ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL OF SCIENCE ENGINEERING AND TECHNOLOGY

SPATIAL TEMPORAL DIMENSIONS OF ACCESSIBILITY IN ISTANBUL, TURKEY

Ph.D. THESIS

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Department of Geomatics Engineering
Geomatics Engineering Programme

JANUARY 2020

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To my dearest mother, dearest father, sister and brothers

FOREWORD

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ABBREVIATIONS

ASS	: Average Spatial Separation
ATT	: Average Travel Time
CFN	: Clustered Feature Numbers
CORINE	: COoRdination of INformation on the Environment
DTT	: Dynamic Travel Time
FHL	: First Hierarchal Level
FIFO	: First-In-First-Out
GCP	: Ground Control Point
GIS	: Geographic Information System
GPS	: Global Position System
HTW	: Home to Work
HTWAV	: Home to Work Attraction Vector
ICT	: Information and Communications Technologies
IDW	: Inverse Distance Weighting
IETT	: Istanbul Electric Tram and Tunel Company
IML	: Istanbul Metrobus Line
IMM	: Istanbul Metropolitan Municipality
LCLU	: Land Cover Land Use
LU	: Land Use
MAPE	: Mean Absolute Percentage Errors
NT-IDW	: Network Inverse Distance Weighting
NW	: Network
OD	: Origins-Destinations
OSM	: OpenStreetMap
PA	: Potential Accessibility
POI	: Point of Interest
RMSE	: Root Mean Square Error
RS	: Remote Sensing
RTMS	: Remote Traffic Microwave Sensors
SHL	: Second Hierarchal Level
STT	: Static Travel Time
TEM	: Trans-European Motorway
TND	: Travel Network Distance
WTH	: Work to Home

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SPATIAL TEMPORAL DIMENSIONS OF ACCESSIBILITY IN ISTANBUL, TURKEY

SUMMARY

Transportation has a pivotal role in shaping citizen's activities and urban sustainability. It also is an essential component of a resident's life and a nation's economy for its roles in improving productivity and justice to reach desired destinations, and by offering easy access to supplies. Effective road networks, per se, uphold a vital level of service despite malfunctioning of certain roads within the network by providing more alternatives to network users. Ultimately, certain features of the road network impact the level of the ease of mobility within urban areas. Researchers argue that the interaction within transportation system components is best presented by the concept of accessibility which is also considered the definitive aim of any transportation system. Evaluating the current accessibility status of the region assists in identifying poor accessibility locations to target them in the future. The location-based measure is considered a very common tool to quantify the accessibility status for spatial locations within the targeted region. Four essential components namely land-use, transport, individual and temporal are required for its calculation. A common issue is capturing such components accurately and within required spatial and temporal resolutions, depending on the aim of the project. Identifying related origins and destinations to each corresponding activity is another issue for this measure. Generally, policymakers aim to steer these components to increase the accessibility of the targeted region. For that, policymakers invest heavily in transportation infrastructures, such as operating a Bus Rapid Transit (BRT) system or constructing new roads. Such investments enhance certain components while negatively affecting others. Balanced growth in all components is required to reach the desired enhanced level of accessibility. Evaluating the changes occurred to accessibility status by changing accessibility components, within a considered time period, assists in identifying the roles of each component on influencing the current status of accessibility. Thus, by learning from that, altering accessibility components more effectively to enhance future accessibility status according to targeted travel users/audience or activities. Among the most important daily activities within urban areas is the accessibility to jobs/workplaces (workplaces accessibility). Modelling accessibility to workplaces is considered the center of accessibility analysis research for its relation to other significant features of urban structure, such as understand the urban form, the spatial mismatch of jobs and housing, job-housing balance, excess traveling and employability. However, accessibility to such locations requires further details due to dissimilarity occurring each travel direction (from homes to work or from work to homes).

Primarily, this thesis aims to provide policymakers with more accurate tools, methodologies and models to capture essential accessibility components, convert them into the required form and quantify the change in accessibility at high spatial resolutions. By that, policymakers are able to disentangle the effects of accessibility components on changing the accessibility status at high spatial resolution, utilizing desired travel/transportation mode (e.g. walking and car). They also can analyze the

effects of transportation investments (e.g. BRT) on changing accessibility components and accessibility status itself. The thesis also considers various travel costs while calculating the accessibility, mainly network distance and dynamic travel time. The dynamic travel time as impedance measure is a newly emerged travel impedance measure that considers the continuous temporal change in accessibility status for the network. Moreover, policymakers have flexible methodologies to target required audience/network users according to targeted activities (e.g. trips to workplace, to homes or to hospitals). This thesis it is the first research that considers modelling accessibility, especially the workplace accessibility, in more than one direction at several time phases of the day. Furthermore, it is the first research of its kind implemented for Istanbul city.

The temporal variations within a day and between several years are modelled and discussed. The study implements its application for a part of Istanbul city with high growth in inhabitants, commercial and industrial activities. For that, the study utilizes Geographic Information System (GIS) and Remote Sensing (RS) framework with an adequate and flexible environment that allows targeting the required location/spatial resolution, audience and time period/resolution.

The research also provides several methodologies to collect the required accessibility components in the required resolution and high accuracy. A methodology to semi-automatically classify satellite imageries using auxiliary data to be in the European standards is introduced. The results are thematic land cover/use (LCLU) maps pointing out locations of related origins and destinations. The high spatial resolutions, geometric accuracy and overall accuracy of the outputs nominate them to be accurate inputs for later calculations. The acquired raster thematic maps are converted to points with attributes of their corresponding LCLU using a proposed gridding system that reduces related errors. Later studies are classified, mainly, into two groups based on the considered impedance measure. The first group considers travel network distance while the second considers the dynamic travel time as an impedance measure. Travel network distance is easier to implement due to the availability of the data for a long period of time. The travel time attribute is not available for the same time period, thus liming the analysis to only network distance as travel impedance. Utilizing travel network distance enables the study to evaluate the effect of the urban change on influencing the accessibility over a long period of time. Impacts of high budget infrastructure transportation projects on influencing the accessibility are analyzed, such as the BRT system in Istanbul.

The research also identifies the impact of changing accessibility components of both the road network and LCLU on influencing the accessibility status to hospitals and healthcare centers. Later studies are implemented using dynamic travel time as an impedance measure. For that, the travel time is acquired using real time average speeds of the network. The study proposes a modified network-based inverse distance weighting spatial interpolation method to identify unknown speed values along the network more accurately. Using the interpolated average speeds, the temporal component is generated for the whole network at all considered time periods.

The research evaluates the change in accessibility at several time periods representing two trip types (i.e. home to work and work to home). The research reference the relationship between dominant accessibility components change at each considered time period. Finally, the study inspects several impedance measures of travel network distance, static travel time (generated from free-flow speeds) and dynamic travel time, when evaluating the spatial-temporal change in accessibility at very high resolutions.

İSTANBUL TÜRKİYE'DE ERİŞİLEBİLİRLİĞİN ZAMANSAL-MEKANSAL BOYUTU

ÖZET

Ulaştırma, kent sakinlerinin faaliyetlerini ve kentsel sürdürülebilirliği şekillendirmede önemli bir role sahiptir. Ulaştırma aynı zamanda hizmetlere kolay erişim sunarak, verimlilik ve sosyal adaleti iyileştirmedeki rolüyle birlikte kent yaşamının ve ülke ekonomisinin önemli bir bileşenidir. Ulaştırma ağları, ağdaki belirli yolların işlevsizliğine rağmen ağ kullanıcılarına daha fazla güzergah alternatifi sunarak, hizmet seviyesini sürdürmektedir. Sonuç olarak, karayolu ağının belirli özellikleri kentsel alanlardaki hareketliliğin verimlilik seviyesini etkilemektedir. Araştırmacılar, ulaşım sistemi bileşenleri içindeki etkileşimin en iyi erişilebilirlik kavramı ile tarif edildiğini ve bu kavramın herhangi bir ulaşım sisteminin kesin amacı olarak kabul edildiğini savunmaktadır. Bölgenin mevcut erişilebilirlik durumunun değerlendirilmesi, gelecekte erişilebilirliği iyileştirilebilecek konumların belirlenmesine ve projelerin önceliklendirilmesine yardımcı olmaktadır. Konuma dayalı ölçüm, hedef bölge içindeki mekansal konumların erişilebilirlik seviyesini ölçmek için çok yaygın bir araç olarak kabul edilmektedir. Erişilebilirliğin hesaplanabilmesi için arazi kullanımı, ulaşım, birey ve zaman olarak adlandırılan dört temel bileşen gerekmektedir. Bununla ilgili karşılaşılan en yaygın problem, projenin amacına bağlı olarak bu bileşenleri doğru bir şekilde, gerekli mekansal ve zamansal çözünürlüklerde elde edilememesidir. İlgili her etkinliğe ilişkin başlangıç ve bitiş noktalarını belirlenmesi ise bu ölçüm için başka bir sorundur. Genel olarak, karar vericiler hedeflenen bölgenin erişilebilirliğini artırmak için bu bileşenlerden ulaşımı öne çıkararak; hızlı toplu taşıma sistemlerinin işletilmesi, yeni yollar inşa edilmesi gibi ulaşım altyapılarına büyük yatırımlar yapmaktadırlar. Bu tür yatırımlar bazı bileşenleri geliştirirken diğer bileşenleri de olumsuz yönde etkilemektedir. İstenen gelişmiş erişilebilirlik düzeyine ulaşabilmek için tüm bileşenlerde dengeli bir büyüme gerçekleştirilmelidir. Belirli bir süre içerisinde erişilebilirlik seviyesinde olan değişikliğin değerlendirilmesi, her bir bileşenin mevcut erişilebilirlik durumunu etkilemedeki rollünün belirlenmesine yardımcı olmaktadır. Buradan elde edilen bilgilerle, hedeflenen kullanıcılara / kitleye veya aktivitelere göre gelecekteki erişilebilirlik durumunu iyileştirmek için erişilebilirlik bileşenleri daha etkili bir şekilde tasarlanabilir. Kentsel alanlarda en önemli günlük faaliyetler arasında işyerine erişim bulunmaktadır. Aslında, işyerlerine erişilebilirliğin modellenmesi, kentsel formun anlaşılması, iş ve konut alanlarının mekânsal uyumsuzluğu, iş-konut dengesi, aşırı seyahat ve istihdam edilebilirlik gibi kentsel yapının diğer önemli özellikleriyle ilişkisi nedeniyle erişilebilirlik analizi araştırmalarının en önemli konusudur. Ancak, bu tür konumlara erişim, her seyahat yönünde (evden işe veya işten eve) meydana gelen farklılıklar nedeniyle daha fazla

ayrıntı içerir, dolayısıyla yüksek mekansal ve zamansal çözünürlüklü veri, veri modelleme ve veri analizi yeteneği gereklidir.
Öncelikle bu tez, karar vericilere temel erişilebilirlik bileşenlerini elde etmek, bunları istenen yapıya dönüştürmek ve yüksek mekansal çözünürlükteki değişikliği ölçmek için daha doğru araçlar, yöntemler ve modeller sunmayı amaçlamaktadır. Böylece, karar vericiler erişilebilirlik bileşenlerinin erişilebilirliğin değişimi üzerindeki etkilerini, yüksek mekansal çözünürlükte, istenen hareket / ulaşım türünü kullanarak (örneğin yürüme ve araç) analiz edebilirler. Ayrıca, ulaşım yatırımlarının, örneğin metrobüs, erişilebilirlik bileşenleri ve erişilebilirliliğin üzerindeki etkilerini değerlendirebilirler. Bu tez aynı zamanda erişilebilirliği hesaplarken, yol ağı mesafesi ve dinamik seyahat süresi gibi çeşitli yolculuk maliyetlerini de dikkate almaktadır. Empedans (direnç) ölçüsü olarak dinamik seyahat süresi, ağ için erişilebilirlik durumundaki sürekli zamansal değişikliği dikkate alan ve yeni bir seyahat direnci ölçüm aracıdır. Geliştirilen yöntem ve araçlar ile, karar vericiler farklı ihtiyaçlar için anlık göstergelerinde ölçülebileceği farklı araçlara ve esnek yöntemlere kavuşmuştur. Bu tez özellikle günün çeşitli zaman aralıklarında, birden fazla yönde, işyeri erişilebilirliğini içerecek şekilde erişilebilirliğin modellenmesi konusunda yapılan ilk çalışmadır. Üstelik İstanbul kenti için bu türde uygulanan ilk araştırmadır.
Bu çalışmada çok geniş bir ölçekte, zamansal değişimler –örneğin bir gün ve birkaç yıl- modellenmiş ve tartışılmıştır. Çalışma İstanbul'un ticari ve endüstriyel faaliyetlerinde yüksek büyüme gösteren on bir ilçesini oluşturan bir alanda uygulanmıştır. Bunun için çalışmada gerekli yer / mekansal çözünürlüğü, kitleyi ve zaman dilimini / çözünürlüğü hedeflemeye, yeterli ve esnek bir ortamla olanak tanıyan Coğrafi Bilgi Sistemi (CBS) ve Uzaktan Algılama (UA) sistemleri kullanılmıştır. Ayrıca araştırma, erişilebilirlik bileşenlerini gerekli çözünürlük ve yüksek doğrulukta toplamak için çeşitli yöntemler önermiş ve test etmiştir. Avrupa Birliği Standardı – Corine– lejandı kullanılarak uydu görüntüleri yarı otomatik olarak sınıflandırılmıştır. Ulaştırma modellerinde kullanılan başlangıç ve hedef noktalarını sınıflandırılmış görüntlerden elde edebilmek için bir yöntem geliştirilmiştir. Sonuçlar, ilgili başlangıç ve varış noktalarının yerlerini gösteren tematik arazi örtüsü / arazi kullanım (AÖAK) haritaları ile elde edilmiştir.
Literatürdeki çalışmalar kullanılan empedans ölçüsüne göre iki gruba ayrılmaktadır. İlk grup seyahat ağı mesafesini, ikinci grup ise dinamik seyahat süresini empedans ölçüsü olarak kabul etmektedir. Aynı çalışma bölgesine ait farklı yılları kapsayan verilerin mevcut olması nedeniyle seyahat ağı mesafesinin uygulanması daha kolay olmaktadır. Seyahat süresi özelliği aynı süre boyunca mevcut değildir ve bu sebeple analiz seyahat empedansı olarak sadece ağ mesafesiyle sınırlandırılmıştır. Seyahat ağı mesafesinin kullanılması, çalışmanın kentsel değişimin uzun bir süre boyunca erişilebilirlik üzerinde ki etkisini değerlendirilmesini sağlamaktadır. İstanbul'daki metrobüs sistemi gibi yüksek bütçeli altyapı ulaşım projelerinin erişilebilirliği etkisi bu şekilde analiz edilebilmektedir. Araştırma, yıllara bağlı değişen karayolu ağının ve AÖAK'nın hastanelere ve sağlık merkezlerine olan erişilebilirlik etkisini de belirlemektedir. Tez kapsamında, empedans ölçüsü olarak dinamik seyahat süresi kullanılarak geliştirilen model test edilmiştir. Bu yöntemde, seyahat süresi yolağının gerçek zamanlı ortalama hızları kullanılarak elde edilmiştir. Çalışma, ağ boyunca bilinmeyen hız değerlerini daha doğru bir şekilde tanımlamak için ağ tabanlı ters mesafe ağırlıklandırmalı bir mekansal enterpolasyon yöntemi geliştirmiştir. Enterpole edilmiş ortalama hızlar kullanılarak, zamansal bileşen, tüm ağ için, analiz edilen tüm dönemlerde üretilmiştir. Araştırma, iki yolculuk türünü (yani evden işe ve evden işe) temsil eden birkaç zaman diliminde erişilebilirlikteki değişikliği değerlendirmektedir.

Bununla birlikte, dikkate alınan her bir zaman diliminde baskın erişilebilirlik bileşenleri değişimin bileşenleri arasındaki ilişkiye referans vermektedir. Son olarak, çalışma çok yüksek çözünürlüklerde erişilebilirlikteki mekansal - zamansal değişimi değerlendirirken, seyahat ağı mesafesi, statik seyahat süresi (serbest akış hızlarından üretilen) ve dinamik seyahat süresi gibi çeşitli empedans ölçümlerini incelemektedir.

1. INTRODUCTION

1.1 Background

Transportation plays a vital role in shaping human activities and urban sustainability. It forms the surrounding areas and influences a geography of opportunities to reach destinations past our direct surroundings (Golub & Martens, 2014). It also is a fundamental component of a resident's life in the nowadays societies for its roles in developing the efficiency of resident's travels to required destinations (Foth, et al., 2013). An efficient transportation system, per se, positively impacts the nation's economy by offering easy access to supplies and by promoting safe and effective travel of individuals (Chen, et al., 2002). Certain features of the transportation network, such as the structure of traffic management, planning policies and capacity, affect the level of the ease of travel between locations. Researchers argue that such interaction within the transportation system is best presented by using the concept of accessibility. They consider it the definitive aim of any transportation system (Litman, 2017). Fundamentally, quantifying accessibility extends to more than that. It assists in evaluating the quality of the current transportation system. It echoes the development of each travel mode. It tracks the modification caused by shifts in land use distribution. Furthermore, it is used to predict the travel demand in transportation modelling, such as locate changes in trip generation and trip distribution steps (Bhat, et al., 2000). The location-based measure is considered a very common tool to quantify the accessibility status for spatial locations within the targeted region. This measure investigates the accessibility spatially and describes the accessibility level to spatially distributed activities (Geurs & Wee, 2004). Four essential components namely land-use, transport, individual and temporal are required for its calculation. First, the land use component denotes the spatial distribution of the origins, destinations and opportunities. Second, transport models the travel time/cost between travel locations. Third, the individual component signifies the stratification of people (e.g. by income or education). Finally, the temporal component accounts for the temporally changing travel time/costs, within the required resolution (Geurs & Wee, 2004). A common issue for these components is capturing them accurately and within required spatial and temporal resolutions, according to aimed projects. Generally, policymakers aim to steer these components to increase the accessibility of the targeted region. For that, policymakers invest heavily in transportation infrastructures, such as operating a Bus Rapid Transit (BRT) system or constructing new roads. Such investments enhance certain components while negatively affecting others. For instance, enhancing the land use component occurs by increasing the number of households and their relative approximate opportunities. The transport component can also be enhanced by executing further transport infrastructure projects that decrease the travel time/travel cost between locations such as the construction of new road links, bridges, tunnels …etc. Enhancing an individual's travel conditions, travel schedules and traffic management also influence the individual and temporal components of accessibility. However, enhancing the accessibility components is a holistic process where these components are modelled altogether. Increasing one component alone without considering the others might lead to undesired results. For instance, increasing the households alone leads to an upsurge in traffic and travel time, thus reducing accessibility. For that, the dynamic interplay between the components is to be modelled to identify the resulted/predicted change in the accessibility status of the targeted region. Identifying locations of poor accessibility locations helps policymakers understand the negative implementations of their plans. Continuously monitoring the accessibility status for the targeted location also favors policymakers to set the right plans, get dynamic feedbacks and update their plans regularly.

Within urban areas, travels are dynamic and set to serve a purpose. Homes-workplaces travels are considered the most vital travel types due to the importance of both locations within urban areas (Levinson, 2013). Evaluating the accessibility of such travel types has always been a research focus. The stress on that is very reasonable considering its relation to other significant features of urban structure (Preston & Raje, 2007). More importantly, it is a decisive mean to comprehend the spatial mismatch of jobs and housing, excess traveling and employability (Cheng & Bertolini, 2013). However, accessibility to such activity requires further details due to dissimilarity in both travel directions. The newly emerged travel impedance of dynamic travel time considers the continuous change of travel time within the road network. Thus, embedding such travel impedance measure within accessibility calculations assists in evaluating the continuous change of accessibility at the required temporal resolution.

Lastly, modelling the accessibility change in high spatial and temporal resolutions provides policymakers powerful tools to evaluate targeted locations more flexible. Geographic Information System (GIS) and Remote Sensing (RS) provide an adequate environment that allows authorities to target the evaluation scale (e.g. region or neighborhood) required activity and time period/temporal resolution. GIS provides a framework for gathering, managing, and analyzing abstract real objects according to the application domain. On the other hand, RS is the knowledge/practice of gaining information about real objects or areas from distance, typically from satellites. Combining both GIS and RS in one framework is extremely helpful for Metropolitan cities. Within such a framework spatial data is modelled and visualized. Also analyzing complex systems is much easier to implement. Finally, data gaps could be easily filled where a solution for collaboration between various stakeholders is achieved.

1.2 Previous Studies and Limitations

Quite a few researches were deployed to assess the transport accessibility level for various purposes and in various disciplines. Within this section, the previous similar works to evaluate accessibility are presented in various disciplines and applications. The related studies are grouped into two groups based on the utilized impedance measure. The limitations of each group are summarized by the end of each group. The section is concluded with a summary of limitations that this thesis aims to handle.

The first group briefly discusses the related studies utilizing network distance as an impedance measure. The studies are presented from the beginning of this century until a recent date in chronological order as follows; Stanilov, (2003) explored the association between change in land use and accessibility status within suburban zones of Seattle city, USA over a long period of time. Accessibility was used to examine the changes in road network and land use relative to the proximate to the Central Business District (CBD). Zhu, (2004) utilized four different accessibility indices to analyze the CBD's accessibility level from the housing centers. He implemented his application to Singapore using a developed integrated GIS tool. The study analyzed the changing spatial patterns carried out by the new rapid transit line. Bagheri, et al., (2005) explained a two-step floating catchment area approach for calculating accessibility to primary healthcare centers in order to meet world health organization rules. The shortest route from housing areas to corresponding facilities was calculated utilizing the mean center of population distribution. The established study was suitable for modelling accessibility at the national level. Sohn, (2006), Taylor, et al., (2006) and Demirel, et al., (2016a) performed road network vulnerability analyses under network disruption scenarios, due to traffic incidents or flood damage. They modelled the road network degradation under these scenarios. They used accessibility measures to illustrate a connectivity evaluation. Later, they evaluated the resulted change in accessibility status. Their work was aimed to guide policymakers to invest in probable poor accessibility areas. Tillema, et al., (2011) compared two types of evaluation measures that are used to evaluate the efficiency of a proposed road pricing measure. They explained that accessibility measures are easier to implement and interpret than economic measures. Hou, et al., (2011) analyzed the accessibility implications of the development of expressways and inter-city railways at a regional level 30 years period. They illustrated the spatial difference in accessibility after the operation of the expressways. They also projected certain accessibility components to predict its status in a certain period of time in the future. Similarly, Geurs, et al., (2012); Gjestland, et al., (2012) and Gulhan, et al., (2014) implemented accessibility analysis from regional-scale perspective to examine the impacts of large transportation infrastructure improvements on accessibility. Levine, et al., (2012) decomposed the influence of density on accessibility to illustrate the different impacts of proximity and speed and assigned their spatial relationships. They revealed that denser regions have longer travel times but greater origin-destination proximity. Cheng & Bertolini, (2013) demonstrated a measurement to characterize, quantify, and understand, job accessibility, by including the competition, distance decay and job diversity in accessibility calculations. They argued that their measurement is balance, easy to represent and accurate. Shaw, et al., (2014) implemented a time table-based accessibility assessment method to examine the changes in travel time/cost, and distance of a rail project in China. The work also investigated the impacts of this project on changes to various vehicle travel times. Wang, et al., (2015) utilized certain accessibility measures to understand and model transportation/land-use interactions by defining adaptive accessibility. Within their work, they considered the competition factor at a territorial level in identifying the optimal implementation scenario of policy measures. Rosik, et al., (2015) proposed a before-after evaluation of changes to potential accessibility of Polish municipalities. Particular attention was paid to the assessment of the impact of projects supported by EU funds. They evaluated the resulted accessibility changes to each level before and after these projects. Ford, et al., (2015) presented a tool developed to allow a fast analysis of accessibility by diverse travel modes. This tool used monetary and distance general costs to measure transportation charges within networks. Bocarejo, et al., (2016) evaluated accessibility implications for diverse fare plans for the integrated transit system of Bogotá. They modeled accessibility as a function of the total travel expenditure and travel times. They focused on examining fluctuations in trip distribution and cost for an integrated transit system of Bogotá routes and their influences on accessibility to employment destinations. Jianghao, et al., (2016) aimed to measure accessibility and its spatial characteristics in Beijing by applying a comprehensive method that combined different data attributes. They revealed the features and changes in accessibility and the construction of road systems in the city. Merlin, (2017) described changes in workplaces accessibility by both cars and public transportation for four metropolitan areas in the USA over 10 years. The consequence of altering housing locations, altering workplace locations, and varying average travel speeds on accessibility was evaluated and disentangled (Merlin, 2017).

The aforementioned studies considered both distance and time as main measures of spatial travel cost, known as travel impedance. Mainly, that is referenced for the travel distance capturing factors that influenced the directness and topological continuity of available routes while evaluating the accessibility (Handy & Clifton, 2001). Also, it is relatively easy to be collected, easy to compute accessibility, and easy to interpret its results. However, the importance of distance as travel impedance in accessibility calculations is declining in use (Kwan & Weber, 2003). This decline in the importance and usage were attributed to a variety of forces that fails to capture the mobility changing status such as road lanes, capacity, and road type. Also, it struggles to illustrate the non-spatial components of the transportation system that extremely influence the job accessibility calculations, such as service plans, traffic management, and planning guidelines (Cheng & Bertolini, 2013). Basically, it is difficult to comprehend a resident's spatial behavior within current urban areas utilizing only distance as a travel cost (Kwan & Weber, 2003). Travel time, on the other hand, is an integral element of individual accessibility. It is gaining much significance in accessibility calculations due to its ability to capture various types of elements influencing mobility improvements, traffic volume, road capacity and average speeds at an instant of time. However, conventional time travel impedance accessibility measures take a static, time-free view of movement and accessibility, which contradicts the expected behaviors and activity patterns differ by a considered time period of the day (Kwan & Weber, 2003). Such limitation in accessibility modelling resulted from the increased influence of Information and Communications Technologies (ICT) on travel behavior. Lately, due to the availability of real-time driving speeds, open-source web-based mapping, mobile phones, navigation systems such as Google Maps, TomTom and GPS data, a recent trend in the literature can examine continuous accessibility patterns is surfacing (Geurs & Östh, 2016). Using such data sources, studies such as (Moya-Gómez & García-Palomares, 2015; Condeço-Melhorado, et al., 2016; Moya-Gómez & Geurs, 2018) were able to examine time-of-day variations utilizing a Dynamic Travel Time (DTT) impedance in accessibility calculations. For such impedance, travel time for each time period is being stored, thus enabling studies to evaluate different trip types within a day e.g. from home to work, and work to home trips. Such impedance provides a more realistic scenario for analyzing the change in accessibility.

This type of study started earlier but it was not widely implemented due to the requirement of very detailed network data, and huge data processing and computing power. The study of Levinson, (1998) is probably the first study to implement this concept in analyzing the effect of accessibility using continuous travel time of the network. He implemented the accessibility analysis to jobs and houses for the commuting times utilizing travel survey of metropolitan Washington, DC (Levinson, 1998). Later, due to the availability of more detailed data, modelling speed profiles for the network become easier. Moya-Gómez & García-Palomares, (2015) modelled the variations in daily accessibility in both Madrid and Barcelona cities with dynamic travel time as impedance. They compared the daily spatial accessibility distribution of both cities and analyzed the local reasons influencing their findings. Moreover, Condeço-Melhorado, et al., (2016) evaluated various forms for estimating travel times in accessibility analysis. They commented on their advantages and drawbacks. Also, they calculated the change in accessibility status due to land use and transportation network interaction change aiming to assist policymakers in their job. Moya-Gómez

& García-Palomares, (2017) evaluated changes in accessibility by car within the day in several European cities. The study used real time average speeds on segments of the road networks. These speeds were gathered over two years to calculate the dynamic perspective of accessibility. The results showed how traffic affected the daily accessibility distribution in detail. Finally, Moya-Gómez & Geurs, (2018) analyzed the changes in workplaces accessibility by car in the Netherlands during the (2009–2014) economic crisis using dynamic travel time as impedance. They assessed which component is the most determinant to such resulted changes, both spatially and temporally.

Generally, the aforementioned studies analyzed the accessibility for different purposes and using different methods. However, very few of them considered the accessibility analysis within high spatial resolution. Mostly, the studies implemented their methods for zone level analysis in low resolution, such as analyzing the whole city, country or a whole continent. Others implemented their applications using ready Point of Interest (POI) or grids with low cell resolution in a GIS environment. Utilizing such data hinders applications to analyze accessibility in more spatial details. On the other hand, before the implication of DTT as impedance measure, none of the studies analyzed the daily change in accessibility due to changes/variations in accessibility components. Mostly, they implemented distance or static time as travel impedance in accessibility calculations. Even studies which implemented DTT as travel impedance, they implemented their applications in the city or region scale. Moreover, none of the aforementioned studies implemented a temporal accessibility analysis to study the workplace/job accessibility variations in both directions (e.g. from home to work and work to home). Researching all of the above limitations contributes to the literature by enhancing the accessibility evaluation process.

This research also has certain limitations mainly attributed to the data acquired. Primarily, this thesis focuses on the car mode of transportation and less on the walking mode. However, accessibility of public transportation is not considered in this research. Moreover, the weighting factor that referenced the significance of workplace locations and home locations are not updated. However, the research developed methodologies to overcome this issue.

This thesis is based on the project of (Demirel, et al., 2018), which started in 2016. Within this project, the LCLU was acquired by developing a methodology to classify the satellite images in high overall geometric accuracy. Later, certain gridding systems were analyzed to convert the classified thematic maps into the required form for later calculations. The outputs of the gridding system were used in the later accessibility calculations to analyze the change in accessibility due to operated transport infrastructure (such as IML). A network spatial interpolation method was developed to find average speeds on the network from a limited speed data source. Finally, a model to detect accessibility changes using dynamic travel time was developed.

1.3 Study Objectives

The general aims of this thesis are illustrated as follows: 1) the research aims to provide methodologies to collect the required accessibility components (e.g. land use, road network, travel time) in high spatial/temporal resolution and/or geometric/overall accuracy to calculate the accessibility more accurately. The emphasis is on A) identifying the origins and destinations of each corresponding activity by the acquisition of land cover/use maps and converting them to the required form. B) generating travel time of the network by developing a method to interpolate real-time speeds of the network. 2) the study develops a model that detects spatial-temporal changes in accessibility at high resolution. For that, the study utilizes a GIS-RS framework to integrate the collected data, calculate the accessibility indices and analyze the findings. 3) Using the developed model, the study aims to evaluate the influence of major infrastructure projects (such as the Istanbul Metrobus Line system) on altering the accessibility status of the considered study area. 4) Different location-based accessibility indices are modelled and inspected separately. The spatial-temporal relationship for change in accessibility for each index is also analyzed. 5) The study inspects the temporal resolution relationship on accessibility calculations and analysis. The temporal variations within the day and between several years are modelled and discussed. 6) The study points out the dynamic interplay of accessibility components on changing workplaces/job accessibility status within the considered temporal resolution. The research reference the relationship between dominant accessibility components change at each considered time period. Finally, 7) the study inspects several most used impedance measures, namely travel network distance, static travel time and DTT, when evaluating the spatial-temporal change in accessibility.

Their ability to capture the alteration in accessibility components within considered temporal resolution is envaulted and discussed.

1.4 Study Contributions

The contributions made in this thesis are summarized as follows:

- The research develops a GIS-RS based decision-making method to model the change in accessibility. The designed model can detect the spatio-temporal interaction between accessibility components before implementing a transport infrastructure investment and after its completion.
- The research captures the LCLU component by using satellite images of the corresponding years. A methodology to integrate GIS and RS data to classify the images using the European standards is introduced. The results are thematic LCLU maps with high accuracy, which can be later used as accurate inputs for the calculations (Shoman, et al., 2017c; Shoman, et al., 2019c).
- In order to utilize the resulted thematic maps in the calculation, the raster maps are converted to points with attributes of their corresponding LCLU. The research compares the most used gridding systems of square, hexagon and triangle in providing accurate representations of the raster thematic LCLU. The research also assesses data loss while changing the resolution. The research investigates the relative accessibility errors of area and feature numbers while changing the resolution. Based on that, the study suggests a suitable gridding system and resolution (Shoman, et al., 2019a; Shoman, et al., 2019b; Shoman, et al., 2017b).
- The research implements the developed model to analyze the accessibility change before and after the operation of the Istanbul Metrobus Line over a period of 40 years. The study is considered with only the change of workplace accessibility. Three temporal periods (1987-1997, 1997- 2007 and 2007-2014), which correlated with important urban changes in the area, are investigated. The change in accessibility values, the locations (where accessibility has increased) and the direct cause for such changes are captured. The study is implemented only using distance as an impedance measure. Both driving and

walking are analyzed as transportation modes. Moreover, four accessibility indices are evaluated (Shoman & Demirel, 2018).

- The research implements the aforementioned/developed model in another application, which is to evaluate the accessibility status to hospitals and health care centers instead of workplaces. The study implements the model for the same selected study area during the period of 2007-2014. Urban areas as origins and hospitals as destinations were spatially identified, projected on a map and later overlaid with the corresponding street network to run an O-D matrix to calculate the accessibility status. Distance as impedance is utilized for two accessibility indices. The changes in urban distribution and urban road network for the selected area are investigated (Shoman & Demirel, 2019a).

- For later applications, the research investigates accessibility change using time as impedance. For that, the time attribute for the network is generated using the average speeds of each link. However, not enough average speed data are collected for the study area using corresponding RTMS speed detectors. Several geostatistical methods seek to leverage the available known speed data to interpolate other unknown links in the network. The study proposes a modified network-based IDW method to interpolate unidentified values along road networks more accurately. The study mainly aims to increase the accuracy of IDW by 1) implementing a proposed empirical three-level topological hierarchy and 2) calibrating IDW variables, by finding the effective cut distance and distance decay. The study employs around 100 RTMS detectors collecting real-time speed data for certain time periods. The research verifies its results using real-time GPS data of vehicles crossing the study area.

- Lately, a recent trend in the literature that considers travel impedance as dynamic travel time took place. Using this impedance, even though it requires very detailed data and more data processing, it is able to examine continuous accessibility patterns. Considering that, the research aims are; first, evaluating the difference between using travel distance, static travel time and dynamic travel time when evaluating the change in accessibility at very high resolutions. Second, pointing out the factors affecting the difference in results. The research calculates the change in accessibility for two accessibility indices being potential accessibility and average spatial separation between two years. The study analyzes two trip types; Home to Work and Work to Home trips within selected weekdays.

- Finally, using all findings above, the research aims are two folds: 1) the study presents a method that provides empirical evidence of workplace accessibility analysis being temporally influenced. 2) The research points out the relation between dominant accessibility components change and spatial variation within the day. For that, the temporal variations within a day (due to traffic conditions and weighting factors) and between two years 2010-2018 (due to road network and to land use changes) are modelled. Two location-based accessibility indices of potential accessibility and average travel time are considered for two trip types, being morning trips of homes to workplaces and evening trips of workplaces to homes. To model the temporal change in the accessibility calculation, the research utilizes dynamic travel time as travel impedance which is generated from real-time speed detectors. The research also utilizes two weighting factors for both trips to delineate the prominence of each trip's destination.

1.5 Thesis Outline

The organization of the thesis is summarized in the following flowchart (Figure 1.1). Each chapter is explained as follows:

Chapter 1 Consists of an introduction including background, previous studies and limitations, study objectives, study contributions and the current section of the thesis outline.

Chapter 2 Introduces the definition of accessibility, its measures and the implemented location-based indices.

Chapter 3 Introduces the acquisition process of Land Cover/ Land Use (LCLU) thematic maps for the purpose of identifying locations of origins and destinations. This chapter introduces the general process. The acquired thematic maps are used for applications within Chapter 4- Chapter 6. Later applications within Chapter 7-Chapter 9 utilize other thematic maps but the utilized framework is the same.

Chapter 4 Introduces the procedure of converting raster acquired thematic maps to representative points. Several gridding systems that deliver the same purpose are compared to recommend a system with a resolution that provides balanced related errors for later OD calculations.

Chapter 5 Provides a GIS-RS framework that utilized network distance as an impedance measure in its accessibility calculations to evaluate the change in several location-based indices more accurately over a long time period. Moreover, it identifies the effect of the Istanbul Metrobus Line on changing the location-based accessibility status for the areas surrounding the study area. Finally, it identifies the urban parameters influencing each identified accessibility index.

Chapter 6 Quantitatively calculate the change in health centers accessibility due to urban transportation investments, again, using network distance as impedance measure.

Chapter 7 Proposes a novel methodology to interpolate real-time traffic speed using a topological hierarchy. The outputs are used to generate travel time for all later considered time periods.

Chapter 8 Presents a method that provides empirical evidence of workplace accessibility analysis being temporally influenced. This chapter utilizes the generated time travel to calculate travel costs dynamically. Furthermore, the earlier methodologies of LCLU acquisition and gridding are utilized to identify the OD corresponding OD matrices. Moreover, this chapter evaluates the dominant change based on trip type, thus evaluating the relation between dominant change and considered time period.

Chapter 9 Evaluating the difference between using the most used impedance measures of Travel Network Distance (TND), Static Travel Time (STT) and Dynamic Travel Time (DTT) when evaluating the change in workplace accessibility at very high resolutions. Furthermore, this chapter references the dominant changes that affect the spatial and temporal accessibility change patterns for each identified impedance.

Chapter 10 The conclusion of this thesis is provided in this chapter.

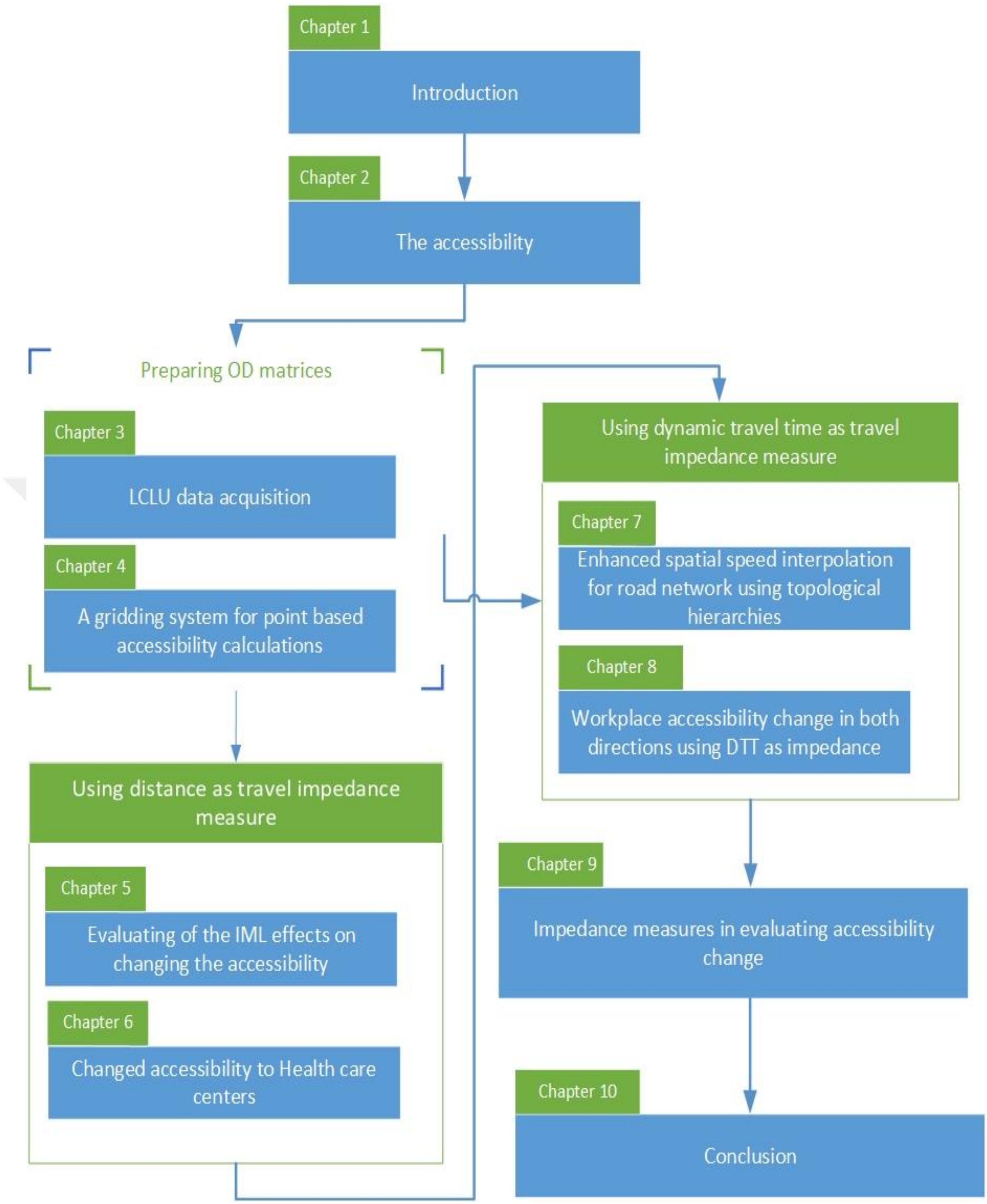

Figure 1.1 : Flowchart showing the thesis outline.

2. THE ACCESSIBILITY

2.1 Definition of Accessibility

Accessibility could be broadly identified as the ease to reach a desired destination within a time span restricted to a transport mode. The concept is used by authorities, policymakers and researchers to evaluate policy plans due to its easiness to calculate and interpret (Geurs & Wee, 2004). However, this concept has evolved over time. An accessible destination nowadays is much different than an accessible destination in the 1900s when it was first defined. The fast developments in many areas, including the urban structure of the cities along with transportation modes and Information Communication Technology (ICT), affected our comprehension of accessible locations. Consequently, the definition of accessibility developed through time to cope with the aims and discipline of the study, as grasped through the literature. Accessibility first appeared in Hansen, (1959)'s study in which he defined accessibility as the ease of reaching required destinations (Hansen, 1959). Shortly later, it was also defined as the ease with which individuals can reach their opportunities (Wachs & Kumagai, 1973). Later, it was still seen as the possibility of interaction and exchange (Engwicht, 1993). Noticeably, these definitions focused on the reachability without explicitly mentioning of land use or the transportation component. In a later stage, it was stated as the ease of individuals to decide whether or not to participate in diverse events/activities (Burns, 1979). But, later, Ben-Akiva & Lerman, (1979) argued that accessibility is the facilities provided by a transportation/land use system (Ben-Akiva & Lerman, 1979). Later on, more different components were integrated into the notion of accessibility. In later definitions, accessibility became a representative of the extent to which the transportation-land use system permits people to reach required destinations using a transportation mode (Morris, et al., 1979; Bhat, et al., 2000; Geurs & Van Eck, 2001; Geurs & Wee, 2004; Neutens, 2015; Tenkanen, et al., 2016). But recently, accessibility is simply redefined as the ease of reaching valued/required destinations to encompass different fields and applications (El-Geneidy & Levinson, 2006; Chen, et al., 2007; Páez, et al., 2012; Tong, et al., 2015).

These definitions were further detailed while calculating/measuring accessibility by incorporating more components or factors to best fit the aimed studies. Bhat, et al., (2000) considered this term for network users as a measure of the ease with which a person can pursue an activity of a chosen type, at a chosen location, by a chosen mode, and at a chosen time. Zhu & Liu, (2004) also saw it as a measure of time and money spent on travel to reach certain activities. Handy & Niemeier, (1997); Bhat, et al., (2000); Kwan & Weber, (2003) and Zhu & Liu, (2004) were among the first studies to integrate time and economic cost (impedances/travel costs) in the accessibility calculation. Accordingly, others saw it as the volume and variety of locations that can be reached within a chosen travel time/cost from an origin location (Bertolini, et al., 2005; Chen, et al., 2011). Finally, it was defined as the spatial distribution and quality of goods and services obtainable to travelers, as well as the transportation system/mode used to reach them (Horner & Wood, 2014).

Through the previously given definitions, accessibility was viewed both as a measure seeking to capture the sheer service, or as a number of opportunities, received by a subject in a given location or, within a given travel time, distance, or cost (Cascetta, et al., 2016). The aforementioned studies in the literature considered four components as main elements to accessibility which they appeared through the development of its definition. These contributors are; individual, transportation type/mode, land use, and time. The first component of individual investigates the desires and abilities of travelers from their starting points. This component was the first to be recognized by researchers as illustrated through the literature review. The transportation type/mode component is concerned with the type of road network and the modes users prefer to reach their destinations. This component takes into account travel time, cost and effort of mobility. The land use component considers the spatial distribution of origins and destinations or opportunities. This component takes into account the spatial distribution of start and end locations for user's trips. Lastly, the time component inspects the time limitations travelers demand for their activities.

2.2 Measures of Accessibility

Most accessibility measures assume that the accessibility between origins and destinations is positively proportional to the associated attraction and inversely proportional to the travel impedance between them. A large and various number of measures of accessibility have been proposed since Hansen first introduced the issue to spatial planning in 1959 (Hansen, 1959). Several studies classified these measures into groups e.g. (Bhat, et al., 2000; Geurs & Wee, 2004; Curtis & Scheurer, 2010; Páez, et al., 2012; Mavoa, et al., 2012; Tong, et al., 2015). Among the pioneering studies, Geurs & Wee, (2004) proposed four significant types of accessibility measures in their classification. These measures include; infrastructure-based, location-based, person-based, and utility-based measures. They are described in their categories as follows:

1. Infrastructure-based measure: it aims to analyze the service level of transport infrastructure. It includes three components in its calculation (i.e. transport, individual and temporal). The transport component is represented by the traveling speed or vehicle-hour lost during a selected status, e.g. congestion. The individual component is illustrated by the trip-based stratification. While the temporal component is captured during a representative status of the network, such as peak-hour period. Examples of indices within this measure are congestion or average speeds of the whole network.

2. Location-based measure: it is used to analyze the accessibility of locations at a macro-level. It describes the status of accessibility to spatially spread activities. The level of complexity is controlled by incorporating the required accessibility components. More complex indices in this measure explicitly incorporate mobility status/capacity limitations of supplied activity characteristics to comprise the competition factor. All four components are included in their calculation. The land use is captured via the amount and spatial distribution of the opportunities. The transport is represented by the travel time/costs between locations of activities. The individual component is illustrated by the stratification of the network users (e.g. by income). While the temporal component is captured during a different considered status of the network such as different time periods of the day/week/month. Examples of indices within this measure are daily, potential and spatial separation.

3. Person-based measure: it analyzes accessibility at the network user level using more detailed information about an individual's preferences. It adds one more dimension to the framework of accessibility corresponding to the time constraints of individuals under consideration, which is well-suited to examine

trip chaining and spatial clustering of activities. The motivation behind this approach to accessibility is that individuals have only limited time periods during which to undertake activities. As travel times increase, the size of their prisms shrinks. This measure considers the complex relationship between individual space and time. This measure is based on the space-time geography of Hägerstraand, (1970) that measures restrictions on an individual's choice of action in the network system (Hägerstraand, 1970). This measure considers two inputs within its calculation of detailed Origin-Destination matrix and detailed travel time diary of each individual. The main criticism of space-time measures is that due to a high level of disaggregation they are difficult to aggregate, and it is difficult to look at the effects of changes on the larger scale such as in land use and the transportation system All four components are included in its calculation. The land use component is captured via the amount and spatial distribution of the demand and opportunities. The transport component is represented by the travel time/costs between locations of activities. The individual component is incorporated in the detailed travel time diaries. While the temporal component is captured by modelling the constrains to other activities within the available time. A well-known index of this measure is space-time prisms.

4. Utility-based measure analyzes the monetary that influence individuals to spatially distributed activities. The individual's behavior and subjective perception of impedance when travelling are further studied within this measure. This is a linear function with elements correspond to factors linked to accessibility such as the quality/attraction of the activity/location and the travel costs associated with reaching that activity/location. Actually, this measure has its origin in economic studies (Discrete choice modelling). Criticisms of this measure are that not all choices are accessible to all people, and there are no ordinary limitations for the choice set (Ben-Akiva & Lerman, 1979). The utility measure only reflects observed behavior and does not echo the advantage of increased choices (Morris, et al., 1979; Páez, et al., 2012). Also, this measure is linked to the uncertainty in what the extent of the indicators expresses (Handy & Niemeier, 1997). Same as the previous two measures, all four components are included in its calculation. The land use is

captured via the amount and spatial distribution of the demand and opportunities. The transport is represented by the travel time/costs between locations of activities. The individual is illustrated by the utility perception of each alternative. While the temporal component is captured during a different considered status of the network such as different time periods of the day/week/month. Examples of indices within this measure are Logsum and balancing factor benefit.

2.3 Location-Based Indices

Mainly, this thesis calculates the change in accessibility for three location-based widely used accessibility measures of spatial separation, cumulative opportunities and gravity as follows:

1. The simplest accessibility measure is the spatial separation derived by graph theory. The only dimension used is travel time/distance. Earlier, this index did not reflect the attraction level, making it similar to a mobility measure or at least a simple infrastructure-based accessibility measure. However, integrating the land use to its calculation helps in distinguishing between origins and destination, thus becoming a useful accessibility index. The most general measure contains the weighted average of the travel constraints to considered destinations. The simplest form of this index is introduced in (Leake & Huzayyin, 1979) as follows:

$$A_{d_i} = \sum_j c_{ij} \tag{2.1}$$

Where A_d is the total distance accessibility index for point i. d_{ij} is the travel impedance between points i and j. The travel impedance changes according to the considered aim. Travel Euclidean/network distance or travel time could be considered as a travel impedance. More on this subject is introduced in later chapters. The form is later developed to simply reflect this impedance for interpretation as shown in the following equation (Allen, et al., 1993):

$$ASS_i^{td} = \frac{1}{nu-1}\sum_{i=1}^{n} c_{ij} \ , i = 1,2,\ldots,nu. \tag{2.2}$$

where ATT_i^{td} is the average spatial separation index for point i at a time period of td when time of the analysis is considered. $c_{ij}$is the travel impedance between i and j. nu is the number of destinations reached from i within a network distance. A drawback of this index is its reflexive nature (Pirie, 1979). Accessibility from m to n is the same as from n to m, which indicates independence from land use component. Moreover, it does not take into account the significance of activities.

2. The simplest location-based accessibility index that considers account both distance and the aim of a trip was the cumulative-opportunities index. This index, based on the definition of isochrones, is by far the most popular of its kind (Cascetta, et al., 2016). It defines a travel threshold, utilizing a travel time, distance or cost, to locate the number of possible activities within as the accessibility for that spatial unit. The only information required for this measure is the location of all the destinations within the assigned threshold. It is quantality introduced in the following equation:

$$A_o = \sum_{th} o_{th} \tag{2.3}$$

where *th* is the threshold and o_j is the desired opportunity at the network within specified threshold *th*. This index avoids the zonal aggregation problem by counting attractions individually. Thus, there is no loss of information due to averaging (Hanson & Schwab, 1987). The main drawback of this index is its inability to model behavioral dimensions. This means that near and far locations/opportunities are modlled equally (Voges & Naude, 1983; Geurs & Van Eck, 2001). Moreover, the index is unable to differentiate activities within the targeted service area, in spite of the actual travel cost clearly vary among activities within the same isochronal line.

3. The gravity-based indices include a significance factor with a separation factor. It uses zonal attractiveness and impedance between zones (Chen, et al., 2007). Gravity-based indices use continuous impedance measures that are then used

to deduct opportunities with increasing travel cost values from origins. The significance factor of the gravity-based indices echoes the quantity of activity within a zone, in opposition to the simple counting of the activities as introduced earlier in the previous index. The group of indices integrates more detailed data of destinations to its calculation to differentiate between destinations according to the aim of the study. Including the travel impedance in the denominator of its calculation provide this group a diminishing effect that undervalues attractions far from the starting point. Within this research, two indices within this group are implemented namely being the potential and daily accessibility indices. The value of potential accessibility indicator is calculated using two functions, the number and the cost of reaching destinations from origins and the attraction of destinations as shown in the following equation:

$$PA_i^{td} = \sum_{i}^{n} \frac{w_j}{(c_{ij})^{\beta}} \tag{2.4}$$

Where PA_i^{td} stands for the potential accessibility index for point i at time period of td. w_j stands for the weight of attraction potential, e.g. the population of destination zone j. c_{ij}indicates the travel cost between corresponding points. β is the distance decay parameter. On the other hand, daily accessibility is a similar index to potential accessibility. It follows the same concept of the potential accessibility but applies a different level of detail in terms of travel impedance (e.g. time, distance or utility) threshold for interaction measures. Using this index impels measuring only the interactions with a zone and its neighboring areas. Its mathematical formula is introduced in the following equation:

$$DA_i^{td} = \sum_{i}^{n} \frac{\delta_{ij} w_j}{(c_{ij})^{\beta}} \tag{2.5}$$

β is the distance decay parameter, while δ_{ij} is a binary variable of daily accessibility, which equals 1 if $c_{ij} \leq c_{max}$and 0 if other. Finally, c_{max} is the daily accessibility threshold limiting the neighboring area.

Numerous works criticize the ability of gravity-based indices to precisely model accessibility. These indices assign an equal level of accessibility to all users within boundaries. However, this does not illustrate the likelihood that different users in the exact place may face dissimilar levels of accessibility, which means the absence of behavioral reasoning, thus neglecting the possibility for corresponding attribute disparities across users (Ben-Akiva & Lerman, 1979; Handy & Niemeier, 1997; Baradaran & Ramjerdi, 2001). Another criticism is that the general form of gravity suggests a trade-off between attraction and travel cost. That means, one unit of attraction is equal to one unit of travel cost (Morris, et al., 1979). One way that researchers address this is by incorporating an exponent to the attraction component of the index. However, the value of this exponent is derived from local data which is another shortcoming. The tailored calibration techniques of such index make it hard to transfer the calibrated models to other study areas (Agyemang-Duah & Hall, 1997).

3. LAND COVER/LAND USE DATA ACQUISITION (1)

Measuring accessibility in spatial resolution requires identifying related origins and destinations according to corresponding activity more accurately. The Land Cover Land Use (LCLU) map identifies such areas according to targeted activities. Even though LCLU changes are observed via traditional land surveys, RS, especially using satellite, delivers greater volumes of data in less time, effort and cost. Most importantly, remotely sensed images deliver effective means of gaining information on higher frequent temporal trends and spatial distribution of corresponding urban areas (Elvidge, 2004). RS also provides the LCLU maps in forms usable in a GIS environment. GIS provides a flexible environment for storing, analyzing, and displaying spatial information necessary for change detection and database development. Both RS and GIS have been widely used for monitoring the dynamic changes of the earth's LCLU for decades (Yuan, et al., 2005).

This chapter aims to acquire the related LCLU thematic maps for the corresponding study area introduced below (Figure 3.1) utilizing a developed GIS-RS framework. The resulted maps have high geometric accuracy, high overall accuracy and high spatial resolution to calculate the accessibility for later applications more accurately.

To fulfill that, the LCLU changes at the corresponding study area within the Istanbul Metropolitan area is determined using five satellite images acquired in 1975, 1987, 1997, 2007 and 2014. The selected dates represent important events for later applications. The images are rectified and classified according to COoRdination of INformation on the Environment (CORINE) standards. Supervised classification using maximum likelihood as a parametric rule is implemented for all images. Later, manual post-classification enhancements are performed to improve the thematic accuracy using GPS information of related polygons. Finally, areal statistics regarding each

(1) This chapter is based on the paper Shoman W., Korkutan M., Alganci U. and Demirel H. 2019. Dynamic Monitoring of Land Cover Change: A Recent Study for Istanbul Metropolitan Area. Fresenius Environmental Bulletin, 28(2) 688-693.

class are calculated for all the inspected dates in order to present the temporal changes regarding LCLU classes.

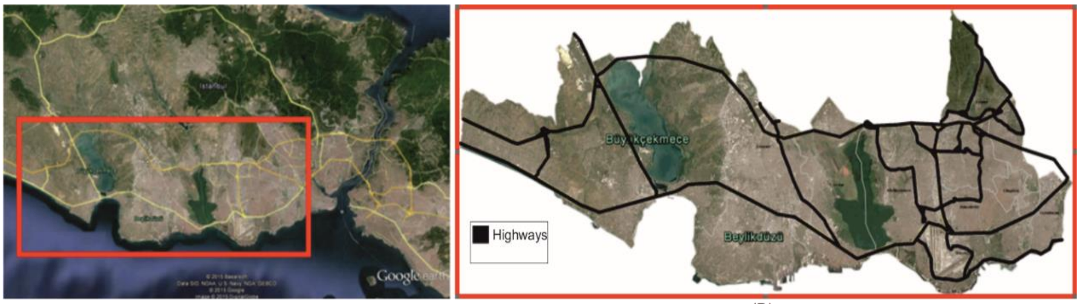

Figure 3.1: The study area (Demirel et al., 2017c).

3.1 Study Area

The study region is selected for the testing and development of the proposed classification methodology. An area covering several districts in the European side of Istanbul Metropolitan Municipality (IMM) is selected. The region contains several districts of Avcılar, Bağcılar, Bakırköy, Bahçelievler, Beylikdüzü and Büyükçekmece, Esenyurt, Esenler, Güngören, Küçükçekmece and Zeytinburnu. The study area contains several significant highways such as E-5, TEM and connection routes. The total area of the study area is about 770 km^2 and the population is approximately 4,864,000. According to the data of the Turkish Statistical Institute, the population of Istanbul grew by 12% between 2007 and 2014, but the population growth of the study area is below the Istanbul average. The highest population growth in the study area is found for Büyükçekmece and Avcılar with rates of 80% and by 20% respectively. The northern portion of the study area is mostly covered with forests, while the southern one hosts industrial and urban areas especially established after the construction of the international highway that connects to Trans-European Motorway (TEM) network. There are many factories, universities and approximately 40 shopping centers in the region. Most importantly, part of the Metrobus line that is one of the major investments for the Istanbul Electricity, Tramway and Tunnel General Management (IETT) is found in this area. This line has been operated by IETT since it was opened in 2007. The length of the highways (E-5, TEM and connecting roads) in the region is around 112 km, as shown in Figure 3.1.

3.2 The LCLU data acquisition framework

In this chapter, five multispectral imageries demonstrating the selected study area are acquired for five different years. The technical specifications for each imagery are presented in Table 3.1. The imageries are geometrically corrected to ensure the location accuracy and reliable mosaicking of images belong to the corresponding acquisition year using corresponding high-resolution orthophotos. Supervised classification using pixel-based maximum likelihood algorithm as a parametric rule is implemented for all imageries. However, the results of the classification do not reach the aimed high overall accuracy, which is set to have an overall classification accuracy of over 80%. To solve this issue, the imageries are manually edited using polygon-based GPS information to enhance their overall accuracy as shown in (Figure 3.2). Finally, the accuracy of the classification process is evaluated using stratified random points that are distributed according to each class.

Table 3.1 : Properties of the acquired multispectral imageries.

Satellite	Date	Spatial Resolution (m)	Ground Control Point (GCP)	RMSE (m)
Landsat 2	1975	60	12	8.0
Spot 1	1987	20	50	4.0
Spot 2	1997	20	55	4.0
Spot 4	2007	20	50	6.0
Spot 6	2014	1.5	50	0.5

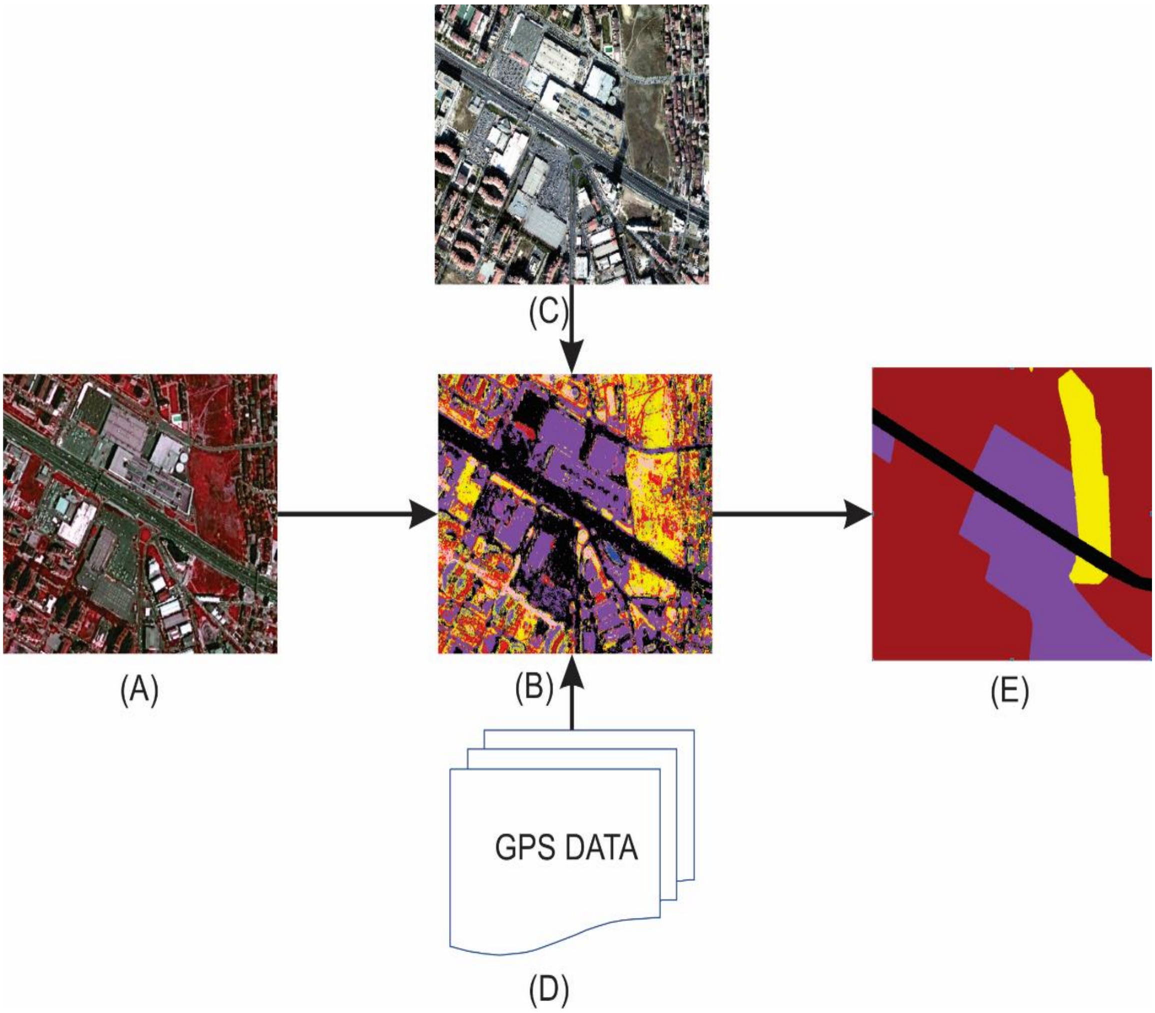

Figure 3.2 : Enhancing the supervised classification using GPS data (Shoman & Demirel, 2018).

3.2.1 Geometric correction

For this chapter, five multi-sensory satellite images belonging to 1975, 1987, 1997, 2007 and 2014 are used to capture the LCLU changes during this period. Satellite images of five different satellites, being Landsat 2, Spot 1, Spot 2, Spot 4 and Spot 6, are used for that purpose. The image of 1975 has the lowest spatial resolution while the image of 2014 has the highest spatial resolution, 60 m and 1.5 m respectively (Table 3.1). The rest of the images have the same medium resolution of 20 m. Images are geometrically corrected to ensure the location accuracy and reliable mosaicking of each image set according to the corresponding acquisition year. The geometric correction is performed utilizing ground control point (GCP) derived from historic high-resolution orthophotos and other GIS databases according to 1st order polynomial model. The number of GCP used for each image during the geometric correction process and their accuracy using Root Mean Square Error (RMSE) are provided in

Table 3.1. The RMSE is a way to measure the accuracy of a geometric rectification algorithm for each point by finding the square root of both the source and retransformed GCP. As shown, utilizing more GCP yielded fewer errors as for 1975's image. However, the low resolution of this image and the lack of enough high-resolution data for the corresponded year hindered the implementation of more GCP points. Primarily, the table reveals adequate RMSE values for all the satellite images, indicating that results are adequate for the next steps.

Later, certain images, that could not fit the boundaries of the study area with one dataset of images, are mosaicked with their corresponding using weighted cutline and color balancing on the overlap areas. Later on, images are clipped according to the boundaries of the selected study area.

3.2.2 Classification and post-processing

The classification is performed according to CORINE standards, mainly used in Europe. CORINE is a geographic LCLU database, encompassing many countries that define a pan-European region. CORINE's LCLU development aims at the establishment of a comprehensive quantitative land cover database, providing consistent information on LCLU across Europe (Stathopoulou, et al., 2007). The CORINE LCLU classification system is a hierarchical structure consisting of three levels under five main groups. These groups are artificial areas, agricultural areas, forests and natural areas, wetlands and water structures. The third level of these standards provides detailed classes valid for the study, along with well-defined criteria for each class in the expected LCLU map. The descriptions provided by the third level in CORINE standards can be used to train the signatures in a supervised classification.

Supervised classification is the method that can be applied when there is available ground truth information on the surface characteristics. In this chapter, a pixel-based maximum likelihood algorithm is utilized as a supervised classifier, which is a robust method already implemented in several previous studies. This method assigns each pixel to a class that shows the maximum similarity according to probability calculations. A peer probability curve is defined for each class. The method identifies the pixel's class according to its brightness and variance-covariance matrix values. The variance-covariance matrix shows the pixel's distribution in the feature space. However, the classification results show that the method failed to create homogenous land cover patches in certain regions especially when most of the area is covered by urban (impervious) surfaces. For that, manual polygon-based vector GPS data editing is implemented to classification results aiming to enhance their thematic accuracy (Figure 3.2). The GPS data of important related Point of Interest (POI) found in the study area assisted in defining the class of inhomogeneous classification. The criteria found in the CORINE methodology are considered while deciding the class of each area shown in Figure 3.3.

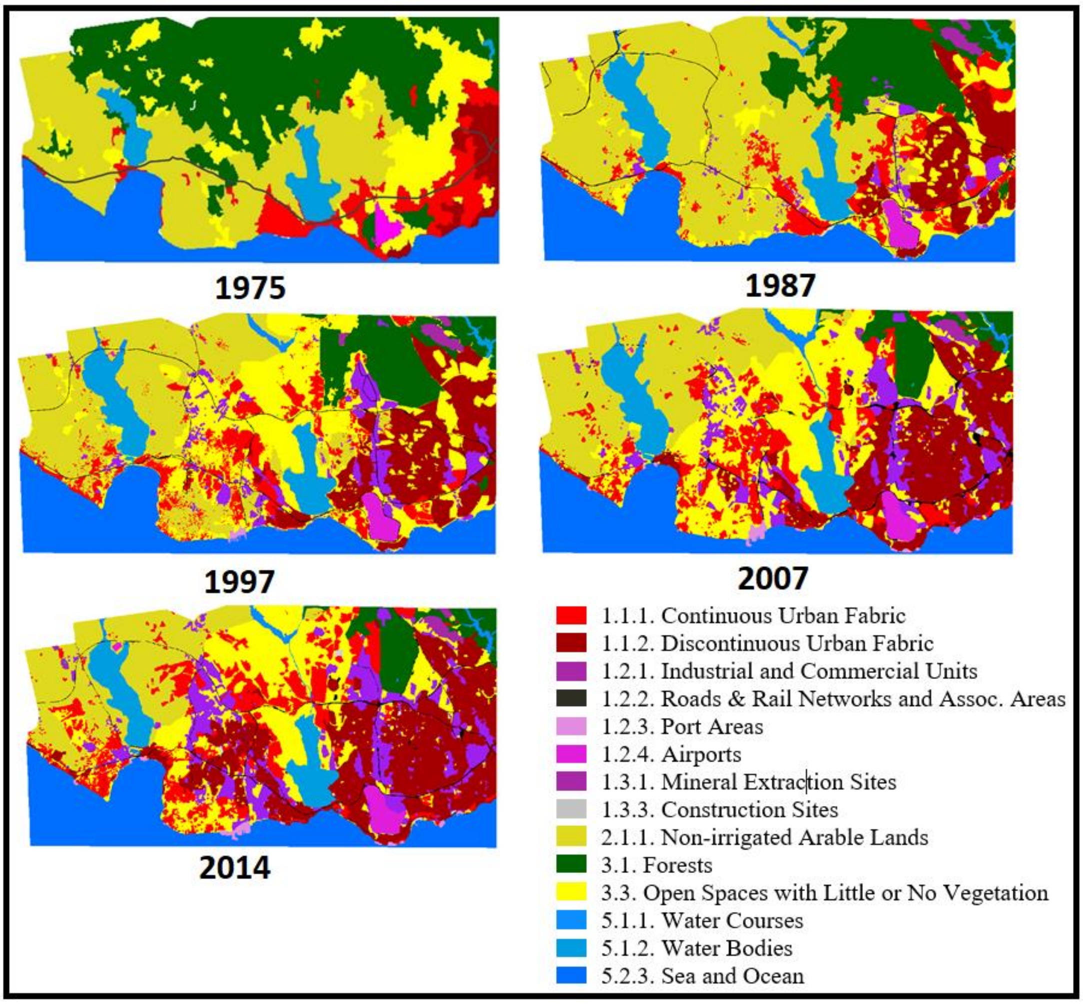

Figure 3.3 : Resulted LCLU thematic maps of the study area (Shoman et al., 2019c).

3.2.3 Accuracy evaluation

The accuracy of the resulted classification process is evaluated using 200 stratified random points that are distributed according to class coverage and significance. Points are compared by their ground truth classes obtained from recent high-resolution ortho-photos and the original images to form the error matrix. Producers and user's accuracy and kappa statistics are calculated from the error matrix. The kappa statistics are calculated using both the observed accuracy and random accuracy. It tabulates the errors by crossing the classified map layer with respect to the reference map layer, which is calculated as follows (Sim & Wright, 2005):

$$kappa\ coffieceint = \frac{total\ accuracy - random\ accuracy}{1 - random\ accuracy} \tag{3. 1}$$

The results showing the accuracy assessment and Kappa statics are shown in Table 3.2. The table indicates that all images are classified with an acceptable accuracy of over 85%.

Table 3.2 : Classification accuracy assessment for all images (Shoman, et al., 2019c).

Image date	Classification accuracy (%)	Kappa Statistics
1975	87.00	0.855
1987	95.91	0.951
1997	93.75	0.928
2007	94.00	0.931
2014	97.00	0.966

3.3 Analysis of the Resulted LCLU Thematic Maps

The used method yielded five thematic maps for their corresponding five dates (Figure 3.3). The resulted accuracy being over 85% assists in evaluating the changes in LCLU between years more dependently. The chapter aimed to provide its classification in the third level of CORINE standards. CORINE has five groups of artificial areas, agricultural areas, forests and natural areas, wetlands and water structures. The group that needs to be classified in detail within the scope of the project is the artificial regions. This group is classified primarily to the third level. However, some classes are out of scope for the main purpose of the thesis (analyzing the accessibility change) and they require more details that could not be obtained within this study. Thus, the third level of CORINE standards for related classes is identified while the rest of the classes are classified until using the second level. Accordingly, classes of “Forests” and “Open Spaces with Limited or No Vegetation” are determined according to the second level of the classification standards. The remaining areal distribution of the LCLU classes is presented in Table 3.3.

Table 3.4 : Areal statistics of the resulted classification for each corresponding year (Shoman et al., 2019c).

Class name	Area (km^2)				
	1975	1987	1997	2007	2014
1.1.1. Continuous Urban Fabric	24.250	65.989	97.013	118.843	153.834
% change		172	47	23	29
1.1.2. Discontinuous Urban Fabric	54.164	59.342	62.287	71.660	83.817
% change	-	10	5	15	17
1.2.1. Industrial and Commercial Units	-	14.372	39.309	53.356	73.266
% change	-	-	174	36	37
1.2.2. Roads & Railway Networks and Assoc. Areas	-	7.286	8.468	8.745	9.206
% change	-	-	16	3	5
1.2.4. Airports	4.525	7.248	7.644	7.578	8.364
% change	-	60	5	-1	10
1.3.1. Mineral Extraction Sites	-	2.400	4.429	5.265	4.473
% change	-	100	85	19	-15
1.3.3. Construction Sites	-	0.230	-	0.460	0.990
% change	-	-	-	-	115
2.1.1. Non-irrigated Arable Lands	190.447	294.646	169.732	129.917	104.258
% change	-	55	-42	-23	-20
3.1. Forests (second level class)	250.598	104.375	64.269	35.196	32.955
% change	-	-58	-38	-45	-6
3.3. Open Spaces with Slight or No Vegetation	93.590	40.540	144.810	160.879	129.650
% change (second level class)	-	-57	257	11	-19
Others	157.336	180.530	178.031	182.654	173.934
% change	-	15	-1	3	-5

For later applications, three classes are identified illustrating home locations and workplaces locations for each corresponding year (Continuous Urban Fabric, Discontinuous Urban Fabric and Industrial and Commercial Units). As illustrated in Table 3.3, an obvious increase in both the Continuous Urban Fabric and Industrial and Commercial Units is noticed in almost all years. The Continuous Urban Fabric class increased its area by more than 530 % between 1975 and 2014. While the Industrial and Commercial Units increased its area more than 400 % within the same period. Discontinuous Urban Fabric class increased modestly in the same period. That is referenced to the continuous loss of this class to Continuous Urban Fabric.

Moreover, the effects of urbanization can be addressed with the major decrease of Non-irrigated Arable Lands and forests classes and the increase of Open Spaces with Slight or No Vegetation class. Non-irrigated Arable Lands decreased by half between the years 1975 and 2014. While the forest lost about 89% of its land area between the same time period. Actually, forest lands reduced by more than half between the years 1975 and 1987 alone. The time period of 1975-1987 shows a systematic conversion of destructed forest lands to other urban classes, including continuous urban fabric, industrial and Open Spaces with Slight or No Vegetation. Green areas are transformed to non-irrigated arable lands, and in turn, barren lands were further converted to urban and industrial areas. However, this study revealed an exceptional trend; a rise in ratios is realized after the transformation instead of a gradual increase. This situation can be rationalized via the Metrobus line that has been constructed and put into operation after the year 2007.

4. A GRIDDING SYSTEM FOR POINT-BASED ACCESSIBILITY CALCULATIONS (2)

The location-based measure relies on OD matrices to calculate and measure the accessibility status for transportation networks. previously acquired LCLU maps presenting class attributes of corresponding areas are converted to points in their centroids, to model this measure in a GIS environment. Within such an environment, converted points should hold the corresponding original class attributes and maintain an accurate representation of neighboring features. However, polygons of LCLU classes are not identical in terms of area and their shapes are geometrically irregular, as presented in the previous section in the classified LCLU thematic maps (Figure 3.3). Thus, assigning a point to represent each isolated polygon is an imprecise mean to execute. For this problem, a method is required to convert the previously classified raster based LCLU thematic maps into reference points, where each converted point grasps the accurate representative attribute of its corresponding LCLU class. Such goal is reached via gridding the map into geometrically regular units/cells, where each unit holds an attribute of its corresponding class and maintains the topological relations with its neighbors.

In most GIS studies, several regular gridding systems are exploited, each of which holds fixed geometric shape as its prime cell. Square, hexagon and triangle are among the elementary and most used gridding systems. That is referenced to many reasons, among them; 1) their simplicity to generate in a GIS environment and 2) the ability to cover areas completely, without leaving unconsidered spaces between their primary cells. However, each of these prime shapes has its exclusive geometric characteristics that distinguish its implementation in GIS applications. Istanbul, a city with a complex urban pattern, has no dominant regular shape to distinguish its urban shape.

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(2) This chapter is based on the paper of Shoman W., Alganci U. and Demirel H. 2018. A comparative analysis of gridding systems for point based land-use analysis. Geocarto International. https://doi.org/10.1080/10106049.2018.1450449.

Considering all that, this chapter has three main aims, namely being;

1. Comparing the identified gridding systems by illustrating their strengths and/or weaknesses in providing more accurate depictions of Istanbul's original LCLU thematic map.
2. Suggesting the suitable gridding system that provides balanced results for later accessibility analysis
3. Assessing the expected data loss while modifying the resolution of the grid.

The chapter identifies certain constraints that indicate the appropriate gridding system which are; a) providing the least areal error related to original LCLU classes, b) determining the least topological errors via assessing the captured clustered features before and after the gridding is implemented and c) Combining both constrains to determine the system with a "*balanced error*". By considering the two errors to be equally important, the best gridding system is expected to represent both errors in one relationship, where both errors are equally the smallest. So, a "*balanced error*" is reaching an optimal form that minimizes both error types the most.

4.1 Test Area and Data

Previously obtained LCLU maps show various patterns for different urban areas within Istanbul city. Certain areas have a high concentration of urbanization while others have a lower concentration of such urban fabric. For that, this research considers two different representative locations of different LCLU distributions within Istanbul Metropolitan Municipality (IMM). Both parts have almost the same area of 7612 hectares (Figure 4.1).

Figure 4.1 : Two parts of the city in boxes A and B as test areas (Shoman, et al., 2019a).

The previously classified thematic LCLU image of Figure 3.3 for the year of 2014 is used to identify the LCLU of the corresponding locations, as seen in Figure 4.2. Using this date is related to the high resolution of original imagery and high overall accuracy of the classification. This chapter aims to capture related important classes for later accessibility analysis, thus (1) continuous and (2) discontinuous urban fabric and (3) industrial or commercial units classes are identified for further analysis. Within used thematic maps, the first part represents a suburban area in IMM (Figure 4.1.B). The residential area (continuous and discontinuous urban fabric) is about 49% while the industrial area is almost 22% (Figure 4.1.A). The second part denotes a part with dense urbanization. It has a residential area of almost 66% and industrial area of almost 19% (Figure 4.1.B).

As noticed, both the continuous urban fabric and discontinuous urban fabric dominate both study parts with an average of 57.12%. Mainly, their clusters are confined between highways. On the other hand, the industrial or commercial units class is mainly surrounding streets or highways. Such areas are mainly located at city boundaries and they present about 20.59% of the study area.

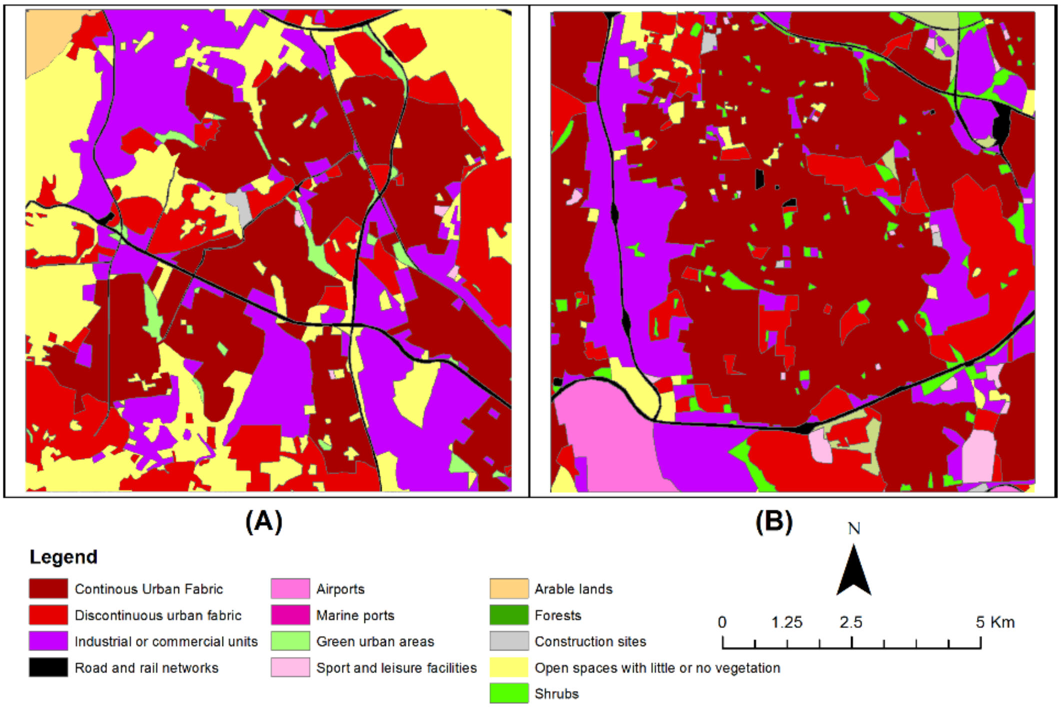

Figure 4.2 : LCLU maps of test areas (Shoman, et al., 2019a).

4.2 The Methodology of Gridding the Raster Maps

To compare the results of the identified gridding systems (i.e. square, hexagon and triangle), the previously acquired raster LCLU thematic maps of the study areas (Figure 4.2) are converted into regular grids at different scales. For each gridding system, the same area is used for its primary cell. Each grid is overlaid with the original raster LCLU thematic map. The class attribute of the dominant/major area is assigned to each cell (Figure 4.3.A). Later on, neighboring cells of the same class are aggregated and they are stored in a separate geodatabase (Figure 4.3.B). The methodology is tested on 23 grid resolution, to assist more accurate models in the later steps. The utilized 23 primary cell areas are 30×30, 40×40, 50×50, 60×60, 70×70, 80×80, 90×90, 100×100, 110×110, 120×120, 130×130, 140×140, 150×150, 160×160, 170×170, 180×180, 190×190, 200×200, 210×210, 220×220, 230×230, 240×240, 250×250 m^2.

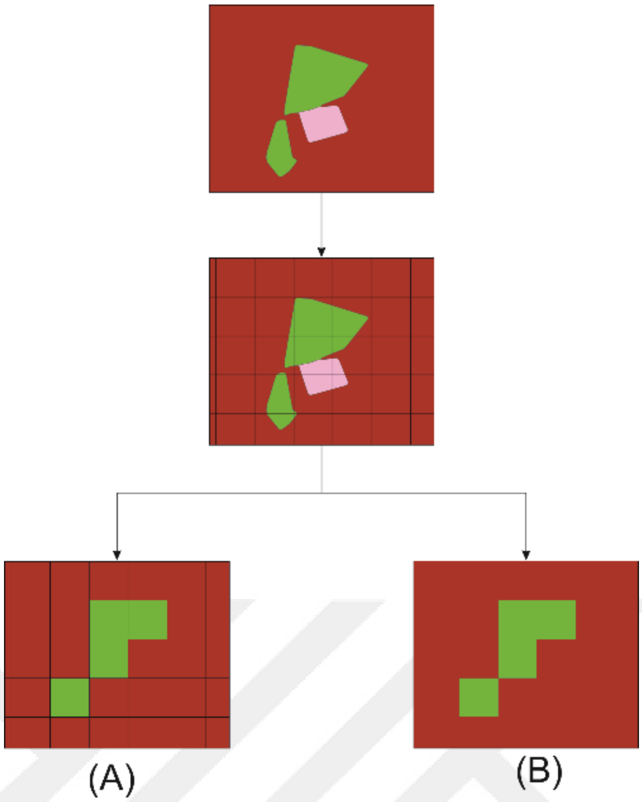

Figure 4.3 : Appointing LCLU class attribute for each and storing them A) for each cell B) for each clustered neighbor (Shoman, et al., 2019a).

The figure below illustrates a sample result of using the identified gridding systems in 100×100 m^2 resolution for a small test area (Figure 4.4). As clearly noticed from the final products, each system provides distinct geometrical output. Moreover, the spatial positions of the cells' centroids are not the same. The given process is implemented in each identified scale level of the previously mentioned 23 scales for all gridding systems.

4.3 Resulted Grids and Discussion

Considering the shape, size and location of newly generated features, the new grids of LCLU produce new generalized maps. All grids have dissimilar results. The idyllic system is likely to reflect the characteristics of the original LCLU map with minimum areal and captured neighbors' errors i.e. "balanced error". Later accessibility analysis considers both continuous urban fabric and discontinuous urban fabric classes as the location of homes/residential areas. Since they share similar properties in such analysis, both classes are merged into one class, in this research, they are referred to as “urban fabric”. While locations of workplaces/industrial areas are identified by the “Industrial or commercial units” class.

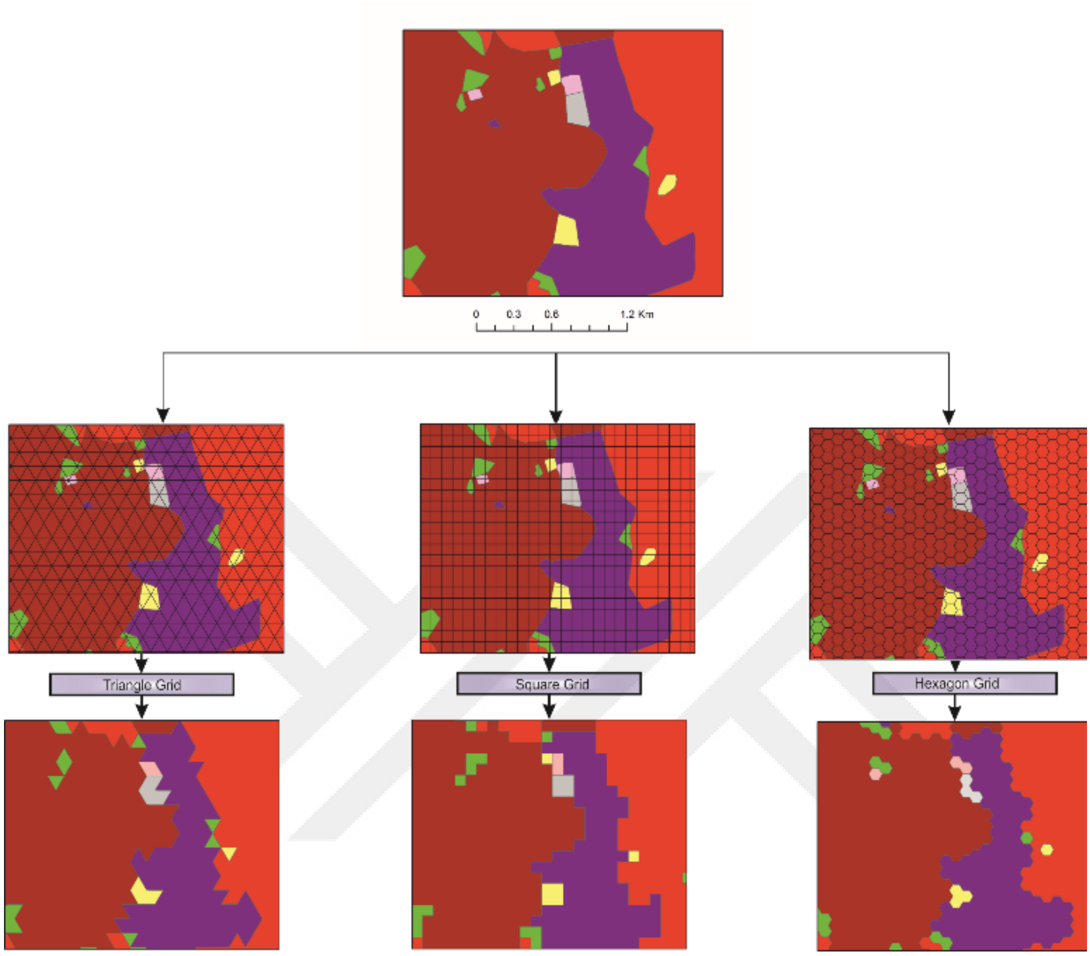

Figure 4.4 : Gridding the same test area using the identified systems (Shoman, et al., 2019a).

Statistical analysis is performed to compare the efficiency of each gridding system for both class types (i.e. urban fabric and Industrial or commercial units). The statics is put together in the below scatter plots. The figures below illustrate the average relative errors for both areal calculations and Clustered Feature Numbers (CFN) using each gridding system (Figure 4.5 and Figure 4.6), respectively compared to the original LCLU maps.

From the modelled relations between errors and scales, the coefficient of determinations (R^2) for all relations is calculated (Table 4.1), to provide the best fit model for all grids. Generally, all relations have high R^2 coefficient values, exceeding 0.95 except for one relation of Industrial or commercial units area errors.

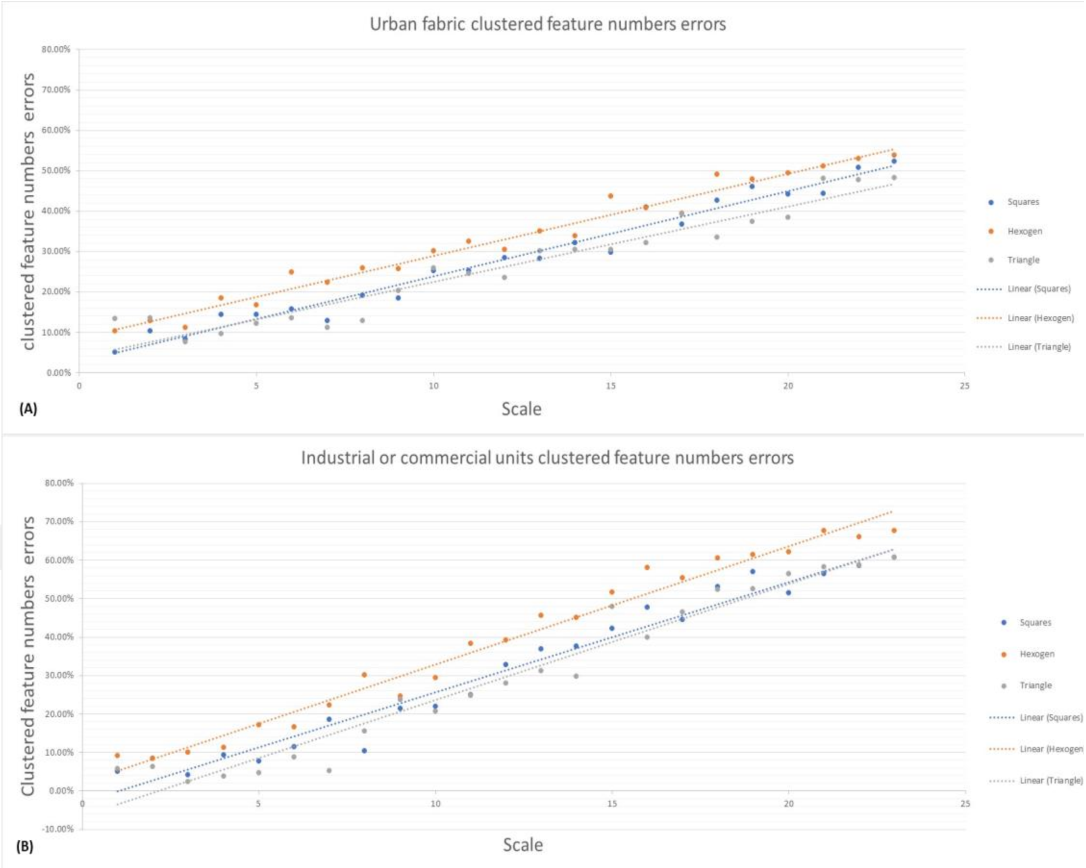

Figure 4.5 : Areal errors in (A) Urban Fabric, and (B) Industrial or commercial units classes (Shoman, et al., 2019a).

The errors in the area for the urban fabric at high scales are similar for all the gridding systems (Figure 4.5.A). All the gridding systems reach areal errors of 2% around the 10th scale (120×120 m^2). On the other hand, the area errors for industrial unit class vary according to the scale due to their lower R^2 values. The relative errors in CFN for both classes of urban fabric and the industrial areas show similar results by generally providing less error in triangle grids followed by square and hexagon grids. Also, it is noted that the errors in CFN are significantly higher than their corresponding areal errors. The errors start with 6.5% and exceed 20% for all grids at the 10th scale (120×120 m^2).

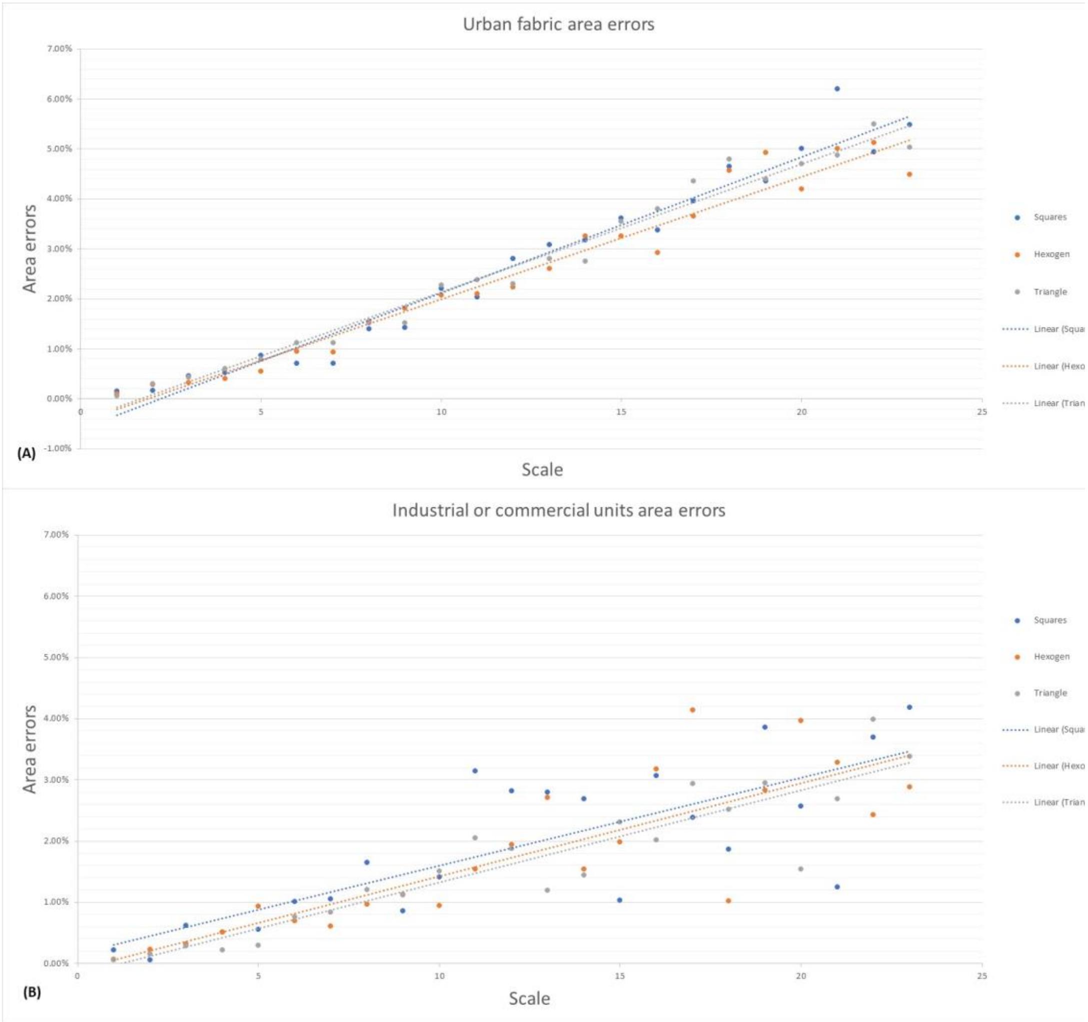

Figure 4.6 : The CFN errors in (A) Urban Fabric, and (B) Industrial or commercial units classes (Shoman, et al., 2019a).

Table 4.1 : R^2 coefficient values (Shoman, et al., 2019a).

	Urban fabric CFN errors			**Urban fabric area errors**			**Industrial area CFN errors**			**Industrial area errors**		
R^2	Squ.	Hex.	Tri.	Squ.	Hex.	Tri.	Squ.	Hex.	Tri.	Squ.	Hex.	Tri.
	0.971	0.974	0.927	0.962	0.962	0.978	0.964	0.977	0.954	0.619	0.714	0.847

The regression results are used to project the expected errors at each scale for two modules (Table 4.2 and Table 4.3). The resulted modules are general and used to predict the faults for each class separately. Considering certain error tolerance, the modules assist in deciding the ideal grid system and scale. Within these modules, the urban fabric class shows that the area errors for the hexagon provides the best solution, an acceptable area error of 2% is reached at scale level of (120×120 - 130×130 m^2) while the same error is reached at scale level of (110×110 - 120×120 m^2) for the triangle and square system (Table 4.2). However, for the same class, both square and triangle grids provide improved results in capturing the CFN. On the other hand, the module of industrial units indicates that the triangle system has the smallest areal errors (Table 4.3). An areal error of 2% is reached at scale level of (160×160 - 170×170 m^2) for the triangle system, while the same error is reached at scales of 150×150 - 160×160 m^2 for both the hexagon and square. Again, both the square and triangle deliver improved outcomes in capturing the CFN (Table 4.2).

The below modules provide univariate contrast for the used systems; both of them illustrate the areal errors or the CFN errors at each scale separately. Noticeably, the errors vary for each grid system and for each considered class. In case considering both errors as significant aspects, deciding the appropriate grid for each class requires modeling both errors into one model. This model delivers signs regarding the best system by pointing out the “balanced error” constrain. That is, an idyllic linear regression for both errors (areal and CFN) has a slope of 45 degrees. To fulfill this, both errors in their projected status, as shown previously in Table 4.2 and Table 4.3, are joint to project a new regression for each considered class separately. That also means that the results are two models for the two considered classes demonstrating both errors in each axis. The resulted regressions are represented by the linear function where the slope variable receipts the coefficient value of the independent variable (x). In that case, a function with a coefficient value of 1 offers the idyllic solution for the above-mentioned problem. For the research case, the relation with a coefficient value closer to 1 is considered the relationship with the “balanced error” for each class.

All systems offer high R^2 coefficient values, where all values are above 0.99, thus the combination of both errors is fitted very well. As noticed, the triangle grid for both classes of urban fabric industrial or commercial units classes represents the identified balance error case (Figure 4.7). Both square and hexagon systems follow the triangle respectively. The area error in all systems is fairly low compared to the CFN errors. Considering the triangle system, an areal error of 2% corresponds to 20% error in CFN within the urban fabric class. That error is reached at the 9th scale of 110x110 m^2. The square system behaves similarly but decreases the areal errors at the same scale. On the other hand, for the industrial areas, the triangle system shows areal errors of 2% corresponding to almost 37% in CFN, while the square system shows areal errors of 2% corresponding to almost 35% at a lower scale. Even though the triangle system has balance errors, the middle areal errors favor the square system the most.

Table 4.2 : Urban fabric projected errors (Shoman, et al., 2019a).

scale	Triangle		Hexagon		Square	
	Area Error %	CFN error %	Area Error %	CFN error %	Area Error %	CFN error %
	y = 0.0026x - 0.0043	y = 0.0186x + 0.0398	y = 0.0024x - 0.0044	y = 0.0204x + 0.0856	y = 0.0027x - 0.006	y = 0.021x + 0.0282
30×30	0.17	5.84	0.20	10.60	0.33	4.92
40×40	0.09	7.70	0.04	12.64	0.06	7.02
50×50	0.35	9.56	0.28	14.68	0.21	9.12
60×60	0.61	11.42	0.52	16.72	0.48	11.22
70×70	0.87	13.28	0.76	18.76	0.75	13.32
80×80	1.13	15.14	1.00	20.80	1.02	15.42
90×90	1.39	17.00	1.24	22.84	1.29	17.52
100×100	1.65	18.86	1.48	24.88	1.56	19.62
110×110	1.91	20.72	1.72	26.92	1.83	21.72
120×120	2.17	22.58	1.96	28.96	2.10	23.82
130×130	2.43	24.44	2.20	31.00	2.37	25.92
140×140	2.69	26.30	2.44	33.04	2.64	28.02
150×150	2.95	28.16	2.68	35.08	2.91	30.12
160×160	3.21	30.02	2.92	37.12	3.18	32.22
170×170	3.47	31.88	3.16	39.16	3.45	34.32
180×180	3.73	33.74	3.40	41.20	3.72	36.42
190×190	3.99	35.60	3.64	43.24	3.99	38.52
200×200	4.25	37.46	3.88	45.28	4.26	40.62
210×210	4.51	39.32	4.12	47.32	4.53	42.72
220×220	4.77	41.18	4.36	49.36	4.80	44.82
230×230	5.03	43.04	4.60	51.40	5.07	46.92
240×240	5.29	44.90	4.84	53.44	5.34	49.02
250×250	5.55	46.76	5.08	55.48	5.61	51.12

Table 4.3 : Industrial or commercial units areas projected errors (Shoman, et al., 2019a).

	Triangle		**Hexagon**		**Square**	
scale	Area Error %	CFN error %	Area Error %	CFN error %	Area Error %	CFN error %
	y = 0.0015x - 0.0019	y = 0.0301x - 0.0641	y = 0.0015x - 0.0009	y = 0.0308x + 0.0211	y = 0.0014x + 0.0016	y = 0.0286x - 0.0294
30×30	0.04	3.40	0.06	5.19	0.30	0.08
40×40	0.11	0.39	0.21	8.27	0.44	2.78
50×50	0.26	2.62	0.36	11.35	0.58	5.64
60×60	0.41	5.63	0.51	14.43	0.72	8.50
70×70	0.56	8.64	0.66	17.51	0.86	11.36
80×80	0.71	11.65	0.81	20.59	1.00	14.22
90×90	0.86	14.66	0.96	23.67	1.14	17.08
100×100	1.01	17.67	1.11	26.75	1.28	19.94
110×110	1.16	20.68	1.26	29.83	1.42	22.80
120×120	1.31	23.69	1.41	32.91	1.56	25.66
130×130	1.46	26.70	1.56	35.99	1.70	28.52
140×140	1.61	29.71	1.71	39.07	1.84	31.38
150×150	1.76	32.72	1.86	42.15	1.98	34.24
160×160	1.91	35.73	2.01	45.23	2.12	37.10
170×170	2.06	38.74	2.16	48.31	2.26	39.96
180×180	2.21	41.75	2.31	51.39	2.40	42.82
190×190	2.36	44.76	2.46	54.47	2.54	45.68
200×200	2.51	47.77	2.61	57.55	2.68	48.54
210×210	2.66	50.78	2.76	60.63	2.82	51.40
220×220	2.81	53.79	2.91	63.71	2.96	54.26
230×230	2.96	56.80	3.06	66.79	3.10	57.12
240×240	3.11	59.81	3.21	69.87	3.24	59.98
250×250	3.26	62.82	3.36	72.95	3.38	62.84

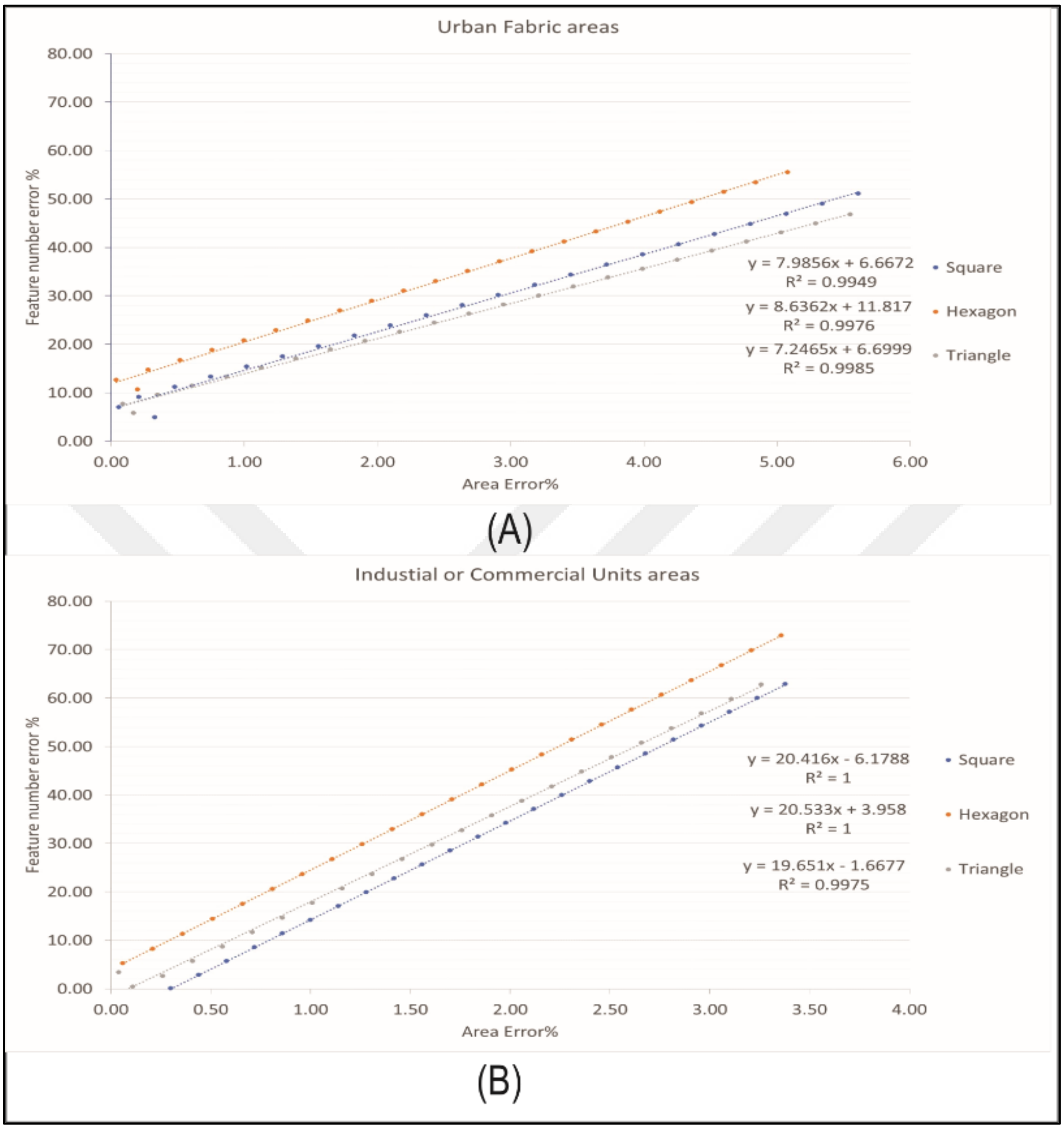

Figure 4.7 : A scatter plot projecting both errors in (a) Urban fabric and (B) Industrial areas classes (Shoman, et al., 2019a).

The triangle system illustrates improved outcomes in most univariate comparisons and in both combined error models for the two identified LCLU classes. Mainly, this is referenced to the geometric distribution of the modeled classes (Figure 4.2). In the study areas, both considered LCLU classes have irregular shapes illustrated by the difference in area and direction of its shape. Most extracted features are extended in a certain direction as seen in Figure 4.2.A. The middle features are easily gridded using any of the identified systems. However, the difference is found within the remaining boundaries which contain more than one attribute inside each polygon. Generally, such features are distributed along boundary lines. Square system follows the dominant attribute in orthogonal directions, while the hexagons system act similarly to circles, collecting information about the major LCLU attributes from all directions. On the other hand, the triangle system is arranged in a distinct matter. The arrangement of its cell directions provides varying area from the base to the far angle. In our study area, irregularity in shapes and directions found at the boundaries privilege the triangle system to follow the direction of boundaries more appropriately and with less errors.

4.4 Identifying the Optimum Gridding System

This chapter compared the previously identified gridding systems, assessing the lost data to suggest a suitable gridding system for the later accessibility calculations. The chapter examined two error types, namely the areal and the CFN. The previous modules provided the chance to select only one error type or one LCLU class while evaluating the lost errors as illustrated in Table 4.2 and Table 4.3. In this case, the triangle system was suggested to lessen the CFN errors for both classes and the areal error for industrial or commercial units class only. However, the hexagon system was suggested to minimize the areal errors for the urban fabric only. Moreover, the recommended modules illustrate the relationship between both errors and used scale, thus illustrating related information regarding the scale-dependent accuracy metric. On the other hand, when considering both errors, a combined evaluation is performed. The implemented “balanced error” term shows that the triangle system provides the best solution to minimize both error types together. The square system follows the triangle in both classes but behaves better for middle considered scales ($100 \times 100\ m^2$). Actually, the square gridding system is superior in reducing the areal errors, compared to others, at the scale of $100 \times 100\ m^2$ while providing similar CFN errors to the triangle system. Upon that, the study utilizes the square system at a resolution of $100 \times 100\ m^2$ to convert all classified thematic maps to representative grids.

5. EVALUATING THE CHANGING IN ACCESSIBILITY USING NETWORK DISTANCE AS IMPEDANCE MEASURE (3)

In 2007, a huge transportation project of Istanbul Metrobus Line (IML) was run and operated in Istanbul by Istanbul Metropolitan Municipality (IMM). The project was considered the main influence on changing the accessibility status and the accessibility components of the city. Previous chapters provided a methodology to acquire one related component of LCLU. The changed LCLU thematic maps were acquired and converted to representative points, thus assigning the locations of corresponding homes and workplaces (industrial areas) for related calculations. The change in LCLU component influences other related components within urban areas. Changes to the transportation network, industrial activities and opportunities found in the area are expected to reflect the changed accessibility status of the corresponding study area. To model the change in accessibility, several indices could be used. Each of them includes certain accessibility components within its calculation. The included components are influenced by the change in urban parameters within the considered time period.

Considering that, this chapter aims to;

1. Calculating the change in location-based accessibility more accurately over the time period of 1987 – 2014 by proposing a GIS-RS framework.
2. Identifying the effect of IML on changing the location-based accessibility status for the areas surrounding the project.
3. Identifying the urban parameters influencing each modelled accessibility index.

This chapter implements its application within the previously selected study area, as illustrated in Figure 3.1, via a designed proposed integrated GIS and RS framework. Four time periods are selected i.e. 1987, 1997, 2007 and 2014. The selected time periods are linked to the plan, construction and management of the IML system found

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(3) This chapter is based on the paper of Shoman W. and Demirel H. 2018. "Spatio-temporal evaluation of transport accessibility of the Istanbul Metrobus Line". Geocarto International. https://www.tandfonline.com/doi/abs/10.1080/10106049.2018.1524515.

within the study area boundaries. The first period between 1987 and 1997 is assigned to check the change in accessibility before the IML was even planned. The second period between 1997-2007 corresponds to the planning and construction of the IML. The last period of 2007-2014 represents the following operating time period. Travel network distance is used as an impedance measure while the location-based accessibility indices are calculated. The limitation of data hinders the use of other impedance measures. The change in accessibility is demonstrated for two travel modes, namely being walking and using automobile/car modes. The implemented framework stands out in its high-resolution accessibility analysis, which has a cell resolution of 100×100 m^2. Such high resolution benefits the research in analyzing accessibility status at the block/neighbor level. Utilizing that, the impact of the changed accessibility components is analyzed spatially and temporally. These altered components are the change in number and distributions of OD, the change in the road network and the distribution of the newly constructed roads. Exploring the impact of IML on accessibility also requires selecting suitable accessibility indices each of which encompasses different components. Spatial separation, cumulative-opportunity, daily accessibility and potential accessibility are used as the location-based indices for this application, as shown earlier in Chapter 2 in Equations 2.1, 2.3, 2.4 and 2.5, respectively. The selected indices play an important role in describing the various relations of accessibility component- accessibility status. Within identified conditions, the locations in each time period that received the most increase in its accessibility values are identified considering each identified factor alone or considering several factors. The accessibility values of each period are calculated and changes in percentages are compared with the previous periods in order to assess the impact of IML quantitatively.

5.1 Istanbul Metrobus Line

City planners in Istanbul have been doing their best to keep up with the huge increase in urbanization by investing in more transportation infrastructure projects to connect the residents with their destinations. One of the implemented projects is a bus rapid transit system that provides a high-capacity transport, cheaper cost and faster to travel than an urban rail system. Such system was not proposed in the original transport master plan of the city, nor was it developed together with the new transport plan that was being put together in the mid-2000s (Babalik-Sutcliffe & Cengiz, 2015). The multi-lane highway found in the study area was selected as the route of IML due to the already high transit demand (Figure 5.1). Moreover, it is located in the central corridor that penetrates the existing urban fabric of the city. The IML also passes through the central business district of the city, which is a major trip generator and has a 52 km dedicated route.

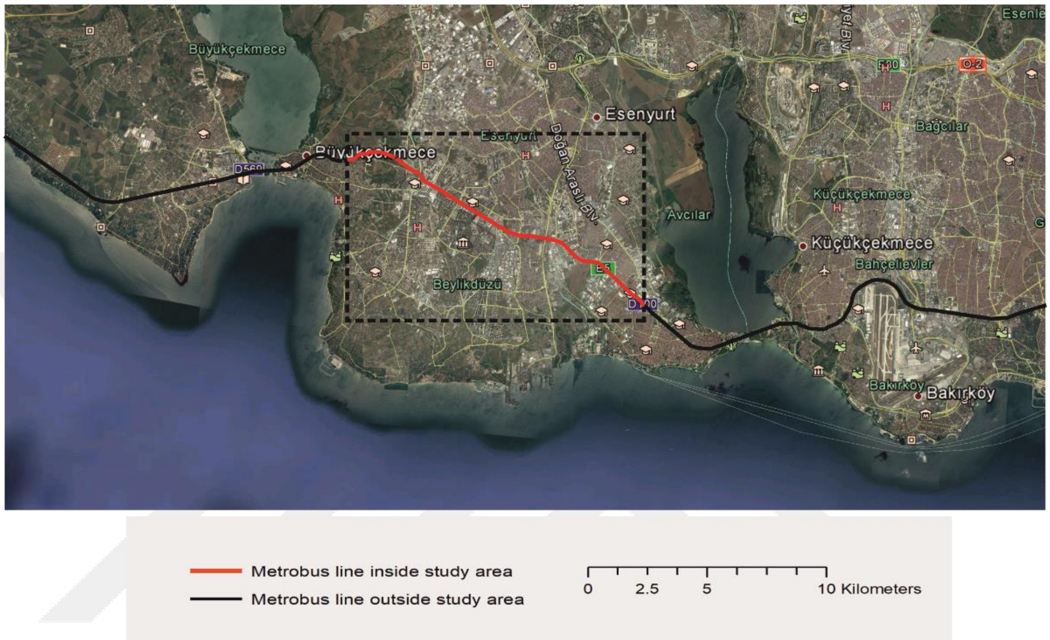


Figure 5.1 : Location of the IML (Shoman & Demirel, 2019a).

5.2 The Proposed GIS-RS Framework to Model Accessibility

In order to analyze the location-based accessibility of the previously identified indices, a GIS-RS based framework is designed and illustrated in (Figure 5.1). The LCLU of the corresponding study area is acquired from the previously classified thematic maps (Figure 3.3). They are converted to points following the methodology introduced earlier (Figure 4.3).

The gridding is implemented while maintaining an aerial error of less than 1.5%. The square gridding system maintains this error at a resolution of 100 x100 m^2 cell area (Figure 5.3.B). The attribute of the dominant area is assigned to each cell (Figure 5.3.C). Only related classes of the urban fabric and industrial areas are stored for further analysis (Figure 5.3.D). Cells are represented by points in their centroids for all relevant classes (Figure 5.3.E).

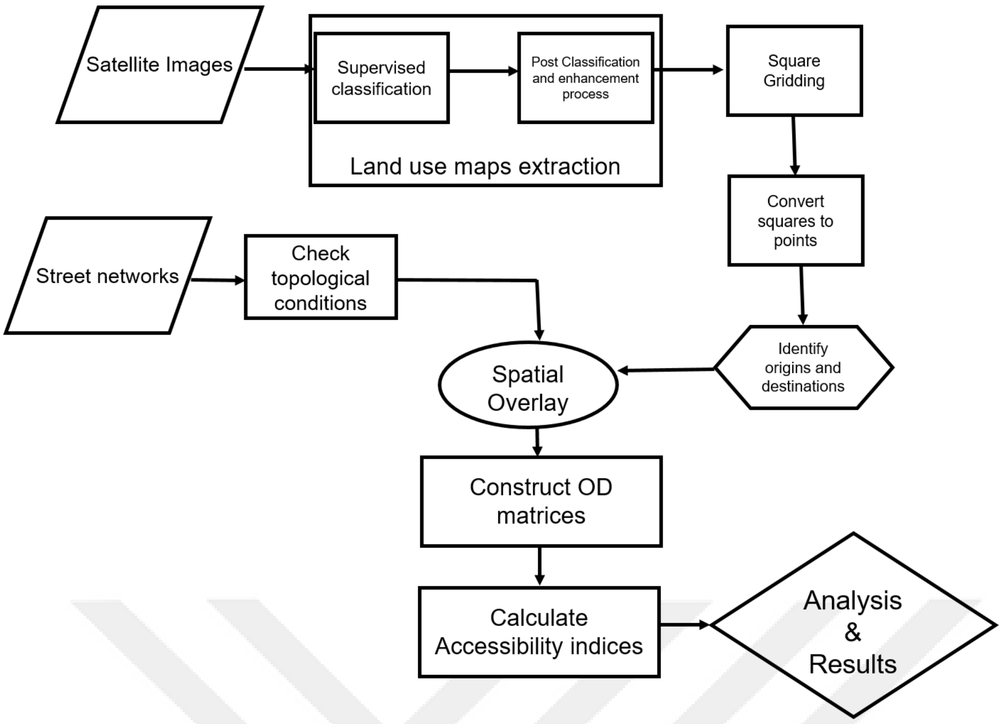


Figure 5.2 : The followed GIS-RS framework for calculating the accessibility (Shoman & Demirel, 2019a).

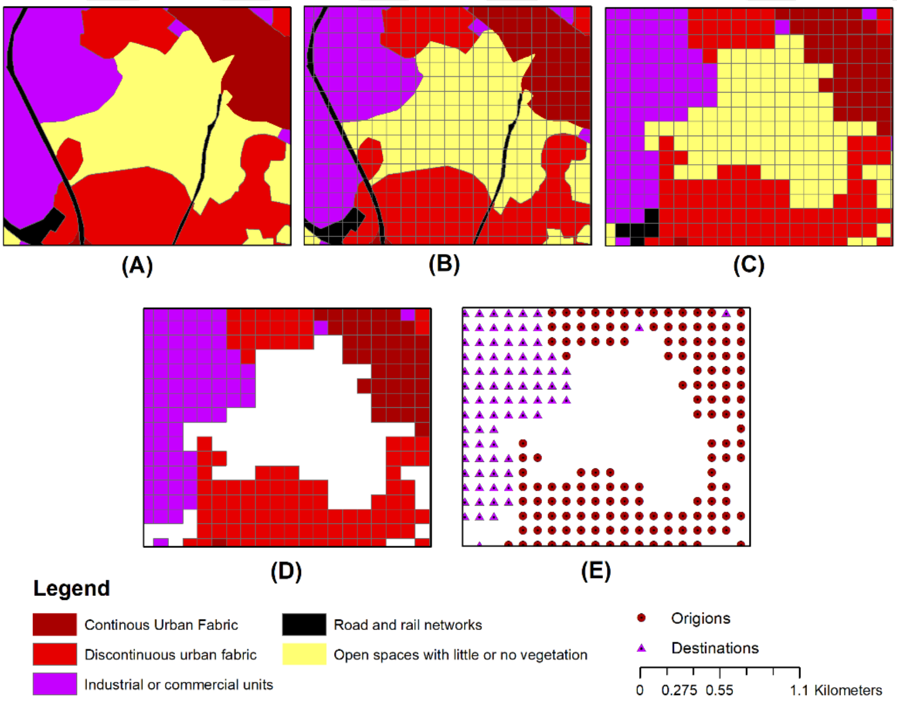


Figure 5.3 : The process of converting raster LCLU to corresponding points (Shoman & Demirel, 2019a).

On the other hand, the road network of the study area has enormously altered during the time analysis. To capture that efficiently, road networks at considered years periods are acquired and checked for topological errors. OpenStreetMap is used as the main source to acquire 2007 and 2014 road networks for each year separately. Earlier networks are not available for Istanbul. However, the road database for the remaining historical two periods is acquired via eliminating the non-existing roads from the 2007 road network using high corresponding resolution satellite imageries and orthophotos for each corresponding year. The number of edges, the total length of all edges with their increase percentage and the average length of edges for the four periods are shown in Table 5.1.

Table 5.1 : The change in urban road network.

Year	The total length of edges (km)	Increase (%)
1987	409.53	-
1997	880.65	137.11%
2007	958.27	11.10%
2014	1157.55	32.37%

Later, in this chapter, the network travel network distance between nodes is used as travel impedance. To calculate the identified accessibility indices OD matrices denoting the origins and destinations are required. In this study, urban fabric points represent the start locations while points of the industrial area represent the destinations. For m origins and n destinations, the network distances for each pair of origin and destination are calculated and the results formed an $m \times n$ OD matrix. The resulted distances are utilized to calculate each index for each pair of nodes. Moreover, destinations are considered equally attractive and their attractiveness is to a value of 1. The network distance matrix function calculated the total travel distance between pair nodes considering travel modes over the transportation network. Two travel modes are considered, being walking and automobile. The walking is unique in being not constrained by direction, unlike automobiles. This provided more routing options for walkers, e.g. walkers can crossroads, use bridges, tunnels and use roadsides in both directions. Moreover, according to (Iacono, et al., 2008), walking trips to working places destinations is reached within distances less than 3 km. The study also stated that most driving trips to destinations such as working places, which also found within the industrial areas class, covered distances between 30-60 km. This distance covers the whole study area. For that, the distance limitation for walking mode is set to be 3 km and no limitation for automobile driving mode is considered. On the other hand, the cumulative opportunity considers the number of destinations available within a specified distance. This index also differs the two modes of walking and driving by considering their corresponding thresholds. The threshold for daily accessibility indicator is set to equal 3 km. Considering all that, the four indices are calculated, and their results are shown in Table 5.2.

Table 5.2 : The change in accessibility status for all considered indices.

Index	Mode	1987-1997	1997-2007	2007-2014
Total Distance	**Walking (%)**	701.64%	54.91%	80.49%
	Automobiles (%)	797.95%	58.19%	99.78%
Cumulative-Opportunity	**Walking (%)**	610.29%	52.83%	80.24%
	Automobiles (%)	767.03%	56.52%	94.83%
Daily Accessibility (%)		503.91%	49.93%	104.19%
Potential Accessibility (%)		655.91%	53.93%	99.07%

5.3 Results and Discussion

5.3.1 Identifying the change in accessibility

First, exploring the first aim of "calculating the change in location-based accessibility more accurately over the identified time period", the methodology successfully quantified the accessibility change over the whole time period. All accessibility components are utilized as explained earlier. The quantifications are presented in the above table (Table 5.2). The results for all indices portray an enormous increase in all values for the first time period of 1987 and 1997. This is influenced by the huge increase in both the road network and the urban areas within this period (Table 5.1). However, a huge drop in all accessibility indices in the second period of 1997 - 2007. Within this period, an average increase of about 53% is observed due to normal growth in urban and industrial activities and network lengths. This normal increase is not associated with any major projects or changes in the urban structure during this time period. On the other hand, in the last period of 7 years (2007-2014), a relatively higher increase in the road network structure is observed. Roughly 93% average increase in all values is observed. That relative high increase is associated with the operation of IML during this period.

5.3.2 Analyzing the change for each accessibility index

All the above are temporal analysis of the change in accessibility status within the study area. Later, results and discussion of the earlier identified aim of “Identifying the urban parameters influencing each modelled accessibility index” are presented as follows. As noticed in Table 5.2, the increase in total distance and cumulative-opportunity indices via automobiles mode is higher than the walking mode. However, a balanced investment for both modes is noticed due to the increase in both modes (Table 5.2). All accessibility indices shared a similar temporal increase rate. Yet, the spatial distribution is uniquely different for each index (Figure 5.4 and Figure 5.5), except for the cumulative-opportunity index. The change in accessibility values for each time period is classified into five classes colored from green to red. The highest increases in accessibility are found in red. As shown, both figures show that the increase in the road network length increases the accessibility values for nodes located at the borders. This impact is strongly observed for automobile mode more than the other mode (Figure 5.4.b, Figure 5.4.d and Figure 5.4.f). Even though the IML is located in the middle and the increase in the network occurred mostly to one side of the study area, the accessibility increased for all boundaries regardless of which side they are located at. This is, for automobiles mode, additional alternative edges in the network increase the total distance accessibility index value. Mainly, the total distance accessibility using automobile for boundary locations increased the most rather than central locations. On the other hand, the total distance accessibility by walking mode witnessed the highest increase for locations near destination locations (Figure 5.4..a, Figure 5.4.c and Figure 5.4.e). This increase was not influenced by the locations of new edges. Meaning that increasing the accessibility for walkers is mainly influenced by proximity to destinations and not by growing in the road network. Moreover, considering the last time period, the highest increase in accessibility are concentrated around the IML. That is an indication of the positive strong relationship between the total distance accessibility and IML.

On the other hand, the increase for both potential and daily accessibility indices are separately demonstrated in Figure 5.5. Similar to Figure 5.4 the change in accessibility vales for both indices are classified into five classes colored from green to red according to each’s nodes quantile increase. Here, both indices have similar spatial distribution for their results for each temporal period.

This is referenced to both LCLU distribution and road network growth. Origin locations that are close to further destinations with additional alternative routes have a higher increase in accessibility values. The increase also tended to occur more toward center locations (Figure 5.5). That is explained as follows. For the first time period of (1987-1997), most origin locations are found in the right half side. Locations colored in red are found concentrated toward the center of the same side, indicating a higher increase in accessibility for that part (Figure 5.5.a and Figure 5.5.b). This occurs due to the proximity to more destinations and the availability of additional routes to destinations. For the second time period of (1997-2007), further home and industrial locations appear. Again, home locations near to more destinations receive the highest increase in accessibility. However, but unlike the previous time period, they are actually distributed around the center of the study area (Figure 5.5.c and Figure 5.5.d). For the last time period of (1997-2007), further home and industrial locations appear spatially distributed over the whole study area. But, the highest increase in accessibility occurred for home locations surrounding the IML (Figure 5.5.e and Figure 5.5.f). These observations are tabulated in Table 5.3.

Table 5.3 : Spatial relation for locations of highest increase of accessibility values and direct influence.

Index	**Total Distance (Walking mode)**	**Total Distance (Automobiles mode)**	**Cumulative-Opportunity**	**Daily Accessibility**	**Potential Accessibility**
Location of highest increase in values	Close to destinations/ centers	Borders	Constant	Centre	Centre
Direct influence	Distribution of origin destinations	Increasing road lengths	Number of destinations	Destinations and increase in alternatives routes to reach them	Destinations and increase in alternatives routes to reach them

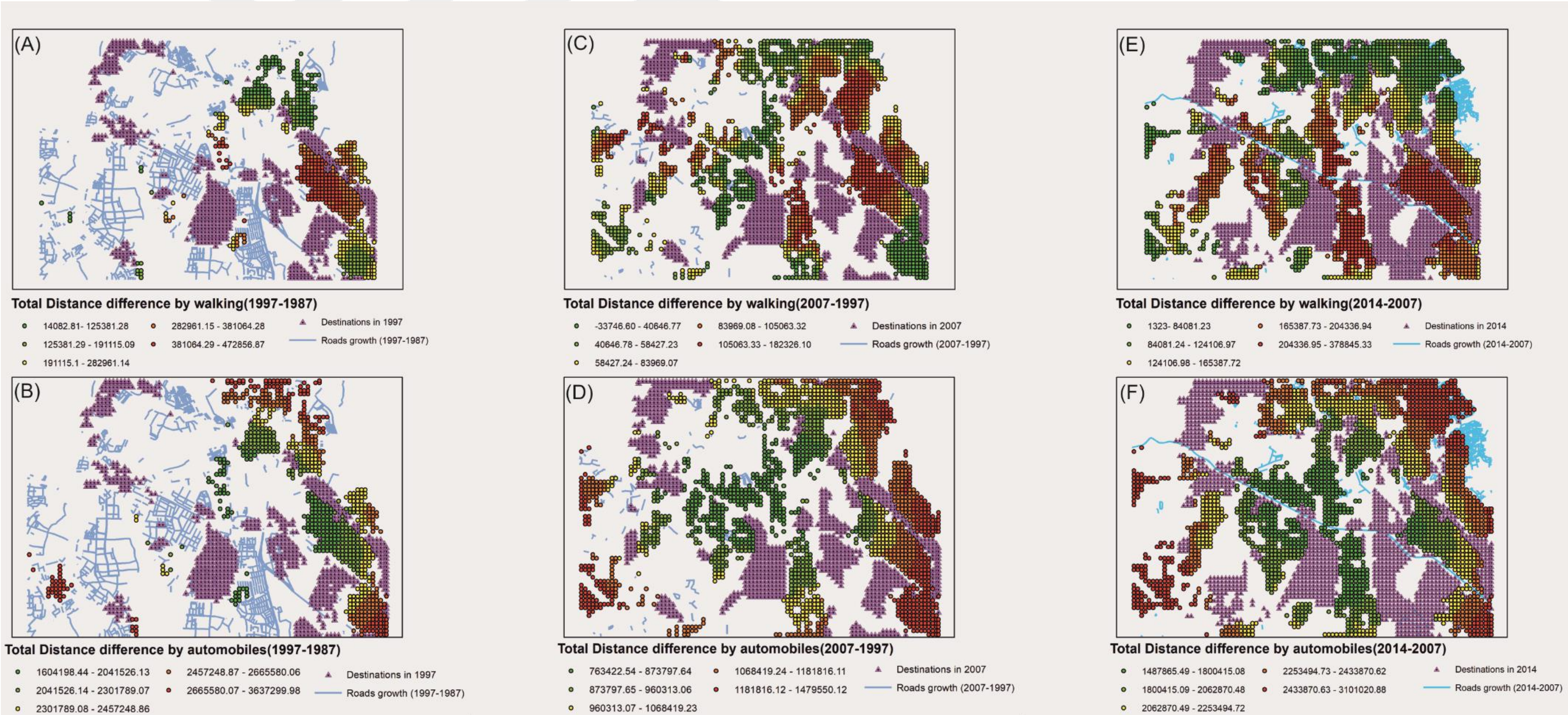


Figure 5.4 : The change in total distance index (Shoman & Demirel, 2019a).

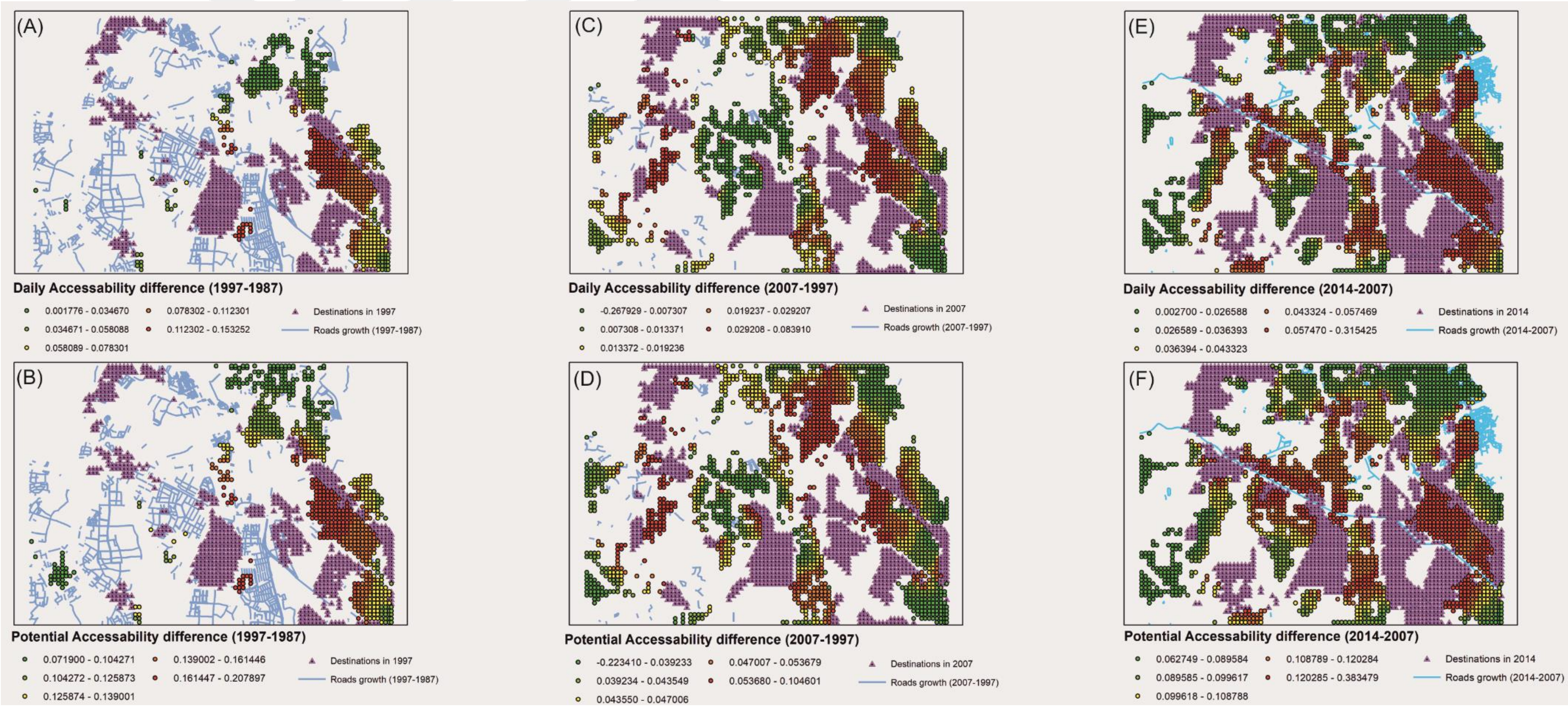


Figure 5.5 : The change in both potential and daily accessibility indices (Shoman & Demirel, 2019a).

5.3.3 Role of IML on changing accessibility

Temporally, in the period of 2007-2014, tracking the change in accessibility shows that it vastly increased compared to the previous one (Table 5.2). Majorly, that is referenced to the construction and operation of IML and consequential road growth. The consequential constructed edges in the study area provide more alternatives to network users, thus decrease average travel time. Moreover, such project is considered a direct reason to increase industrial activities, create new opportunities, find new gravity centers and improve the infrastructure. Consequently, the accessibility status is positively impacted by IML illustrated in Figure 5.6.

For the last time period, about 52% of accessibility change found in Table 5.2 is positioned within only 1.5 km buffer zone around the IML. As noticed, the total distance index using automobile mode behaves differently. The highest increase, in that case, is found near the boundaries and away from the IML, which explains this behavior.

Additionally, the IML promotes home locations near its 11 stops (IML terminals), found within the study area, the most. More than 80% of red locations, (locations that received the highest increase in accessibility values) inside the IML buffer zone are located within a 1 km buffer zone of the IML stops (Figure 5.7). Such an indicator shows a positive direct relationship between the construction of IML and increasing accessibility within the study area.

5.4 Policymakers Utilizing the Various Indices

The aforementioned discussion summarized means policymakers could use in their plans to target certain audience in order to increase the accessibility. Policymakers aiming to enhance accessibility to primary everyday demands, i.e. grocery stores and schools, should consider the walking mode in both total distance and cumulative-opportunity indices. Those type of destinations should be accessed easily via the walking mode in all communities, due to the engagement of all age groups in reaching such destinations. On the other hand, both indices but via automobile mode are used to target destinations of less frequent trips, such as hospitals. Even though such destinations are important to be easily accessed by the public, they are impossible to be located near all households. Improvements in these indices reflect the fair use of all households in the neighboring areas from their services. Finally, the combination of various urban factors in the daily and potential accessibility indices makes them more suited to evaluate the economic performance of locations. Markets and large shopping centers, for instance, are ideally modelled using these indices to evaluate the ease of potential participation of consumers.

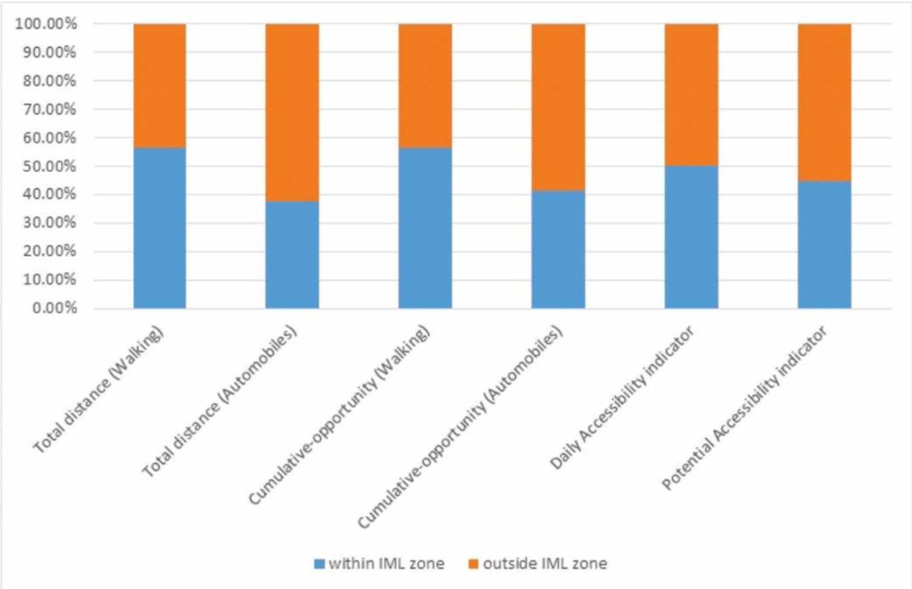


Figure 5.6 : The sum of accessibility values inside the IML's 1.5 km buffer zone (blue) and outside it (red).

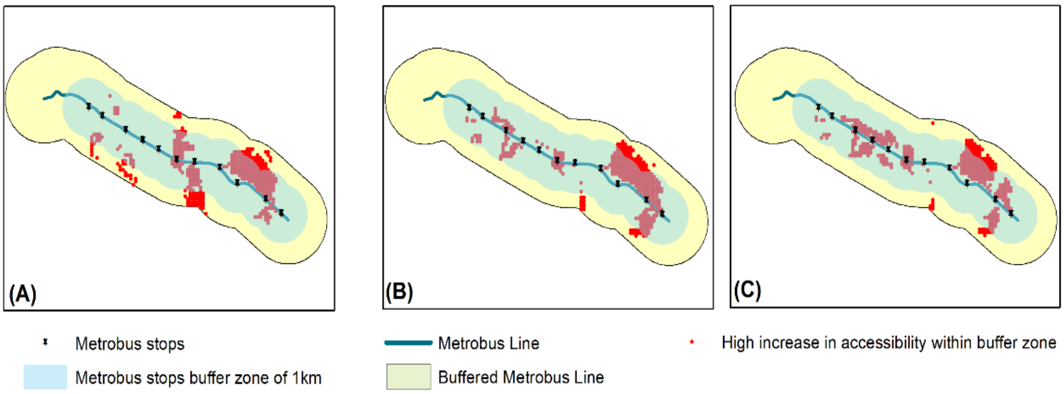


Figure 5.7 : Locations that received the highest increase for A) Daily accessibility, B) Total distance (walking) and C) Potential indicator.

6. CHANGE IN ACCESSIBILITY TO HEALTHCARE CENTERS

Istanbul Metropolitan Municipality (IMM) strive to keep up with its enormous increase in population, urban fabric and urban activities by connecting all related areas. The city also endeavors to offer its inhabitants with well-connected facilities such as health care centers/hospitals. Because accessibility reveals the relationship between the transportation system and land use patterns, the index to measure accessibility should respond to changes in either, or both, of these elements. Accessibility indices are found in some categories each of which highlights dissimilar features of the network (Bhat, et al., 2000; Geurs & Wee, 2004; Geurs, et al., 2012). Among these indices the potential accessibility and daily accessibility indices. The potential accessibility index estimates the level of opportunities from an origin to all probable destinations by considering the distant diminishing influence. On the other hand, the daily accessibility considers a fixed cost for travel, such as distance or travel cost, in which a destination is to be reached to be of interest (Crisioni, et al., 2016). Both of them are substantial to illustrate the primary change of hospitals/health care centers accessibility status due to network growth and land use change.

This chapter provides another application to transportation accessibility analysis. It aims to quantitatively calculate the change in accessibility to healthcare centers due to urban transportation investments in the area. It utilizes the earlier described GIS-RS framework (elaborated in the previous chapter) to deliver its aim. Both indices of potential and daily accessibility are exploited to estimate the accessibility change for the same study area. Walking and cars are the two considered travel modes. The change of accessibility is considered for the time period of 2007- 2014 only. Moreover, travel network distance is utilized as the travel impedance measure. Locations of hospitals and health care centers are identified via GPS while home locations are identified using earlier given LCLU thematic maps for corresponding dates (Figure 4.2). Both locations are converted to corresponding points and, later, overlaid with the road network to calculate both indices.

6.1 Accessibility to Healthcare Centers

Both potential and daily accessibility indices are calculated using the Equation (2.4) and Equation (2.5), respectively. The potential accessibility measures activity volume of a particular area and can be interpreted as the volume of activity to which an area has access considering the travel cost as travel distance/time increases (Iacono, et al., 2008). Within this chapter, the potential accessibility is considered only for car users. Due to the limited area of study, the weight of all hospitals is considered equal and the distance decay is assumed to be equal to 1. On the other hand, the daily accessibility indicator is a similar index to the previous one (potential accessibility). However, this measure is implemented to calculate daily accessibility for the walking mode to their destinations. Thus, walkers are willing to walk to hospitals up to a max distance of 3 km (Iacono, et al., 2008). Daily accessibility for cars is not considered due to the limited area of study. Similarly, weights for hospitals are considered equal and the distance decay is set to a value of 1. For both indices, network distance is used as an impedance measure.

Identify the destination points which are the hospitals and health care centers found within the study area is acquired by GPS data obtained from Here Maps@. Locations of homes are identified from the previously gridded LCLU thematic maps for both years of 2007 and 2014 (Figure 3.3. Road networks of corresponding years are also acquired from the previous section (section 5.2). Both locations of origins and destinations are overlaid to their corresponding road networks. Finally, OD matrices for both dates are run to calculate the aforementioned indices. The results are presented in Table 6.1 below.

Table 6.1 : Results of both accessibility indices (Shoman & Demirel, 2019a).

	Using distance constraint for walking mode		**Without using any distance constraint for car mode**	
Year	**2007**	**2014**	**2007**	**2014**
Number of origins	1036	1446	2559	3430
Total distance (1000 km)	3488.85	5734.20	34368.78	44051.27
Index value	**Daily accessibility**		**Potential accessibility**	
	1.41	2.08	2.60	3.60

As noticed from the table above, the number of hospitals and health care centers remain the same for both years. Results and statistics of the generated OD matrices are introduced in Table 6.1. They are grouped into two sets being; using a distance constraint and without any distance constraint. The constraint is set to represent the walking mode, which is 3 kilometers, which is later included in the daily accessibility calculations. While results of no constraints present the results of using a car mode, which is later used in the potential accessibility calculations.

The number of home locations increased for both modes about 39.58% and 34.04%, respectively, from 2007 to 2014 (Table 6.1). This increase has positively influenced the citizens to benefit from proximate hospitals. Accordingly, the distances from origins to hospitals that contributed to the accessibility calculation increased as well, being 64.36% and 28.17% for both conditions respectively. This represents the increase in used travel distances to reach their destinations (hospitals or health care centers). Even though only 39.58% of home locations found within 3km walking distance from hospitals increased between 2007 and 2014, the walking distance increased by 64.36%. On the other hand, the car mode shows less traveled distances. The increase in home locations in the whole study area is about 34.04% while traveled distances increased only 28.17% (Table 6.1). Thus, the increase in home locations is not similar to the increase in used distances to reach destinations for both modes.

The interplay effect of both OD and road network reveals a huge increase in daily and potential accessibility indices, being 47.52% and 38.4% respectively. As noticed, the walking mode benefited the most from urban change. This is referenced to the construction of more local edges /residential roads than collectors or arterials in the network. Policymakers are successful in promoting the walking mode by providing more routes and alternatives hospitals.

Mainly, travel network distances to hospitals dropped due to the emergence of new alternative roads/routes in the urban road network for the year 2014. This is explained in the figure below where an assessment of both road networks for an origin to reach both hospitals in this test area is illustrated (Figure 6.1). Starting from an origin and using a car as a transportation mode, reaching the near two hospitals (# 1 and # 2) is illustrated with two routes for both years. The traveling network distance to reach hospitals 1 and 2 decreased by 9% and 6% respectively in 2014 (Figure 6.1). Although, this assumption provides a preliminary indicator for the performance of the network, integrating further travel impedance such as the average travel time of the network could reveal more information on such policy decisions. Hence, the use of traffic speed information could provide more insights for policymakers (which is illustrated in later chapters of Chapter 8 and Chapter 9). Furthermore, integrating other significant data in both indices helps in weighting destination based on their importance, such as the integration of bed number which is also illustrated in later chapters of Chapter 8 and Chapter 9).

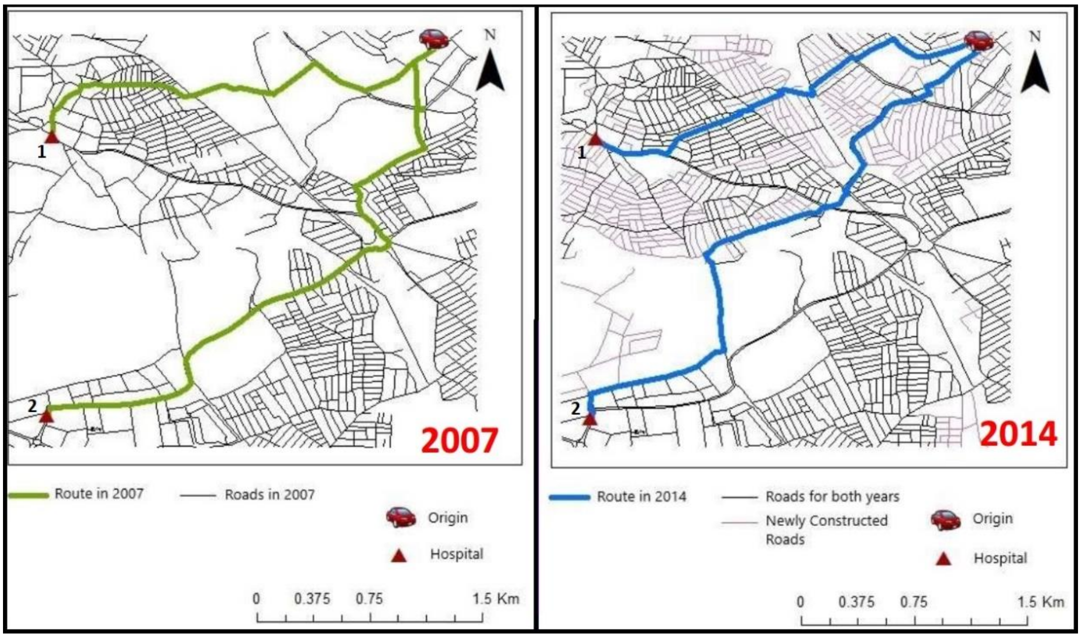


Figure 6.1: Routes from an origin to hospitals for 2007 and 2014 (Shoman & Demirel, 2019a).

6.2 Comments on the Results

Generally, the development of the road network and the interplay of homes and hospitals locations contributed to increasing the accessibility status. The growth of urbanization near hospitals increased significantly, same to the development of road networks. However, the increase in travel distances increased more to reach hospitals within identified conditions. When considering this factor only the general impression is that the accessibility of the area is decreasing. However, identifying each factor alone does not reflect the accessibility status of the area. Both accessibility indices increased significantly for healthcare centers' accessibility. The construction of more local roads favored the walking mode thus increasing the considered daily accessibility indicator. Increasing the potential accessibility index compels developing more collectors, arterial and higher hierarchal roads. Therefore, increasing both accessibility indices compels a balanced growth in both factors for effective planning.

7. ENHANCED SPATIAL SPEED INTERPOLATION FOR ROAD NETWORKS USING TOPOLOGICAL HIERARCHIES

In earlier applications of accessibility calculations, network distance is used as the travel impedance measure. This measure has several drawbacks that are discussed later in Chapter 9. To avoid them, later studies focus on exploring the location-based accessibility change using time as an impedance measure. For that, real-time average speed estimation of the corresponding road network is investigated in this chapter to be later converted to time.

Real-time average speed estimation is an important topic to several other implications such as dynamic traffic monitoring, traffic assignment, and neighborhood planning. For that, several data collection methods are used such as Remote Traffic Microwave Sensors (RTMS). Such means are installed and managed relatively cheaper compared to other means such as inductive loops. Nonetheless, they collect speeds only for the mounted roads which are considered a very small portion of the whole network. Covering all roads with speed detectors is unlikely to implement by municipalities and authorities due to the expected high cost. Moreover, the collected information still needs processing to be fully incorporated into later applications. In order to overcome such an issue, spatial interpolation utilizes this limited info to find speeds of other unknown links, such as the method of Inverse Distance Weighting (IDW).

Interpolation methods aim to estimate the unobserved value at a specific location and time to improve the accuracy of further analyses. Even though a plethora of studies discussed IDW from transportation perspective to interpolate speeds (e.g. (Shiode & Shiode, 2011; Zou, et al., 2012; Shamo, et al., 2015) this issue has not been well addressed in such field (Ni & Leonard, 2005; Bae, et al., 2018) and results still have a room to be enhanced. The IDW implements a cut distance to illustrate the limits where adjacent locations are used. It also implements a distance decay which influences observed values at the target to weaken as the distance between them grows. Among the recent promise road network applications studies, Shiode and Shiode (2011) modified IDW by including the network distance in its calculations (NT-IDW).

However, the study only included distance decay in its calculation, hence leaving room for research and improvement of the current form. It stands to reason that using adjacent roads in the interpolations provides more accurate results. But, using short cut distances reduces the number of interpolated roads due to the scarce and limited number of used known values. Increasing the distance, without doubt, increases the error but makes sure more roads and links/edges are interpolated. A balanced value for both terms should be investigated.

Moreover, previous interpolation studies utilized values of nearest roads without considering the topological characteristics of the network (Zou, et al., 2012; Menga, et al., 2013; Bae, et al., 2018; Shiode & Shiode, 2011). Yet, such a factor has a vital role in several road network applications such as transport management. The topology of a network helps to determine prominent/marginal roads according to the overall structure of the network (Jiang & Claramunt, 2004; Jiang, et al., 2014). (Jiang, 2009) proved that urban streets are hierarchically organized in the sense that a majority of streets are trivial, while a minority of them is vital. Jiang (2009) also illustrated that 20% of top roads accommodate 80% of traffic flow. Ultimately, identifying such information for road networks aided transportation engineers to estimate average speeds for roads of the same level in transport modelling.

Considering all the above, this chapter proposes a novel methodology to interpolate real-time traffic speed using a topological hierarchy within the Shiode and Shiode (2011) NT-IDW method. In order to test and validate the developed concepts, 100 RTMS detectors found in the study area are used. The topological hierarchy information is retrieved from OpenStreetMap via using the “road tagging” attribute. The research verifies its results using real-time GPS data of vehicles crossing the study area. Results are investigated by the percentage of interpolated links in both topological hierarchical levels (First Hierarchal Level (FHL) and Second Hierarchal Level (SHL)) and Mean Absolute Percentage Errors (MAPE).

7.1 The Enhanced Interpolation Method

Inverse Distance Weighting (IDW) is a local and exact interpolation method that forecasts unknown values at locations using observed values at other adjacent locations within a distance and gives a weight that is inversely relative to the distance from the sample location (Lloyd, 2010). Shiode & Shiode (2011) developed the form of the introduced IDW by including a network distance (NT-IDW). Utilizing this form enables the use of limited speed data sources to interpolate more locations according to transport applications. Within Shiode & Shiode (2011)'s study, the effect a cut distance was not investigated. However, this chapter initiates the effect of this concept on interpolating the speeds more accurately. This chapter also investigates the effect of finding the distance decay value that is associated with choosing the optimum value for cut distances. A cut distance refers to the maximum network distance from the estimated point to other observed points with known speed values. The distance decay denotes the exponential function of modifying the spatial relationship between these locations (Fotheringham & O'Kelly, 1989; Lu & Wong, 2008). Incorporating both of these concepts means choosing interpolation data sources that yield accurate interpolation of unknown values. Including all known speed data in the calculations yields large errors, same as avoiding speed data. For that, a solution is required to increase the number of interpolated roads while maintaining the level of interpolation accuracy.

Furthermore, previous studies did not distinguish the significance of road hierarchies in the interpolation. They relate the speed values for all roads belonging to all hierarchal levels together, neglecting the topological influence in such a process. Embedding that in the process distinguishes the role of each level in the interpolation. The hierarchy sorts road edges in the network according to their significance. Implementing a topological hierarchy assumes that drivers prefer using higher topological hierarchal level roads, as much as possible, to reach their destinations. The reason for that is referenced to their usability for network users and topological connectivity between their corresponding links (Jiang, 2009). Therefore, drivers start their trips using the closer/approximate roads found in the low hierarchy then transport to higher levels (to roads in higher hierarchical levels). When reaching such roads, drivers expected to continue in their paths than to turn to roads of lower levels. Using roads of lower levels is the least preferred choice before reaching destinations. By means of this, the highest percentage of vehicles use higher hierarchal roads for longer distances/time. Drivers transport to the closest higher hierarchal level roads from low levels. In other words, users steer their vehicles to nearest roads of higher levels using the nearest junction. Furthermore, this implies that such hierarchal level (high hierarchal levels) has significant speed information for the network users due to the higher percentage usage of these roads.

In this chapter, this concept is utilized in NT-IDW by using speed readings found on higher hierarchal level roads to interpolate surrounding higher hierarchal level roads, then use them as new speed sources to interpolate later road found on other lower hierarchal levels as shown in Figure 7.1. The research further demonstrates its practice using the sample shown in Figure 7.2. Assuming implementing this idea for a two-level road hierarchy within a cut distance of β (Figure 7.2.A). Then, the proposed practice interpolates edges found in the First Hierarchal Level (FHL) within β from the RTMSs (Figure 7.2.A). Interpolated edges are used as new speed sources (Figure 7.2.B). Finally, Second Hierarchal Level (SHL) edges that can reach beforehand interpolated edges are interpolated (Figure 7.2.C). Confined FHL roads are the roads found between SHL roads, which are to be interpolated in this step, and the previously interpolated FHL links.

7.2 The Methodology to Implement the Proposed Interpolation Process

The proposed methodology is introduced in the following chart (Figure 7.3), where C and β represent the cut distances and distance decay coefficient, respectively. First, an empirical topological hierarchy is created. Later, the NT-IDW is modified to include the cut distance in its calculations. The road network is prepared, and the speed sources are collected for the selected time periods. Following that, a comparison between interpolation results of 1) using the proposed hierarchy and 2) without using any hierarchies is implemented. Finally, the results are evaluated.

7.2.1 Topological hierarchy creation for the study area

Jiang & Claramunt (2004) and Jiang (2009) noticed a three classes topological pattern for road networks while studying several cities. Considering significant roads, both studies found that a minority of roads service the majority of traffic flow. They also demonstrated that this minority of roads is well connected. Moreover, a very low percentage of these roads are extremely well connected. They demonstrated that this pattern is valid to all cities all over the world. Thus, the general topological hierarchy for cities includes three levels that considers the connectivity and usability in the network.

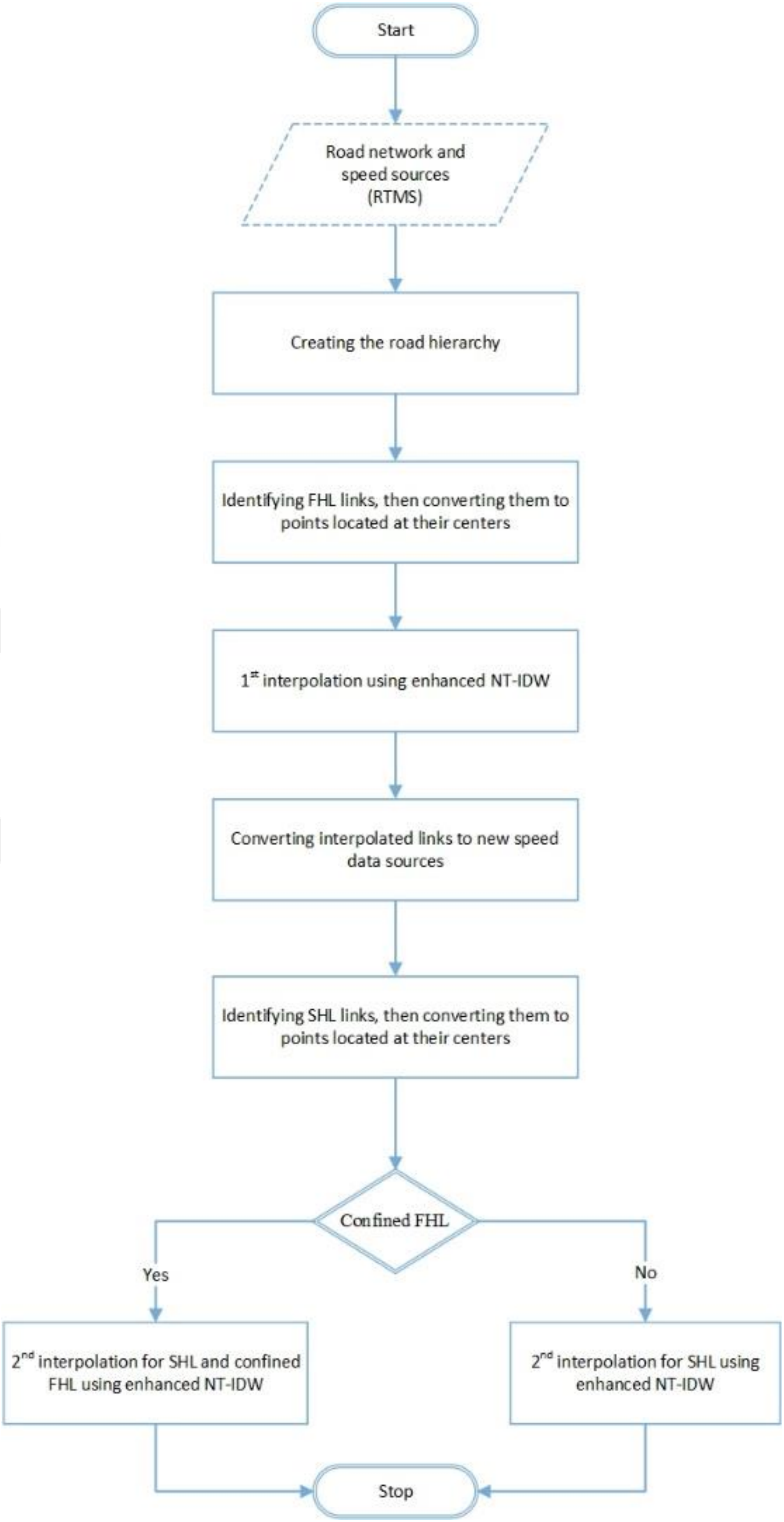


Figure 7.1 : Flowchart showing the enhanced interpolation method.

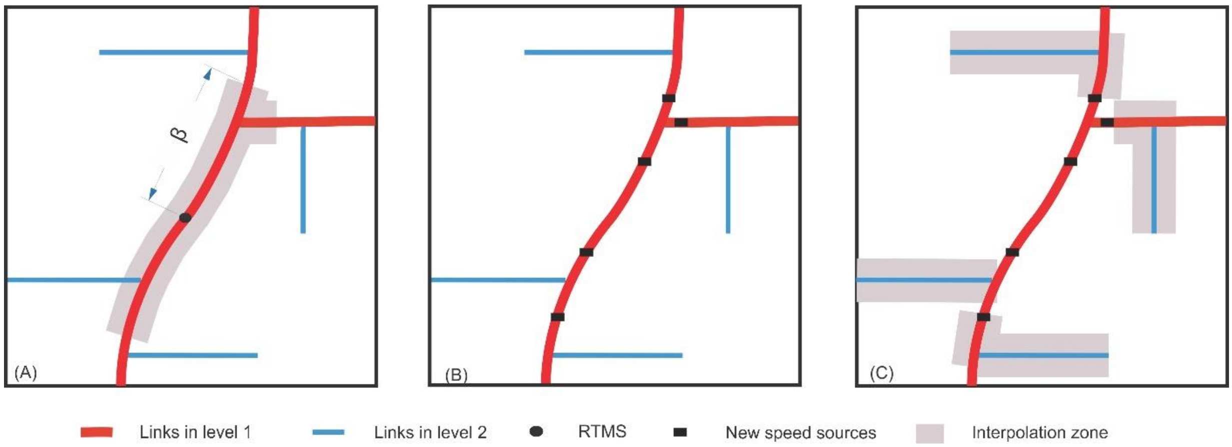


Figure 7.2 : Interpolation using the proposed methodology.

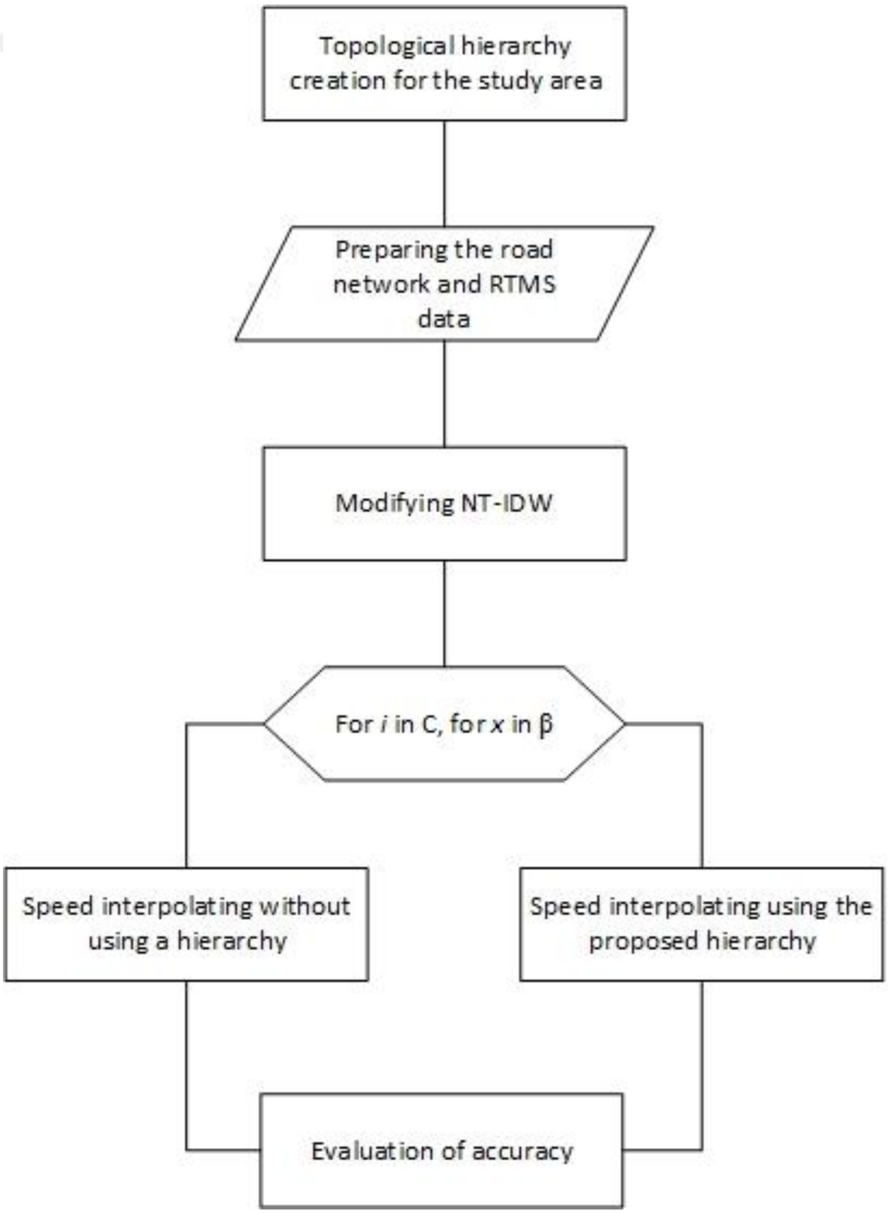


Figure 7.3 : The methodology to implement the proposed interpolation.

Accordingly, this study utilizes a three-level empirical topological hierarchy that classifies each class according to its significance to users and topological connectivity. The research implements its application using OpenStreetMap (OSM) road network for a part of Istanbul (Figure 7.4). OSM's "type" attribute indicates the significance of each road according to their standards (OpenStreetMap Wiki, 2019). OSM classifies its road types according to their significance as follows; motorway, trunk, primary, secondary, tertiary, unclassified and residential. Using this attribute, an empirical topological road hierarchy of three topological levels is created (Figure 7.4). We did not interpolate roads in the third level due to its irrelevant to the main aim. Figure 7.4 represents the spatial distribution of the proposed topological road hierarchy in the study area. Links found in FHL are about 7% of the total length while links found in SHL are about 19 %.

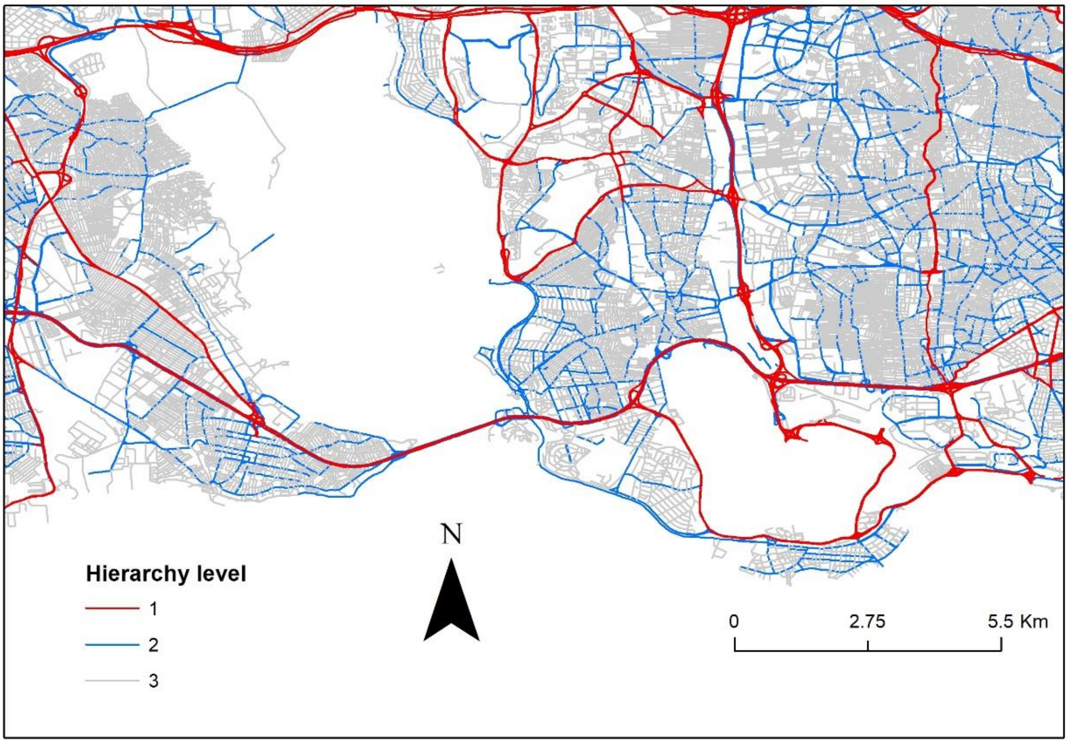


Figure 7.4 : The proposed three-level topological road hierarchy.

7.2.2 Collecting the RTMS speed data

Due to the high accuracy (Ma, et al., 2015) and availability, RTMS average travel speeds are used as the predictor in this chapter. But, not all RTMS detectors provide accurate readings. By checking the density-flow relation, problematic RTMS readings were eliminated. The study area contains 100 RTMS speed sensors (Figure 7.5).

RTMS readings of 01/01/2018 for 6 time periods, i.e. 07:30, 08:30, 11:30, 12:30, 17:30 and 18:30, were collected. Selected times represent important time periods of the day. Time periods of 07:30 and 08:30 display “to work” journeys, 11:30 and 12:30 illustrate “mid-day” traffic flows and 17:30 and18:30 present “to home” journeys. Some of RTMS sensors had no readings during some of the selected times. As a result of that, an average of 2 RTMS sensors was not used at each time period. The study used available detectors to interpolate roads on the network at each selected time.

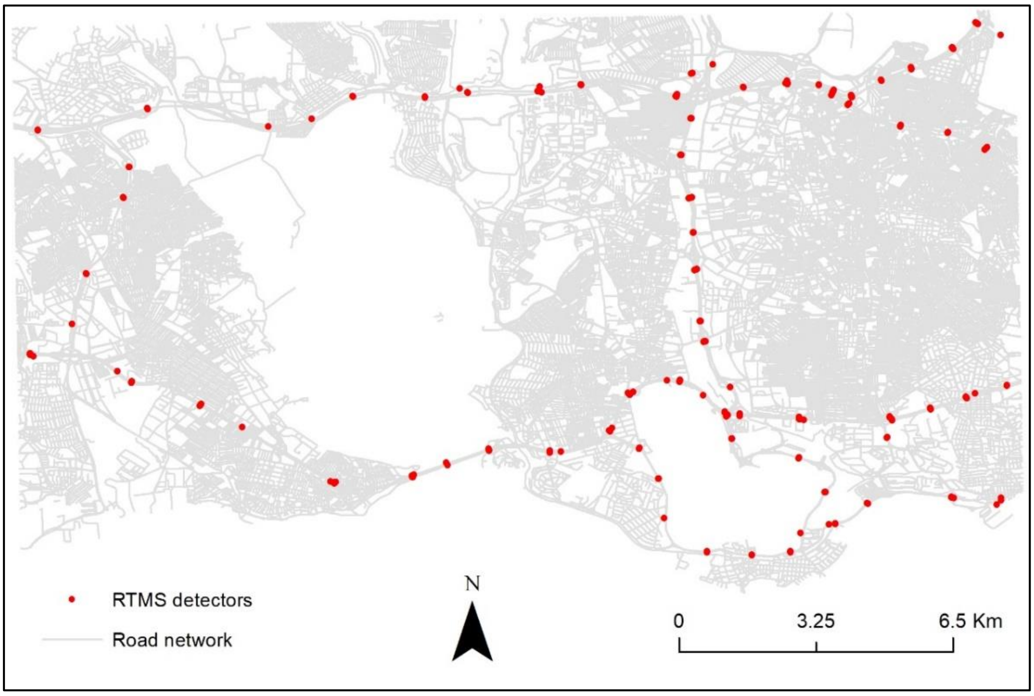


Figure 7.5 : RTMS locations within the study area.

7.2.3 Modifying the NT-IDW

While the power coefficient influence was modeled in the Shiode & Shiode, (2011)’s NT-IDW, the influence of cut distances is not included. This chapter modifies the Shiode & Shiode, (2011)’s NT-IDW mathematical formula by including the cut distance influence as shown below in Equation (7.1). The effect of distance decay, the inverse power function of $d_{NW}$is introduced by δ. P_0 is considered to be the target location on the network, and $\widehat{X_0}$ is considered to be the unknown value of P_0. Network distance of d_{NW} (p_0, p_i) denotes the shortest- network path distance from a nearby sample location p_i to the target location P_0 along the network within c. X_i refers the observed value of the nearby known speed locations. s refers to the nearest neighbors within ian dentified cut distance (c). This chapter investigates several values for c as

[1-9 km] to investigate ideal cut distance value and δ as [1- 5] to investigate the ideal power coefficient value.

$$\widehat{X_0} = \frac{\sum_{i=1}^{s} f(d_{NW<c}(p_0, p_i))^{-\delta} X_i}{\sum_{i=1}^{s} f(d_{NW<c}(p_0, p_i))^{-\delta}} \tag{7.1}$$

7.2.4 Evaluation of the interpolation

Mean Absolute Percentage Errors (MAPE) is employed to assess the performance of the proposed interpolation. This is a measure of prediction accuracy of a forecasting method which provides an average over the test sample of the absolute differences between prediction and actual observation. The measurement is formulated as seen in Equation 7.2:

$$MAPE = \frac{100\%}{n} \sum_{i=1}^{n} \frac{|y_i - x_i|}{y_i} \tag{7.2}$$

where y_i is the speed value of known reading, x_i is the interpolated road speed for the corresponding location and n is the number of observations. A cross validation using speed data (GPS data) collected from vehicles crossing the network was used in the MAPE calculations. The dataset was obtained from IMM for all selected time periods. Its readings ranged in number (120-160) according to the number of vehicles crossing the study area at each corresponding time period.

In order to investigate the results of using RTMS as the main source for interpolating the speeds of the network, IMM's speed data is used. Correlation analysis is carried out between the RTMS and acquired speed data. The suggested correlation coefficient ranges from -1 to 1. A coefficient of -1 or +1 indicates a perfect negative/positive linear relationship between variables, respectively, while a coefficient of zero indicates no linear relationship between variables. The relationship between the correlation coefficient matrix, R, and the covariance matrix, C, is presented in Equation 7.3.

$$R_{ij} = \frac{C_{ij}}{\sqrt{C_{ii} * C_{jj}}} \tag{7.3}$$

The result of the implemented correlation is found to be 0.80, which is a strong positive correlation. GPS speeds for vehicles within 5 meters and their corresponding RTMS sensors are used to calculate MAPE value, which is found to be 6.8%. Results indicate that the GPS data could be used as an evaluator, but some errors are expected.

7.3 Application of the Proposed Interpolation Method

A sample of the resulted traffic status for (01/01/2018) at all tested time periods is presented in (Figure 7.6) using the proposed methodology. The sample shows the average speed of interpolated links in both FHL and SHL.

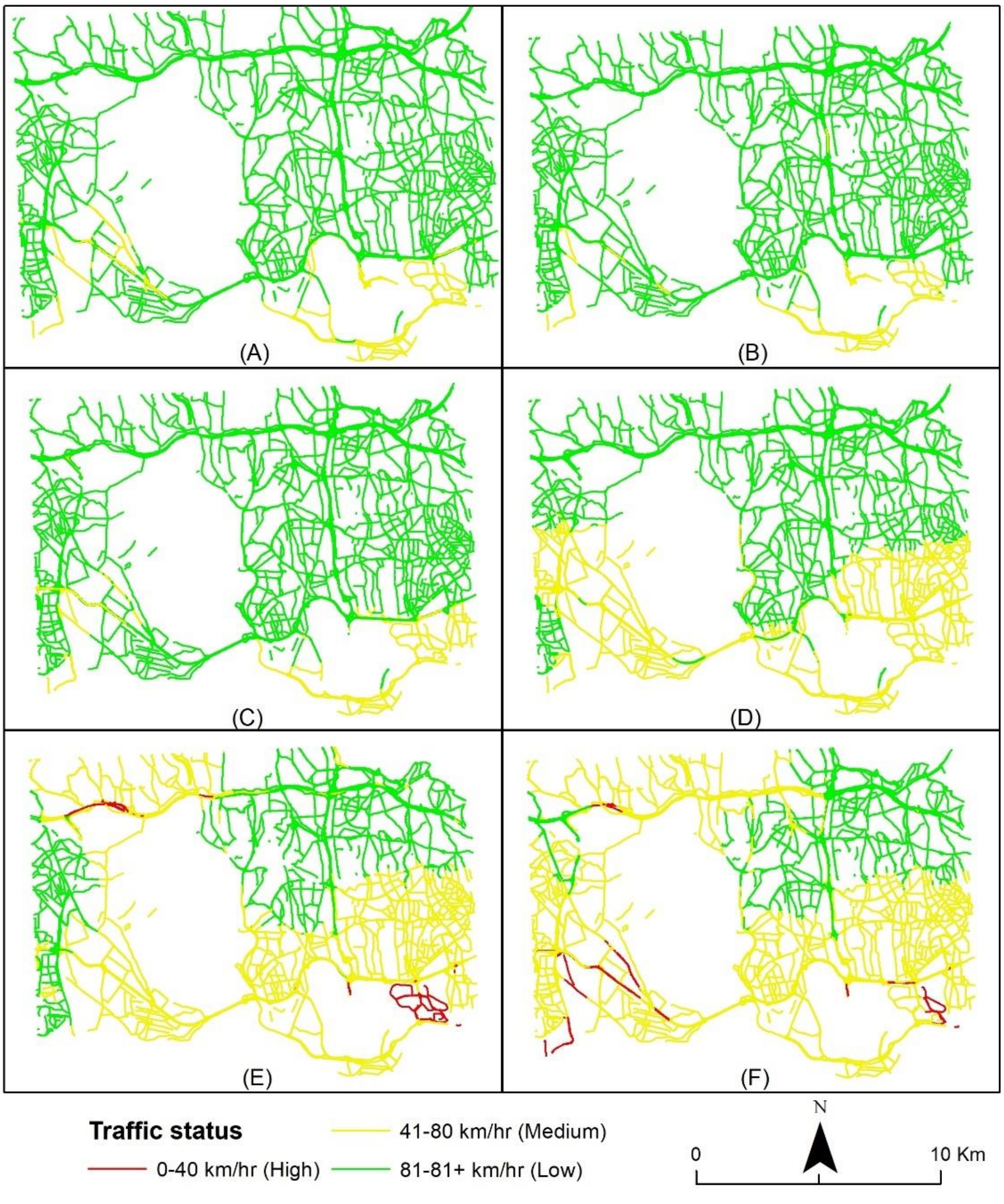


Figure 7.6 : Traffic status for the network using the proposed methodology at times of A) 07:30, B) 08:30, C) 11:30, D) 12:30, E) 17:30 and F) 18:30.

To evaluate the proposed methodology, the resulted interpolated lengths at each time period are presented (Figure 7.7). The length of interpolated links for the FHL and

SHL are illustrated separately (Figure 7.7.A & Figure 7.7.B). The average results show that the length of interpolated links jumped up till it reached a cut distance of 6km, for both levels. For cut distances of 1km-6km, the enhanced NT-IDW interpolates more links for FHL and SHL roads with averages of 2.9% and 9.87% respectively. Meanwhile, for all used cut distances, the hierarchy interpolates more links in both levels. The maximum percentage of interpolated lengths using the proposed methodology is 92.3% at a cut distance of 7km. Overall, utilizing the hierarchy in both levels at all used cut distances increased the length by 6.37, which corresponds to 56 km of road lengths.

The methodology increased the lengths of significant links using short cut distances. However, such results should have increased or at least maintained the accuracy of the interpolation. To investigate that, MAPE is calculated for as shown in Figure 7.8. The proposed methodology maintains lower MAPE errors compared to not using a hierarchy, showing the advantage of utilizing the proposed topological hierarchy in enhancing NT-IDW. Overall, as expected, the accuracy of the enhanced NT-IDW interpolation keeps dropping as cut distances increase (Figure 7.8.G). The average decrease of MAPE resulting from using the hierarchy is 13.98% within all tested variables (cut distances and time periods).

Earlier results present differences in the average MAPE at each time period. Generally, results are grouped into two groups. Generally, the first group (time periods of 07:30-11:30) show relatively low MAPE compared to the second group (time periods of 12:30- 18:30) found in (Figure 7.8.A, Figure 7.8.B and Figure 7.8.C), (Figure 7.8.D, Figure 7.8.E and Figure 7.8.F) respectively. This is an interesting result that is further analyzed for both FHL and SHL separately as shown in Figure 7.9. Similar to the previous, a pattern showing two MAPE change patterns in both groups is observed. Accordingly, the first group has low average MAPE at all scales compared to relatively high within the second group. Furthermore, the first group has less average MAPE for SHL. On the other hand, the second group has significantly low MAPE for FHL.

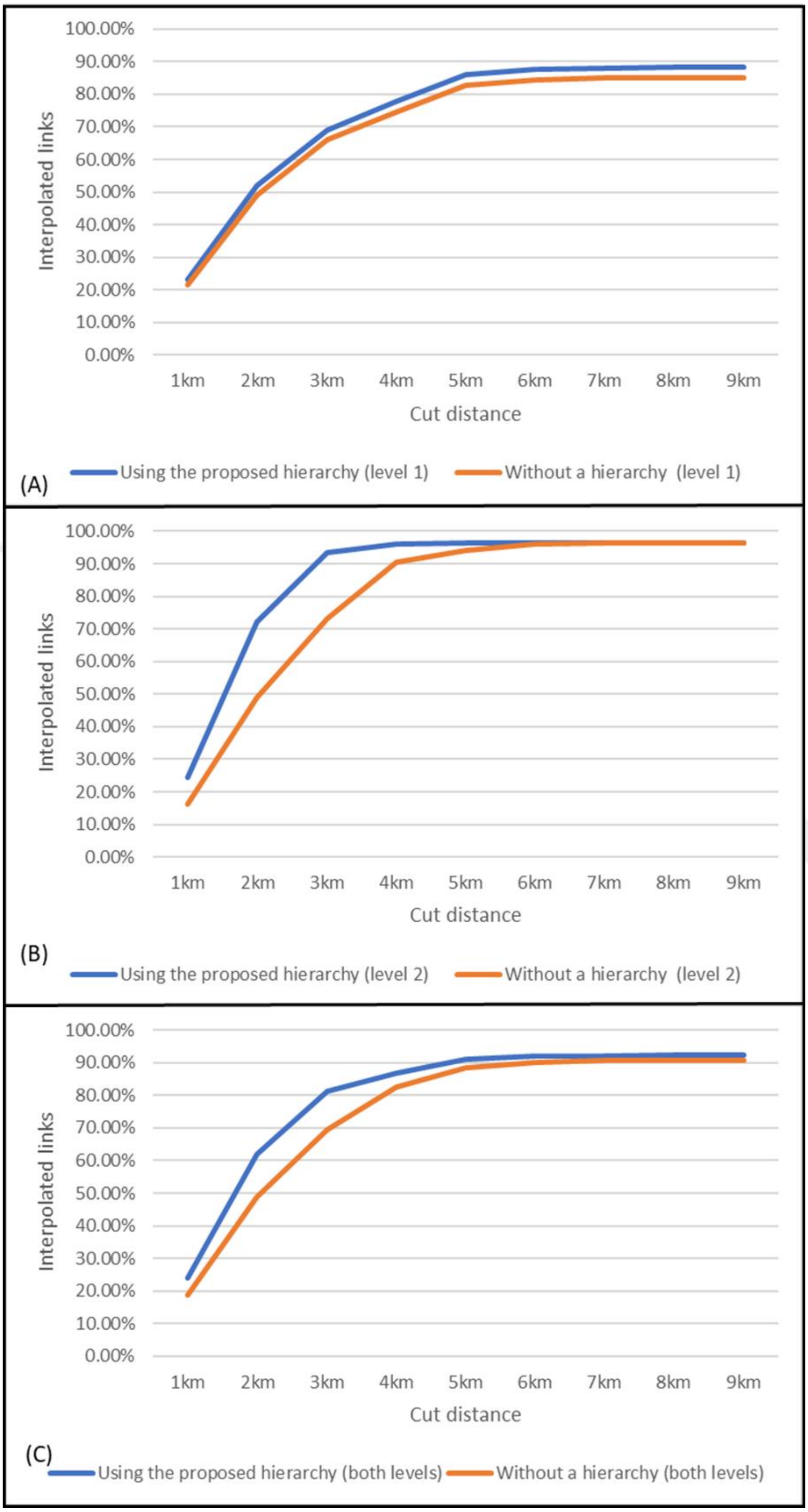


Figure 7.7 : Interpolated lengths using the enhanced NT-IDW with and without using the proposed hierarchy in A) level 1, b) level 2 and c) in both levels.

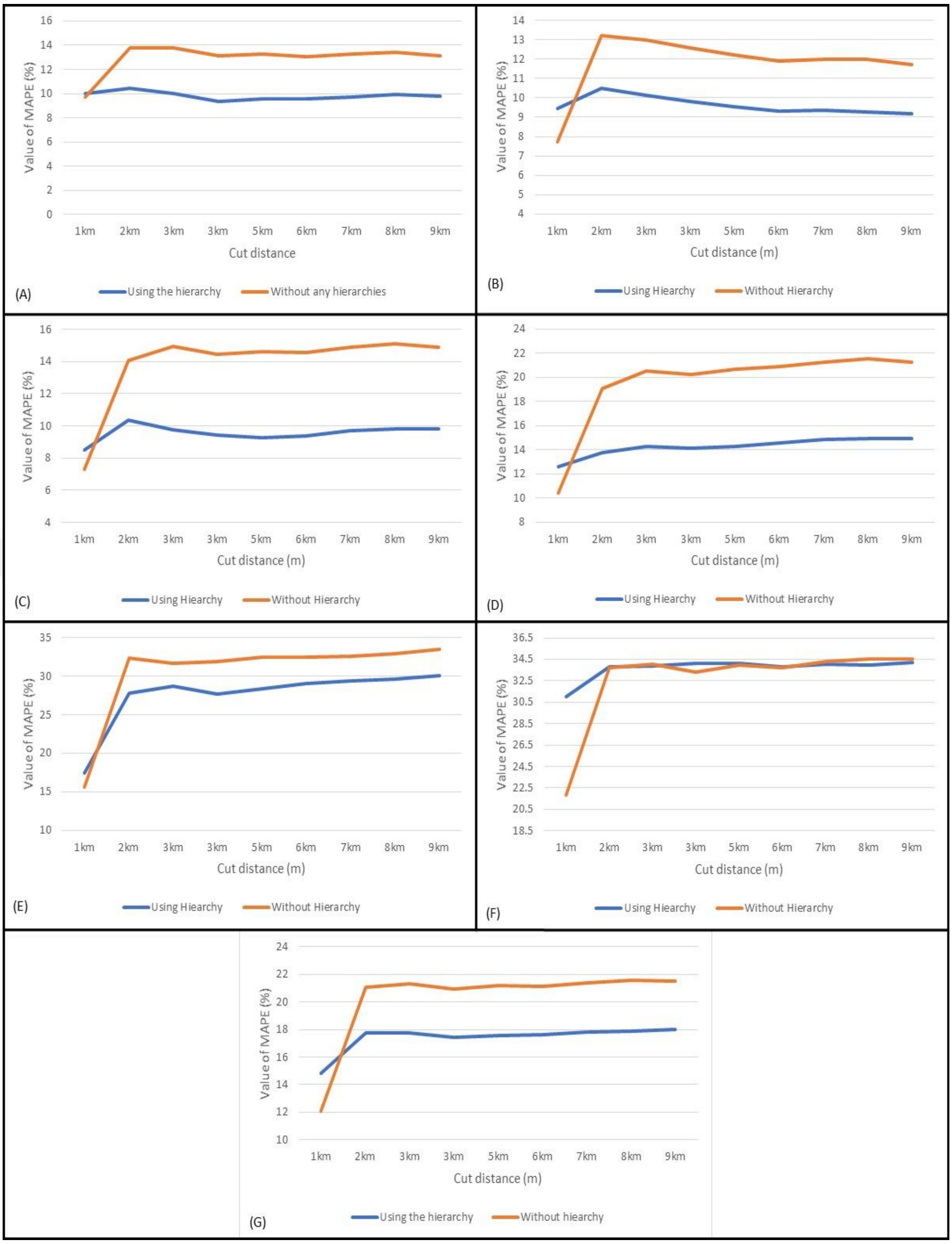


Figure 7.8 : MAPE difference using the hierarchy and without using any hierarchy at A) 07:30, B) 08:30, C) 11:30, D) 12:30, E) 17:30, F) 18:30 and G) Average of all times.

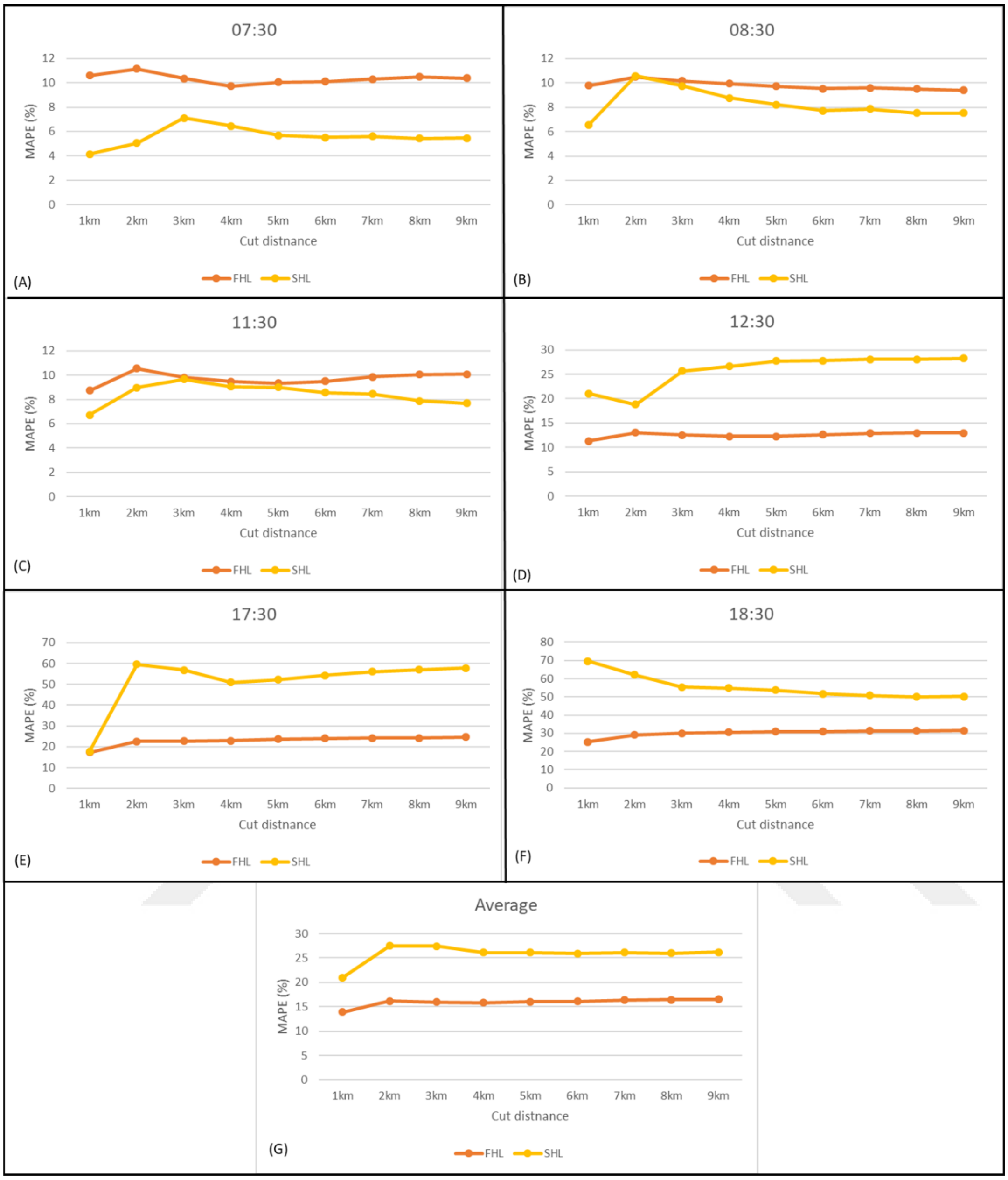


Figure 7.9 : MAPE variation using the proposed hierarchy for the two classes at time periods of A) 07:30, B) 08:30, C) 11:30, D) 12:30, E) 17:30, F) 18:30 and G) Average of all times.

The chapter seeks to interpolate maximum link interpolations with decreasing interpolation errors. For that, overlaying the average interpolated lengths (Figure 7.8.C) and the average MAPE (Figure 7.9.G) is illustrated in a chart showing their relation (Figure 7.10). The chart shows the relation between interpolated links, MAPE and used cut distances. At a cut distance of 3km, the MAPE and the percentage of interpolated lengths are found to be 14.67 % and 72.9% respectively. On the other hand, at the cut distance of 5km, the interpolation links increased by 8.1% but the

MAPE increased by about 0.6%. Results found in cut distances of 3km-6km could be considered valid because they provide relatively high accuracy with a total length of interpolated links. On the other hand, results for cut distances above 6km provide slightly more interpolated links with almost no improvement for MAPE.

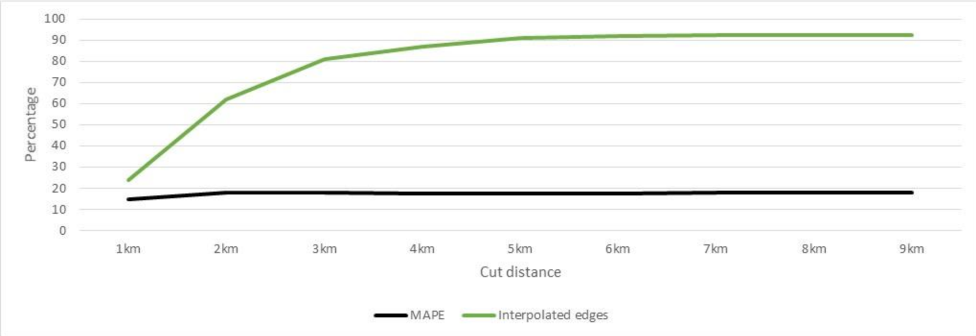


Figure 7.10 : Relation between interpolated lengths and MAPE at each cut distance.

Moreover, this research analyses the effect of δ, which is represented by the inverse power function. It is tested for values of 1-5 for cut distances of 3-6 km. Results for each value is averaged for all time periods (Figure 7.11). The graph displays the relation between resulted MAPE for each δ at cut distances of overlaid with interpolated lengths. As noticed, low MAPE is associated with low δ value which reaches its minimum at δ of 1.

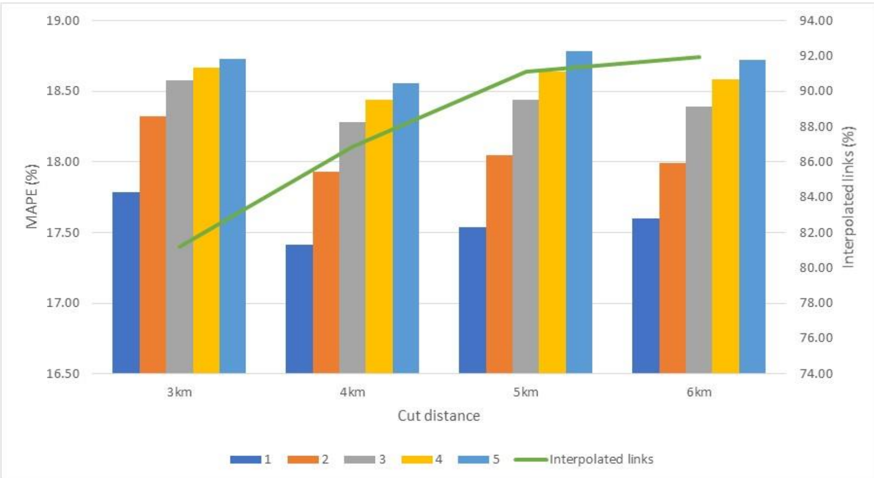


Figure 7.11 : MAPE results for each tested power coefficient at each cut distance.

7.4 Discussion of the Proposed Interpolation Method

The proposed methodology interpolated more significant links with less MAPE (Figure 7.8.c). Using RTMS data to generate new speed sources helped in increasing the total length of interpolated links by 1) interpolating more FHL due to interpolating links of confined FHL. Such links were unable to be reached within identified cut distance from the original RTMS. They were reached using the new speed sources of FHL. Mainly, they were interpolated to preserve topological connectivity between interpolated FHL and SHL. 2) interpolating further SHL links by using the newly generated speed sources, especially for cut distances between 1km and 5 km.

However, the maximum length of the interpolated links of FHL is 88.34%. The remaining links could not be interpolated even if longer cut distances were to be used because; 1) the direction of some one-way roads limited the reachability of RTMS detectors to reach corresponding points, especially at the boundaries and 2) the boundary effect resulting discontinuity of certain roads in the network due to the study area being a subset of a big connected road network, as shown in a sample using 9km as a cut distance (Figure 7.12).

Roads of SHL were interpolated more for cut distances of 1k-5km (Figure 7.7.b). Similar to FHL, raising the cut distance did not improve the lengths of interpolation because of 1) the limitation of the locations and number of interpolated when used as sources in the second step to interpolate links of the SHL, 2) the not interpolated roads found in the FHL. Beyond 5km, no/very rare new links in the FHL appeared to be used as new sources in the interpolation.

Generally, the proposed methodology reduced the MAPE by 14.46%. However, at a cut distance of 1km, the proposed methodology performed poorly but in later cut distances, MAPE was reversed (Figure 7.8). This is referenced to the average distance between RTMS detectors and the average distance for roads in the FHL to reach at least two RTMS detectors which are 1710 and 1997 m respectively. Utilizing a cut distance less than both these distances indicates a) The average distance between RTMS restricted the interpolation process from reaching enough accurate close speed sources. b) The second step in the interpolation passed the same error from FHL, sometimes errors were even multiplied, to interpolated roads.

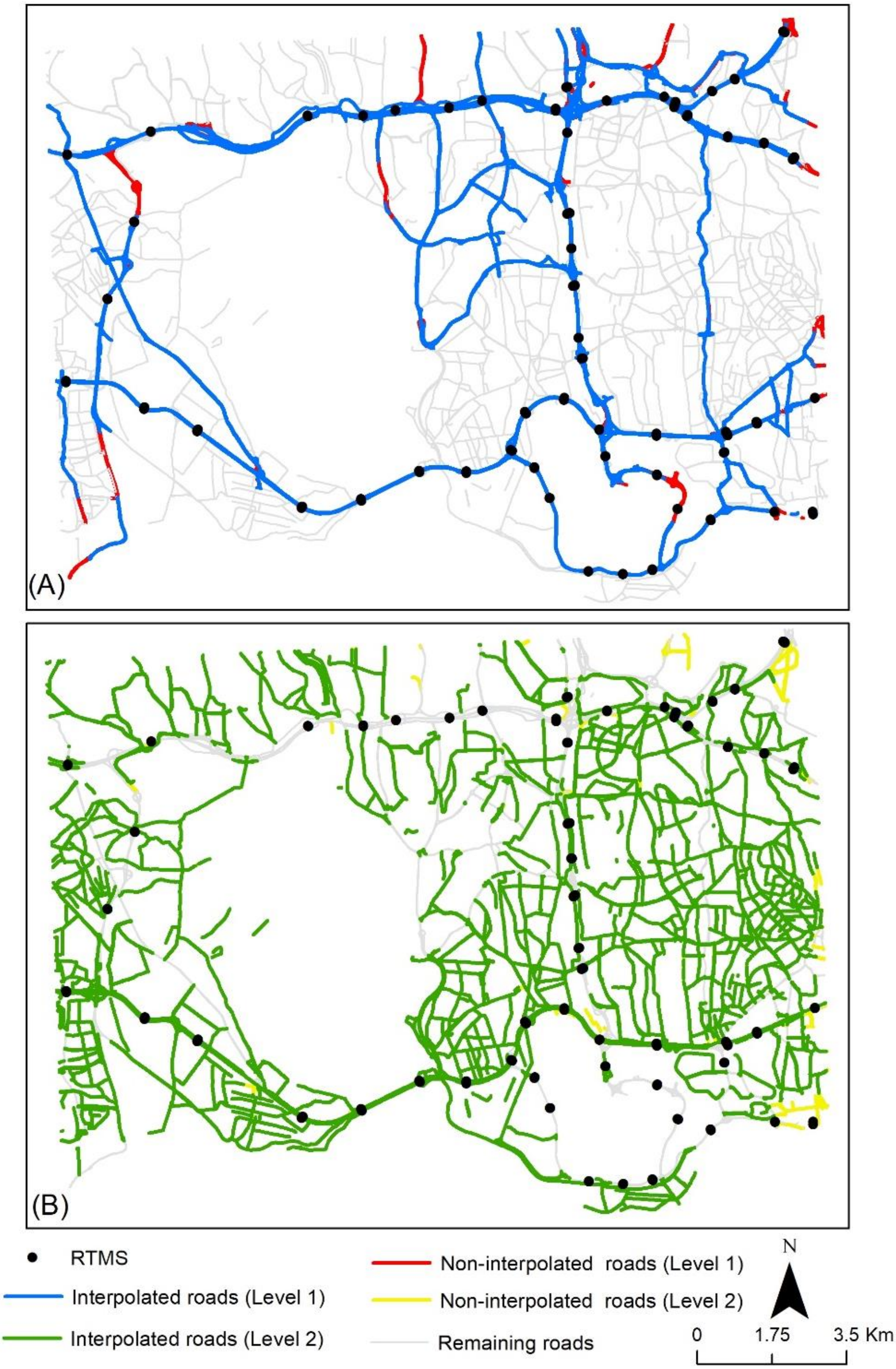


Figure 7.12 : Locations of interpolated and non-interpolated links using the proposed topological hierarchy.

Figure 7.13 shows the effect of using a 1km cut distance at the time period of 18:30. Figure 7.13.A shows the results of not implementing a hierarchy, while Figure 7.13.B shows the results of the implemented proposed hierarchy. The boxed areas found in Figure 7.13.a & Figure 7.13.b show the high MAPE roads that are colored in red. Figure 7.13.c shows the results of not implementing the hierarchy while Figure 7.13. D shows the results of implementing the proposed hierarchy in the interpolation process. As it could be clearly noticed, higher MAPE results are found in Figure 7.13.d that utilizes the hierarchy. The reason is that the value of one detector was passed to more roads, thus more links with high MAPE errors appeared while using implementing the proposed methodology. Instead of two links with high MAPE without using the hierarchy, the number increased to four links.

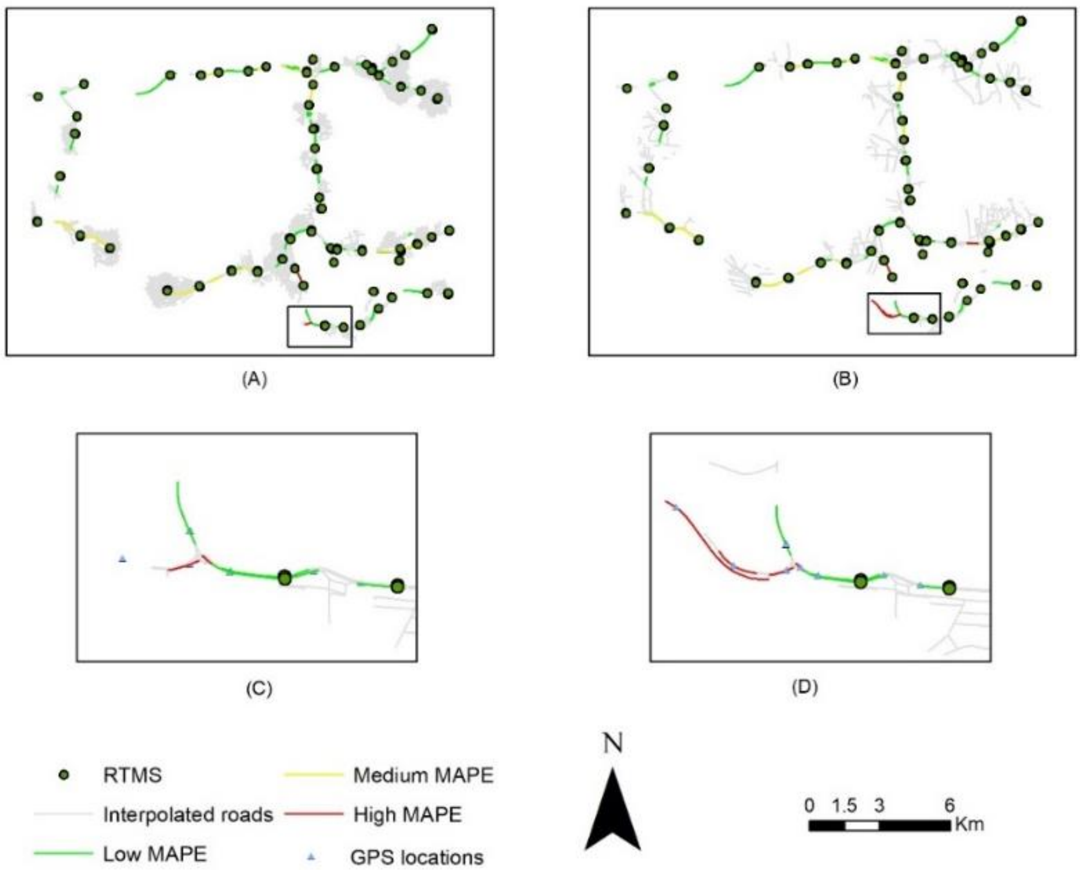


Figure 7.13 : Role of the average distance between RTMS detectors on increasing the MAPE.

Using the proposed methodology at cut distances of 2-9km, the MAPE reduced significantly. However, an average of 17.4% MAPE is still found because; 1) Inaccurate RTMS or GPS readings of some locations at such times. 2) The used empirical topological hierarchy. The hierarchy was introduced according to OSM's definition of significant roads. Moreover, a number of roads are not connected to roads at the same level, especially in FHL. 3) The variance in speed data sources (RTMS and GPS data). While GPS data were used to validate the interpolation, RTMS detectors were used to interpolate the network. Two different data sources are utilized in the application. Errors were likely in ideal cases due to the before mentioned 6.8% MAPE difference for points in the same locations and 0.80 positive correlation between the two data sources. 4) Locations of roads and RTMS at the boundaries also affected the errors significantly. Links found at the boundary reach the least number of RTMS detectors, thus reducing their accuracy significantly (Figure 7.14).

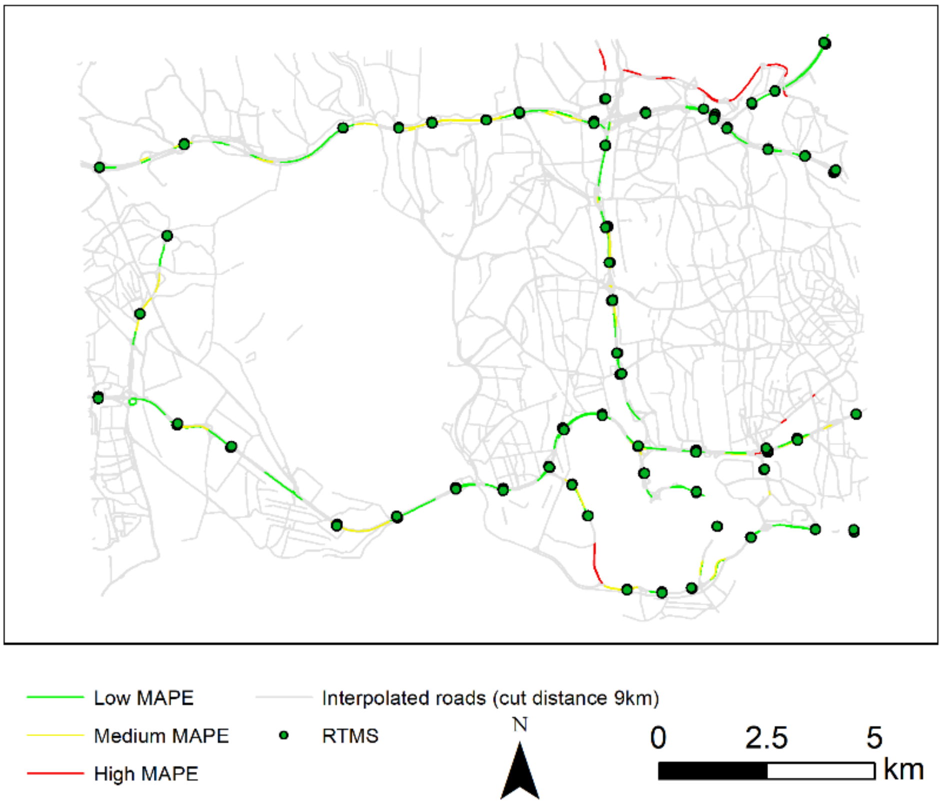


Figure 7.14 : locations of evaluated roads at 08:30 (02/01/2018) using 9km as a cut distance.

A distinct MAPE pattern was observed for each topological hierarchy level. Using the proposed methodology, MAPE of the first group of the used time periods (07:30 - 11:30 am) is minimized compared to the second group (Figure 7.9). Such results are also correlated with the change in traffic/average speeds of the network (Figure 7.15). At the first group, speeds for FHL and SHL are higher and the difference between them is higher. However, the second group shows less speed averages and less difference between the average speed of both classes (FHL and SHL). Apparently, the dynamic of the traffic within the study area is distinct for each time group. That implies that the proposed methodology provides is more accurate for the first-time group (time period until 11:30 am.). This confirms the impact of utilizing topological hierarchies in the proposed methodology. That is referenced to the topological connectivity and continuous use of roads belonging to the same topological class increase the average speed similarity between user vehicles.

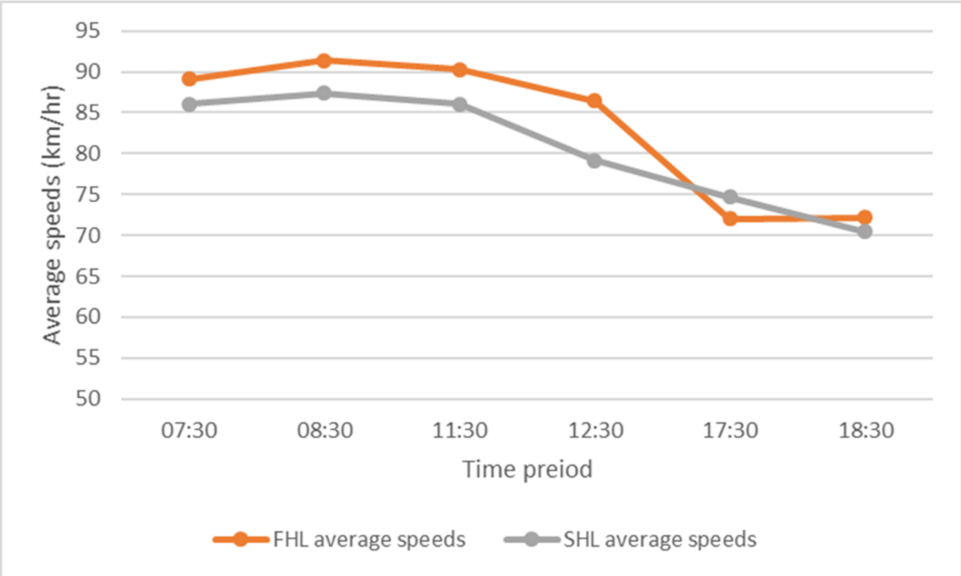


Figure 7.15 : Average speeds for both FHL and SHL at each time period.

Ultimately, a cut distance of 5km with δ of 1 is recommended due to its interpolation of 91.1% of the important link with MAPE of 17.53% which are considered acceptable and balanced results.

8. WORKPLACE ACCESSIBILITY CHANGE IN BOTH DIRECTIONS USING DYNAMIC TRAVEL TIME AS IMPEDANCE

Evaluating accessibility to workplaces, in particular, has always been a research focus. Workplaces are, indeed, the most significant nonhome destinations (Levinson, 2013). The emphasis on that is understandable given its link to other important aspects of urban structure, such as choice of residential location, the spatial mismatch of jobs and housing, modal mismatch, social network mismatch and employability (Preston & Raje, 2007; Cheng & Bertolini, 2013). Although there are many studies looking at location-based accessibility from Home To Workplaces (HTW) by car as a transportation mode (Geurs & Wee, 2004; Bocarejo S. & Oviedo H., 2012; Levinson, 2013; Moya-Gómez & Geurs, 2018; Moya-Gómez, et al., 2018; Shoman & Demirel, 2018), there is really little to no research cases considering the ride back journeys of Workplaces to Homes (WTH). That is, previous study cases consider evaluating accessibility during one time period of the day, neglecting the various changed conditions when the accessibility during another part of the day is considered. This is largely referenced to two main reasons; 1) most studies generate static/fixed travel time from using methods of; max identified speeds, peak traffic speeds, free-flow speeds or rough average speed estimation of the network (Handy & Niemeier, 1997; Hou, et al., 2011; Cheng, et al., 2016). Such methods lack the ability to provide enough details about the fluctuating traffic within the day. They fail to capture the varying mobility status of the network such as road capacity, traffic volume and speeds of lanes. Moreover, they struggle to illustrate the non-spatial elements of the transport sub-system that extremely influence the job accessibility calculations, such as traffic management and planning policies (Cheng & Bertolini, 2013). 2) Most studies consider a weighting factor to incorporate the effect of variations in the attractiveness of destinations (e.g. population or employment) (Moya-Gómez, et al., 2018). Yet, the journey distribution varies temporally depending on the type of activities that predominate in each time period (e.g. to work, to shopping journeys). Additionally, the dynamic of the urban movement within the city proves that residences travel to diverse locations within the day before completing a circuit back to their home locations (Hanson, 1980). Thus, the weighting factor that indicates the significance of destinations for each trip should be assigned accordingly. Providing a methodology to integrate the varying network statuses with the significance of destinations for each trip type solves workplace accessibility.

Considering the aforementioned motivations, the chapter aims are twofold: 1) to provide empirical evidence of workplace accessibility analysis being temporally influenced within the day temporal resolution. For that, the research evaluates the change in accessibility between 2010-2018 at two time periods representing two trip types (i.e. HTW and WTH). 2) to evaluate the dominant change influencing locations based on the considered time period of the day. This helps in answering an important question of “Do both trip types get influenced by the same factors?”.

The change in workplace accessibility components at each considered time period of the day is considered. For that, two location-based accessibility indices of Potential Accessibility (PA) and Average Travel Time (ATT) are considered introduced earlier in Chapter 2 Equations 2.2 and 2.4, respectively. In both indices, the varying travel time is dynamically captured at each time period (trip type). The travel time represents a key element that impacts two main related accessibility components (i.e. transport and temporal). Generating accurate travel time to targeted temporal accessibility calculations reflects the altered traffic condition and mobility status of the network. Lately, due to the availability of real-time driving speeds, travel time is represented dynamically at the required temporal resolution (Geurs & Östh, 2016). Speed information for the network is continuously stored and later used to calculate the accessibility continuously and dynamically (Condeço-Melhorado, et al., 2016; Moya-Gómez & Geurs, 2018). Following that, real-time average speeds from RTMS speed detectors, introduced in the earlier, are collected chapter. Moreover, PA considers the significance of each travel’s destination during its calculation. For that, the significance of each travel’s destination based on the considered trip type is identified. A methodology to assess workplaces is developed to assign weights of HTW using an attraction vector referring to the number of trips attracted to the corresponding destination. On the other hand, the population attribute is used to assign weights for WTH trips, after fitting/projecting the data to the required resolution and for each considered year. Spatial and temporal analysis is implemented to evaluate the resulted change in accessibility between the corresponding years. The correlation matrix is calculated to evaluate their spatial similarity at each time period and for each index. Later on, to disentangle the effect of changed conditions, the method presented by (Geurs & Eck, 2003) is utilized within this study. Dominant changes that spatially predominantly influenced the changes in accessibility are referenced to each considered case.

8.1 Framework to Calculate the Workplace Accessibility using Dynamic Travel Time

The chapter implements its methodology in the framework presented in the chart below (Figure 8.1). First, the data are collected and later processed to be in the required form. Subsequently, the processed data are utilized to calculate each identified accessibility index for each considered year. The change is calculated, and the results are presented. Later on, the findings are analyzed and commented on.

8.1.1 Collecting data

The study area for this application is the same as shown earlier in Figure 7.4. To identify the LCLU, Landsat 7 ETM and Landsat 8 OLI/TIRS for the study area are captured for 2010 and 2018 respectively (Figure 8.2.a and Figure 8.2.b). The road network illustrated earlier in Figure 7.4 is also used as the 2018's road network for this part. To weight the destinations of each trip type, two weight factors are generated being, (1) the number of trips attracted to the corresponding area based on a zone-based survey implemented in 2011 (IBB, 2011) and (2) the population data from the Turkish National Statistics Institute (Institute, 2013). Finally, average speeds are obtained from 100 RTMS speed detectors for times of 07:30, 08:00, 08:30, 17:30, 18:00 and 18:30 within the dates of (11-15/01/2010 and 08-12/01/2018) using the methodology proposed in the previous chapter. The selection of the year 2010 is due to the limitation of available data sources. No earlier RTMS speed data for the study area is found for earlier dates, thus the change in accessibility is evaluated between 2010-2018.

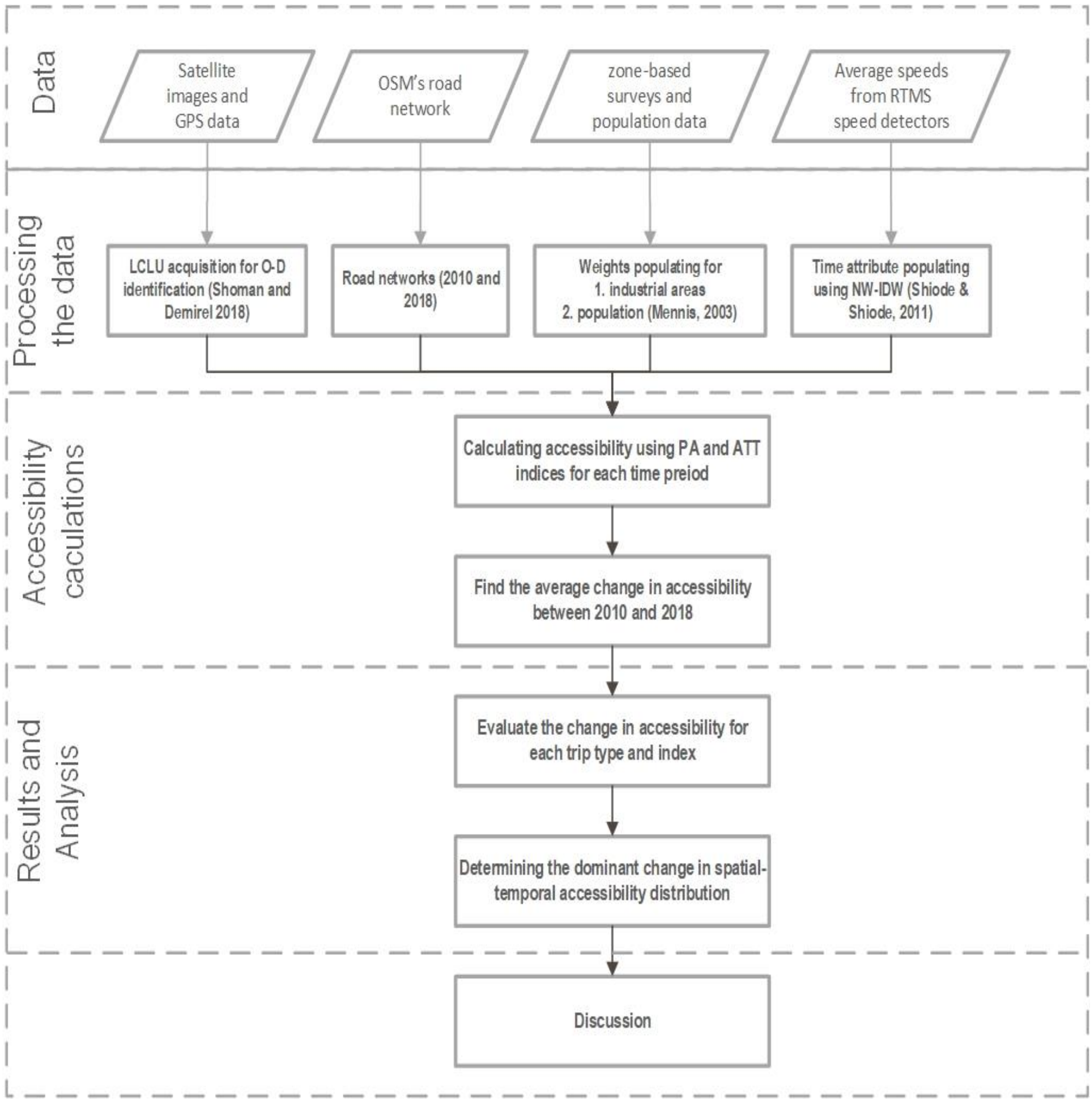


Figure 8.1 : The utilized framework to calculate workplace accessibility.

8.1.2 Processing the data

8.1.2.1 Land cover land use

Land uses for the corresponding area is captured via classification multispectral images following the method presented in (Shoman, et al., 2019c). Accordingly, Landsat 7 ETM and Landsat 8 OLI/TIRS for the study area are captured for 2010 and 2018 respectively (Figure 8.2.a and Figure 8.2b). The third level of CORINE's LCLU classes was used to provide detailed classes valid for the study purposes. The accuracy of the classification process was evaluated using 100 stratified random points that were distributed according to class coverage and importance compared by their ground truth values derived from closer dated ortho-photos to form the error matrix. The resulted accuracy assessment indicated that all images were classified with an acceptable accuracy of over 93%. The resulted LCLU of the study area for each corresponding year is shown in Figure 8.2.

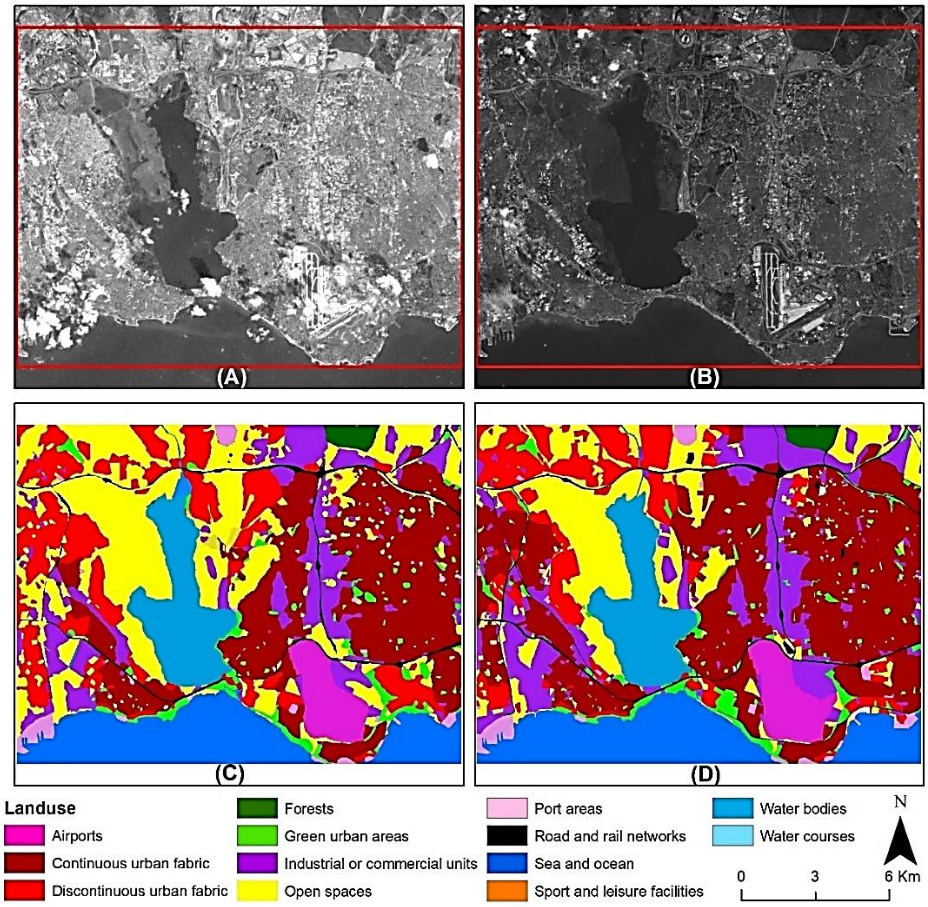


Figure 8.2 : The satellite imageries of the study area for A) 2010 and B) 2018 and their LCLU maps of C) 2010 and D) 2018.

When the classification results are examined, some of the CORINE LCLU classes available in the study area could be identified up to the 3rd level. The classification revealed an areal change in these classes from 2010 to 2018. The change is found to be significant as shown in (Table 8.1). Noticeably, some classes have significant areal increase while others have a large areal drop. The classes that have the highest increase are sorted from most areal percentage increase to highest drop as seen in Table 8.2.

Table 8.1 : The change in class areas between 2010 and 2018.

Class Name	2010 Area (km^2)	2018 Area (km^2)	Change (Km^2)
Continuous urban fabric	59.66	82.86	23.2
Discontinuous urban fabric	35.61	27.18	-8.43
Industrial or commercial units	26.41	33.53	7.12
Road and rail networks	3.87	3.95	0.08
Port areas	1.89	2.15	0.26
Airports	7.7	7.99	0.29
Construction sites	0	0.37	0.37
Green urban areas	6.57	7.06	0.49
Sport and leisure facilities	1.25	1.61	0.36
Forests	1.97	1.99	0.02
Open spaces	59.6	36.79	-22.81
Water courses	0.71	0.2	-0.51
Water bodies	16.58	16.48	-0.1
Sea and ocean	29.42	29.14	-0.28
Total	251.3	251.3	-

As urbanization continuous the high areal increase in the *Continuous urban fabric* is completely expected to occur. This increase is accompanied by an increase in several facilities found in several classes (i.e. *Sport and leisure facilities, Industrial or commercial units, Port areas, Green urban areas, Airports, Road and rail networks*) (Table 8.2). This increase occurred at the expense of several classes (i.e. *Water bodies, Sea and ocean, Discontinuous urban fabric, Open spaces, Water courses*).

Table 8.2 : The sorted percentage change in classified classes.

Class	Change
Continuous urban fabric	38.89%
Sport and leisure facilities	28.80%
Industrial or commercial units	26.96%
Port areas	13.76%
Green urban areas	7.46%
Airports	3.77%
Road and rail networks	2.07%
Forests	1.02%
Water bodies	-0.60%
Sea and ocean	-0.95%
Discontinuous urban fabric	-23.67%
Open spaces	-38.27%
Water courses	-71.83%

Both the Continuous urban fabric and Discontinuous urban fabric classes found in the classification results are used to represent home locations. Hence, both classes are merged into one class representing the class of the homes. On the other hand, the workplace locations are represented by the industrial or commercial units' class. The remaining classes are out of scope for this study.

The LCLU data for both years (Figure 8.2.C and Figure 8.2.D) is converted to 100x100 m^2 resolution grids (Figure 5.3). Each cell represents a class attribute. However, some cells contain several attributes belonging to different classes. The class with the major areal attribute is chosen to represent each polygon within the grid, as explained in an earlier chapter of this thesis (Chapter 4).

8.1.2.2 Road network

The road network illustrated earlier in Figure 7.4 is used as the 2018 road for the study area. The obtained network of 2018 was used to generate 2010's network by eliminating the newly constructed roads within these eight years period as earlier implemented in section (5.2) and (Shoman & Demirel, 2018). Similarly, high-resolution orthophotos, google maps history dataset and Istanbul Metropolitan Municipality (IMM)'s network of 2011 was used to identify newly constructed road links between 2010 and 2018. Figure 8.3 shows the road network of 2010 and newly constructed road links between 2010 and 2018.

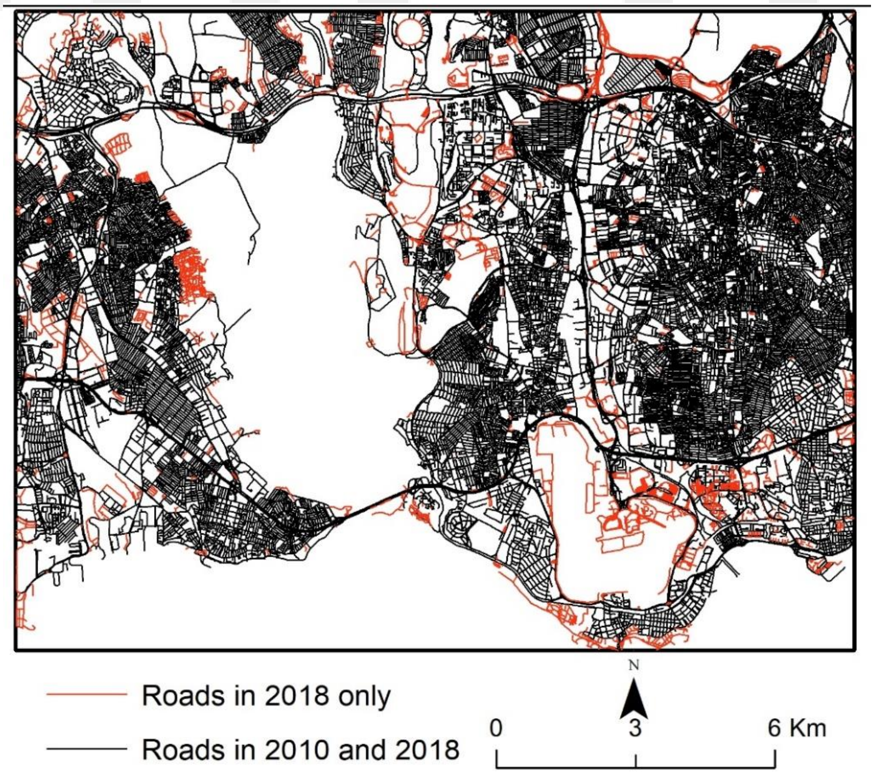


Figure 8.3 : The growth of the road network between the years 2010 and 2018.

8.1.2.3 Weighting industrial areas

For HTW trips, weighting industrial areas has been a tricky part due to a lack of updated surveys and information for the study area. However, the researcher managed to derive a mechanism to weight industrial areas in both years based on zone-based surveys implemented in 2011 for the whole of Istanbul (IBB, 2011). An attraction vector, referring to the number of trips attracted to the corresponding area, is calculated using the surveys. From that, Home to Work Attraction Vector (HTWAV) to each transportation zone is calculated using the following equation:

$$HTWAV = \text{total employment in the study area} \times \frac{area\ of\ trasnporation\ zone}{area\ of\ the\ whole\ study\ area} \tag{8.1}$$

The resulted HTWAV is assumed to be valid for both years (2010-2018). Zones are classified into five classes based on the HTWAV values which shows the significance of each zone during HTW trips (Figure 8.4). A value of five represents zones with high attraction.

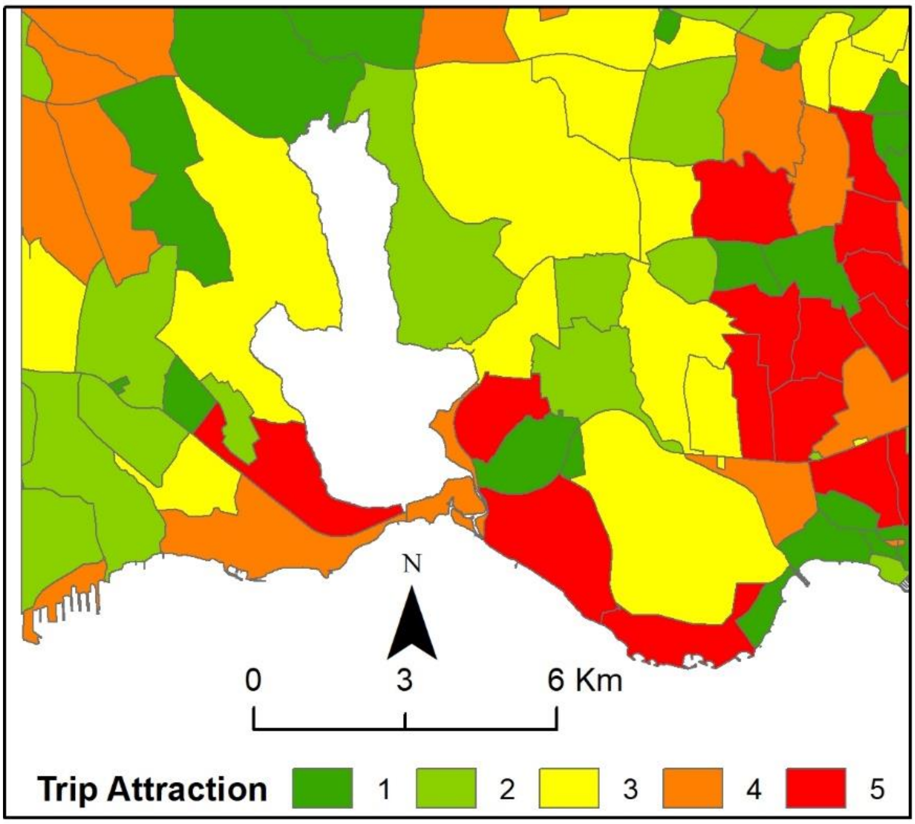


Figure 8.4 : HTWAV Transportation zone classification. 1 represents zones with the lowest HTWAV while 5 represents the highest HTWAV.

8.1.2.4 Weighting home locations

Within WTHs trips, the population of origins is used to weight the importance of the origin-destination path and their frequency use in the network. For that, this chapter uses the population data from the Turkish National Statistics Institute (Institute, 2013). However, the acquired data represent a $1km^2$ grid shapefile of the study area in 2013 as shown in Figure 8.5. The acquired data represent neither the aimed years (2010 and 2018) nor the required scale of ($100\times100\ m^2$).

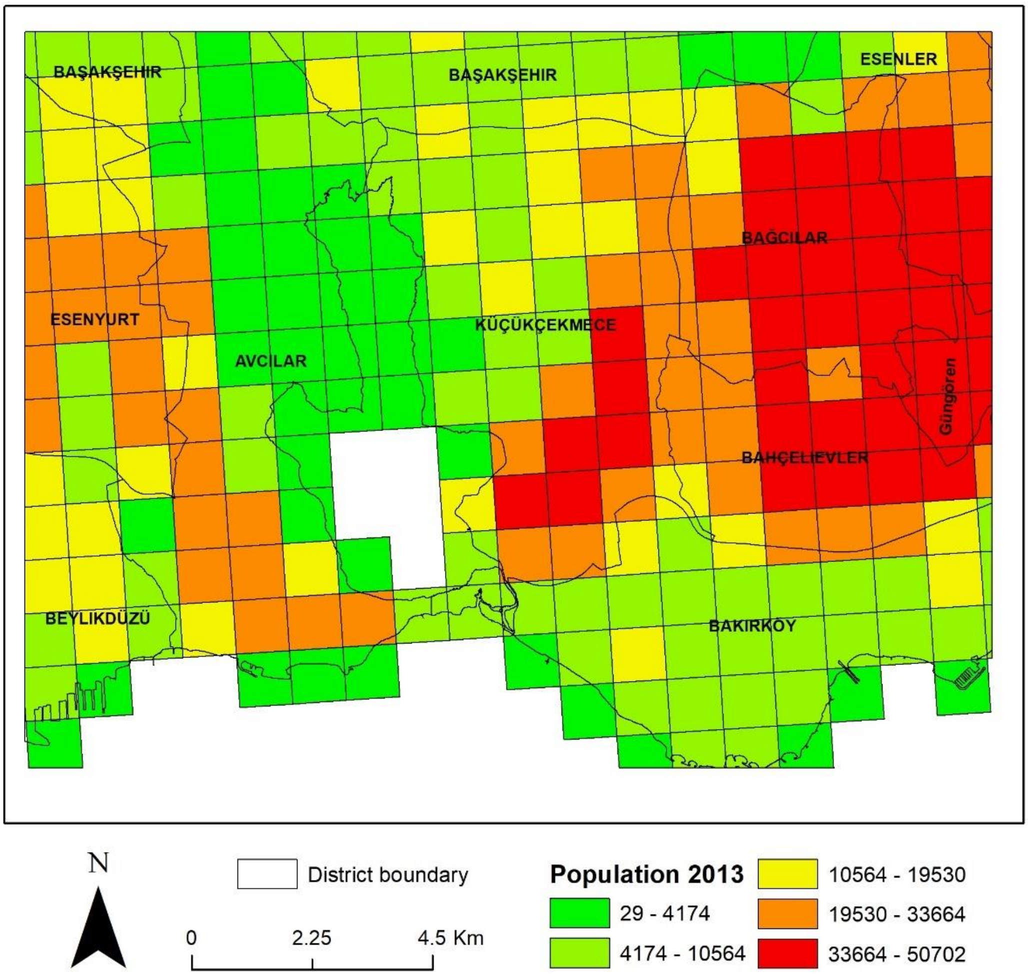


Figure 8.5 : Grid cells for the 2013 population of the corresponding study area.

Projecting the Population Data for Corresponding Years

After consistency check with the obtained population census, each district's population growth data was used to project the 2010 and 2018 population in the same resolution (Brinkhoff, 2019). The corresponding population grids for each year are recalculated using the found growth rate. Figure 8.6 shows grid thematic maps for both years after projecting them in each corresponding year. Some districts had a positive increase in their population while others had the opposite (Table 8.3). Overall, the total population of the corresponding study area grew from 3.5 million to 4.3 million in 8 years, a growing rate of 22.86%. This indicates that the corresponding area has a population density of 19,409.72 capita per km^2.

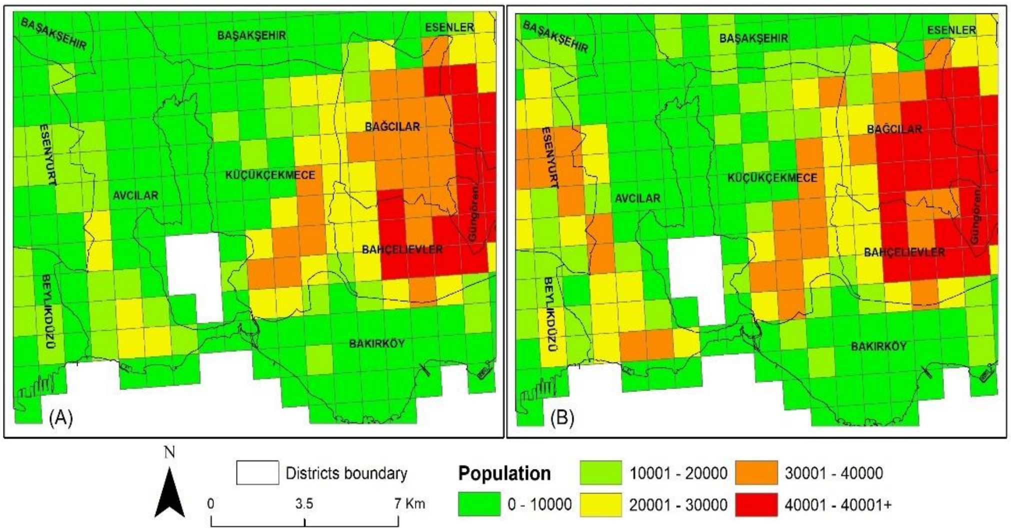


Figure 8.6 : Projected population grids for A) 2010 and B) 2018.

Table 8.3 : Population change in each district between 2010 and 2018.

Districts	Total Population (2010)	Total Population (2018)	Growth
Avcılar	315437.8	405658.9	28.60%
Bagcilar	718844.4	743988.6	3.50%
Bahçelievler	618673.5	643220.9	3.97%
Bakırköy	228907.5	233153.4	1.85%
Başakşehir	132074.5	297486.1	125.24%
Beylikdüzü	126321.1	220006.3	74.16%
Esenler	366351.6	362046.6	-1.18%
Esenyurt	164939	493098.7	198.96%
Güngören	251465.1	239658	-4.70%
Küçükçekmece	610795	703916.9	15.25%
Total	3535820	4344253	22.86%

Generating population data for higher resolution grids

The generated population maps for both years (Figure 8.6) represent the aggregated demographic dataset of $1km^2$ surface areas. The corresponding datasets are found in low resolution compared to the research aim of high-resolution analysis. The problem of creating a population surface/grids from larger areal unit dataset grids is essentially one of areal interpolation, the transformation of geographic data from one set of boundaries to another (Mennis, 2003). Areal interpolation is typically used to compare two or more spatial datasets that are stored in incompatible areal units, such as congressional districts and census tracts. In a sense, the generation of a raster population surface is a special case of areal interpolation, because the desired (target) areal unit (a raster grid cell) is intended to approximate a continuous surface; hence, it is necessarily much smaller than the size of the original areal unit of data aggregation. A prominent method in areal interpolation is dasymetric mapping, defined here generally like the use of an ancillary data set to disaggregate coarse resolution population data to a finer resolution (Eicher & Brewer, 2001).

This thesis exploits the methodology of (Mennis, 2003) for generating surface-based representations of the population data using a dasymetric mapping technique that incorporates the previously acquired land-use data for both years (2010 and 2018).

The population of each block group is distributed to each grid cell in the population surface based on two factors: (1) the relative difference in population densities among the found land use classes; and (2) the percentage of the total area of each block group occupied by each of the land use classes. Factor one concerns the fact that a grid cell with a high urbanization class has a higher population density than a grid cell with a low or nonurban urbanization class (as derived from empirical measurement, described later). Thus, the high-urbanization grid cell should receive a greater share of the total population assigned to a block group than a low or nonurban urbanization grid cell in the same block group.

The land use data for both years (Figure 8.2.C and Figure 8.2.D) were initially converted to a 100 ×100 m^2 resolution grids. This grid cell resolution serves as the resolution for the final raster population surface. The class with the major areal attribute is chosen to represent each polygon within the grid, as explained earlier in (Shoman, et al., 2017a).

In order to determine the relative difference in population density among the found land use classes, population density values for each class were sampled. The sampling process selected all block groups that are entirely contained within each class, found their total population and area, and calculated their aggregated population density.

Each urbanization class within each county was assigned a ‘‘population density fraction’’ number that indicates, based on the relative differences in population density, the percentage of a block group's total population that should be assigned to a particular urbanization class within the block group. The population density fraction is calculated by dividing a class's population density by the sum of the population density values for all other urbanization classes, as follows:

$$d_u = \sum_{n=i}^{n=j} \frac{p_u}{(p_i + \cdots + p_j)} \tag{8.2}$$

$d_{uc}$is the *population density fraction* of a land use class u, p_i is the population density (persons/10,000 m^2) of a land use class *u* in the block divided by all other population densities (persons/10,000 m^2) of all found land use class in the block $(p_i + \cdots + p_j)$ including p_u.

Till now, this approach assumes that the block group is evenly spatially partitioned among the land use classes. This occurrence, of course, is an extremely rare event. Factor two thus addresses the difference in the block group area occupied by each land use class. In order to accurately assign a portion of a given block group's total population to a class, the population density fraction must be adjusted by the percentage of that block group's total area that that land use class occupies. In other words, the county-level urbanization class's population density fraction must be adjusted for each individual block group according to the difference in the area occupied by each class within that block group. This adjustment is made by calculating the ''*area ratio*'' for each urbanization class for each block group. This factor represents the ratio of the percentage of area that a class actually occupies within a block group, which is expressed as:

$$a_u = \frac{n_u}{n_{total}} \tag{8.3}$$

where a_u is the *area ratio* of urbanization class u in a block group, n_u is the area of all grid cells of the class u in the block group, and n_{total} is the total area of all grid cells in that block group.

The *population density fraction* and area ratio may be integrated into one term, referred to as the ''*total fraction*'' which represents the fraction of a given block group's total population that should be assigned to a given a class within that block group, accounting for variation in both population density and area of the different land use classes. The total fraction may be calculated by multiplying the *population density* *fraction* and *area ratio* of a given urbanization class in a given block group and dividing that result by the result of that same expression for land use classes in that block group. This calculation may be expressed as:

$$f_u = \sum_{n=i}^{n=j} \frac{d_u \times a_u}{(d_i \times a_i) \ldots + (d_j \times a_j)} \quad (8.4)$$

where f_u is the *total fraction* of class u in block group, d_u is the *population density fraction* of class u, $a_u$is the *area ratio* of class u in the block group, $d_n \times a_n$ represent *population density fraction* and *area ratio* of all classes found in the block group.

Once the *total fraction* for each class for each block group is determined, a portion of a block group's total population may be assigned to each class's grid cells within that block group. To assign a population value to a given grid cell with that class, one merely divides the population assigned to that urbanization class evenly among the grid cells in that block group that have that class. The calculation to assign a population value to a given grid cell within a given block group is expressed as:

$$pop_{ub} = \frac{(f_{ub} \times pop_p)}{area_{ub}} \quad (8.5)$$

where pop_u is the population assigned to one grid cell of land use class *u* in block group b and, f_{ub} is the *total fraction* for class u in block group b, pop_p is the total population of block group b, and $area_{ub}$ is the area of grid cells of class u in block group b. The results for implementing the aforementioned method is shown in Figure 8.7. The changes in this resolution are also shown in Figure 8.8.

8.1.2.5 Dynamic travel time populating

The time attribute is an important element to calculate accessibility realistically in urban areas. Using such attribute as impedance measure helps in finding the change in accessibility when time changes within a day, week …etc. In this chapter, the time attribute is populated from the average speed of road segments in the study area, as explained in the earlier chapter. Temporal dynamics are partially introduced by using dynamic impedances, that is, impedance depends on when links are used on every route and its temporal variation in impedance across the day. Since travel speeds continuously change due to congestion, each origin-destination relationship is calculated several times over a day to approximate the dynamic variation. These impedances are calculated as travel times by the hierarchical first-in-first-out (FIFO) dynamic shortest-path algorithm in ArcGIS: waiting is not an option to arrive earlier at any destination (Dean, 2004). The method introduced in the previous chapter of (Enhanced Spatial Speed Interpolation for Road Networks Using Topological Hierarchies) is used to calculate the average speed for each time period. Dates of (11-15/01/2010 and 08-12/01/2018) are selected to represent both years respectively. Average speeds for times of 07:30, 08:00, 08:30, 17:30, 18:00 and 18:30 are calculated for each selected date as shown in Figure 8.9.

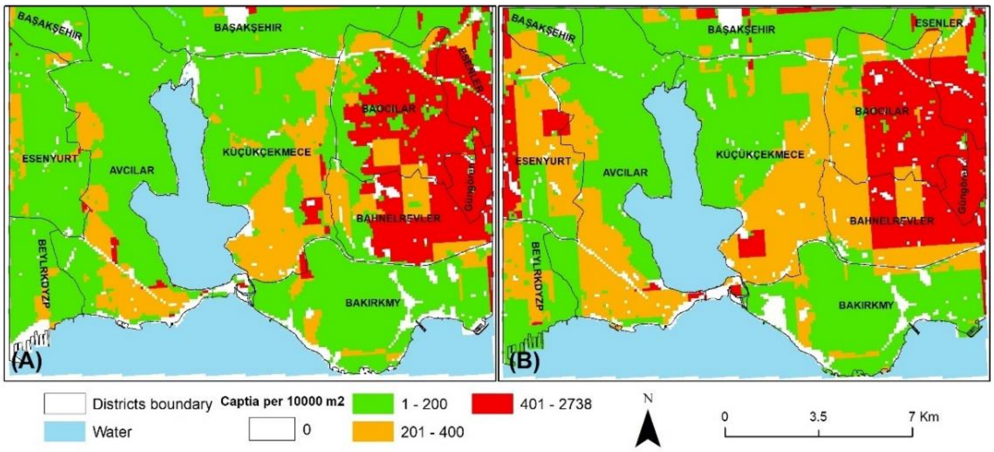


Figure 8.7 : Population grids of 100 × 100 m^2 for A) 2010 and B) 2018.

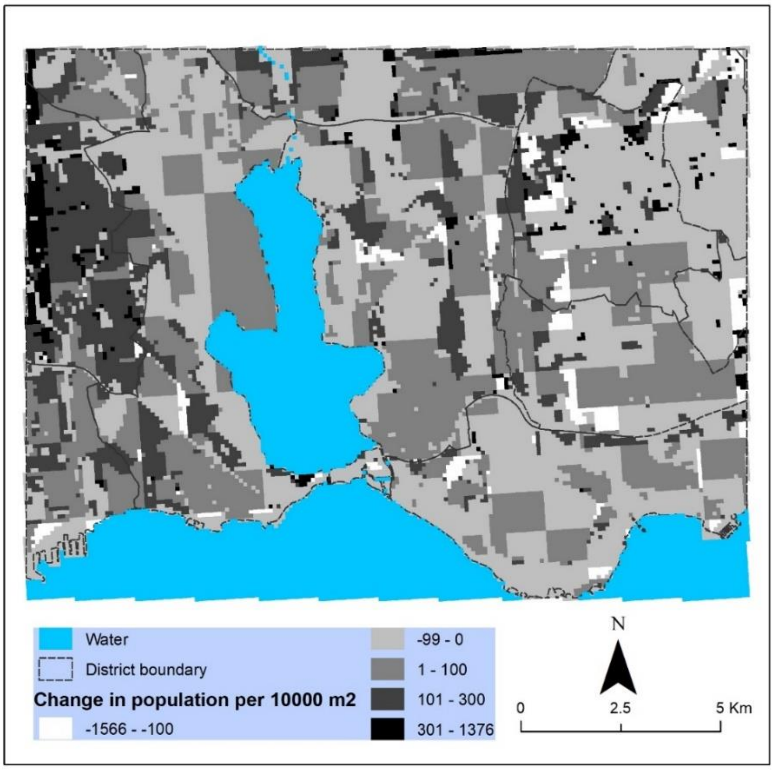


Figure 8.8 : Change in population between 2010 and 2018 per 10000 m^2.

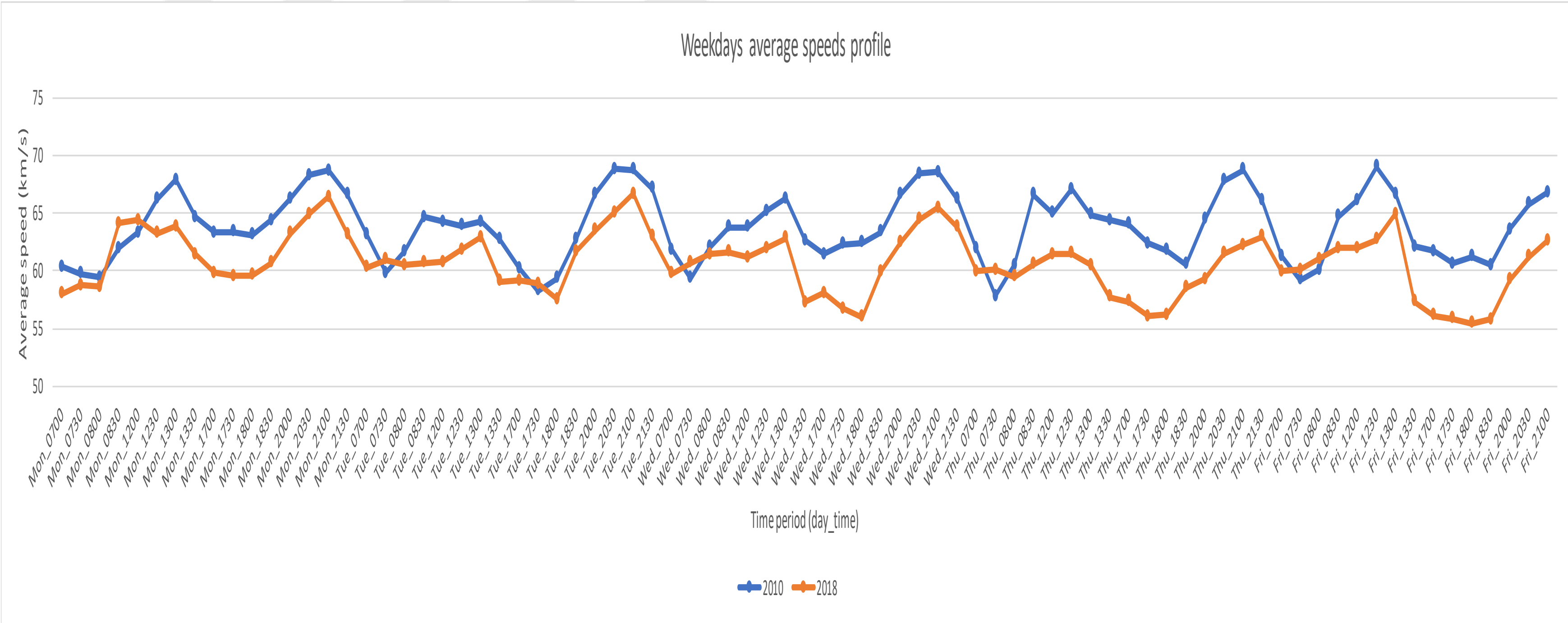


Figure 8.9 : Average speeds change for weekdays between 2010 and 2018.

8.2 Workplace Accessibility Calculations

Using the processed data, two accessibility indices namely Potential Accessibility (PA) and Average Travel Time (ATT) are calculated utilizing Equations (2.4) and Equation (2.2), respectively. The main difference between these indices is PA utilizes weights of destinations while ATT does not include the weight of destinations. ATT focuses mainly on the cost of travel between points. Both accessibility indices are calculated at each identified time period using the dynamic accessibility approach proposed by (Moya-Gómez, et al., 2018). Time periods found in the morning period of (07:30, 08:00, 08:30) are used to represent Home to Work (HTW) trips. For that, the industrial zone weights are used to weight destinations of working places. Similarly, time periods found in the evening periods of (17:30, 18:00, 18:30) are used to represent Work to Home (WTH) trips. For that, the population attribute is used to weight the destinations of home locations. Accessibility indices are calculated for origins based on the significance of their corresponding destinations. However, since two different trip types are evaluated, the change in accessibility is projected to represent home locations for both trips to ease the evaluation.

The result provides a sequence of high-resolution time maps, instead of several snapshots, as implemented in (Moya-Gómez & Gutiérrez, 2018). Later, accessibility values for all time periods are averaged into one map for each index and trip type. Hence, the final product is presented as four figures. The averaged values are later used to calculate the change in accessibility between the corresponding years for both indices, which is later referenced as the change in accessibility. The spatial and temporal changes in accessibility for the study area are presented. The correlation coefficient matrix between 1. PA for HTW, 2. PA for WTH, 3. ATT for HTW and 4. ATT for WTH is presented and further analyzed. By doing that, the first aim of investigating the temporal influence of workplace accessibility analysis is achieved.

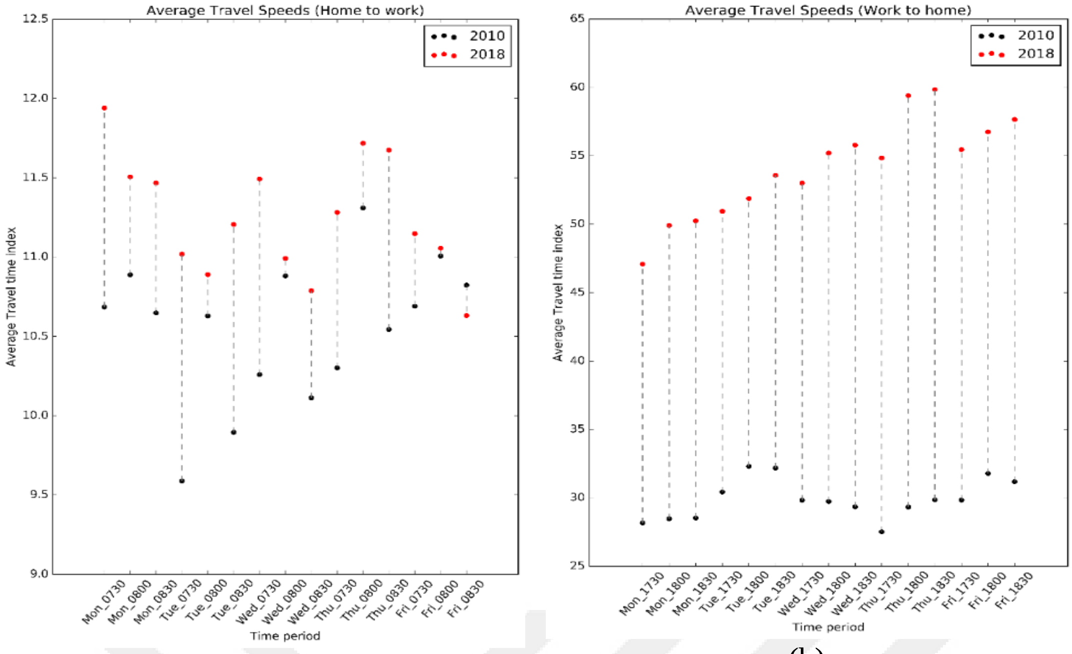
Several elements contributing to accessibility calculations changed between the corresponding years (2010 and 2018) are modelled, primarily being A.) the congestion conditions resulting from network grow and traffic change, and B.) LCLU change affecting the interplay between origin and destination locations. In order to disentangle the effect of changing congestion conditions from that of land use changes the method presented by (Geurs & Eck, 2003) is utilized. Using this method, dominant changes that spatially predominantly influenced the average changes in accessibility is referenced to both trip types. By doing so, the second aim of evaluating the dominant change based on trip type is achieved.

8.3 Change in Workplace Accessibility

To facilitate the spatial evaluation and visualization process for both trips, further accessibility results are illustrated for home locations only. For that, all accessibility indices are calculated for each trip type then mapped to represent the change in accessibility for home locations.

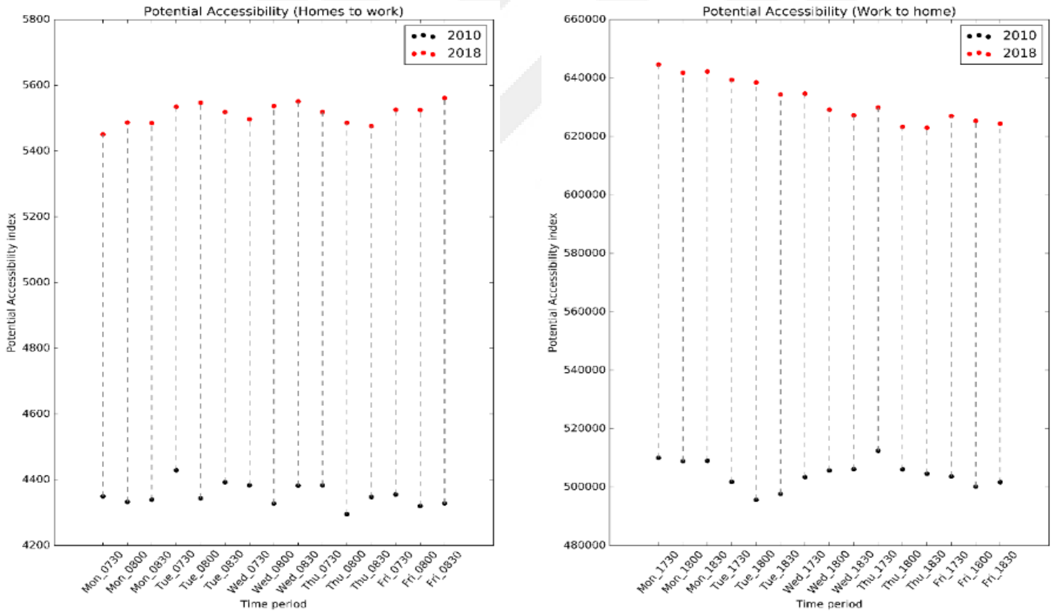
The achieved results for the Average Travel Time index (ATT) alone are presented in Figure 8.10. The results for all time periods of ATT for a) morning trips (07:30, 08:00, 08:30), b) evening trips (17:30, 18:00, 18:30) are illustrated separately. This figure summarizes ATT variation at each time period within the selected week of 2010 and 2018. It shows that ATT increased in 2018, especially for WTH trips. This increase is not advantageous for the area's accessibility status. Values of the second accessibility index (PA) are presented for a) morning trips, b) evening trips as shown in Figure 8.11. The difference in the results between the two trips is heavily influenced by the used weights. However, in both trips, Potential Accessibility (PA) results show improvement in accessibility status for 2018. Hence, PA shows reversed results compared with the ATT index's results. That is analyzed in detail in the later section.

The calculated values are reduced to represent HTW and WTH trips each day. Morning and evening results are averaged to represent HTW and WTH trips, respectively. The resulted lower to upper quartile values of all days are presented in Figure 8.12 and Figure 8.13. The box extends from the lower to upper quartile values of the data, with a line at the median. The whiskers extend from the box to show the range of the data. Red lines in Figure 8.12 represent the median of the averages (median value of all values for all used days) for ATT for both trips at both dates. Similarly, the same are presented for the PA index as shown in Figure 8.13. ATT during HTW trips slightly differs between 2010 and 2018 while a huge difference in WTH trips is noted (Figure 8.12). On the other hand, PA increases its average value in 2018 for similar percentages in the two trip types.



(a) (b)

Figure 8.10 : ATT in minutes for all used time periods of a) HTW, b) WTH trips.



(a) (b)

Figure 8.11 : PA for all used time periods of a) HTW, b) WTH trips.

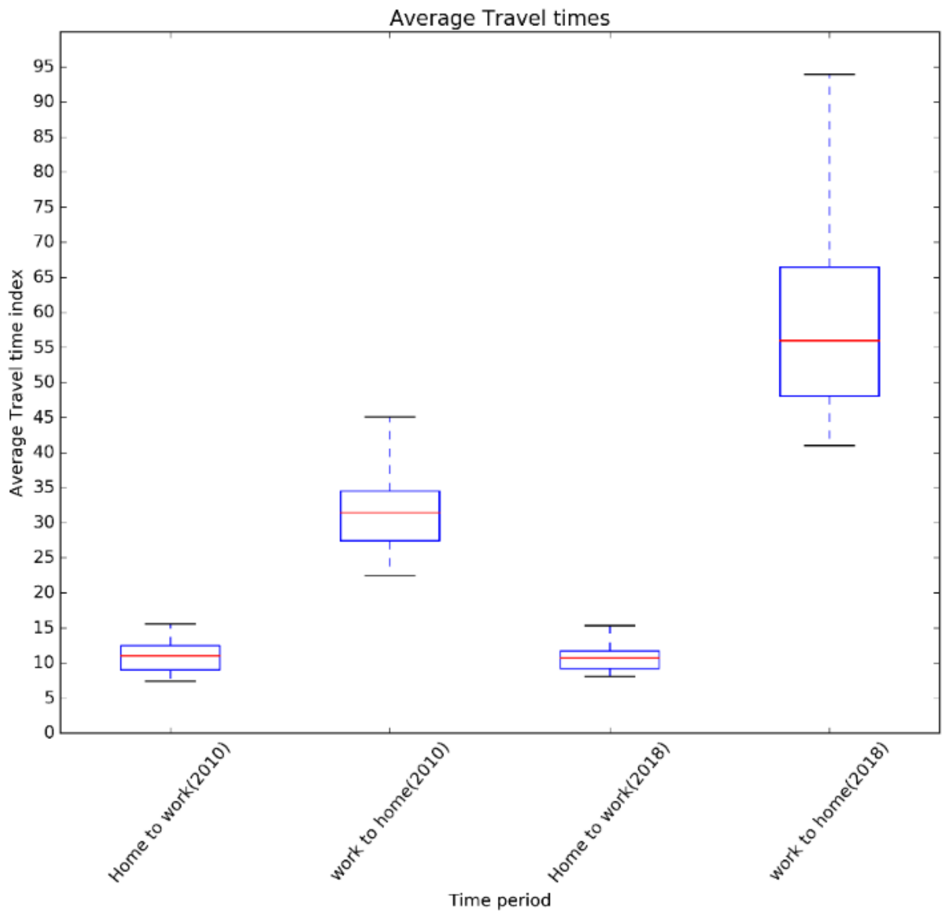
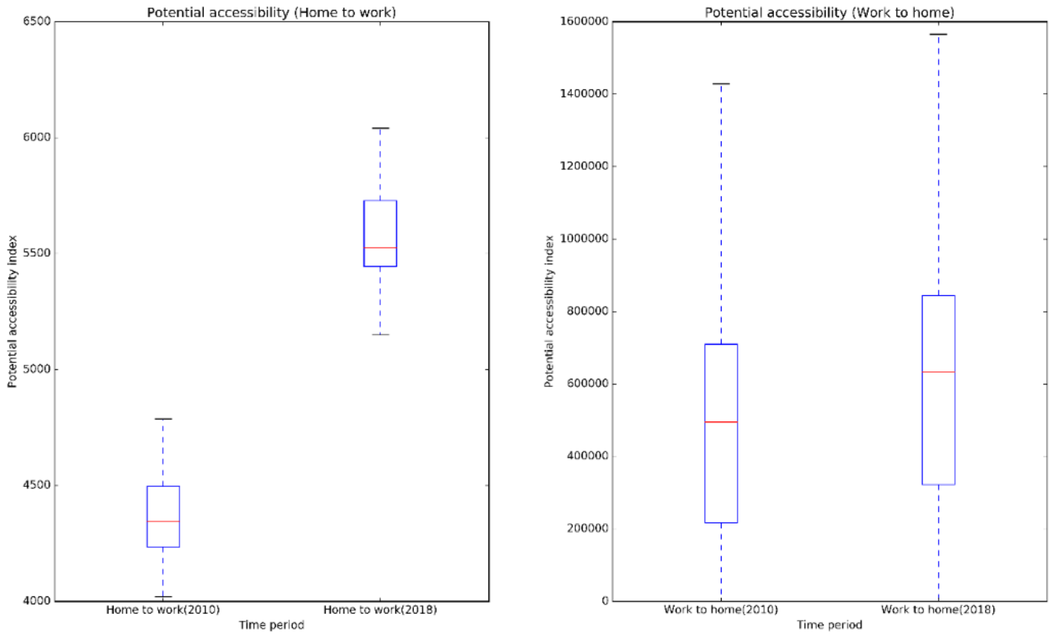


Figure 8.12 : Average ATT for all considered time trip types in 2010 and 2018.



(a) (b)

Figure 8.13 : Average PA for all considered time trip types in 2010 and 2018.

The change in accessibility indices is calculated by finding the change ratio of each trip type for each day. Later, all changes are averaged to four maps that show the change in a) potential accessibility for home-to-work trips, b) The Average Travel Time index for home-to-work trips, c) potential accessibility for work-to-home trips and d) The Average Travel Time index for work-to-home trips as displayed in Figure 8.14 and Figure 8.15. As noticed, visually both figures portray diverse changes in accessibility patterns for each index and for each trip purpose. That is, locations that gained or lost accessibility are not similar in all cases. To illustrate that more clearly, correlation analysis is carried out between all results. Such analysis provides an easy to understand measure of the associations between all results. The results also illustrate that there is no relation between all considered cases except for one (a strong relationship in the opposite direction between only PA home-to-work and ATT home-to-work), as seen in Table 8.4.

Commenting on the previous results, the difference between both indices (PA and ATT) is expected due to the difference in used mathematical formals which also includes the difference in considered accessibility components. However, what is not expected is when using the same index, a different change in accessibility patterns is revealed. The change in accessibility for each considered time/trip type is dissimilar. That is well illustrated for the results of ATT index, where considered accessibility components are the same for both trip types yet they have different results (Figure 8.14.b and Figure 8.15.b). On the other hand, the PA examines the same components for both trip types but considers different weighting factors for destinations. As explained before, the weights are distinct for each trip type. The different weighting factors and the changing travel times contributed to changing the accessibility status at each time period. However, one weighting factor has a limitation due to the acquired data. While in population, the change between 2010-2018 is captured and modeled, in HTWAV the values are maintained constant for both years. The change that occurred to the HTWAV values in 2018 is not modelled, thus the accurate change in accessibility values in 2018 is not achieved. This is a drawback of the data and a limitation to this paper. However, in this article, we assume the change in the HTWAV value for each zone is neglectable. Assuming that is true and considering the results above, the change in accessibility for each index differs according to the considered time of the day.

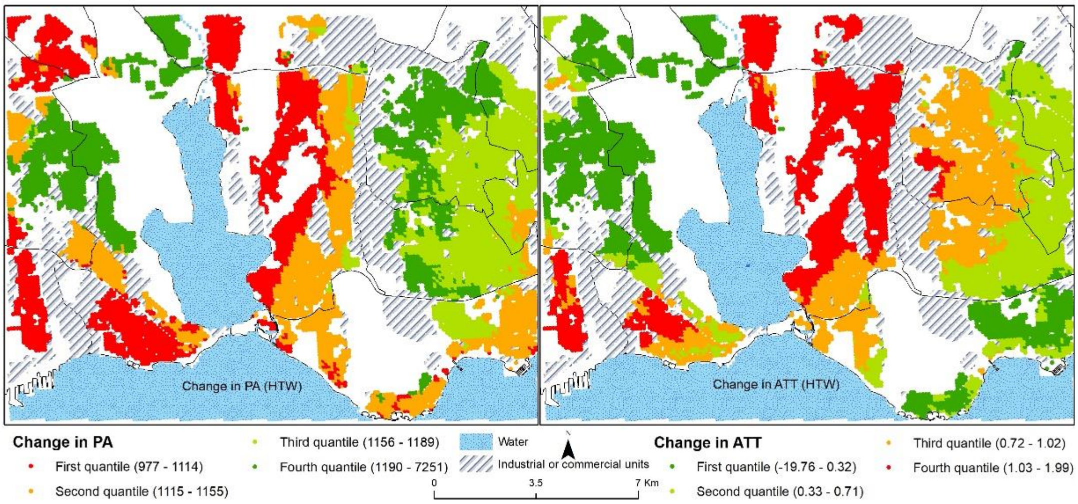


Figure 8.14 : Average change in accessibility for HTW trips between 2010 and 2018 for both indices.

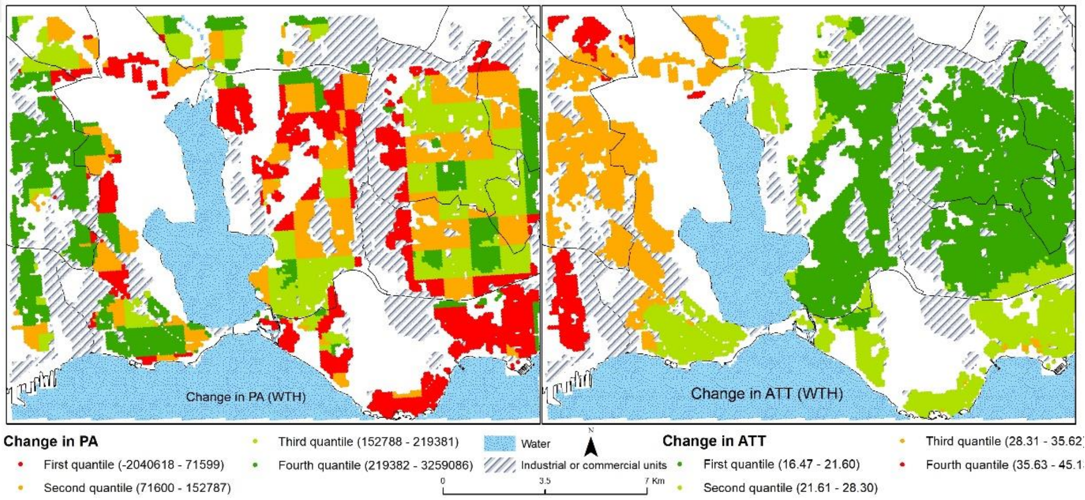


Figure 8.15 : Average change in accessibility for WTH trips between 2010 and 2018 for both indices.

Table 8.4 : Correlation coefficients for change in accessibility indices and trip type.

	PA_HTW	ATT_HTW	PA_WTH	ATT_WTH
PA_HTW	1	-0.78	0.23	0.48
ATT_HTW	-0.78	1	-0.12	-0.39
PA_WTH	0.23	-0.12	1	0.30
ATT_WTH	0.48	-0.39	0.30	1

When accessibility change was evaluated for each time period, two discrete results were obtained. PA was improved in 2018 while the ATT increased, thus reducing the accessibility in 2018. Two contradicting results show the importance of selecting the accurate accessibility index to the project/study's aims. While ATT mainly focuses on changes in traffic conditions, mobility status of the network and number of opportunities reached from origins, the PA considers the interplay between LCLU, road network, the significance of destinations and travel time altogether. Thus, ATT was negatively influenced by the drop in average speeds in the network, while PA was positively influenced by the increase in opportunities. PA was also influenced by used weights in each trip type. The obvious example of that was the change in accessibility while evaluating the average PA change for WTH trips. The changes were similar to boxes representing the previously collected population cells. Spatially, no relation is found between each index at any trip type as found in the correlation coefficients matrix. One case is considered an exception, which is the strong relationship in the opposite direction between PA and ATT for HTW trip. Primarily, the changes in accessibility differed for each trip type even though they are calculated for the same area. This shows that, spatially and temporally, accessibility changed differently at the considered spatial resolution. This is mainly referenced to the change in traffic passing the study area at each time period. Other trip types, e.g. education centers, shopping…etc., impact WTH trip type more than HTW thus reducing its accessibility. One drawback to these results is the limitation of used data to weight the industrial areas in 2018. To overcome that, this part of the thesis assumes that there is no significant change in this weight between 2010 and 2018.

8.4 Dominant Change in Spatial-Temporal Accessibility Distribution

The second aim of evaluating the dominant changes of network and LCLU is to be considered in this section. By doing so, both accessibility components are disentangled to better comprehend the factors influencing change in accessibility the most. Furthermore, the study evaluates the dominant changes based on trip type. By that, the temporal dominant change for the study area is evaluated.

To evaluate the dominant change affecting accessibility, a benchmark is set to compare the results of changing both components alone (i.e. Network and LCLU changes). The benchmark represents realistic combined changes of both components. Four states are considered to compare the effects of the component changes on accessibility, excluding possible interactions between the components, each of which is represented in the following equations:

$$A^{RY} = g(D^{RY}, f(\emptyset, C^{RY})) \tag{8.6}$$

$$A^{LC} = g(D^{FY}, f(\emptyset, C^{RY})) \tag{8.7}$$

$$A^{TC} = g(D^{RY}, f(\emptyset, C^{FY})) \tag{8.8}$$

$$A^{FY} = g(D^{FY}, f(\emptyset, C^{FY})) \tag{8.9}$$

where RY is the reference year (2010). LC stands for LCLU changes $and\ TC$ network/transportation changes. $The\ FY$ is the final year (2018). Other parameters are; A is the data set of accessibility; $g(\ )$ is an accessibility measurement function; D is the land-use component; C is the impedance measure vector; $f(u, c)$ is the impedance function, and $\emptyset$ are the parameters of the impedance-decay function. The DTT impedance is used to calculate the accessibility at each considered travel time. Later it is averaged as implemented earlier in the accessibility change calculation process.

Based upon that, three ratios are used to recognize the effects of each component, based on the reference situation as illustrated in the following equations:

$$LU\ change\ effects = \frac{A^{LC}}{A^{RY}} \tag{8.10}$$

$$LU\ change\ effects = \frac{A^{LC}}{A^{RY}} \tag{8.11}$$

$$Benchmark\ situation = \frac{A^{FY}}{A^{RY}} \tag{8.12}$$

After calculating the three ratios for all identified impedance measures, changes in Land Use (LU) and Network (NW) are compared to the results of the benchmark. Based on that, 10 spatial areas resulted in coded from 1.1. to 1.5. and 2.1. to 2.5. Codes starting with 1 represent an increase in accessibility while codes starting with 2 represent accessibility decrease. These areas and their corresponding codes are shown in the following chart (Figure 8.16). The resulted spatial distribution of dominant components is shown in (Figure 8.17 and Figure 8.18).

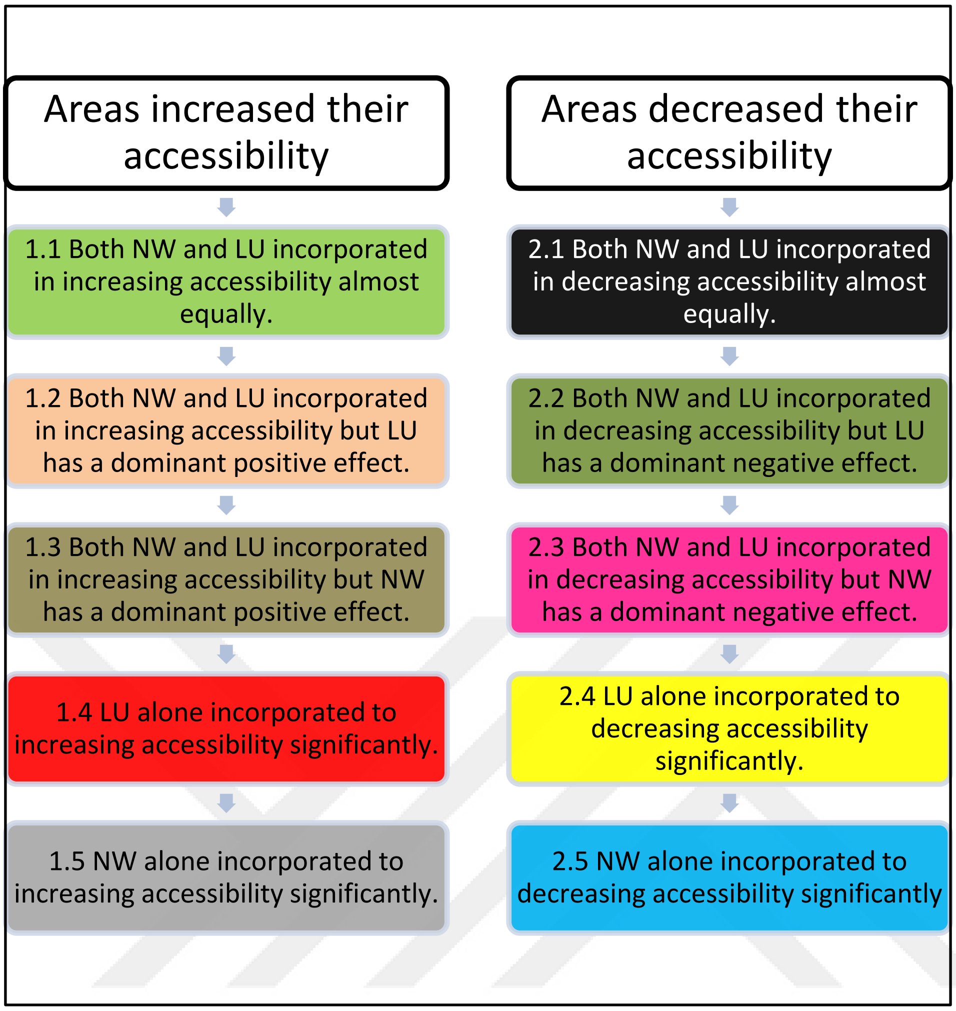


Figure 8.16 : Dominant areas, their codes and corresponding thematic colors.

Further discussion uses the aforementioned codes to describe the change cases. The dominant change of LU and NW is assigned to the attribute that resulted in changing accessibility index of more than 10% compared to the other attribute. Such cases are shown in area coded (1.2.), (1.3.), (2.2.) and (2.3.) (Figure 8.17 and Figure 8.18). As noticed from the figures, LU affects the PA change significantly for both trips, either by only increasing PA significantly, as seen in areas coded 1.2., or by being the dominant element, as noticed in area coded 1.4, as illustrated in Figure 8.17. That is referenced to increase in opportunities and appearance of more residential areas close to workplaces. However, certain limited areas have a drop in PA for WTH trips, especially noticed in the right half of the study area (Figure 8.17.b). In such areas, both accessibility elements of LU and NW affected the PA negatively.

On the other hand, mostly ATT increased significantly between 2010 and 2018, thus decreasing accessibility. Both changes contributed to an increase in ATT as seen

(Figure 8.18.a and Figure 8.18.b). Even though most of the study area has increased ATT due to both land use and network, some parts have decreased their ATT. That is noticed for the northwest side of the study area during home to work trips (Figure 8.18.a). The same part has a positive change in PA due to land use and negative change in ATT due to both accessibility elements of land use and network. Implemented policies in this area are considered the most successful ones compared to other parts of the study area. It could be observed that implemented policies to land use and network improved accessibility status considering both indices during all trip types, except for one case of ATT index during WTH trips, seen in Figure 8.18.B.

The dominant changes in the road network and LCLU were disentangled to understand what influences accessibility change. The relation was found to be related to both analyzed accessibility index and trip type. Clearly, the LCLU is considered the dominant element that contributes to increasing PA for both trips. On the other hand, both of LCLU and road network contributed to influencing the ATT change almost equally for both trips. However, the spatial dominant change patterns for the morning (HTW) and evening trips (WTH) are dissimilar. PA index is clearly enhanced by mostly modifying the LCLU, especially for WTH trips, while both elements equally contributed to altering the ATT for both trips.

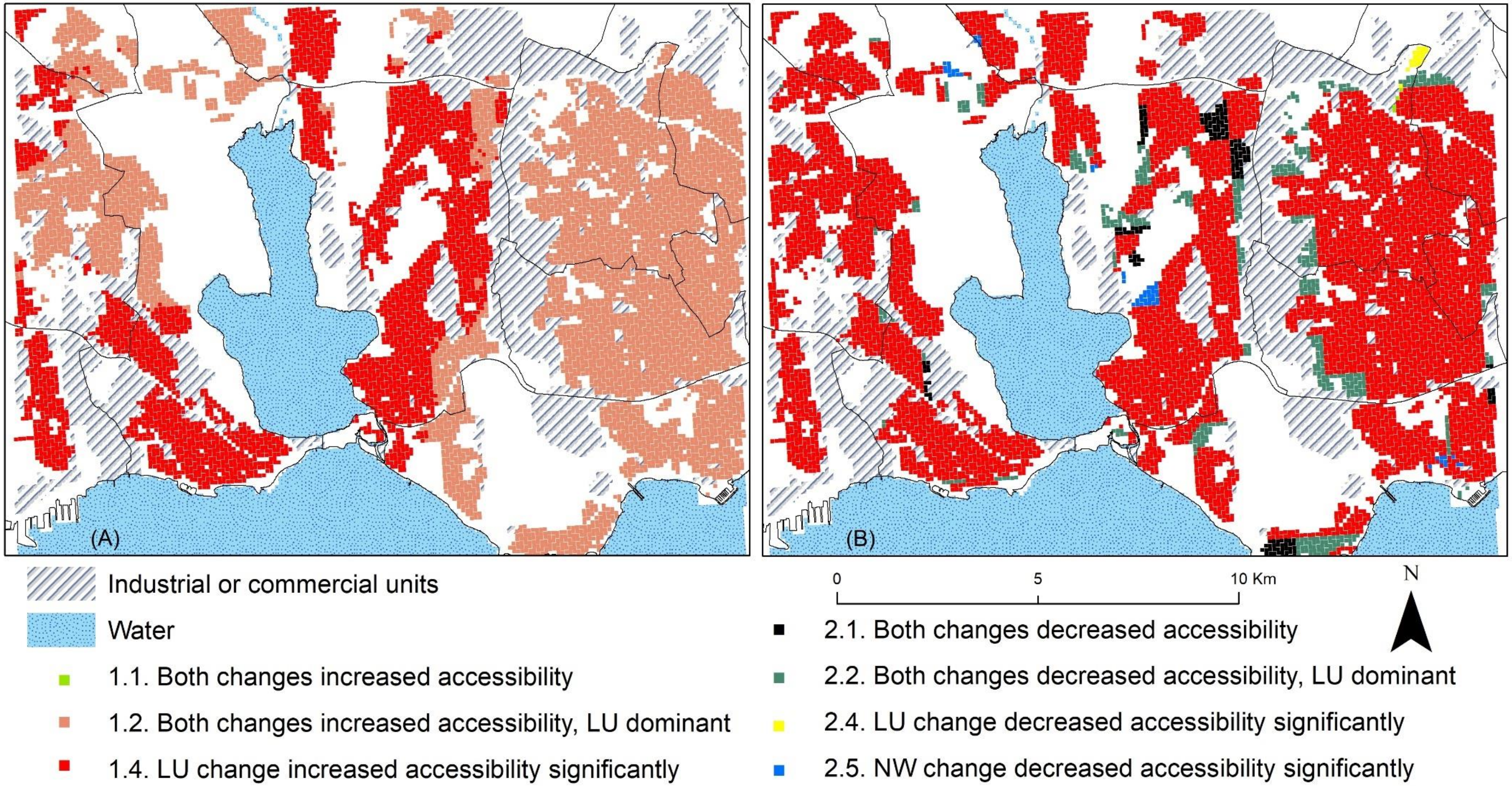


Figure 8.17 : Spatial distribution of most determinant changes on PA for both A) HTW and B) WTH.

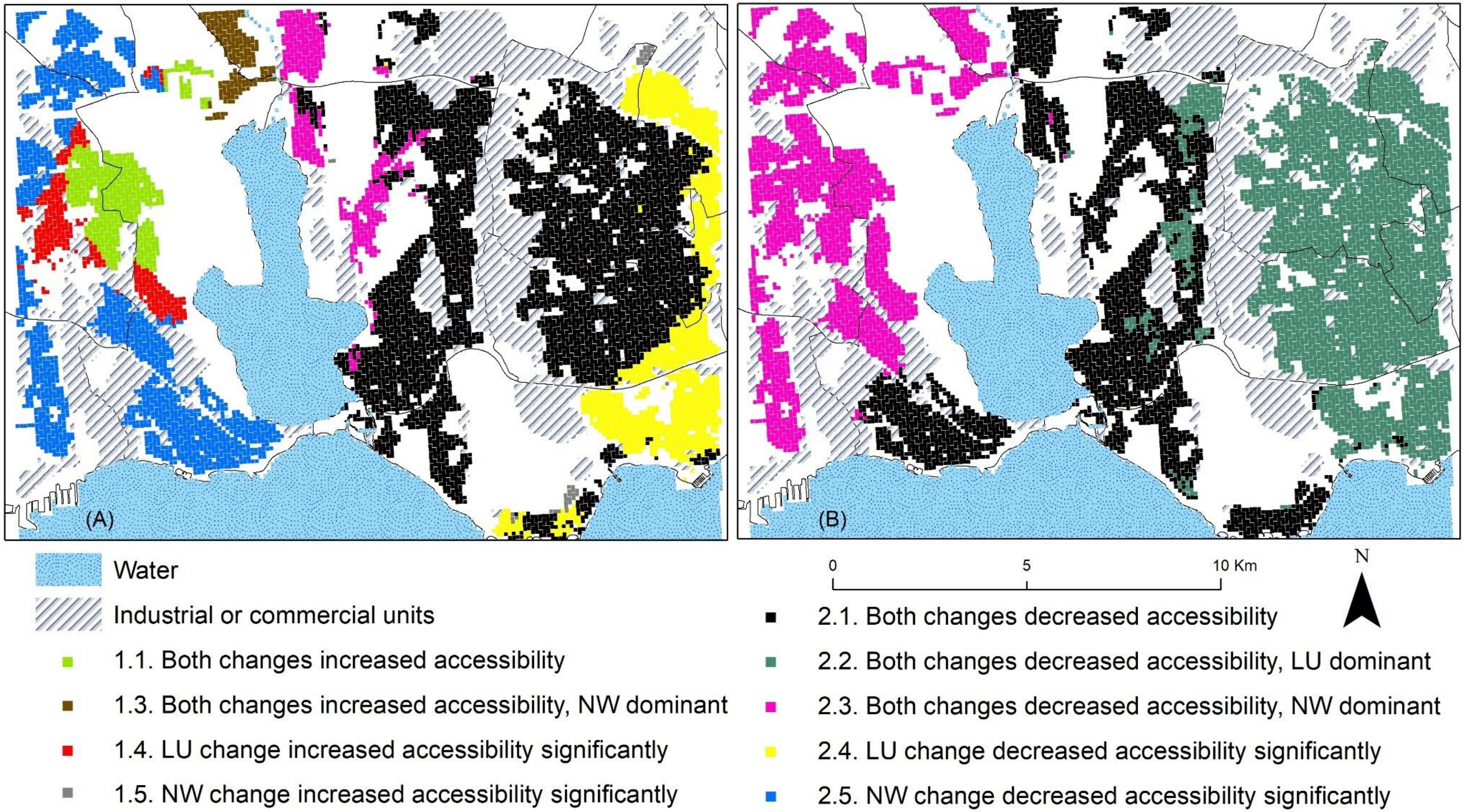


Figure 8.18 : Spatial distribution of most determinant changes on ATT for both A) HTW and B) WTH.

9. IMPEDANCE MEASURES IN EVALUATING ACCESSIBILITY CHANGE

Within previous chapters, location-based accessibility indices were evaluated using both network distance and DTT as impedance measures. Even though network distance was easier to implement, the DTT provides more realistic and accurate results for modelling the change in accessibility within a day, as shown in the previous chapter. Another impedance measure of static travel time was also implemented in similar applications. This measure considers a representative travel time of the day in accessibility calculations.

Considering that, the chapter aims are twofold 1) evaluating the difference between using the most used impedance measures of Travel Network Distance (TND), Static Travel Time (STT) and DTT when evaluating the change in workplace accessibility at very high resolutions. 2) Referencing the change in results that affect the spatial and temporal accessibility change patterns for each impedance.

To accomplish the announced aims, the change in workplace accessibility for two location-based accessibility indices, being PA index and Average Spatial Separation (AVSPSE), between 2010 and 2018 are calculated, for the same study area (Figure 7.4). This chapter finds its analysis of change in accessibility for two trip types; HTW and WTH trips within the previously selected weekdays. Three impedances are evaluated being TND, STT and DTT. The research evaluates the temporal and spatial similarity of the average change in accessibility for each identified impedance. The correlation matrix for all considered variables is analyzed. A discussion of the results is provided. Finally, the reason influencing the spatial and temporal patterns for each impedance is referenced. Thus, the dominant change influencing each impedance's results for each trip type is provided.

9.1 Background to the Impedance Measure Problem

Location-based measures consider travel impedance as a vital element in accessibility quantification. A travel impedance represents the degree of spatial separation between origins and destinations. It depends on the transport system and the network user mobility level. Generally, the impedance is considered using different measures, such as TND or time, estimated by straight-line distance, network distance, network models simulating travel demand, field surveys of actual driving times or surveys of residents' perceived distance, travel time (Handy & Niemeier, 1997; Cheng, et al., 2016), the average free-flow speed identified according to road's hierarchy or peak travel speeds (Rosik, et al., 2015). For calculating location-based accessibility, studies of (Ingram, 1971; Keeble, et al., 1988; Harris, 2002; Stanilov, 2003 ; Wang, 2007; Salze, et al., 2011; Shoman & Demirel, 2018; Shoman & Demirel, 2019b) utilized distance as travel impedance, whether it is Euclidean distance or network distance. While studies of (Handy & Niemeier, 1997; Kim, et al., 2003; Bagheri, et al., 2005; Chin & Foong, 2006; Zhu, 2004; Chin & Foong, 2006; Hou, et al., 2011; Rosik, et al., 2015; Cheng, et al., 2016) used travel time as an impedance. Other impedance measures were also utilized such as combining both of them in the impedance function (Linneker & Spence, 1996), developing a new impedance that considers other factors in the accessibility quantification such as the network efficiency (Gutierrez, et al., 1998).

Obviously, the literature mostly considered both distance and travel time as main measures of spatial travel cost. While (Salze, et al., 2011) found that distance results are very associated with time travel justifying their use for distance as impedance over travel time for its easiness to implement. Others found that it is not accurate for most intraurban applications to utilize TND over time, in which movement is confined to street networks (Kwan & Weber, 2003). From the start, Hansen (1959) saw accessibility related to distance, explaining the reliance on distance in accessibility calculations. Actually, for much of the twentieth century, most conceptualizations and formal models of the urban structure have been based on a spatial logic that shapes individual mobility and urban form through the impedance of distance. Moreover, it captured factors that influenced the directness and topological continuity of available routes while evaluating the accessibility (Handy & Clifton, 2001). Using TND as impedance provides an advantage in the easiness of computing accessibility, collecting data, and interpreting the results. However, recently distance as conventionally understood is of declining importance as an organizing principle of urban form and accessibility (Kwan & Weber, 2003). This decline in the importance of distance has been attributed to a variety of forces that fails to capture the mobility status such as road lanes, capacity, and road type. Also, it struggles to illustrate the non-spatial elements of the transport sub-system that extremely influence the job accessibility calculations, such as service schedules, traffic management, and planning policies (Cheng & Bertolini, 2013). Basically, it is increasingly difficult to understand human spatial behavior within contemporary cities using distance as a travel cost (Kwan & Weber, 2003). Travel time, on the other hand, is an integral element of individual accessibility. It is gaining much significance in accessibility calculations due to its ability to capture various types of elements influencing mobility improvements, traffic volume, road capacity and average speeds at an instant of time. However, conventional time travel impedance accessibility measures take a static, timeless view of mobility and accessibility, which denies the ways in which behavior, activity patterns, and even population composition vary by time of the day (Kwan & Weber, 2003). Such limitation in accessibility modelling resulted from the increased influence of Information and Communications Technologies (ICTs) on spatial behavior. Lately, due to the availability of real-time driving speeds, open-source web-based mapping, mobile phones, navigation systems such as TomTom or NavTeq and GPS data, a recent trend in the literature is able to examine continuous accessibility patterns (Geurs & Östh, 2016). Using such data sources, studies such as (Moya-Gómez & García-Palomares, 2015; Condeço-Melhorado, et al., 2016; Moya-Gómez & Geurs, 2018) are able to examine time-of-day variations utilizing a Dynamic Travel Time impedance (DTT) in accessibility calculations. For such impedance, travel time for each time period is being stored, thus enabling studies to evaluate different trip types within a day e.g. from home to work and work to home. Such impedance provides a more realistic scenario for analyzing the change in accessibility. However, utilizing the DTT impedance requires very detailed data for the network, more data processing and computing power.

9.2 Travel Impedance Attributes

To generate the network TND, the Dijkstra algorithm is used to find the shortest network distance between all corresponding origins and destinations. On the other hand, the STT is generated using the OSM's speeds identified in their web page (OpenStreetMap, n.d.). OSM identifies their speeds according to each's road type tagging. The used max speeds for all types of roads are summarized in Table 9.1. The static time attribute needed to cross each link is generated using the corresponding speed.

Table 9.1 : Max speeds for each link's type, according to OSM.

Road type	**Motorway main**	**Motorway ink**	**Trunk main**	**Trunk link**	**Primary main**	**Primary link**	**Secondary main**	**Secondary link**	**Tertiary main**	**Tertiary link**	**Residentia l main**
Speed (km/hr)	120	90	110	82	90	70	90	60	70	50	50

For DTT impedance, the results of the previous section (Section 0) are used to represent the changed average travel time at each considered time period. The considered time periods are the same considered in the previous chapter.

9.3 Evaluating the Difference Between Considered Travel Impedances

OD matrices are used to calculate the identified indices as introduced by (Liu & Zhu, 2004). Locations of homes and workplaces are used to generate the OD, both of which are assigned according to trip type (i.e. HTW or WTH). Accordingly, the research assigns the significance of destinations as explained in the previous chapter (Section 8.1). The research calculates the change in accessibility for PA index and AVSPSE introduced earlier in Equations (2.4) and (2.2), respectively. In both indices, the three identified impedances are utilized to quantify accessibility, separately, using the aforementioned travel impedance for each impedance measure. Both shortest network TND s and OSM's travel speed are used to generate the TND and STT impedances respectively. The accessibility status at each year is calculated separately. Later, the accessibility change ratio between 2010 and 2018 for both trip types (i.e. HTW and WTH) is calculated. On the other hand, the DTT impedance requires quantifying the accessibility for each identified time period separately. The morning time periods are averaged to represent HTW while the evening time periods correspond for the WTH trips each identified day. The average ratio for change in accessibility between 2010 and 2018 is generated for each impedance measure separately. The spatial similarity in results is evaluated and analyzed using the correlation coefficient introduced earlier in section (7.2). Lastly, the dominant changes that spatially predominantly influenced the average changes for each impedance measure are explained using the method presented by (Geurs & Eck, 2003). The interaction between both of LCLU and road network resulting is analyzed in detail for each travel impedance measure.

9.4 Results For The Considered Impedance Measures

9.4.1 Change in accessibility for considered impedance measures

The spatial distribution of PA ratio for change in accessibility between 2010 and 2018 using each impedance is shown in Figure 9.1. For HTW trips, results for accessibility change using DTT, TND and STT as impedances are shown in Figure 9.1.A, Figure 9.1.B, and Figure 9.1.C, respectively. On the other hand, results of WTH trips that show the accessibility change using DTT, TND and STT as impedance are shown in Figure 9.1.d, Figure 9.1.e, and Figure 9.1.f, respectively. The change in accessibility ratio values is illustrated using 4 equal quantiles. Locations represented in red color illustrate the lowest relative increase in PA, while the green locations represent the relatively highest increase in PA (Figure 9.1). Similarly, the spatial distribution of AVSPSE change ratio using each impedance is shown in Figure 9.2. The first three subfigures show an illustration of HTW trips, while the last three subfigures illustrate the results of WTH trips. Locations colored in green represent the relative lowest increase in AVSPSE, while the red locations illustrate the highest relative increase in AVSPSE. For both figures, green locations are associated with preferred accessibility status. Apparently, the increase in accessibly using DTT is different than STT and TND. Considering that, policymakers evaluate their policies and plans differently using each impedance measure.

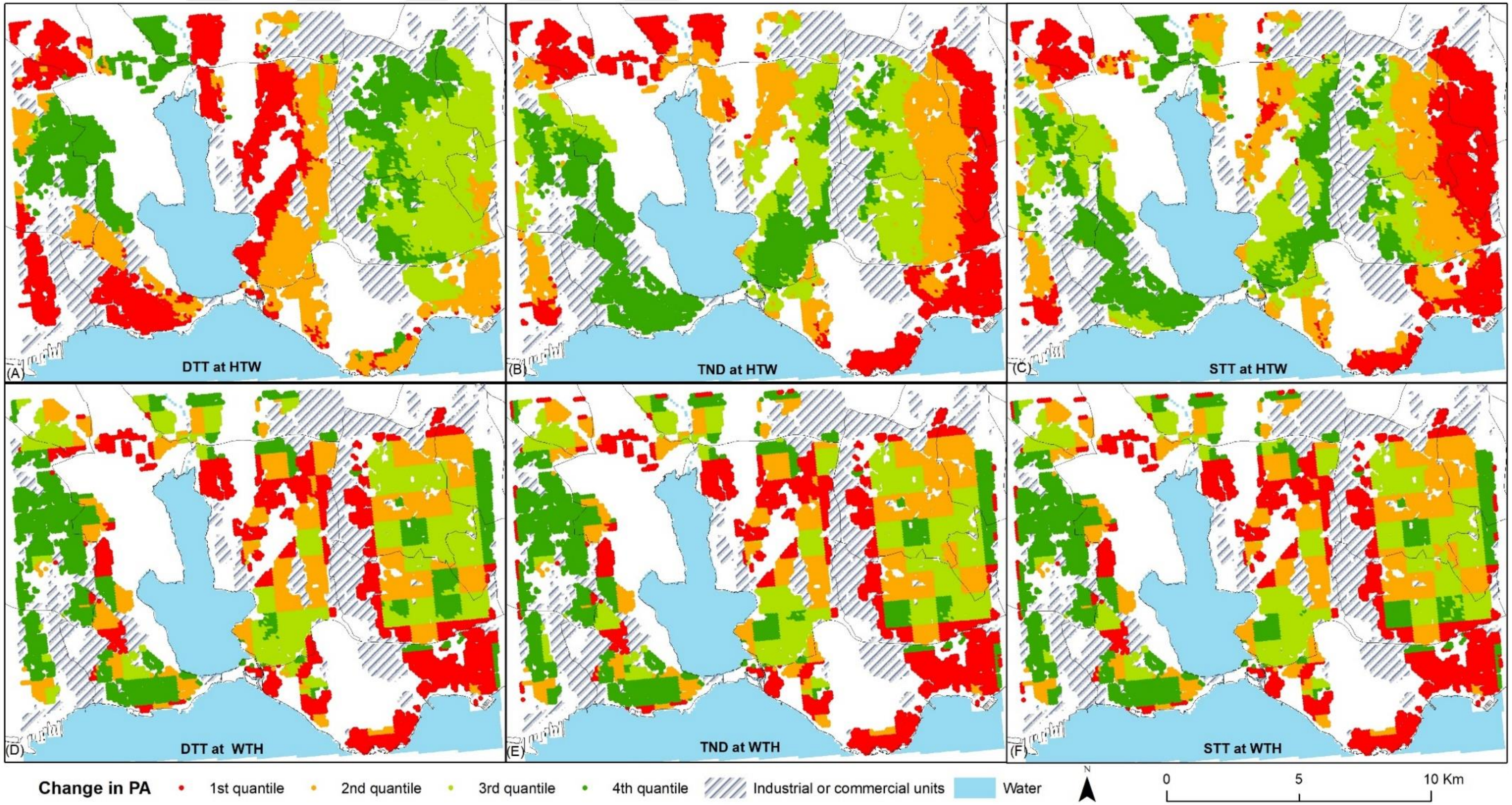


Figure 9.1 : Ratio change for PA for both trips using the three considered travel impedance measures.

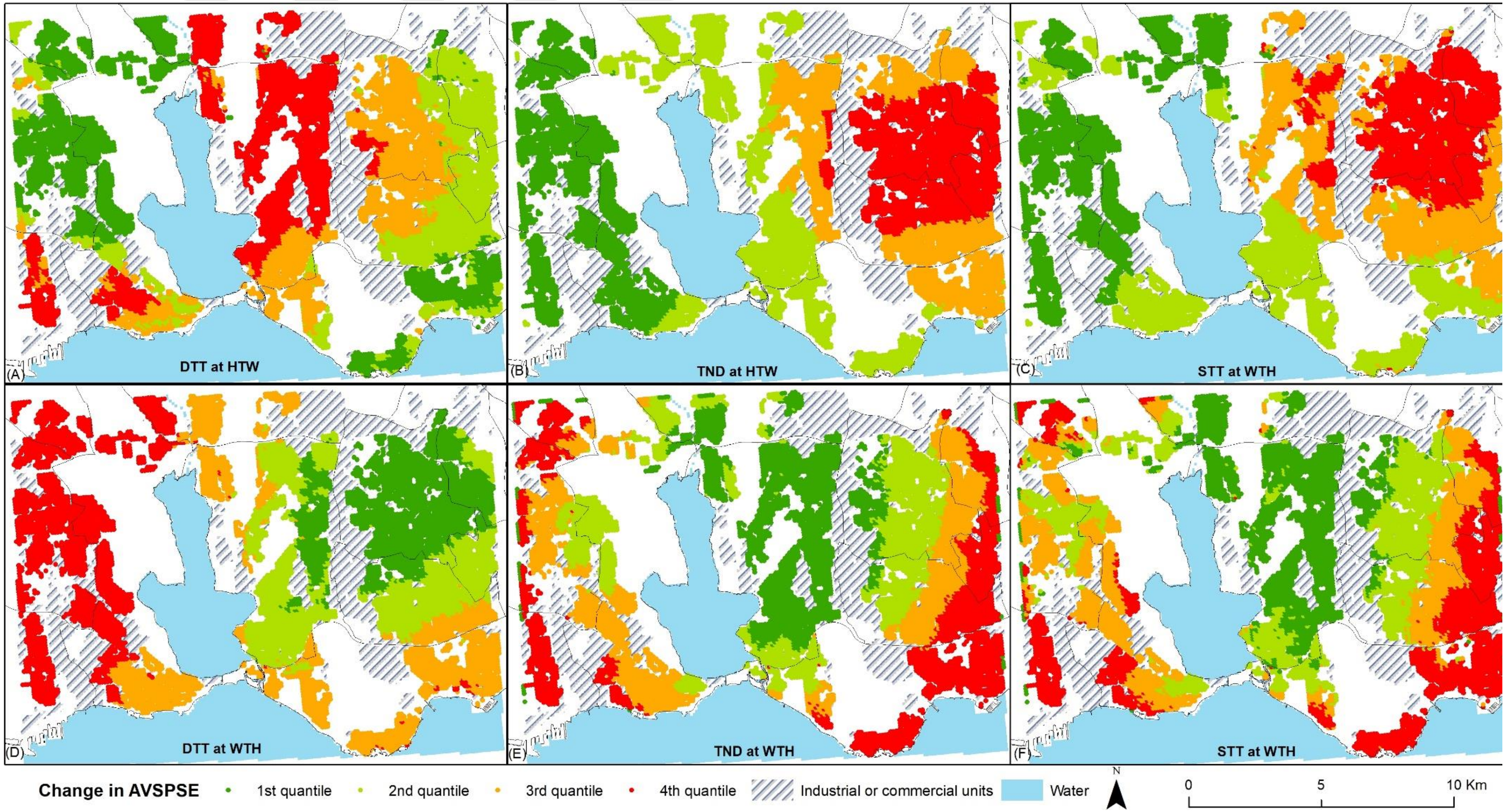


Figure 9.2 : Ratio change for AVSPSE for both trips using the three considered travel impedance measures.

Due to considered accessibility elements in both accessibility indices, the difference in their results is expected. The difference between considered impedance measures is also distinguished. Generally, both figures reveal spatially dissimilar results for the change in accessibility using each impedance. To illustrate that quantitively, correlation analysis is carried out between all results using the correlation coefficient R (Equation (7.3) in section 7.2). The resulted correlation coefficient matrices for both indices PA and AVSPSE is provided in Table 9.2 and Table 9.3, respectively. First, evaluating the change in PA between 2010 and 2018 shows a perfect relation between STT and TND (Table 9.2). The R coefficient between their results equals to 1 for both trip types. Note that this analysis is implemented for results of the same trip type (e.g. results of HTW using TND and HTW using STT are strongly correlated). The DTT shows a strong correlation with the other impedances during the WTH trips only. The used weight factor during such time period of analysis has a big influence on this result. Considering the difference in their range, the classified transportation zones has a range of 5 (from 1 to 5), while the population has a range of 2734, varying from 1 to 2734. Apparently, increasing the range of weights reduces the impedance effect, thus increasing the correlation between different impedances.

Table 9.2 : Correlation coefficient matrix for PA values.

Impedance Trip type	**DTT HTW**	**DTT WTH**	**Distance HTW**	**Distance WTH**	**Static time HTW**	**Static time WTH**
DTT HTW	1,00					
DTT WTH	0,14	1,00				
Distance HTW	0,30	0,16	1,00			
Distance WTH	0,14	1,00	0,16	1,00		
Static time HTW	0,48	0,16	0,99	0,16	1,00	
Static time WTH	0,14	1,00	0,16	1,00	0,16	1,00

Considering the AVSPSE index's results, a strong correlation between both TND and STT results (Table 9.3). The correlation coefficients between both measures for HTW and WTH are 0.93 and 1, respectively. Moreover, a weak relation between all measures for HTW trip is observed (Table 9.3). The correlation coefficient between DTT and TND is 0.50 while it is 0.65 for the relation of DTT and STT (Table 9.3). For WTH trip, a relation in the opposite direction is found between DTT and STT. The correlation coefficient between their results is -0.52. This relation provides conflicting information about the spatial change in accessibility for the PA index. Here, the relations found between DTT and both impedance measures are random. The DTT proposes different spatial results than other impedances.

Table 9.3 : Correlation coefficient matrix for AVSPSE values.

Impedance Trip type	DTT HTW	DTT WTH	Distance HTW	Distance WTH	Static time HTW	Static time WTH
DTT HTW	1,00					
DTT WTH	-0,35	1,00				
Distance HTW	0,50	-0,53	1,00			
Distance WTH	0,10	-0,49	0,29	1,00		
Static time HTW	0,65	-0,58	0,93	0,34	1,00	
Static time WTH	0,13	-0,52	0,29	0,99	0,32	1,00

Another note considering both tables is the disassociation between HTW and WTH results for both indices. This is noticed for all identified impedance measures. Accessibility change between 2010 and 2018 differs significantly within the day for all measures. Thus, all identified impedance measures manage to point out the temporal influence for the change in accessibility considering the identified trip types and times.

The earlier results show that the accessibility change between 2010 and 2018 for both TND and STT are alike for both trip types. However, the DTT shows distinct results. As all components considered in calculating the accessibility indices are identical for all impedance measures, the results are not the same. Clearly, the considered components interacted differently for each identified measure. At least both TND and STT react differently than DTT to considered accessibility components. By that, the first aim of this research is reached.

9.4.2 Dominant change for each impedance measure

Later on, the change in two major accessibility components of LCLU (e.g. home locations and opportunities) and network (e.g. road network infrastructure, travel time and mobility status) are disentangled to understand what influence the change in accessibility the most. This is evaluated considering each impedance measure alone by implementing the previously introduced method of (Geurs & Eck, 2003).

To evaluate the dominant change affecting accessibility the methodology utilized earlier in section (8.3) is implemented. For all impedance measures, all variables in the equations (Equation 8.6, Equation 8.7, Equation 8.8 and Equation 8.9) are the same, except for the variable C. This variable differs according to the considered impedance measure. Moreover, for DTT impedance, the accessibility is calculated at each considered travel time. Later on, all calculated values are averaged to present both trip types, as implemented earlier in "calculating the change in accessibility process". After calculating the three ratios (i.e. Equation 8.10, Equation 8.11 and 8.12) for all identified impedance measures, changes in LCLU and NW are compared to the results of the benchmark. The resulted spatial distribution of dominant components is shown in (Figure 9.3, Figure 9.4, Figure 9.5 and Figure 9.6). To ease the comprehension of the visualization within these figures, the major patterns of change are illustrated while minor patters are illustrated as others for each case. The explanation of all coded areas showing the dominant change component is illustrated in Figure 8.16.

Similar to earlier results showing the change in accessibility between 2010 and 2018, components influencing the change in accessibility for both TND and STT are also almost identical. Locations that have an increase in PA are influenced positively and equally by both NW and LCLU changes (Figure 9.3 and Figure 9.4). Similarly, the locations that have a drop in PA are influenced negatively and equally by both elements (Figure 9.5 and Figure 9.6). Noticeably very few differences are detected between the results of TND and STT. This is attributed to the used travel time within STT impedance. STT assigns speeds according to the road type within the network. Roads with high hierarchal importance are assigned high speeds, thus shorter travel time. On the other hand, TND does not differentiate between all roads within the network, assigning fixed travel times for all road types. This impacted the accessibility calculations resulting in the relatively small difference between STT and TND results.

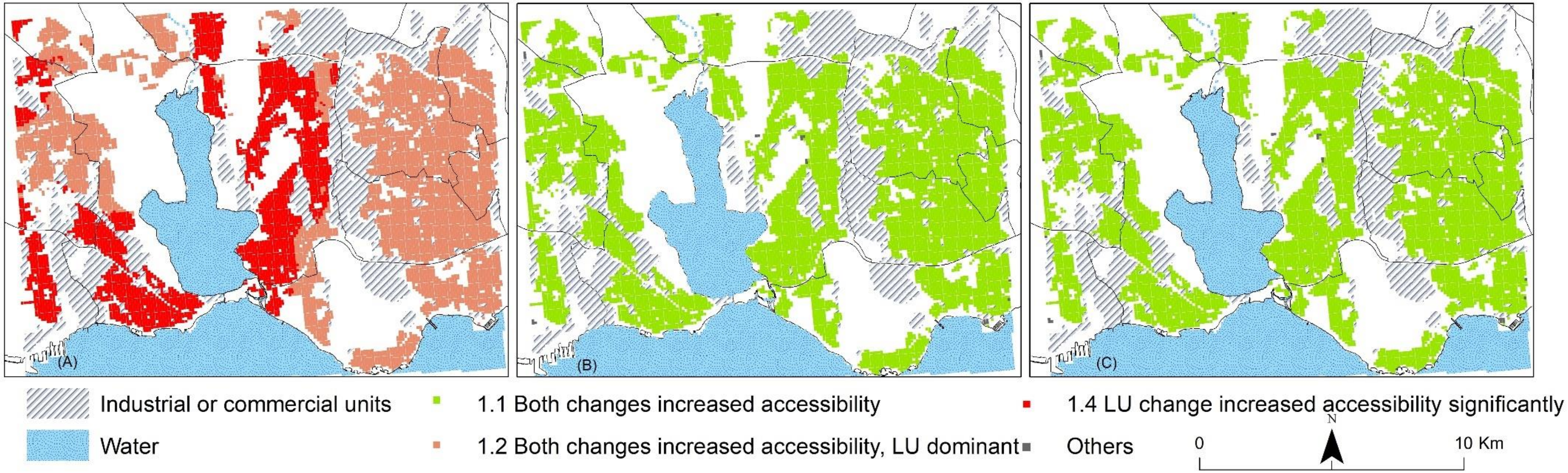


Figure 9.3 : Spatial distribution of most determinant changes on PA for both HTW trips using A) dynamic travel time, b) TND and C) STT.

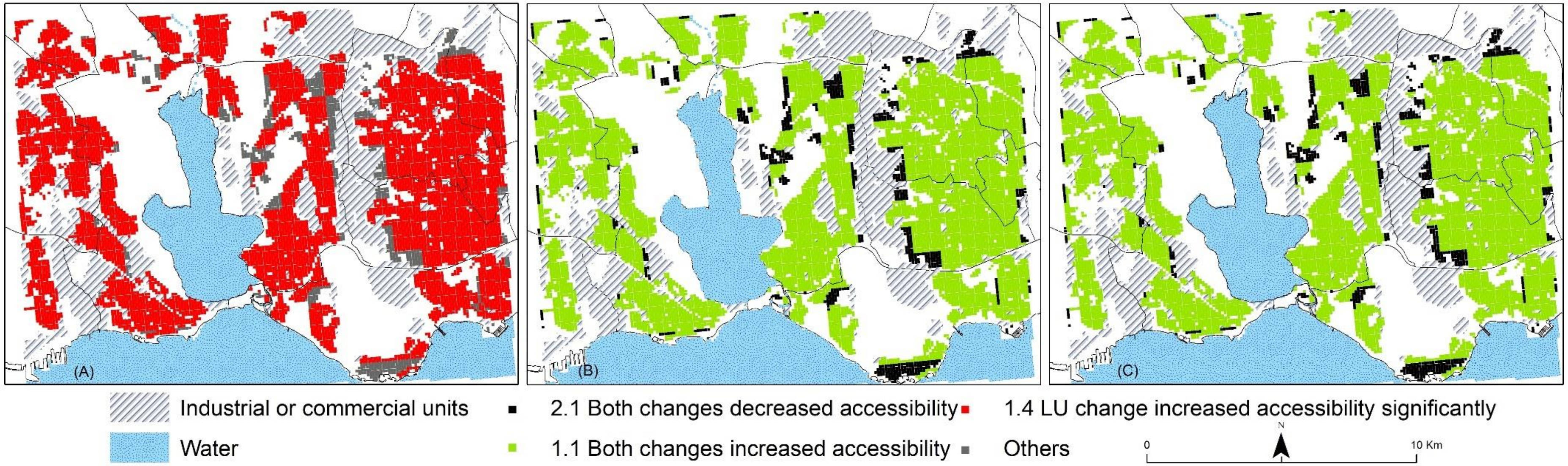


Figure 9.4 : Spatial distribution of most determinant changes on PA for both WTH trips using A) dynamic travel time, b) TND and C) STT.

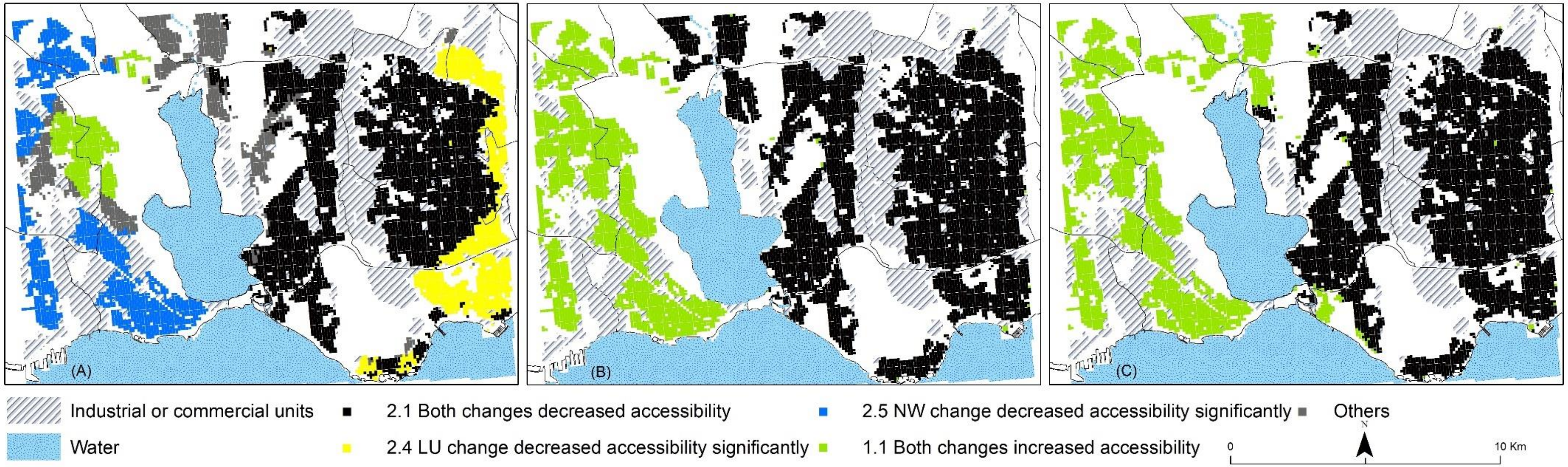


Figure 9.5 : Spatial distribution of most determinant changes on AVSPSE for both HTW trips using A) dynamic travel time, b) TND and C) STT.

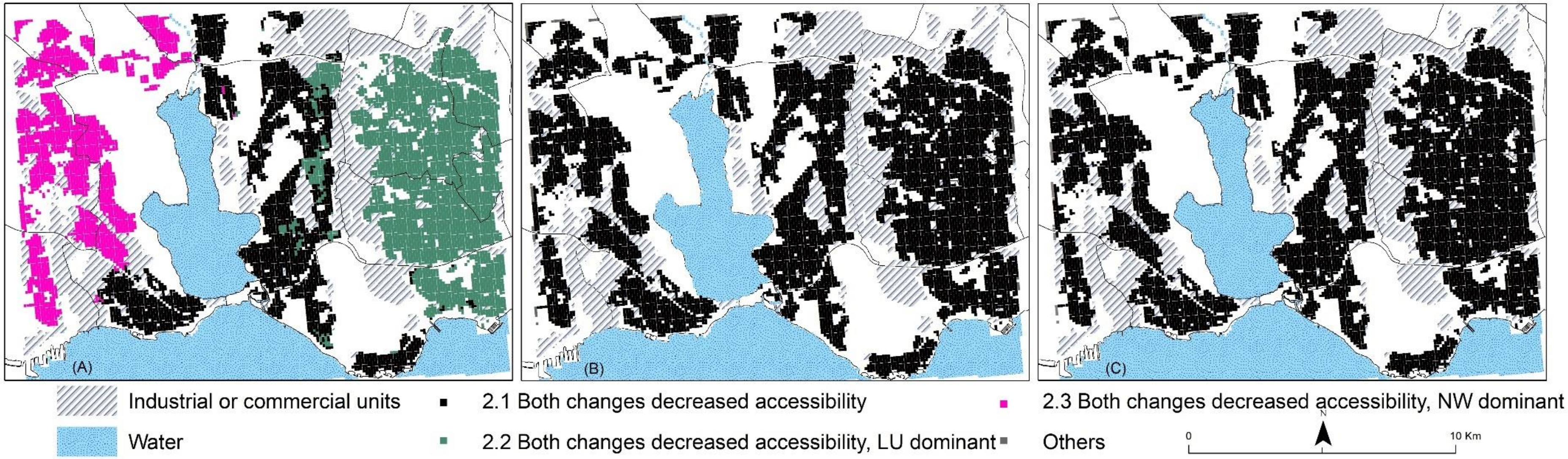


Figure 9.6 : Spatial distribution of most determinant changes on AVSPSE for both WTH trips using A) dynamic travel time, b) TND and C) STT.

However, as noticed from previous figures, DTT is influenced distinctively by accessibility components for each trip type. The dominant changes influencing the DTT results are different from other impedances. To illustrate the results of DTT alone in more detail, Figure 9.7 is illustrated for all considered cases. The legend for this figure is introduced earlier in Figure 8.16. Mainly, the increase in job density influenced the PA increase in HTW trips (Figure 9.7.a). That is reflected by pointing out LCLU exclusively as a dominant factor. Similar results for WTH trips are attributed to the increase in population, which is also reflected by LCLU (Figure 9.7.b). The difference between HTW and WTH is attributed to the used weighting factor. However, some areas witnessed a decrease in PA due to an increase in travel time, a decrease in reached job locations or both (Figure 9.7.b). This is referenced to a negative dominant effect of NW. On the other hand, even though most of the study area has decreased its AVSPSE due to both LCLU and NW almost equal negative effect (Figure 9.7.c and Figure 9.7.d), some parts increased their AVSPSE values. This is illustrated in HTW trips for the northwest side of the study area (Figure 9.7.c). This increase is attributed to the dominant effects of both accessibility elements. At this resolution, corresponding areas are associated with successful traffic management, infrastructure projects and urban propagation within 2010 and 2018, but only for morning trips.

Evidently, the DTT shows more details that both other impedances fail to capture. The continuously changed values of the average speed of the network are influenced by the mobility status of the network. The average speed is a major indicator of the network's traffic volume, capacity and traffic management. Modelling that as an impedance measure reflects the current status of NW more accurately. For instance, locations that are close to more congested roads have more travel times to reach their destinations, thus they have a decrease in their accessibility status. Primarily, the interplay between main accessibility elements of LCLU and network are evaluated within the required temporal resolution of the day via utilizing the DTT impedance. Therefore, dynamic accessibility patterns are examined more accurately according to the plans and aims of the application.

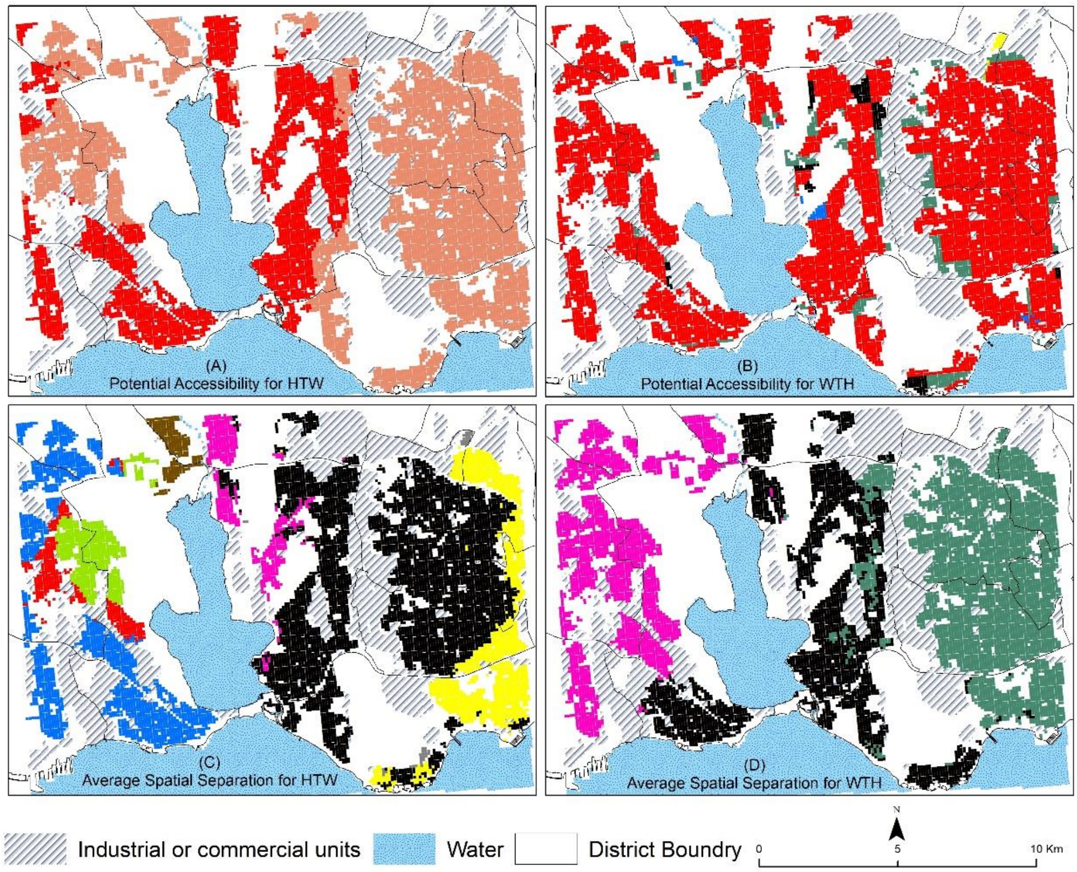


Figure 9.7 : Spatial distribution of most determinant changes using DTT as impedance for change in (A) PA at HTW and (B) WTH and for change in AVSPSE at (C) HTW and (D) WTH.

9.5 Comments on Results of the Impedance Measures

Primarily, impedance measures of TND and STT represent almost identical results, unlike DTT. While travel impedance values between origins and destinations have changed between the selected years, changes remain constant during all time periods of the day for both TND and STT. TND is also constant for all time periods. Hence, both of them cannot designate further temporal changes. Obviously, using any of them provides the same results when evaluating the change in accessibility between considered years. Moreover, both of them are influenced by an equal effect of LCLU and network change. Thus, there are no dominant elements that impact accessibility change for both TND and STT, unlike DTT.

The DTT illustrates varying spatial and temporal results for all considered cases. All results of the change in accessibility are not correlated with the results of other impedances, except for one case of PA in WTH. The PA of DTT is completely correlated with the results of both other impedances when evaluating WTH trip type. That is referenced to the used weight factor when considering the significance of destinations. While the attraction of transportation zones classified values of 1 to 5 is used weight the workplaces during HTW trips, the population of each cell with much more range varying from 1 to 2734 is used to evaluate the significance of home locations. That indicates if the selected weights have a wide range, as population data in WTH trips, the significance of impedance continuously vanishes. On the other hand, the AVSPSE index with DTT shows no positive spatial relation (correlation) between any result of the other impedances. That occurs due to AVSPSE prioritizing travel impedance in quantifying accessibility. DTT as impedance captures more accurate results (compared to other measures) when used for AVSPSE. Results of DTT are attributed to capturing the change in mobility status, which are more realistic scenarios to the results of the change in urban movement within the day. This change is captured by modelling the dynamic average speeds which reflect the fluctuating in road capacity, traffic management and traffic volume.

For the study area, the LCLU distribution dominates the PA change while both the network and LCLU influence the AVSPSE change equally. It is observed that policies implemented to LCLU distribution within the study area between 2010 to 2018 influence PA positively. On the other hand, the same policies affect AVSPSE negatively. Meaning that more countermeasures are required to ease the mobility services in the study area.

Finally, considering the variation of accessibility values within the day, all impedances successfully point out the change in accessibility status for each trip type. However, the alteration in accessibility change for TND and STT remains constant for each day all the week, while DTT shows more details and variation at the required time resolution.

10. CONCLUSION

The main aim of this thesis was to provide policymakers with more adequate tools, methodologies and models to capture essential accessibility components, convert them into the required form and quantify the change in accessibility at high spatial resolutions. The thesis started by introducing methodologies to identify OD locations by capturing LCLU data and convert related classes to representative points. The first applications utilized network distance as an impedance measure due to the limitation of related required data. Using that, the proposed model evaluated the influence of major infrastructure projects within the study area (i.e. Istanbul Metrobus line system) on altering the accessibility status. The influence of changed urban parameters on each modelled accessibility index was evaluated as well. The research also inspected the influence of changed accessibility components on altering the status of accessibility to hospitals and health care centers. Later on, the thesis developed a methodology to generate average speeds of the network at all time periods, thus generating the travel time for each considered time period. Using that, the thesis generated dynamic travel times as the impedance measure to inspect the temporal resolution/period aspect while evaluating the change in workplace accessibility. The temporal variations within the day and between several years were modelled and discussed. Additionally, the study pointed out the dynamic interplay of accessibility components on changing the workplace accessibility status within the considered time period. The research referenced the dominant components changing accessibility at each considered time period/trip type. Finally, the study inspected the difference in using three most used travel impedances while evaluating the change in accessibility.

The research proposed an integrated model that utilizes both GIS and RS to acquire the required data, calculating the accessibility indices and analyzing the findings. First, the research acquired the LCLU component effectively utilizing a RS-GIS framework. The methodology enhanced the accuracy of implemented supervised classification by manual post-processing of the images. The results illustrated the areal variation between the analyzed years. Later on, the resulted thematic LCLU were converted to representative points of their corresponding attributes. The study evaluated related errors while changing the resolution. Using the proposed modules, the study found out that both the triangle and square gridding systems provide minimum balanced areal and CFN errors. However, at a resolution of 100×100 m^2, the square maintained significantly lower areal errors for the evaluated study area. This resolution represented enough details for authorities to inspect the neighborhood/ block level within urban areas.

Later studies were classified, mainly, into two groups based on the considered impedance measure. The first group considered travel network distance while the second group considered dynamic travel time as an impedance measure. Travel network distance was easier to implement due to the availability of the data for the considered long period of time (1987-2014). The travel time attribute was not available for the same time period, thus liming the analysis to only network distance as travel impedance. Utilizing travel network distance enabled the study to evaluate the effect of the urban change on influencing the accessibility over a long period of time (e.g. changes in LCLU and physical network growth). Using that, the study evaluated the effect of huge transport infrastructure projects such as the Istanbul Metrobus Line (IML) on changing the location-based accessibility status for the surrounding area. The research also identified the urban parameters influencing each utilized accessibility index and their spatial distribution according to the IML. The main results of that evaluation were noticed after the operation of IML, where new home locations appeared closer to IML. These locations were positively influenced by their proximity to IML more than other distributed locations. Moreover, the IML illustrated its direct influence in increasing the accessibility of all surrounding locations. Around 80% of locations with the highest increase are found surrounding the IML. 80% of these locations are surrounding IML's terminals. This was noticed for both considered travel modes of walking and cars. A number of accessibility indices were calculated, each of which focused on assessing one or more changed accessibility components. In accordance, the selected indices illustrated different spatial patterns while evaluating the change in accessibility. The main use of each index was explained for policymakers within urban areas according to the project's aim and transportation mode. Later on, the thesis evaluated the development of the road network and the interplay of homes and hospitals locations that contributed to changing the accessibility status. The growth of urbanization near hospitals increased significantly, same to the development of road networks. The construction of more local roads favored the walking mode thus increasing the considered daily accessibility index more. Increasing the potential accessibility index compels developing more collectors, arterial and higher hierarchal roads. Generally, increasing both accessibility indices compels balanced growth in both factors for effective planning.

Later studies focused on exploring the workplace location-based accessibility change using DTT as an impedance measure. For that, real-time average speed estimation of corresponding road networks was investigated. The study proposed a novel methodology to interpolate real-time traffic speed using a topological hierarchy within the NT-IDW method. The study validated its applicability by investigating the MAPE changes happening to high hierarchal roads in detail. The research also illustrated the relationship between used cut distances, the total lengths of interpolated links and MAPE. In general, implementing the proposed methodology interpolated further links, an average increase in total lengths of 6.37%, and yields less MAPE with an average decrease of 14.47%.

The following analyses utilized the calculated average speeds to generate the average travel time of the network. Within these studies, the dynamic travel time of several considered times representing several trip types was generated. The study presented a method that provided empirical evidence of workplace accessibility analysis being temporally influenced. The proposed methodology integrated both of the varying network statuses and the significance of destinations for each trip type to model the workplace accessibility in each direction (HTW trips and WTH trips). For that, the study modeled the temporal variations within a day (due to traffic conditions and weighting factors) and between two years 2010-2018 (due to transport and land use changes). The study showed the distinct patterns of change in accessibility at each considered time period for both considered indices. The study also investigated the dominant change influencing the change in accessibility spatially and temporally. The relation was found to be related to both analyzed accessibility index and trip type/time. The LCLU was considered the dominant element that contributes to increasing PA for both trips. On the other hand, both of LCLU and NW contributed to influencing the ATT change almost equally for both trips. However, the spatial dominant change patterns for the morning (HTW) and evening trips (WTH) are dissimilar. PA index is clearly enhanced by mostly modifying the LCLU, especially for WTH trips, while both elements equally contributed to altering the ATT for both trips.

Finally, the research evaluated the difference between using the impedance measures of TND, STT and DTT when evaluating the change in accessibility at high resolutions. Impedances of TND and STT represent almost identical results for all considered cases. For both impedances, while travel impedance values between origins and destinations had changed between the selected years, changes were constant during all time periods. Hence, both of these impedances could not describe further temporal changes. However, both impedances (TND and STT) were strongly spatially correlated for both trip types (HTW and WTH). Obviously, using any of them provided the same results when evaluating the change in accessibility. On the other hand, the DTT illustrated varying spatial and temporal results for all cases when compared to other impedances. Results of accessibility change were not correlated with other impedances, except for one case of PA in WTH. The PA of DTT was completely correlated with the results of both other impedances when evaluating WTH trips alone. That was referenced to the used weight factor when considering the significance of destinations. Evidently, using weight factors that have a wide range, as population data in WTH trips, diminished the significance of impedance measures. Furthermore, DTT as impedance captured more accurate results when used for evaluating the change in AVSPSE. Results of DTT were attributed to capturing the change in mobility status, which are more realistic scenarios of the change in urban movement within the day. This change was captured by modelling the dynamic average speeds which reflect the fluctuating in road capacity, traffic management and traffic volume. The research also referenced the dominant changes that affected their results. Both TND and STT were influenced by an equal effect of LCLU and NW change. Thus, there were no dominant elements that impacted accessibility change. This scenario was not realistic to identify actual reasons setting behind increasing or decreasing in accessibility status for locations at considered spatial resolution. However, DTT illustrated different dominant changes at each considered time period and index related to change in mobility.

This thesis discussed accessibility via using automobiles and to a limited extent walking mode as a transportation mode. Due to the limitation of data sources, the research could not explore accessibility via public transit mode. The public transit is considered a vital transportation mode within the multimodal transportation system found in Istanbul. Future research should integrate public transit in accessibility evaluation. The current framework could be modified to include public transit transportation mode.

Finally, this thesis provided research methodologies and technical tools to evaluate the change in accessibility at high resolutions. Utilizing that, policymakers can track their policies/plans on changing the accessibility status in required spatial and temporal details, such as considering the neighborhoods/block scales. They could easily control their targeted audience/travelers or desired urban activities. Finally, they could utilize the provided framework to suit their planning scope more dynamically, accurately and easily.

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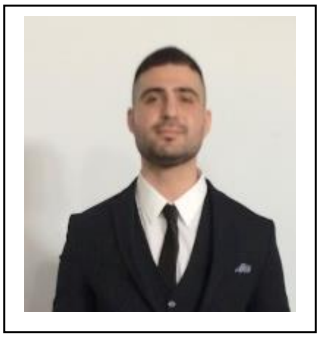
CURRICULUM VITAE



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REWARDS

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- Akın Ö., Demirel H., **Shoman W.,** Aldoğan C. and Eroğlu A. 2018: Spatial accessibility analysis for road transportation. International Conference on Traffic and Transport Engineering. September 27-28th, 2018 Belgrade, Serbia.
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