 ** (.71 – .93)	.82 ** (.71 – .94)	.81 ** (.71 – .93)	.82 ** (.71 – .93)	.86 (.66 – 1.13)	.80 ** (.70 – .92)	.81 ** (.71 – .93)
The 3rd trimester	.96 (.81 – 1.13)	1.01 (.85 – 1.20)	.94 (.80 – 1.12)	.93 (.79 – 1.10)	.96 (.81 – 1.13)	.93 (.69 – 1.27)	.95 (.80 – 1.12)
Maternal age	.99 (.97 – 1.01)	.99 (.97 – 1.01)	.99 (.97 – 1.01)	.99 (.96 – 1.01)	.99 (.96 – 1.01)	.99 (.96 – 1.01)	.99 (.96 – 1.01)
Education: Some college/Graduate	.70 * (.53 – .92)	.69 ** (.52 – .91)	.67 ** (.50 – .88)	.67 ** (.50 – .89)	.66 ** (.50 – .88)	.66 ** (.49 – .88)	.66 ** (.49 – .89)
Pre-pregnancy BMI: Obesity	.92 (.68 – 1.25)	.92 (.60 – 1.42)	.90 (.67 – 1.22)	.95 (.71 – 1.27)	.95 (.71 – 1.27)	.96 (.72 – 1.29)	.94 (.71 – 1.26)
Pre-pregnancy BMI: Overweight	.66 ** (.49 – .89)	.55 ** (.35 – .87)	.69 * (.52 – .93)	.66 ** (.49 – .87)	.65 ** (.49 – .86)	.66 ** (.50 – .88)	.66 ** (.49 – .87)
Neighborhood cohesion and safety score (range from 1 to 5)	1.04 (.93 – 1.16)	1.05 (.93 – 1.17)	1.23 * (1.01 – 1.50)	1.02 (.92 – 1.14)	1.03 (.92 – 1.15)	1.04 (.93 – 1.16)	1.02 (.91 – 1.15)
Daily accelerometer wearing hours	1.09 *** (1.06 – 1.12)	1.09 *** (1.06 – 1.13)	1.09 *** (1.06 – 1.13)	1.09 *** (1.06 – 1.13)	1.09 *** (1.06 – 1.13)	1.08 *** (1.05 – 1.12)	1.09 *** (1.06 – 1.13)
% Green space along walkable roads (WS) x 4-6 months postpartum	.98 (.94 – 1.03)						
Distance to the nearest park entrance (WS) x 4-6 months postpartum	.96 (.85 – 1.09)						
Walkability index score (WS) x 4-6 months postpartum x 4-6 months postpartum	.72 * (.54 – .97)						

	MVPA min/d						
	250 m KDE x 4-6 months postpartum	*250 m KDE x Pre-pregnancy BMI*	*250 m KDE x Neighborhood safety*	*250 m RB Average daily temperature*	*250 m RB x Weekend days*	*250 m RB x the 3rd trimester*	*250 m RB x First-born*
Predictors				*Estimates (95%CI)*			
Daily parks and open space exposure (WS) x 4-6 months postpartum	.80 (.56 – 1.15)						
Parity: First-born							.97 (.63 – 1.50)
% Green space along walkable roads (WS) x Parity: First-born							1.04 (.99 – 1.09)
Distance to the nearest park entrance (WS) x Parity: First-born							1.04 (.96 – 1.12)
Walkability index score (WS) x 4-6 months postpartum x Parity: First-born							1.23 * (1.02 – 1.49)
Daily parks and open space exposure (WS) x Parity: First-born							1.04 (.69 – 1.58)
% Green space along walkable roads (WS) x Pre-pregnancy BMI: Obesity		.92 ** (.87 – .97)					
% Green space along walkable roads (WS) x Pre-pregnancy BMI: Overweight		.97 (.93 – 1.02)					
Distance to the nearest park entrance (WS) x Pre-pregnancy BMI: Obesity		1.01 (.84 – 1.20)					

	MVPA min/d						
	250 m KDE x 4-6 months postpartum	*250 m KDE x Pre-pregnancy BMI*	*250 m KDE x Neighborhood safety*	*250 m RB Average daily temperature*	*250 m RB x Weekend days*	*250 m RB x the 3rd trimester*	*250 m RB x First-born*
Predictors				*Estimates (95%CI)*			
Distance to the nearest park entrance (WS) x Pre-pregnancy BMI: Overweight		.85 (.71 – 1.03)					
Walkability index score (WS) x 4-6 months postpartum x Pre-pregnancy BMI: Obesity		1.49 * (1.04 – 2.12)					
Walkability index score (WS) x 4-6 months postpartum x Pre-pregnancy BMI: Overweight		1.17 (.80 – 1.70)					
Daily parks and open space exposure (WS) x Pre-pregnancy BMI: Obesity		1.01 (.64 – 1.59)					
Daily parks and open space exposure (WS) x Pre-pregnancy BMI: Overweight		1.33 (.84 – 2.10)					
% Green space along walkable roads (WS) x Neighborhood cohesion and safety			.98 * (.96 – 1.00)				
Distance to the nearest park entrance (WS) x Neighborhood cohesion and safety			.99 (.90 – 1.09)				
Walkability index score (WS) x 4-6 months postpartum x Neighborhood cohesion and safety			.99 (.81 – 1.21)				

	MVPA min/d						
	250 m KDE x 4-6 months postpartum	*250 m KDE x Pre-pregnancy BMI*	*250 m KDE x Neighborhood safety*	*250 m RB Average daily temperature*	*250 m RB x Weekend days*	*250 m RB x the 3rd trimester*	*250 m RB x First-born*
Predictors				*Estimates (95%CI)*			
Daily parks and open space exposure (WS) x Neighborhood cohesion and safety			.78 * (.62 – .97)				
% Green space along walkable roads (WS) x Average daily temperature				1.00 (.99 – 1.00)			
Distance to the nearest park entrance (WS) x Average daily temperature				1.00 (1.00 – 1.01)			
Walkability index score (WS) x Average daily temperature				1.02 ** (1.01 – 1.04)			
Daily parks and open space exposure (WS) x Average daily temperature				.99 (.95 – 1.02)			
% Green space along walkable roads (WS) x Weekend days					1.02 (.98 – 1.06)		
Distance to the nearest park entrance (WS) x Weekend days					1.01 (.94 – 1.08)		
Walkability index score (WS) x Weekend days					1.25 * (1.04 – 1.51)		
Daily parks and open space exposure (WS) x Weekend days					.92 (.67 – 1.25)		

	MVPA min/d						
	250 m KDE x 4-6 months postpartum	*250 m KDE x Pre-pregnancy BMI*	*250 m KDE x Neighborhood safety*	*250 m RB Average daily temperature*	*250 m RB x Weekend days*	*250 m RB x the 3rd trimester*	*250 m RB x First-born*
Predictors	*Estimates (95%CI)*						
% Green space along walkable roads (WS) x the 3rd trimester						1.00 (.96 – 1.05)	
Distance to the nearest park entrance (WS) x the 3rd trimester						1.10 * (1.01 – 1.20)	
Walkability index score (WS) x the 3rd trimester						1.20 (.95 – 1.53)	
Daily parks and open space exposure (WS) x the 3rd trimester						1.01 (.71 – 1.43)	

* p<.05   ** p<.01   *** p<.001. Estimates were exponentiated for the ease of interpretation.

Note: KDE = Kernel Density Estimation. MVPA = Moderate-to-Vigorous Physical Activity. RB = Route Buffer.