DOKUZ EYLÜL UNIVERSITY
GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES

INTELLIGENT GEOGRAPHICAL INFORMATION SYSTEM FOR CRIMINOLOGY

by
Özlem DALAN

January, 2015
İZMİR

INTELLIGENT GEOGRAPHICAL INFORMATION SYSTEM FOR CRIMINOLOGY

A Thesis Submitted to the
Graduate School of Natural and Applied Sciences of Dokuz Eylül University
In Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Geographical Information Systems

by
Özlem DALAN

January, 2015
İZMİR

Ph.D. THESIS EXAMINATION RESULT FORM

We have read the thesis entitled **"INTELLIGENT GEOGRAPHICAL INFORMATION SYSTEM FOR CRIMINOLOGY"** completed by **ÖZLEM DALAN** under supervision of **PROF.DR. VAHAP TECİM** and we certify that in our opinion it is fully adequate, in scope and in quality, as a thesis for the degree of Doctor of Philosophy.

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ACKNOWLEDGEMENTS

I am very grateful to my supervisor Professor Vahap TECİM of the Faculty of Economics and Administrative Science for his contribution, support and constructive suggestions throughout the period of my research. I would like to thank to my thesis committee members, Professor Şaban EREN of Department of Statistics in Yaşar University and Assistant Professor M. Güven KOÇAK of Department of Technical Programs in Dokuz Eylül University for their valuable suggestions and guidance during the period of my dissertation.

I intend to express my special thanks to Assistant Professor M. Güven KOÇAK for supporting me with high motivation and Assistant Professor Serkan ARAS of the Faculty of Economics and Administrative Science in Dokuz Eylül University for sharing his extensive knowledge about the area of expertise.

I also want to thank to members of Izmir Police Department for their co-operation and support of this research, besides providing data.

I would like to give biggest thanks to my dearest husband Ömür D. DALAN for his never ending support and encouragement and my beautiful family Fatih YAVUZ, Nermin YAVUZ, Ayferi DALAN for gaining insight according to this study.

I am very grateful to Phoebe WILES YAZIR and Esat YAZIR for their help to give their special time for proofreading of this thesis.

Finally, I would like to give many thanks to my late father Mehmet YAVUZ for releasing amazing memories to my life.

Özlem DALAN

INTELLIGENT GEOGRAPHICAL INFORMATION SYSTEM FOR CRIMINOLOGY

ABSTRACT

Many researchers have worked on understanding crime occurrences as crime prevention studies. The best practice for crime prevention is to investigate the cause of crime and to prevent it before it occurs again. Correspondingly, it can be said that crime occurrences are not distributed randomly in space and also they can be affected by various factors. Thus, if factors affecting the crime occurrences are identified, a spatial decision support system could developed for decision makers in Police Departments to make high accuracy crime prevention studies. This research aims predicting the potential risk areas of singular criminal activities before they occur according to examine the factors affecting Theft occurrences.

The research was performed on two different scale, regional and local scales, to determine which scale is suitable for predicting potential locations of future Theft incidents with various data from a wide range of data sources. Geographically weighted regression method was used to determine factors affecting Theft incidents. Despite crime can be described better at regional scale, security units which take measures of prevention activities has responsibility areas limited by neighborhood borders. Therefore, spatial prediction was performed at local scale.

Prediction was carried out in two different output set by using artificial neural networks and geographical information systems together to make spatial decision support system. One of them was estimating the actual number of Theft incidents. The other one was estimating whether a Theft committed in that location or not. Input variables which obtained from geographically weighted regression results were used in the structure of artificial neural networks.

At the end of the process, predicted Theft incidents were explained target values with the accuracy of 32.6 percent better than regression methods. As a result, prediction algorithm was performed 91 percent successfully while predicting whether a Theft committed in that location or not.

Keywords: Geographical information systems, artificial neural networks, theft incidents, decision support, prediction

SUÇ BİLİMİ İÇİN AKILLI COĞRAFİ BİLGİ SİSTEMLERİ

ÖZ

Birçok araştırmacı, suç önleme çalışmaları kapsamında suçların oluşumlarını anlamak üzerine çalışmalar yürütmüştür. Suç önleme kapsamında gerçekleştirilen en iyi uygulama suçun oluşma nedenini araştırmak ve tekrar meydana gelmeden önce oluşmasını önlemektir. Bu bağlamda, suç oluşumlarının mekanda rastgele dağılmadığı çeşitli faktörler tarafından etkilenerek oluştuğu söylenebilir. Böylece, suçun oluşumunda etkili olan faktörler tespit edilirse Emniyet Müdürlükleri'nde görev alan karar vericilerin yüksek doğruluklu suç önleme çalışmaları yapabilmeleri için mekansal karar destek sistemi geliştirilebilir. Bu çalışma ile hırsızlık suçlarının oluşumuna etki eden faktörler belirlenerek tekil suç faaliyetleri oluşmadan önce potansiyel risk alanlarının belirlenmesi amaçlanmaktadır.

Araştırma, farklı veri kaynaklarından elde edilen çeşitli veriler kullanılarak gelecekte oluşabilcek hırsızlık suçlarının potansiyel lokasyonlarının tahminlemesine uygun çalışma ölçeğinin belirlenebilmesi için bölgesel ve yerel olmak üzere iki farklı çalışma ölçeğinde yürütülmüştür. Hırsızlık suçuna etki eden faktörler coğrafi olarak ağırlıklandırılmış regresyon metodu kullanılarak belirlenmiştir. Buna göre suçlar bölgesel ölçekte daha iyi açıklanabilmektedir. Ancak suç faaliyetlerine karşı önlemler alan güvenlik birimlerinin sorumluluk alanları mahalle sınırlarına göre belirlenmiştir. Buna göre, gelecekte oluşabilecek hırsızlık suçlarının tahminlenmesi çalışmaları da yerel ölçekte yürütülmüştür.

Tahminleme çalışmaları gerçekleştirilirken mekansal karar destek sistemi sağlayabilmek için yapay sinir ağları ve coğrafi bilgi sistemleri birlikte kullanılmıştır. Tahminleme sonuçları iki farklı çıktı setinden oluşmaktadır. Bunlardan bir tanesi, hırsızlık sayılarının tahminlenmesidir. Diğeri ise tahminlemenin gerçekleştirildiği alanda hırsızlık suçunun oluşup oluşmama durumunun tahminlenmesidir. coğrafi olarak ağırlıklandırılmış regresyon sonuçlarından elde edilen değişkenler yapay sinir ağı yapısında girdi veri seti olarak kullanılmıştır.

Tahminleme işleminin sonunda, tahminlenen hırsızlık sayılarının hedeflenen değerleri regresyon modeline göre yüzde 32,6 daha iyi açıkladığı görülmüştür. Sonuç olarak, hırsıszlık suçlarının tahminlenen lokasyonda gerçekleşip gerçekleşmeyeceği yüzde 91 oranında başarı ile tahminlenmiştir.

Anahtar kelimeler: Coğrafi bilgi sistemleri, yapay sinir ağları, hırsızlık olayları, karar destek, tahminleme

CONTENTS

Page

Ph.D. THESIS EXAMINATION RESULT FORM ii
ACKNOWLEDGEMENTS iii
ABSTRACT iv
ÖZ vi
LIST OF FIGURES xi
LIST OF TABLES xiii

CHAPTER ONE - INTRODUCTION 1

1.1 Problem Definition 1
1.2 Research Question 3
1.3 Goals 4
1.4 Scope of the Research...5

CHAPTER TWO - LITERATURE REVIEW 7

2.1 Spatial Decision Support System (SDSS) 7
2.2 Crime Prevention Studies 9
2.2.1 Crime Prevention Studies via World Wide Web 9
2.2.2 Geographic Profiling 20
2.2.3 Ecology of Crime 24
2.2.4 Prospective Prediction Studies...30
2.2.4.1 Basics of Prediction Studies 32
2.2.4.2 Crime Estimation Studies..34

CHAPTER THREE - RESEARCH DESIGN...38

3.1 The Reason for the Selection of Theft Crime 38

3.2 The Reason for the Selection of Spatial Prediction..39
3.3 Data..39
3.3.1 Crime Data..41
3.3.2 Facility Data..42
3.3.3 Meteorology Data 44
3.3.4 Social Data..45
3.4 Methodology 45
3.4.1 Framework of the Research 47
3.4.2 Organization of Data 53
3.4.2.1 Positioning..53
3.4.2.2 Inverse Distance Weighted Interpolation Method...........................54
3.4.2.3 Computing Number of Households...58
3.4.2.4 Measuring Distance 60
3.4.2.5 Geographically Weighted Regression Analysis 61
3.4.2.6 Artificial Neural Networks...62
3.4.3 System Design 65

CHAPTER FOUR - ANALYSIS...67

4.1 Spatial Visualization of Crime Incidents 68
4.2 Temporal Analysis of Theft Incidents 71
4.3 Exploring Factors on Affecting Theft Incidents 80
4.4 Spatial Prediction 88
4.4.1 Prediction of Actual Number of Theft Incidents 88
4.4.2 Prediction of Theft Occurrences in a Neighborhood Boundary 96

CHAPTER FIVE - CONCLUSION AND DISCUSSION 102

5.1 Research Limitations 103
5.2 Research Results...104
5.3 Further Studies 110

REFERENCES 112

APPENDICES...122

LIST OF FIGURES

Page

Figure 1.1 Prediction of probable locations of future crime events according to current crime incidents in similar conditions 5
Figure 2.1 A conceptual model of a geographical system used in decision making 8
Figure 2.2 Athens crime map 11
Figure 2.3 Los Angeles crime map 11
Figure 2.4 Chicago crime map 12
Figure 2.5 San Francisco crime map 13
Figure 2.6 Crime map of Crime Reports...13
Figure 2.7 Crime map of British train and stations 14
Figure 2.8 Crime map of Crime Mapping...15
Figure 2.9 Vermont crime map 16
Figure 2.10 London crime map 17
Figure 2.11 Trulia crime map..18
Figure 2.12 Oakland crime map 18
Figure 2.13 Global scale of determining probable location of the criminal 21
Figure 2.14 Predicted probable location of the Osama bin Laden 22
Figure 2.15 Border of the research area..23
Figure 2.16 Concentric zone model..25
Figure 2.17 Graph theory 33
Figure 2.18 Dynamic route detection..33
Figure 2.19 Game of life theory 35
Figure 3.1 Study Area 40
Figure 3.2 Spatial decision support system schema 46
Figure 3.3 Methodology of the research 49
Figure 3.4 Grid size selection...50
Figure 3.5 Data editing for spatial support system...52
Figure 3.6 The interpolation method applied to temperature data 56

Figure 3.7 The model which developed to assign meteorology data to center points of grid cells 57
Figure 3.8 Part of the vector map showing the residential areas and building footprints 59
Figure 3.9 Common structure of ANN 63
Figure 3.10 System design 66
Figure 4.1 Spatial visualization of crime incidents between days in 1-31 August with the year of 2009 69
Figure 4.2 The information table of a crime incident 70
Figure 4.3 Graph of the distribution of different types of crime events in a district ..71
Figure 4.4 The analysis of Theft incidents by the times of the day 72
Figure 4.5 The analysis of Theft incidents by the days of the week 73
Figure 4.6 The analysis of Theft incidents by the time intervals of the day 74
Figure 4.7 The analysis of Theft incidents by the time intervals yearly 75
Figure 4.8 The output map of GWR method applied on Theft incidents at morning 84
Figure 4.9 Responsibility areas of security units 86
Figure 4.10 The output map of GWR method applied on Theft incidents with the limitation of neighborhood boundaries 87
Figure 4.11 Architecture of Levenberg-Marquardt algorithm 89
Figure 4.12 Regression and performance results of selected prediction algorithm....92
Figure 4.13 Map of standard deviations 93
Figure 4.14 Map of target and output sets of the study 94
Figure 4.15 Architecture of Scaled Conjugate Gradient backpropagation algorithm 96
Figure 4.16 Graphs of learning algorithm 99
Figure 4.17 Distribution of standard deviations of differences between current Theft existence and predicted Theft existence 100
Figure 4.18 Distribution of current and predicted Theft existence 101
Figure 5.1 Risk map 107
Figure 5.2 Density map of risky areas of future Theft events 108
Figure 5.3 Density map of risky areas with current Theft locations 109

LIST OF TABLES

Page

Table 2.1 Comparison of features of web based crime maps 19
Table 2.2 Physical structure extraction in order to characteristics of the criminal 21
Table 2.3 Table of methods applied to understand crime occurrences according to literature 29
Table 2.4 Table of variables found as affected on crime according to literature 30
Table 3.1 Facility categories 43
Table 3.2 Meteorological data types 44
Table 3.3 Demographic data 45
Table 3.4 Steps which were used in spatial support system 51
Table 3.5 Threshold values of residential buildings 59
Table 4.1 The result of linear regression analysis applied on Theft incidents with time intervals 77
Table 4.2 The result of linear regression analysis applied on Theft incidents with both time intervals and days of the week 79
Table 4.3 Descriptive statistics of explanatory variables 82
Table 4.4 Relationship between crime events and explanatory variables at regional and local scale 85
Table 4.5 Error results of validation set for different hidden layer sizes 90
Table 4.6 Results for different weights of hidden layer size 17 91
Table 4.7 Results of linear regression and ANN 95
Table 4.8 Experiment results of validation set for different number of hidden neurons 97

CHAPTER ONE
INTRODUCTION

1.1 Problem Definition

Crime is a global event which has existed from the early days of human civilization. It can be explained as the result of difference between the behaviors of the member and the society (Dönmezer, 1994). General Police Department of Anti-Smuggling and Organized Crime [GPD-ASOC] (2011) states that due to limited resources and unblocked distribution of it, crime will continue to happen as long as people live with their ambitions. Many researchers have worked on understanding crime occurrences as a disadvantage of living in a society (Yavuz & Tecim, 2013). Crime prevention studies are also one of these researches. The best practice for crime prevention is to investigate the cause of crime and to prevent it before it occurs again. For this reason, many researches have been made to understand the reasons of crime since 20th century.

Density maps were rendered by using the current locations of previous crime incidents. According to this kind of pin maps represented by Shaw and McKay at Chicago School in 1930s, it was deduced that the locations of crime incidents have vital importance to understanding the reasons for crime occurrences (Chainey & Ratcliffe, 2005). Correspondingly, it can be said that crime occurrences are not distributed randomly in space (Brantingham & Brantingham, 1997; Alpdemir & Çabuk, 2005) and also they can be affected by various factors.

Thus, crime mapping methods are not effective by themselves. It is important to investigate the factors which affect crime occurrences geographically (Yavuz & Tecim, 2011). In this context, urban geographers began to perform studies named crime ecology to examine the relationship between crime and land use, environmental structures, facility areas and so on (Olligschlaeger, 1997).

More than paper maps are needed to follow incidents which changes location in hours or minutes. Geographical Information Systems (GIS) developed in 1960s were able to store, analyze and visualize related spatial and attribute data (Longley, Goodchild, Maguire, & Rhind, 2001; Tecim, 2008). Also this technology associates locations with different data sets obtained from different sources (Taylor & Blewitt, 2006, p.7) and is able to extract information from dense data (Thurston, 2002). With these features GIS has come into use in crime prevention.

"Use of these very expansive computer systems on crime prevention" (Chainey & Ratcliffe, 2005, p.8) were possible in 1997, just after the decrease in costs of development of computer technologies (Longley et al., 2001). In addition to this, GIS is used as a spatial database management system (Taylor & Blewitt, 2006). For years, internet use has become a great factor in the advancement of GIS (Lake, Burggraf, Trninic & Rae, 2004). This enables crime data to be shared over World Wide Web (www). Thus, spatial decision techniques which are part of usual activity for people and organizations are used in crime prevention (Jankowski & Nyerges, 2001). For example; when choosing schools for children, residential locations, or a hotel, it is necessary to make a decision that results in a lower crime rate than the others. Police Departments who want to prevent future crime by using recent incidents have to make spatial decisions. To achieve this, it is necessary to estimate future crime incident locations. Literature review on this subject shows that Artificial Intelligence (AI) techniques have successful results in predicting future crime locations. In 1990s Artificial Neural Networks (ANN), a sub technique of AI, and GIS were used together in crime prevention researches with up to 70% success in predicting future crime locations (Olligschlaeger, 1997). It is known that ANN had only been successful when used on serial crime up to now. However, the number of unrelated crime incidents is much higher than that of serial crimes. According to these, the aim of this dissertation is to use both GIS techniques, which have begun to be used recently in our country, and ANN techniques on singular crime incidents to create a framework for Police Departments to be used for crime prevention.

1.2 Research Question

To predict a crime location, the factors which affect crime occurrence must be known. A number of researchers are focused on demographic, social, cultural, economic and environmental factors, one by one or with multiple correlations. After recognizing the significance of geographic location on understanding crime occurrences, this spatial factor is also added to researches. The results expose how different factors effect crime occurrences in every divergent studies. Due to the fact that investigating these factors on different dates and different locations, it has been found that the factors that were identified as factors that affected a crime occurrence in one research area do not affected a crime at another research area (Yavuz & Tecim, 2013). In this way, reasons for crime are changed from country to country, region to region and culture to culture according to the social and economic structure of the region (Aksoy, 2004).

Researchers have used data to explain crime limited by their study areas, so inferences are limited to those areas. This limitation explaining the crime incidents in the research area is an important consequence of the Modifiable Areal Unit Problem (MAUP). The use of different areal units may influence the results of ecology of crime studies (Openshaw, 1984). To our knowledge, no study attempts to make inferences on a whole study area by changing the scale and thus changing the significance of explanatory variables (Yavuz & Tecim, 2013). This dissertation wants to answer following research questions to predict crime with high accuracy:

- How to determine locations for crime prevention decision makers (DMs) of Police Departments to use without any areal limitations ?
- What is the systematic path for it ?
- What techniques are necessary to use in addition to GIS for achieving this purpose ?

1.3 Goals

From the point of the proverb “A picture is worth a thousand words”, which Harries (1999) expressed the truth of this phrase before, the results of this dissertation are visualized as GIS maps with the help of statistical reports. In this way, GIS maps would support managers who are the target group of this dissertation more efficiently in making spatial crime prevention decisions.

In this context, the goal of this research is to predict the potential risk areas of future crime incidents before they occur. The prediction is built by examining the factors that affect the crime occurrences with respect to previous research findings with using GIS techniques (Figure 1.1). By developing a system to predict future crime incidents geographically, a Spatial Decision Support System (SDSS) is to be composed. With this system, DMs in Police Departments are able to make highly accurate crime prevention studies.

This research depends on predicting non-serial crime incidents. Thus, the research does not show any similarity to previous studies reviewed in literature. In addition, this study is particularly important to transform a well designed GIS technologies into a SDSS.

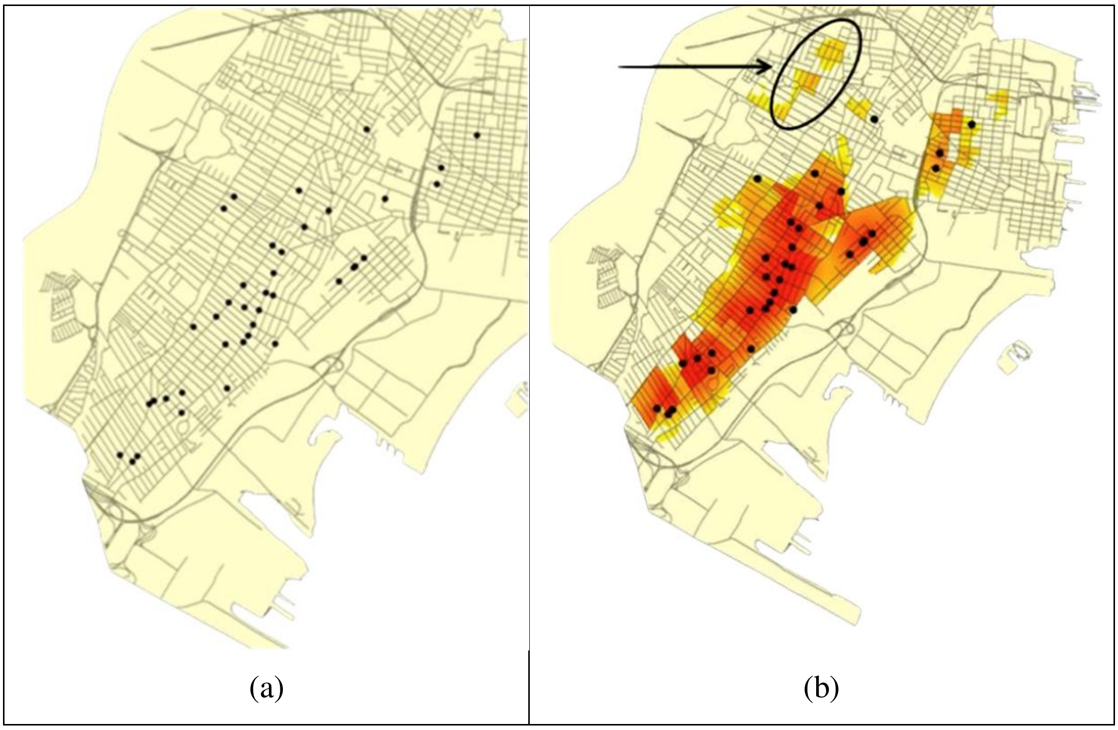


Figure 1.1 Prediction of probable locations of future crime events according to current crime incidents in similar conditions a) current crime locations b) density map of potential risk areas of future crime events

1.4 Scope of the Research

Studies which are made to simplify spatial decision making, encounters lots of spatial problems defined as “difficult” (Rittel & Webber, 1973, p. 161). Supporting a spatial decision needs data from very different sources. Using this kind of distributed data from various data sources in an information system needs the ability to supply intelligence decision making capabilities. Only a limited number of information systems has this feature. For this reason, it is important to have GIS which can learn from dynamically changing data and can represent a predicted visual map of its results.

Literature review starts with the studies for preventing crime up until today. The focused subject is to respond to this question: Which methods should be used with GIS to reduce non-serial crime incidents? In this context, GIS is approached as a database management system and a visualization tool. The ANN technique is approached as a tool that teaches computers to learn data from factors of crime and that try to predict future crime locations.

This dissertation is going to end with the selection of an optimum technique and an example implementation. In short terms GIS, statistics, spatial statistics and AI form the scope of this study.

CHAPTER TWO
LITERATURE REVIEW

2.1 Spatial Decision Support System (SDSS)

SDSS is developed based on Decision Support System (DSS) with using spatial data and spatial data analysis techniques. DSS had been developed in management science since late 1970s (Turban, 1995). “DSS is an information system ‘application’, with characteristics that make it significantly different from a typical data processing application. It is the hardware/software that allows a specific or group of decision maker/s to deal with a set of related problems” (Sprague, 1980, p. 6).

DSS also can be described as interactive computer-based decision making system to support DMs to solve semi-structured or unstructured problems. “Beginning at 1980s many activities with building and studying DSS had occurred in universities and organizations that resulted in expanding the scope of DSS applications” (Yavuz, 2008, p. 43).

After new technology which is GIS, came through as an geographical tool and software since 1980s, it causes development of SDSS since 1985 (Flacke, 2012). “The benefits of using GIS based systems for decision making are increasingly recognized” (Keenan, 1996, p. 36).

“Many types of decision making have geographic (spatial) components, because the choice of ‘where’ is an important part of deciding ‘how’” (Yavuz, 2008, p. 43). “GIS not only provide users with an array of tools for managing and linking attribute and spatial data, but they also provide users with advanced modeling functions, tools for design and planning, conceptual and logical approach and advanced imaging capabilities” (Das & Choudhury, 2014, p. 002).

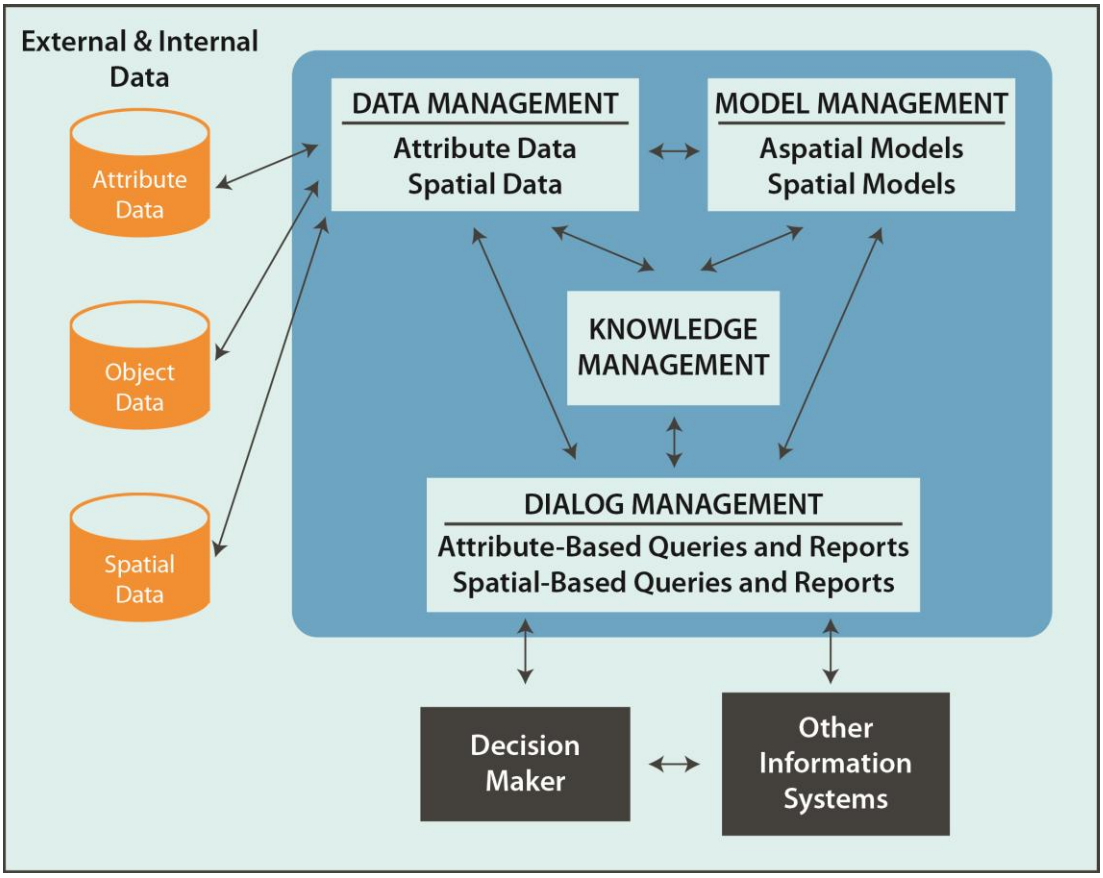


Figure 2.1 A conceptual model of a geographical system used in decision making (Das & Choudhury, 2014)

According to Das and Choudhury (2014) a DSS includes model management, knowledge management and dialog management subsystems. Integrating DSS with GIS which has similar subsystems in a spatial manner, a new system called SDSS is formed as shown in Figure 2.1.

DSS is designed to support a user or a group of users to achieve a higher effectiveness of decision making while solving a semi-structured or unstructured decision problem (Flacke, 2012). “Spatially enabled decision support technologies such as GIS are available and can be used by decision makers to capitalize on the wealth of information that is present in spatial data” (Das & Choudhury, 2014, p. 001). GIS can be seen as an increasingly important technology for DMs (Keenan, 2008). Thus, SDSS produces spatial feedback to DMs easily.

"There is no universally accepted model of the decision making process" (Sprague, 1980, p. 13). In generally three main steps are defined as decision process model (Simon, 1960). First step is begun with identifying problems named as *intelligence*, second step include more than one courses which involves processes to understand the problem, implement solutions, analyze and test the solutions named as *design*. The final step named *choice*, includes the selection of a particular course of action (Sprague, 1980; Flacke, 2012).

According to these steps, SDSS is performed with using variety of spatial modeling and spatial or non-spatial statistical computation in this thesis. Spatial data availability, transformation and integration capabilities are bewared to make well-designed SDSS.

2.2 Crime Prevention Studies

Main purpose of literature review is to have an idea from studies up until today, to have information about spatial precautions for crime prevention and to know the utility of these successful or unsuccessful progresses with their propositions for future studies.

In this manner, crime prevention studies were investigated which studies implemented via world wide web, geographical profiling, ecology of crime and prospective prediction studies.

2.2.1 Crime Prevention Studies via World Wide Web

Crime prevention is carried out activities by an individual or group, public or private to eliminate criminal behavior which are being performed before it occurred (Brantingham & Faust, 1976).

Researchers get more useful results from crime prevention studies with the use of developing technologies. Just after 1990s, GIS had begun to use for crime prevention studies. These studies include spatial analysis of crime and criminal activities, determining the factors of crime and publishing crime maps over internet for public consciousness.

Crime maps which published over internet serve three different purposes which can be categorized as following:

- Publishing information for public use to present only data and statistics
- Publishing approximate crime locations on a map
- Publishing information for consumers about their neighborhood

Crime maps are published by U.S.A. at first, then England and Greece for general public consciousness. These are web based maps with crime data which belongs to their whole country. By this tool, people can explore an address of their choice and crime types to get information about occurrence of the selected crime type and time intervals.

Greece Crime Map

Crime map which prepared for city Athens uses Google maps (https://www.google.com/maps) for its base map. Crimes occurred in the city is categorized by Assault, Gunfire, Theft, Robbery and Snatching. Athens Crime Map has limited information for public use but it has date and address information at least. This map has some common internet experience opportunities which Google map service presents as seen in Figure 2.2.

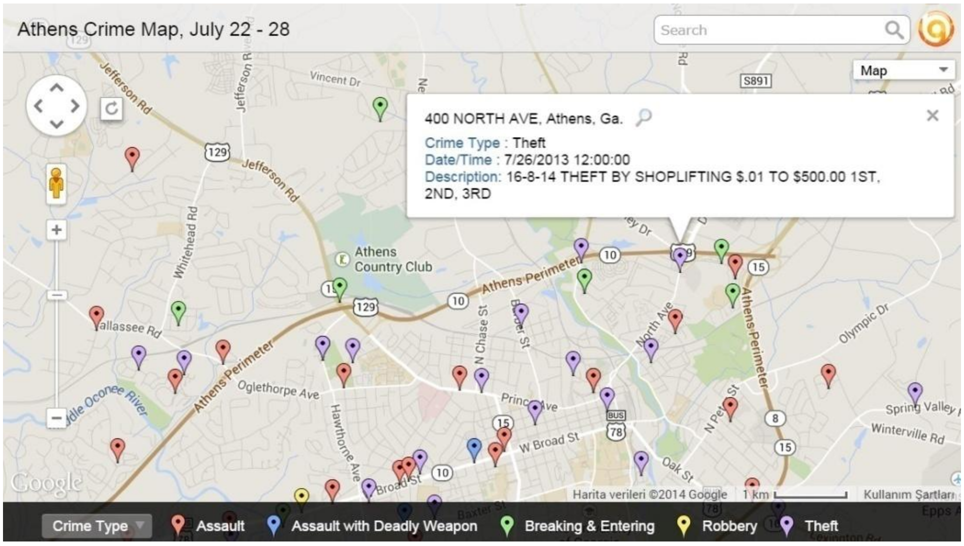


Figure 2.2 Athens crime map (Red & Black, nd)

Los Angeles Crime Map

Los Angeles has a crime map which uses Open Street Map (http://www.openstreetmap.org) project as its base map. Crimes are categorized in two types which are Assault and Crime Against Property. They also have some sub categories like Robbery, Motor Vehicle Theft, Theft from Motor Vehicle, Snatching, Assault, Sexual Crime and Homicide. This map has less information than Greece Crime Map. As seen on Figure 2.3, crimes are grouped by monthly. According to this feature, it is possible to track the increase or decrease of rate in different time periods.

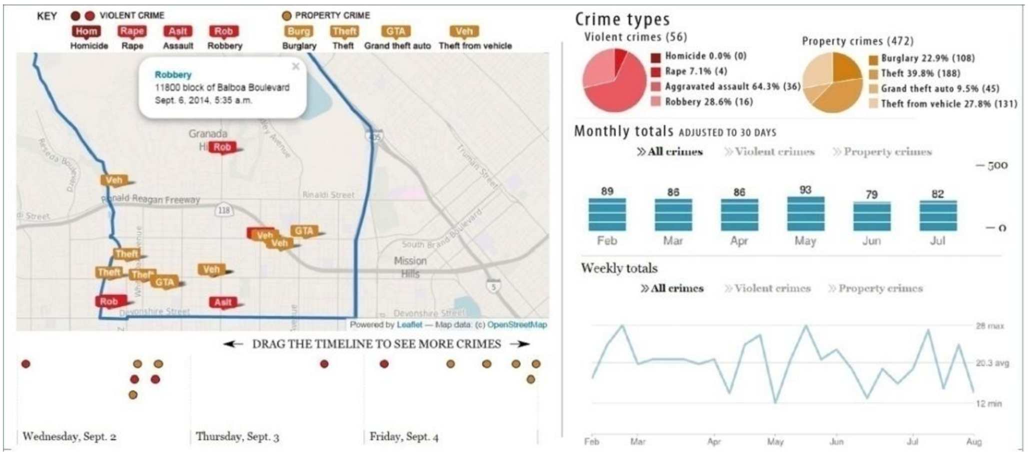


Figure 2.3 Los Angeles crime map (L. A. Times, nd)

Chicago Crime Map

The online map which is prepared for Chicago uses a custom base map. It has crime types as Theft, Theft of Motor Vehicle, Theft from Motor Vehicle, Snatching, Sexual Crime, Homicide and more. Crime classification of Chicago Crime Map is very detailed. Detail level of information which presented to public use is same as Greece crime map and can be seen in Figure 2.4. Additionally, detailed query can be build on address, zip code, area and nearest known point. Results are represented as point and point clouds according to zoom level to the map.

Figure 2.4 Chicago crime map (Chicago Police, nd)

San Francisco Crime Map

Base map which is used for San Francisco is optional. Visitors of the site is able to select one from Bing, Google or ESRI Free base map layers. Crimes occurred in the city are categorized as Robbery, Theft of Motor Vehicle, Theft from Motor Vehicle, Snatching, Assault, Sexual Crime, Homicide, Arson, Narcotic and Vandalism. Visualization of San Francisco Crime Map is shown in Figure 2.5. Map has ability to search crimes with a query on a known location, point or address. Results can be shown as points, thematic polygons, tables or even in charts. In addition to these, crime data can be exported in .csv, .json, .pdf, .rss, .xls, xlsx and .xml formats.

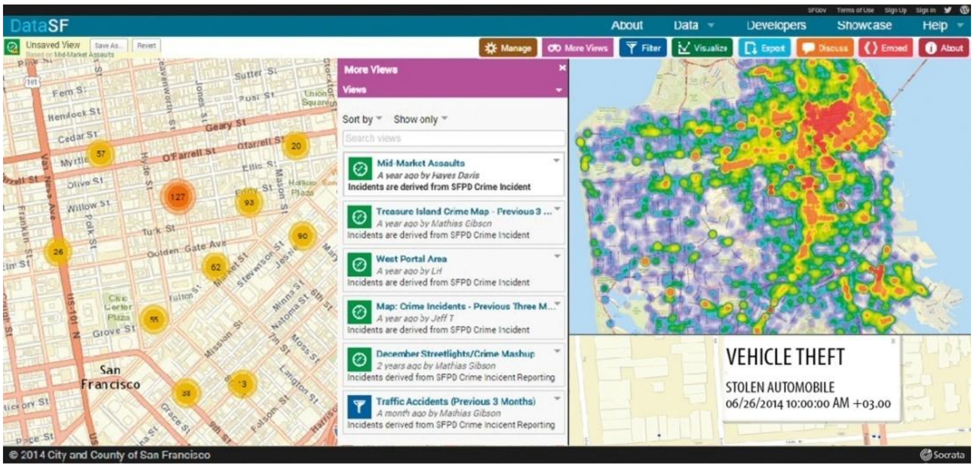


Figure 2.5 San Francisco crime map (San Francisco data, nd)

Crime Reports

This is a crime map service that includes all U.S.A. states and Canada. It uses Google Maps service as a base map layer. It has Robbery, Theft of Motor Vehicle, Theft from Motor Vehicle, Snatching, Assault, Sexual Crime, Homicide, Traffic Crime, Fire Raising, Abduction and more as crime categories. Visualization of the map is shown in Figure 2.6. There is more different functions in this crime map than others explained earlier in text. This one can show crime incident updates on display as a notification in weekly or monthly period reports if they set before or even can send emails to user about updates.

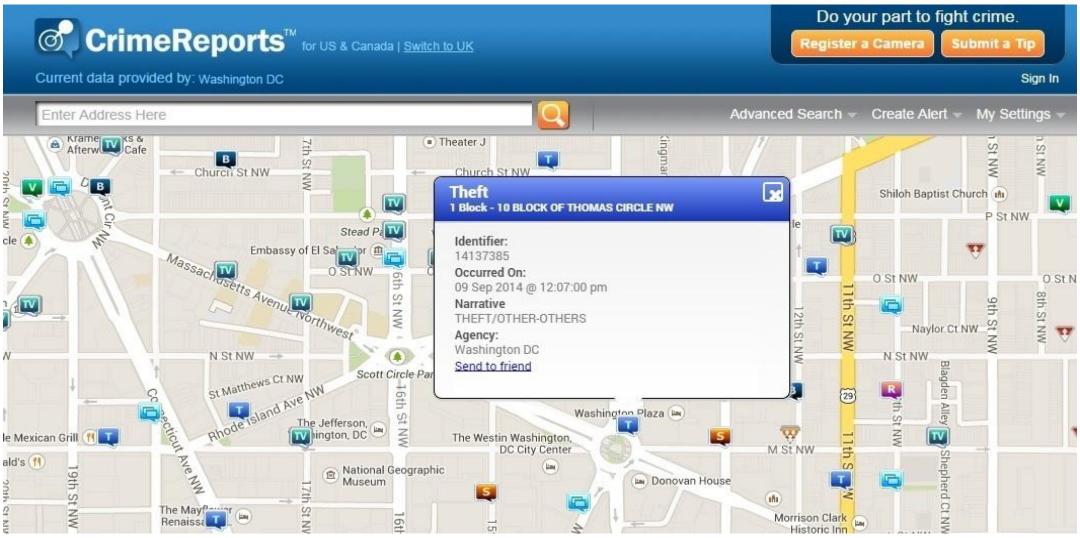


Figure 2.6 Crime map of Crime Reports (Crime reports, nd)

Crime Map of British Transport Police

British Transport Police Crime Map is interested in crimes occurred inside the border of England and occurred in trains and train stations. A custom map prepared by the organization is used as a base map layer. Crimes occurred in British trains and train stations are categorized as Theft, Theft of Motor Vehicle, Assault and Anti-Social Crimes. Crime map is visualized as shown in Figure 2.7. Crime rates are shown on graphs according to selected station.

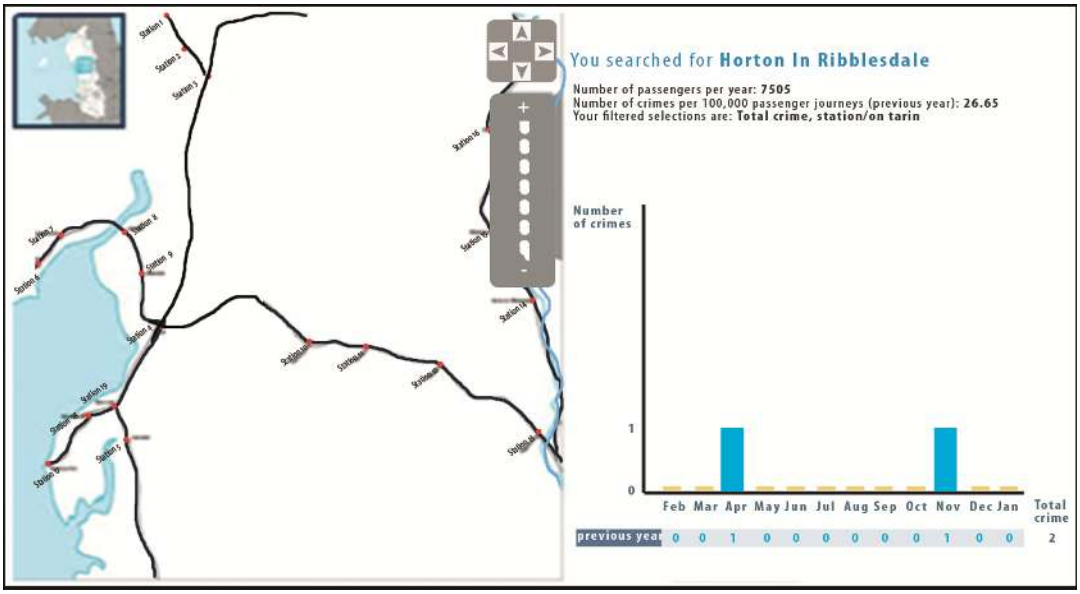


Figure 2.7 Crime map of British train and stations (British Transport Police, nd)

Crime Mapping

Crimes occurred in U.S.A. are located on the map. Map layer which is prepared by ESRI is used as a base map. Crime incidents can be analyzed by selected address or radius of a location point. Map can report location information and also can report some statistical information about the selected crime. Users can print the map with its statistics as shown in Figure 2.8.

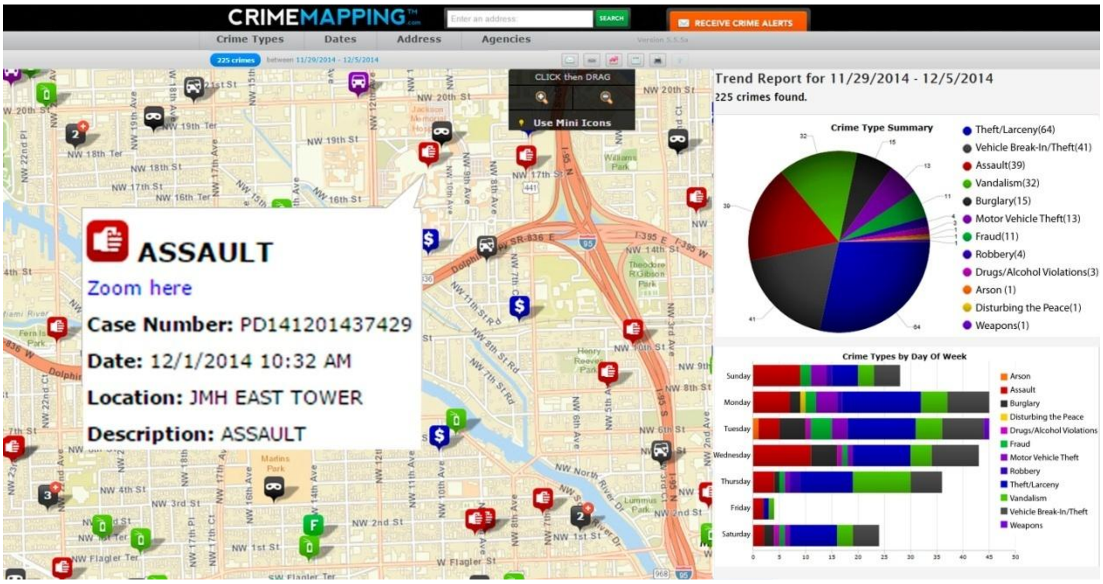


Figure 2.8 Crime map of Crime Mapping (Crime mapping, nd)

Spot Crime Map of Vermont

In this map, crime incidents are located on a interactive map with using Google Maps base layer. Crimes in Vermont are categorized as Crime against person, Crime against property, Social crimes and Missing. But none of these categories has sub-categories. Crimes are presented as points on the map. Layer properties can be switched as shown in Figure 2.9. Selected points details are shown in tables.

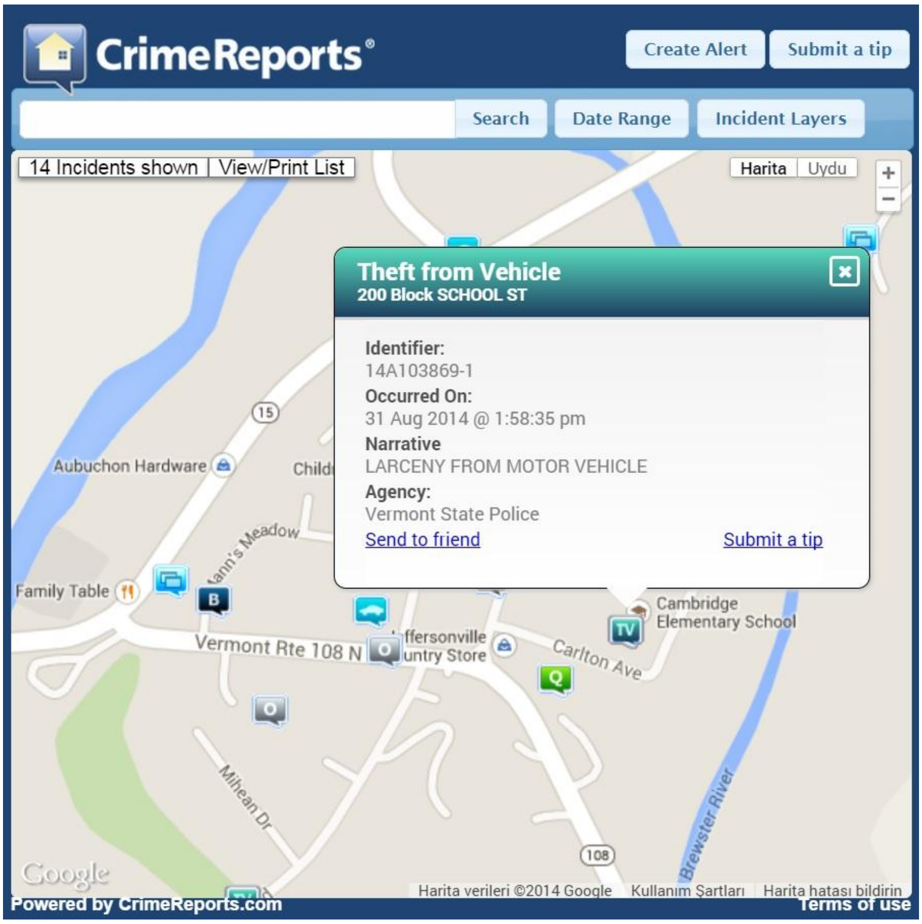


Figure 2.9 Vermont crime map (Vermont crime reports, nd)

London Crime Map

With a use of Open Street Maps, London Crime Map shows crime incidents which were occurred in metropolitan area of London in Figure 2.10. Crimes are categorized as Robbery, Theft from Motor Vehicle, Theft of Motor Vehicle, Snatching, Assault, Anti-social crimes. Users can refine their search by selecting an area, by defining a point and a radius, or by a polygonal drawing. Data is shown in bubble groups, when users are at top zoom level. When users zoom in to the map, bubble sizes would be change. Also this map has functionality of searching by dates.

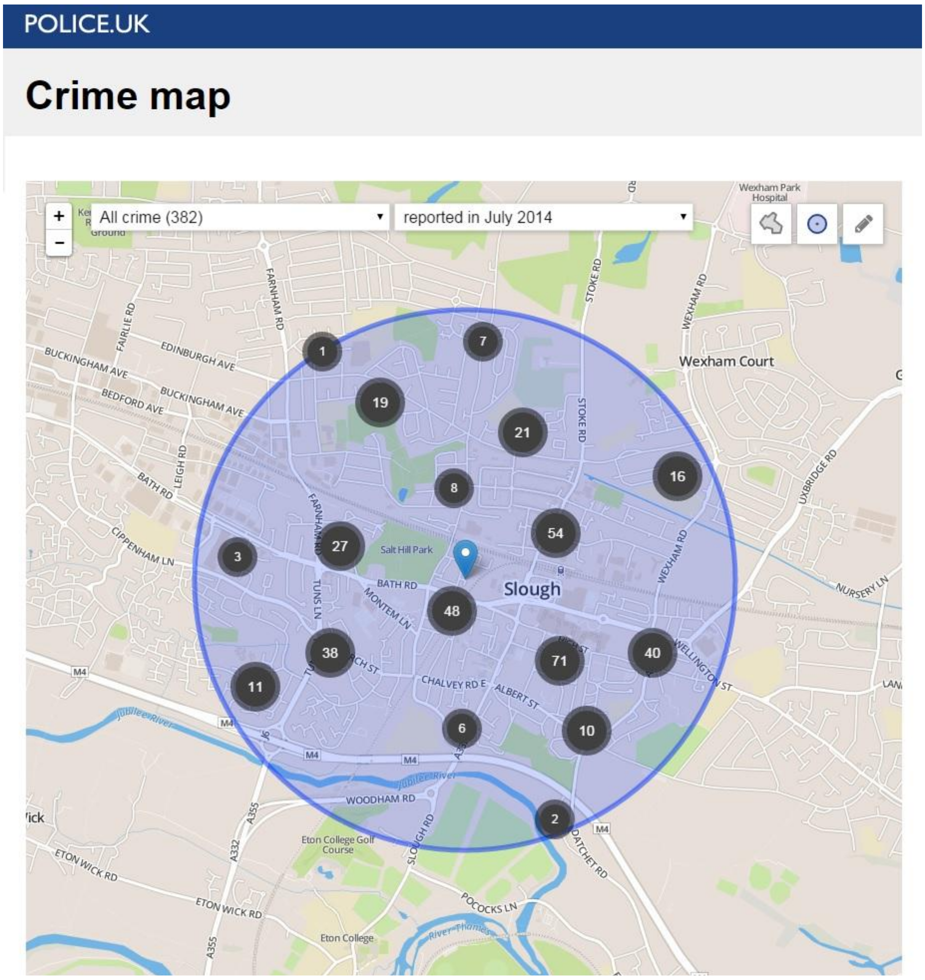


Figure 2.10 London crime map (London Police, nd)

Trulia Crime Map

Crimes occurred in U.S.A. are located on a map with a base layer of Google Maps. Users can define address, postcode or an area on the map and search the crime incidents. Thematic reports can be analyzed by using this map. Areas with high risk factors can be determined as shown in Figure 2.11.

Figure 2.11 Trulia crime map (Trulia, nd)

Oakland Crime Map

Oakland crime map has a base layer depends on Open Street Map. Crime types are categorized as Theft, Theft from Motor Vehicle, Theft of Motor Vehicle, Snatching, Assault, Vandalism, Prostitution, Alcohol and Narcotic. It has data from 2007 to 2014. View of the map is shown in Figure 2.12. Every crime incident has information about location, date, time and day of the week information.

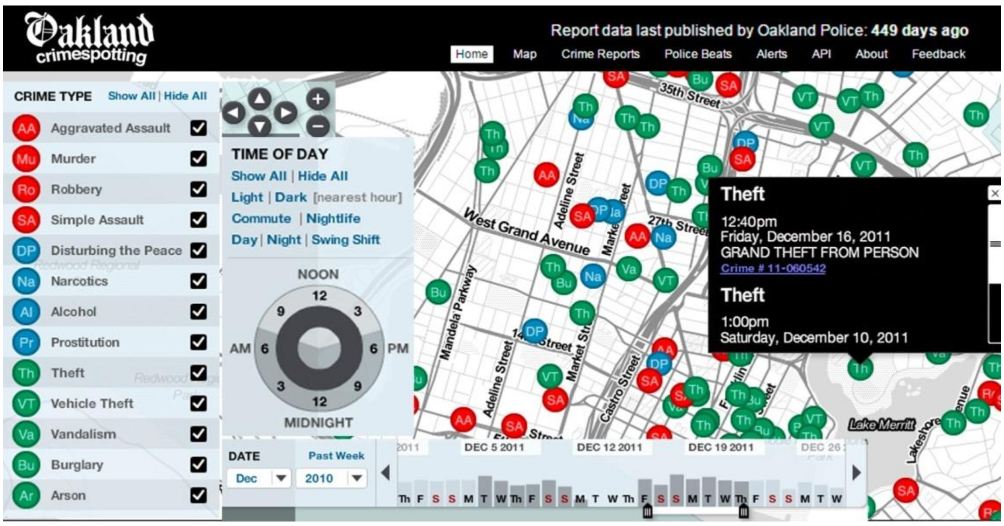


Figure 2.12 Oakland crime map (Crime spotting, nd)

Features of studied crime maps during literature review are listed in Table 2.1.

Table 2.1 Comparison of features of web based crime maps

Properties / Applications	BASE MAP					DETAILS			CRIME TYPES									SEARCH CRITERIA							DISPLAY TYPE		
	Google maps	Bing maps	ESRI maps	Open Street maps	Derived maps	Crime date	Address of crime	Distance from crime location	Vandalism	Robbery	Theft	Assault	Sexual Crime	Narcotic	Person of Interest	Homicide	Traffic	Address	Zip code	Region	Known location	Crime type	Date	Interfered unit	Spot maps	Thematic maps	Graphs
Athens	X					X	X			X	X	X										X			X		
Los Angeles				X		X	X			X	X	X	X			X				X			X		X		X
Chicago					X	X	X			X	X	X	X			X		X	X	X	X				X	X	
San Francisco	X	X	X			X	X		X	X	X	X	X	X		X	X	X		X	X				X	X	
Crime Reports	X					X	X		X	X	X	X	X		X		X	X	X		X	X	X		X		
British Transport Police					X		X					X									X				X		X
Crime Mapping			X			X	X	X	X	X	X	X	X	X		X		X	X	X	X	X	X	X	X		X
Vermont	X					X			X	X	X	X	X	X		X	X	X		X	X				X		
London				X		X				X	X	X		X				X		X		X	X		X		
Trulia	X					X				X	X	X						X	X					X	X	X	
Oakland				X		X	X			X		X	X	X						X	X	X	X		X		

According to Table 2.1, web based crime maps are usually categorized by Theft, Assault, Robbery and Sexual Crime types. As a base map, Google maps are mostly used and Open Street maps are secondarily most used map. Detailed information contains crime date and address almost in every applications. Crimes are searched by address, region and known location with the ratio of 64% in all applications.

2.2.2 Geographic Profiling

In the early 20th century, it is thought that the biological and physiological characteristics of individuals are associated with crime incidents. Geographic profiling is studied on often the perpetrators of the crimes committed in series to determine who would be and/or where it could be committed. This kind of geographic profiling studies had began with Kim D. Rossmo who developed first Commercial Geographic Profiling software. Dr. Kim Rossmo said that 85% of homicide incidents in Canada were solved by this method (Aksoy, 2004). Geographic profiling has been improved for crime prevention studies in order to achieve offender's identity or residence location according to information obtained from crime scenes.

Geographic profiling is a research methodology to determine highly probable residence of the offender with using interrelated areas of serial crime locations or physiological characteristics of suspects. This methodology works on the basis of information obtained from past examples. According to a thought, no one come from a remote distance to commit more than one crime. Thus, it is believed that offender would process series of crime in the vicinity of his/her own residential area. However, the purpose of geographic profiling is not to determine the point of offender's residence. In fact, the data obtained about crime is so simple to make an estimation possible. Research areas are identified in the risk index. Thus, places which have high risk index are defined as probable residence of the offender.

In a study, satellite imagery and GIS techniques were used to find the location of Osama bin Laden according to demands which are consist of the result of his characteristics (Gillespie, Agnew, Mariano, Mossler, Jones, Braughton & Gonzalez, 2009). In that study, researchers were tried to determine the location of Osama bin Laden from his last seen location and his personal characteristics (dialysis machine should be a place to connect, place of residence must be like the last place of residence he had before, etc.) As a result a properties table was organized as shown in Table 2.2.

Table 2.2 Physical structure extraction in order to characteristics of the criminal (Gillespie et al., 2009)

Life history characteristics	**Physical structure attribute**
Is 6'4" tall	Tall building
Requires a dialysis machine that uses electricity	Electric grid hookup or generator
Prefers physical protection	Walls over three meters high
Enjoys personal privacy	Space between structures
Retains a small number of body guards	More than three rooms
Prefers to remain protected from aerial view	Trees for cover when outside

Remote sensing data (Landsat ETM+, Shuttle Radar Topography Mission, Defense Meteorological Satellite, Quickbird) over three spatial scales (global, regional, local) were used to apply distance-decay theory to identify where bin Laden is most probably currently located as shown in Figure 2.13.

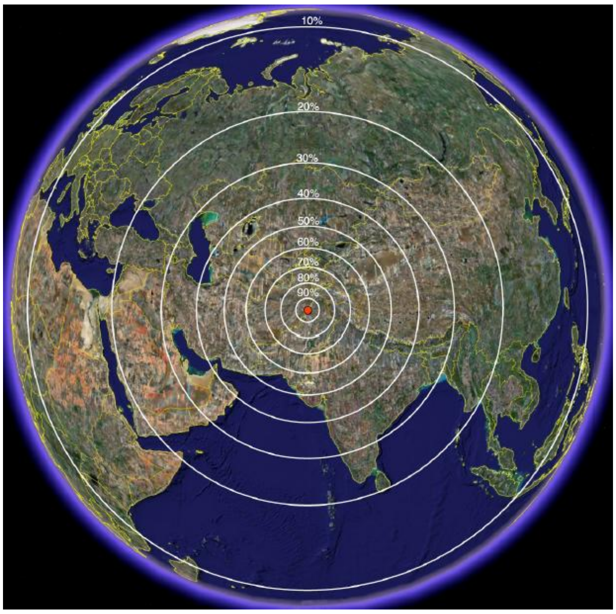
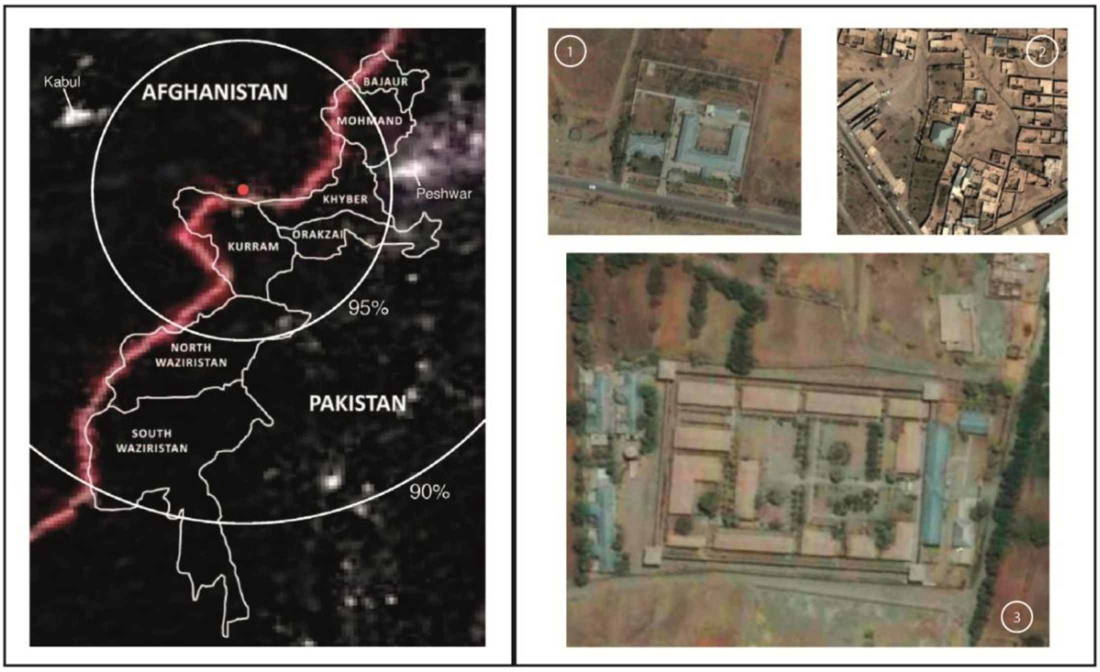


Figure 2.13 Global scale of determining probable location of the criminal (Gillespie et al., 2009)

Finally, based on life history characteristics of Osama bin Laden, three buildings were monitored that he could probably live at local scale (see Figure 2.14).



(a) (b)

Figure 2.14 Predicted probable location of the Osama bin Laden (a) Regional scale (b) Local scale (Gillespie et al., 2009)

Gorr (2004) was conducted a research to develop a systematic approach for measuring the accuracy of the geographic profiling packages or methods. Gorr was used resolved series of crimes including information about crime locations, criminal's residence and other spots that connected to the crime such as working place, the home of criminal's girl/boy friend, etc. to achieve his goal.

In this context, research area was selected which had serial crime incidents included. This area usually consists of a rectangular form. It contains rivers, cemeteries and trade areas as sub-fields. In order to determine the location of crime, past crime locations were used as data sets of crimes. The coordinate information of the offender's residence or place was intended to be determined by using information about temporal frequency of crime (number of crimes committed per day) and the coordinates of committed serial crimes.

From the fact that criminals reside close to the areas which serial crimes committed in, a rectangular area was drawn which covers both crime sites and criminal's residence with a minimum size. This was assumed as the boundary of research as shown in Figure 2.15.

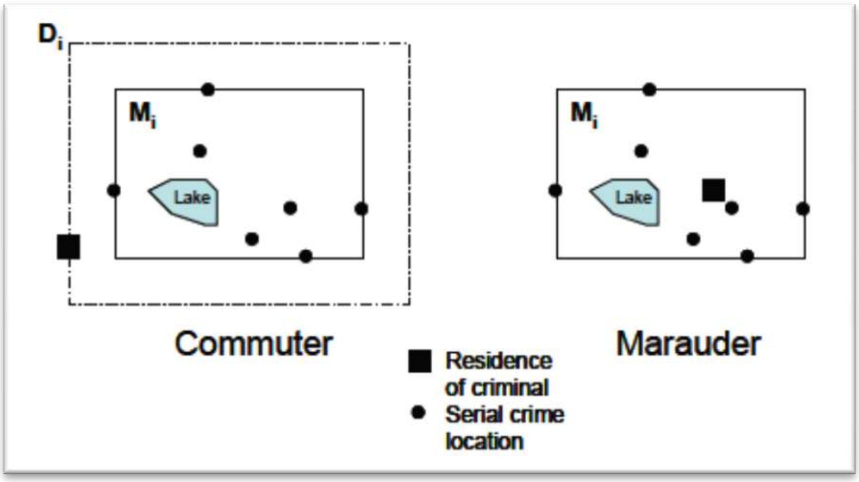


Figure 2.15 Border of the research area (Gorr, 2004)

After removal of places independent from crime such as lakes etc., criminal investigation field of remaining research area was divided in evenly spaced cells called grids. If grid size is chosen larger than optimum, researcher can move away from result determination. If it is chosen smaller than optimum, too many calculations could be needed and this causes time consuming. Because of this reason, an optimum medium grid size was chosen. Every generated grid’s risk index was calculated by distance decay method. Risk index was calculated by dividing the total study area into grids and computed risk values of each grid cell.

The point of view is that the crime could not commit neither so near nor too much away from criminal’s residence. According to this approach, distance should be a straight line (like Manhattan distance as diagonal). Then crimes had been attempted to estimate the location by drawing growing buffer zones around past crime locations. However, for the fact that criminal may not have a fixed place, a threshold value was determined for the buffer zones. In this study, threshold was chosen 30 meters. It was believed that criminal is living in the borders of study area if threshold was found below 30 meters. Otherwise residence of criminal is located far from research area. Thus, areas with the highest risk indexes indicate high probability of finding criminal. Although this method was inconclusive, it is important for criminologists that it presents a start point to find location of criminals.

Unlike the other studies, Strano (2004) was focused on determining not only the offender of serial crime activities but also the offender of singular crime activities. With this study an additional tool was developed for a crime profiling software which had begun to built in 2002 by another team which had American, British and Italian members from different disciplines. This tool was used for determining what kind of a person would be committed that crime by considering criminal field analysis, autopsy reports, forensic reports and interview of victim or witnesses rather than specific characteristics of the offender.

For this aspect, implementation is seen very similar to techniques which used by FBI at the beginning of 1980s and currently used in U.S.A. This technique is more widely used for the detection of serial murder or guilty of rape cases committed by the same person. It is thought that singular crimes can be modeled with using ANN techniques. So, characteristics of offenders, who attended a crime before, can be stored in a database to gain crime profiles with implemented tool. The purpose of this method is to define profile of the criminal who committed a new crime by comparing the psychological profile of the previous offenders recorded in database. If the style of criminal is very similar to a record in the database it is likely can be said perpetrator of the crime is found. However, if it is the first record of the criminal there will be no match from the database and perpetrator cannot be found.

2.2.3 Ecology of Crime

Crime mapping cannot be enough to provide crime prevention studies by itself. The identification and mapping of the factors is essential as well (Yavuz & Tecim, 2013). Hence, researchers were begun to study about sociological origins of criminal behaviors in 1930s and 1940s (Ergün & Yirmibeşoğlu, 2007). From this period of time, urban geographers has begun to study on ecology of crime which examines the relationships among factors affecting the crime and crime occurrence as a branch of science (Olligschlaeger, 1997).

Ecology of crime studies on factors affecting occurrence of criminal offenses can be investigated under four main headings:

- socio-economic factors
- demographic factors
- spatio-temporal factors
- geographical factors

One of the first researches which is performed with linking ecology of crime studies was held in Chicago by Shaw and McKay (1969). In their research, *ecological approach* and *concentric zone theory* were used together. According to concentric zone theory, city model was composed with central business district, transition zone, working class zone, residential zone and commuter zone as shown in Figure 2.16.

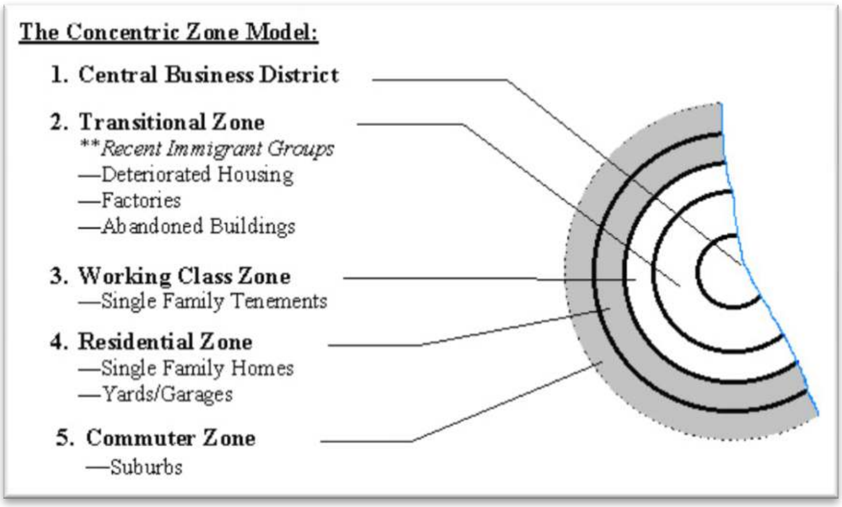


Figure 2.16 Concentric zone model (This model was transferred from the Criminal Justice Program of Calvin College)

In this study, social disorganization was explained with industrialization, urbanization and migration parameters which were described as social change by the help of zone theory. When behaviors related to the crime were examined, the areas which have poverty, mobility of housing, different cultures together like transition zone of the city have been found crime events mostly occurred in.

In later times, the study held in Chicago, was applied in different societies and countries. In developing countries, it was observed that crime and spatial distribution of crime events were closely associated with physical, social and demographic characteristics and economic structures of settlements. According to socio-economic findings of many ecology of crime researches had studied since 1960s, crimes were found highly correlated with poverty (Gorr & Olligschlaeger, 1994; Olligschlaeger, 1997; Cahill & Mulligan, 2003; Ceccato, Haining & Signoretta, 2002; Gruenewald, Freisthler, Remer, LaScala & Treno, 2006), unemployment (Schmid, 1960; Ackerman, 1998; Ceccato et al., 2002; Gruenewald et al., 2006), lower income (Schmid, 1960; Ackerman, 1998), educational levels (Schmid, 1960; Ackerman, 1998; Cahill & Mulligan, 2003; Cozens, 2002; Gruenewald et al., 2006), being a renter (Ackerman, 1998), population density (Ackerman, 1998; Cahill & Mulligan, 2003; Ceccato et al., 2002; Cozens, 2002; Malczewski & Poetz, 2005), migration (Ackerman, 1998; Ceccato et al., 2002), minority (Ackerman, 1998; Gruenewald et al., 2006), marital status (Ackerman, 1998), number of children in a family (Ackerman, 1998; Olligschlaeger, 1997; Gruenewald et al., 2006), young population (Olligschlaeger, 1997; Gruenewald et al., 2006), family structure (Cahill & Mulligan, 2003; Ceccato et al., 2002; Malczewski & Poetz, 2005) and ethnicity (Ergün & Yirmibeşoğlu, 2005; Gruenewald et al., 2006).

These socioeconomic variables change slowly over time and cannot explain short-term variations in crime rates (Yavuz & Tecim, 2013). However, daily and hourly fluctuations in crime are far more variable than year to year shifts (Cohn, 1990). In this manner, spatio-temporal variables were investigated that might also lead to an increasing number of crime. The studies, performed in 1980s, were found significant linear relationship between ambient temperature and crime (Anderson & Anderson, 1984; Cohn, 1990; Field, 1992; Salleh, Mansor, Yusoff & Nasir, 2012). According to Cohn (1990), distribution of crime rates was also linked to temporal and ecological factors like surface temperature, sunlight, rain and wind. Salleh (2012) explained that the reason of this situation by stress and discomfort among inhabitants which are induced from these factors.

Not only weather conditions but also physical environment has certain magnitude towards the level of human behavior (Cohn, 1990; Field, 1992). Some geographical findings were revealed that crimes are considerably correlated with distance from city center (Ceccato et al., 2002; Ergün & Yirmibeşoğlu, 2005), accessibility (Ceccato et al., 2002; Ergün & Yirmibeşoğlu, 2005), design of a housing (Newman, 1972; Ceccato et al., 2002; Cozens, 2002), number of public transport (Murray, McGuffog, Western & Mullins, 2001; Ayhan, 2007), building environments (Newman, 1972; Ayhan, 2007) and commercial land uses (Olligschlaeger, 1997; Cozens, 2002; Ergün & Yirmibeşoğlu, 2005).

For instance; Ergün and Yirmibeşoğlu (2007) investigated the crimes which are Murders, Attempt to Murder, Assaults, Violent Assaults, Theft (from Motor Vehicle, Work, Home), Snatching in 32 districts of Istanbul, Turkey to determine the relationship between distribution of these crimes and social and physical structures. The study was performed with using data from year 2000. The data was divided into 3 groups for years of foundation of districts (before 1987, 1987 and 1992), 4 groups for distance from city center (below 10 km, between 10 km and 20 km, between 20 km and 30 km, above 30 km) and 3 groups for land use types according to master plan in 1995 (residential, residential+commercial, residential+industrial). As a result high correlation was found between land use, population, density, age and crime rates by applying explanatory and correlation analysis. Results were summarized as if distance from city center or foundation years of districts or population increases or educational level decreases or economic development increases; an increase in crime rates is observed.

In another study, carried out by Ergün and Yirmibeşoğlu (2007), Theft and Snatching was considered as Crimes Against Property, Murder and Assault was considered as Crimes Against Person in same study area. The relationships between defined crime types and physical and demographic characteristics of districts were examined by using correlation techniques. As the result of the study, a positive relation was found between crimes which were Crime Against Property, Crimes Against Person and population, population density, number of households, average land prices. And negative relation was found between crimes and distance from city center, spatial size of the districts.

Different statistical methods were used to determine factors contributed to the formation of crime. Regression models are one of these statistical methods. For instance; Ayhan (2007) applied multiple regression analysis to identify the factors affected on crimes which were committed in randomly selected 50 streets in Izmir province. Regression model was conducted by adding so many variables. At the end of the regression, lengths of the streets, height of the walls and iron bars were defined as indicators of crime.

Cited studies were aimed to understand crime occurrences by using spatial statistics techniques such as weighted spatial adaptive filtering (Gorr & Olligschlaeger, 1994), chaotic cellular forecasting (Olligschlaeger, 1997), Getis-Ord statistics (Murray et al., 2001; Ceccato et al., 2002; Gruenewald et al., 2006), Geographically Weighted Regression (GWR) (Malczewski & Poetz, 2005), or non-spatial statistics techniques such as linear regression (Ackerman, 1998; Ayhan, 2007) and correlation analysis (Ergün & Yirmibeşoğlu, 2005; Salleh et al., 2012). Methods used to define factors affected on crime incidents are summarized in Table 2.3.

Table 2.3 Table of methods applied to understand crime occurrences according to literature

Applied methods \ Researchers		Gorr & Olligschlaeger, 1994	Olligschlaeger, 1997	Murray et al., 2001	Ceccato et al., 2002	Gruenewald et al., 2006	Malczewski & Poetz, 2005	Ackerman, 1998	Ayhan, 2007	Ergün & Yirmibeşoğlu, 2005	Salleh et al., 2012
Spatial Statistics Techniques	Weighted Spatial Adaptive Filtering	X									
	Chaotic Cellular Forecasting		X								
	Getis-Ord Statistics			X	X	X					
	Geographically Weighted Regression						X				
Non-Spatial Statistics Techniques	Linear Regression							X	X		
	Correlation Analysis									X	X

Researchers not only use different types of methods but also different scales of workspace in their studies. Some of them focused on street level crime explanation like Gorr & Olligschlaeger (1994) and Ayhan (2007), whereas some of them studied on city or district level like Schmid (1960) and Ackerman (1998). The variables which were investigated in studies on ecology of crime are summarized in Table 2.4.

Table 2.4 Table of variables found as affected on crime according to literature

		Variables \ Researchers	Strano, 2004	Gillespie et al., 2009	Gorr & Olligschlaeger, 1994	Olligschlaeger, 1997	Cahill & Mulligan, 2003	Ceccato et al., 2002	Gruenewald et al., 2006	Schmid, 1960	Ackerman, 1998	Cozens, 2002	Malczewski & Poetz, 2005	Ergün & Yirmibeşoğlu, 2005	Newman, 1972	Murray et al., 2001	Ayhan, 2007	Anderson & Anderson, 1984	Cohn, 1990	Field, 1992	Salleh et al., 2012
Psychological	**Characteristic**	Characteristic features of criminal	X	X																	
Society	**Economic**	Poverty			X	X	X	X	X												
		Unemployment						X	X	X	X										
		Lower income								X	X										
		House ownership									X										
	Cultural	Education level					X		X	X	X	X									
	Demographic	Population density					X	X			X	X	X								
	Social	Age				X			X												
		Migration						X			X										
Environment	**Geographical**	Commercial area				X						X									
		Distance from city center												X							
		Shape of building										X			X						
		Number of bus station														X	X				
		Building surrounding													X		X				
	Spatio-temporal	Temperature																X	X	X	X
		Wind																			X
		Rain																			X
		Surface temperature																			X

2.2.4 Prospective Prediction Studies

As a result of the examination of research studies about the identification of factors affecting crime occurrences, GIS was generally observed to be used as an analysis tool. In addition to this feature, GIS technologies have been used for development of crime prevention software and evaluation of phases of this software (Groff, 1996; Groff, Fleury & Stoe, 2000; LaVigne & Wartell, 1998, 2000).

> While the use of mapping in criminal justice has increased over the last 30 years, most applications are retrospective- that is; they examine criminal phenomena and related factors that have already occurred. While such retrospective mapping efforts are useful, the true promise of crime mapping lies in its ability to identify early warning signs across time and space, and inform a proactive approach to police problem solving and crime prevention. Recently, attempts to develop predictive models of crime has increased, and while many of these efforts are still in the early stages, enough new knowledge has been built to merit a review of the range of methods employed to date (Groff & LaVigne, 2002, p. 28).

As it known, information obtained dispersedly from many different sources causes problems in the use of Information Systems. It also provides limited help on making intelligent decision support for dynamic data about uncertain conditions. Although GIS remains partially outside of this definition by having satellite communication, use of different techniques is important that GIS has the ability to learn from data changed dynamically or to make real world simulations for Knowledge Based Systems.

Thurston (2002) emphasized in his article titled *Does Your GIS Think?* that AI is necessarily used to increase the significance of GIS data for decision making processes. He also mentioned that GIS is very useful on evaluation, visualization and decision making when associated with AI.

At this point, it is possible to mention about two important issues:

- Optimization techniques
- Heuristic methods

In the simplest case, optimization includes finding best available values of some objective function given a defined domain (or a set of constraints), including a variety of different types of objective functions and different types of domains. Optimization techniques are known best for solution of small problems. However, they are not enough to resolve major problems by themselves. In this case, decision making problems which are subject of this study needs heuristic methods to produce more accurate results. In this case 4 subjects come into field.

- Neural Networks
- Genetic Algorithms
- Fuzzy Logic
- Expert Systems

2.2.4.1 Basics of Prediction Studies

In traditional (hard) computing, the prime requirements are precision, certainty and rigor. By contrast, the point of departure in soft computing in the thesis that precision and certainty carry a cost and that computation, reasoning, and decision making should exploit (wherever possible) the tolerance for imprecision and uncertainty. The exploitation of the tolerance for impression and uncertainty underlies the remarkable human ability to understand distorted speech, decipher sloppy handwriting, comprehend nuances of natural language, summarize text, recognize and classify images, drive a vehicle in dense traffic and more generally, make rational decisions in an environment of uncertainty and imprecision. Soft computing uses the human mind as a role model and at the same time, aims at a formalization of the cognitive processes humans employ so effectively in the performance of daily tasks (Zadeh, 1994, p. 77).

Studies modeled dynamically are available with using soft computing approach. For instance; there are certain routes must be followed to stroll in an urban traffic. At this point, it is important to use shortest path. Selected path has beginning and end points. While following the shortest path, some delays may occur because of different reasons such as congested traffic, road constructions, etc. Soft computing approach presents intelligent system design and simulation by proposing an alternative route to drivers with evaluating data which come from positioned devices on road like cameras. Briefly, alternative routes can be computed with the help of GPS data on road cameras and vehicles. It can also be tested on geographical areas.

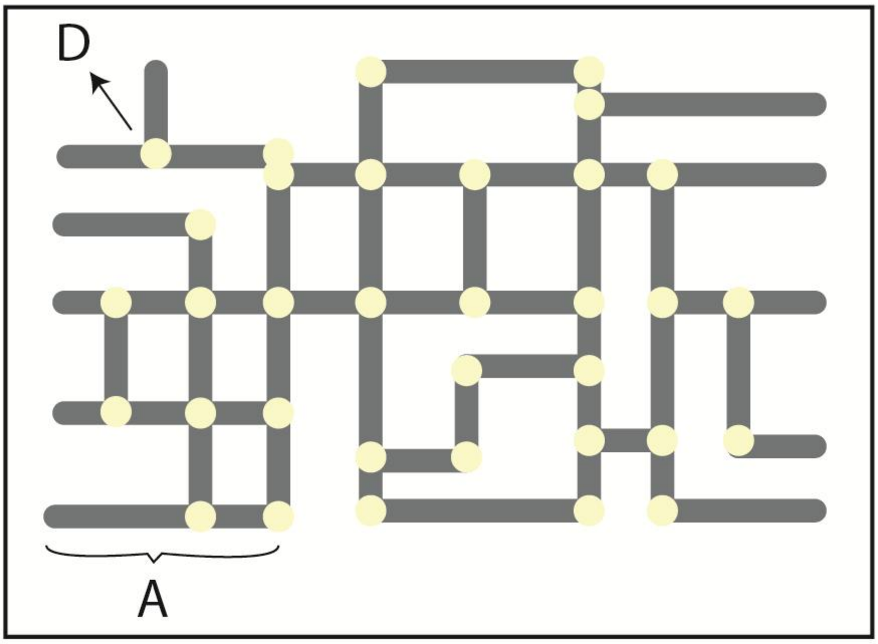


Figure 2.17 Graph theory

For solving this problem, Graph theory is used. Graph theory is the expression of an event using nodes and lines. As seen in Figure 2.17, corners are represented by Nodes (D) and edges are represented by lines (A). Mathematical form of the graph is G=(D,A).

Effect of dynamic data on computing shortest path of a road map was expressed in Figure 2.18 by using graph theory.

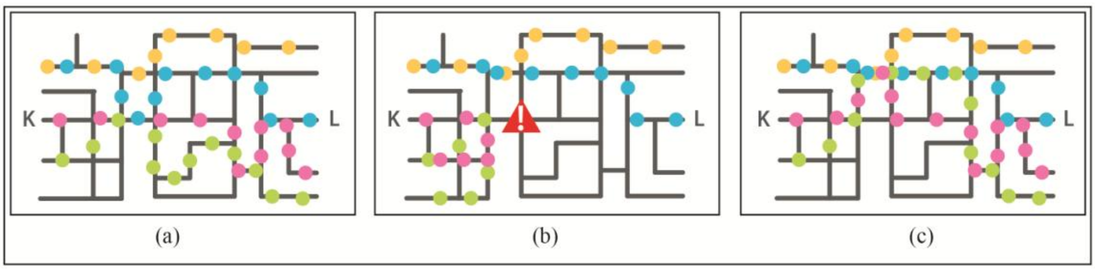


Figure 2.18 Dynamic route detection

According to this, routes of 4 different vehicles which want to go from starting point (K) to destination point (L) are shown in Figure 2.18(a). Exclamation mark shows that there is a road work on the route. So, green and pink colored vehicles which use this route cannot reach to the destination point as shown in Figure 2.18(b). However, if some devices are positioned on each node and if they can transmit information about possible problems on each node to vehicles simultaneously, all vehicles will be able to find an alternative route to destination as shown in Figure 2.18(c).

Until today, this technique has been used mostly in traffic planning and route identification fields. The other usages of this method are;

- To direct the ambulances to the hospitals through most appropriate route from the scene of emergencies
- Sedimentation (soil formation) estimation in harbors
- Determination of the tendency of tropical forest destruction
- Estimation of water quality
- Spectral classification of remotely sensed images

2.2.4.2 Crime Estimation Studies

Like as dynamic route detection, potential future crime locations can be predicted by analyzing social, economic, geographical, spatio-temporal factors. In this context, future prediction model for serial crime events was developed firstly with using ANN techniques by Olligschlaeger. During transition from sensitive period to prospective prediction in forensic cases, Olligschlaeger (1997) stated that there are some tools needed to forecasting future crime incidents. His research became successful for predicting future crime locations using ANN techniques in addition to ability of GIS in monitoring crime activities.

Olligschlaeger (1997; 1998) tried to predict locations of drug sales in 1992 by using machine learning on 911 calls which has drug reports from 1990 and 1991.

Workspace was divided into grid cells to predict locations by using feed-forward back propagation learning algorithm with *Game of Life* theory.

Game of life theory assumes that cells (divided grids) are affecting each other if they have neighborhood relationship.

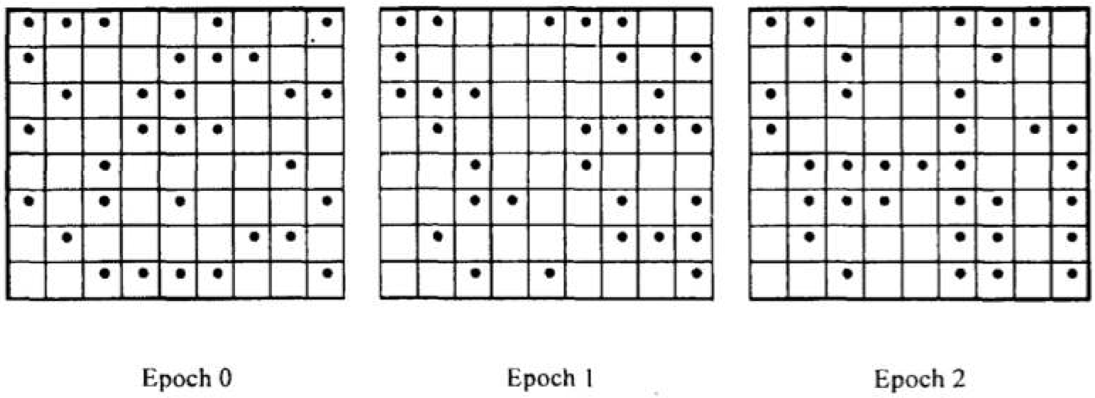


Figure 2.19 Game of life theory (Olligschlaeger, 1997)

According to this, if two cells which have neighborhood relationship to a specific cell are fill, that cell should not be empty in next epoch as shown in Figure 2.19. From this point, the study was performed with using population, percentage of black population, percentage at risk population (ages 12 to 24), percentage of female headed households, median household income, number of bars, percent commercial, percent of public housing family, sum of drug arrests in Pittsburg city. Study area was divided into 445 equal sized (each of them has $600m^2$) grid cells. 911 calls, which have totally 15,575 calls about drug sales, located by their coordinates in the study area. Data related to 1990 and 1991 was trained to computer by using machine learning. Potential drug sale locations in 1992 were predicted with the help of ANN and regression methods separately. When regression method and ANN compared by using test data from 1992, it was realized that ANN had better prediction result than regression method.

Another study carried out using ANN had been also created to solve crime series. Kangas (2001) argued that the series of events requires long-term research, because then ongoing crimes can be committed. Thus, information obtained through research is so crucial to manage them temporally and effectively by developing computer programs. Kangas (2001) were developed two software prototypes. One of them has ability to monitor and categorize Murders by computer based systems named as CATCH. The other one allows the analysis of Murder and Rape data named as CATCHRAPE. Both software run similar applications on different databases. So that, the research was described on the application of CATCH.

CATCH has functions like comparison of crimes with using advanced algorithms and also has ability to determine same crime patterns. CATCH makes transactions by using information like education level, occupation, physical appearance and alcohol/drug addicted about criminals obtained from HITS database which has similar features like VICAP which is used by FBI. HITS provides historical crime data for the software CATCH. Thus, criminal behaviors are learned with the algorithm modeled in the software by CATCH. Hence, unsolved crimes could be characterized to compare and analyze by the use of this software.

In the next step, specific crimes are associated with other crimes which are committed by known criminals to find out whether same criminal commit these crimes or not. CATCH software learns from subset of existing crime cases using parameters describing Modus Operandi and signature characteristics of offenders. The software includes query tools, clustering maps and geographic maps. The ANN clusters represents two-dimensional visualization, according to the similarity of offender patterns. This study allows the analyst to identify serial Murder/Sexual Assaults.

As seen in above examples, using technique of ANN, has brought a different dimension to crime prevention studies. Although rare studies were conducted on prediction of non-serial crimes, prediction systems can be produced by using intense data of singular crime incidents with spatial factors. For this purpose, GIS and ANN techniques should be used together. GIS become an important tool for decision support with the help of AI techniques (Aslantaş & Kurban, 2007). And also GIS provides a significant contribution about decision making process to senior managers in national Police Departments for crime prevention activities.

The advantages of GIS studies using ANN are listed as follows:

- As in many areas, ANN helps GIS to set out more precise results. And also ANN models are quite useful for GIS to analyze relationships (Olligschlaeger, 1998).
- It has superior achievements according to regression-based methods (Olligschlaeger, 1997; Aslantaş & Kurban, 2007). Still, number of studies which GIS and ANN used together are relatively small. On the other hand, researchers are used adaptive neuro-fuzzy systems for more powerful GIS systems.
- Estimation with a complex spatial data can be done.
- Spatial data can be visualized by producing scenarios.

As a result of the literature review, it can be said that crime types and reasons of crime occurrences are changed according to the location where crime occurred. However, determination of the reasons of crime occurrences is not sufficient to prevent crime activities by itself. Therefore, this dissertation is focused on predicting potential crime locations with the repeated formation of same and/or similar conditions come together, after determining factors affected on Theft incidents. And according to the examples mentioned above, it is possible to say that ANN is the best method so far to build an intelligent decision making system with GIS.

CHAPTER THREE
RESEARCH DESIGN

3.1 The Reason for the Selection of Theft Crime

While selecting the type of crime, organized crime, which consists of Theft, Abduction, Murder, Assault, Narcotic, Terrorism and Sexual crimes, was considered. Unlike the organized crime, Traffic Offenses, Informatics and Forgery have low interaction to environmental, economic or socio-cultural factors. Therefore, these type of crimes were excluded from the scope of this study.

Organized crime which encountered with complex relationships (Demirci & Çoban, 2002), has shown that there are more than one dependent variable affecting the crime incidents. According to Göksu (2003), majority of crime cases occurred in Izmir had been consisted of Theft, Fraud, Burglary, Snatching during world economic crisis in 1929. These type of criminal offenses, occurring in this period of time, were punished in forensic ways, if it could be possible. Otherwise, they had been pushed away from the city center. Crime and criminals who had been pushed to the distant from the city center in time, they are located exactly in the center of the city with the expansion of the city center, today. As reported in 2006, 298,097 number of Theft crime was committed in Turkey in total crime of 785,500 (Sevim & Soyaslan, 2009). Number of crime incidents was raised up to 1,491,769 which consisted of 405,405 Theft occurrences in 2012 (Polat, Eren & Erbakıcı, 2013). Considering the recent reports, Theft rate within whole crime types are still remain at high levels. In our country 30% of total crime is occurred by Theft cases. It means every 1 of 3 crime is committed by Theft offenders.

Researchers have been studying to explain factors affecting Theft events. Because of the difficulties on estimating non-serial crime incidents, researches have not been respond on predicting future Theft locations. Theft cases are not distributed randomly in space like crime events does (Brantingham & Brantingham, 1997; Alpdemir & Çabuk, 2005).

Theft offender comes from a geographical location to commit a crime. And crime is occurred in a geographical space. Therefore, as Chainey and Ratcliffe (2005) mentioned that place plays a vital role in management of crime. Various factors, which are social, economic, demographic and geographical, can be identified and mapped to understand the effects on Theft incidents to make crime prevention for Theft cases. Defined factors are used for predicting the future Theft locations.

3.2 The Reason for the Selection of Spatial Prediction

Traditional methods predict crime rates for unknown locations. For this reason, crime prevention activities cannot be taken appropriately for different locations. It is important to apply the techniques which are used for estimating crime with considering spatial factors to predict future locations of crime occurrences. Thus, predicting results could remark a location. This will support profitability in terms of both time and cost to interference to the incidents.

3.3 Data

Data acquisition and preparation processes are time-consuming. And also it requires high costs. Thus, in this section, collecting and editing data processes are described.

The research is performed in 21 central districts of Izmir which covers 52% of province area. These districts are hold various urban activities in its border line. Study area consists of districts of Izmir which are Aliağa, Balçova, Bayraklı, Bayındır, Bornova, Buca, Çiğli, Gaziemir, Güzelbahçe, Foça, Karşıyaka, Karabağlar, Konak, Kemalpaşa, Menderes, Menemen, Narlıdere, Seferihisar, Selçuk, Torbalı ve Urla as shown in Figure 3.1.

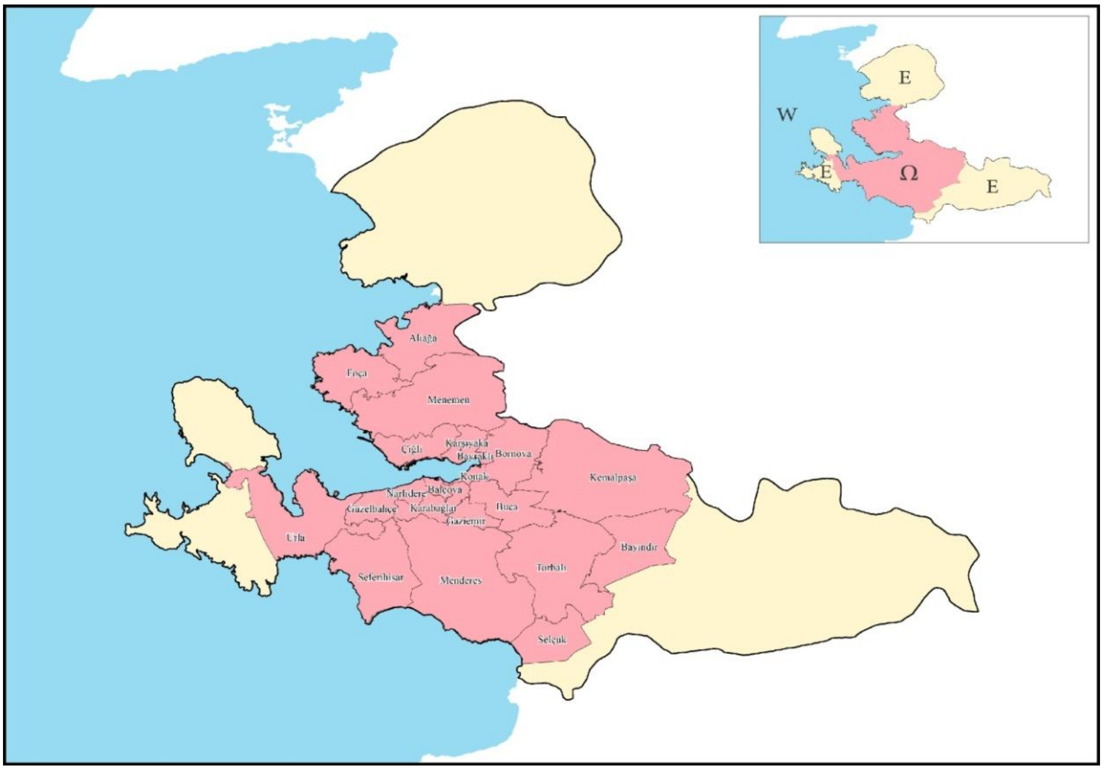


Figure 3.1 Study Area (Ω: “jurisdiction(s)” Crime and anchor points may be located here. E: “elsewhere” Anchor points may be lie here, but there are no data on crime here. W: “water” Neither anchor points nor crime may be located here.)

In order to perform a successful spatial prediction, following steps are firstly applied:

- Identification of physical environment of crime scene
- Mapping a land use including geographical features of study area
- Obtaining data about dependent and independent variables

In this context, information about population, population density, migration, age, temperature, wind speed, commercial, residential, military and recreation areas, public station locations and so on are needed. The data are obtained from different institutions and organizations.

3.3.1 Crime Data

Crime data are obtained from Izmir Police Department (IPD) for years 2009, 2010 and 2011 to cover the whole month of August. In Izmir 7,585 crime incidents had occurred between the dates of 1 - 31 August in 2009. 1,954 of crime incidents were committed outside of the study area and coordinate information was not received from 726 number of crime incidents. Thus, research is dealt with 4,905 crime incidents in 2009. In 2010, 5,564 crime incidents which have complete coordinate information are used from total number of 7,792. In 2011, 6,543 crime incidents which have complete coordinate information are used from total number of 8,603.

Crime incidents have 77 different types of crime. These types are grouped in 9 categories to make spatial analysis simplest.

- *Informatics Crime* (Informatics Crime)
- *Economic Crime* (Financial case, Financial smuggling, Infraction of Passport Law numbered 5682, gambling, Fraud, Fraud (assertion), Bribe, Passport case)
- *Narcotic* (Narcotic (marijuana/heroin/cocaine etc.), Narcotic (drug))
- *Sexual Crime* (Rape, Sexual abuse, Prostitution, Encouraging prostitution, Deflower someone with promising of marriage)
- *Assault* (Obscene behaviors, Unclassified crime (against person), Cruel treatment to family, Pounding (beating), Unclassified crime (against property), Insult, Insult (assertion), Crimes against residential use, Attack or Insult to law enforcement agency, Extort and despoil (from someone), Extort and despoil (assertion), Attack or Insult to public officer, Extort and despoil (attempt), Extort and despoil (from working place),)
- *Crime Against Property* (Theft (from working place), Theft (pick pocketing), Theft (fraud), Theft (from automobile), Theft (burglary), Theft (motorcycle), Theft (other), Theft (automobile), Theft (from public enterprise), Theft (snatching), Attempt to Theft (from working place), Attempt to Theft (burglary), Attempt to Theft (from automobile), Attempt to Theft (other), Attempt to Theft (motorcycle), Attempt to Theft (from public enterprise),

Attempt to Theft (fraud), Endamagement, Arson (intentionally), Arson (inattention), Buy or sale villainy)

- *Crime Against Person* (Abduction, Threat, Threat (assertion), Suspicious death, Attempt to suicide, Missing, Accident of employment, Murder (intentionally), Murder (inattention), Injure (intentionally), Injure (inattention), Suicide, Kidnapping)
- *Traffic* (Traffic accident with injury, Traffic accident with material damage, Traffic accident end-up with death, TEM cases)
- *Other* (Opposition of law numbered 6136, Fire a weapon at urbanized area, Impropriety, Breach of confidence, Breach of confidence (assertion), Breach of safety (opposition of law numbered 5846), Opposition of government orders, Foreign branch cases

After grouping the crime data, Theft incidents are inferenced from whole data. Finally in this research, 1,083, 1,139 and 1,208 records are used as Theft incidents committed in August respectively years in 2009, 2010 and 2011.

Day information is added into Theft data with using date information of crime data and calendar of related year. August 29-30-31 in 2009 and 30th August in 2010, 2011 are also added into data as official holidays.

3.3.2 Facility Data

Geographical data used in this research, are obtained from Izmir Metropolitan Municipality (IMM) and General Dictorate of ESHOT. Facility data is consisted of 10,536 point data. The data has totally 124 different types. Whole data is grouped into 18 categories with their types in Table 3.1.

Table 3.1 Facility categories

Categories	Type
Gas stations	Gas station
Military zone	Military area, Military flat, Military healthcare center, Military hospital, Military social activity area
Banks	ATM, Branch of bank
Religious structures	Church, Temple, Mosque
Education buildings	Kinder garden, Public training center, Nursery/Daycare center, Elementary school (private), Secondary school (private), College, Institution of education, Secondary school (commonwealth), Teaching school, University (commonwealth), Library, Cultural center, Theatre, Art gallery, Apprenticeship school, University (private), Training center, Quran training class, Elementary school (commonwealth)
Security units	Police department, Police hut, Constabulary, Police station
Residential areas	Dorm (commonwealth), Dorm (private), Site, Cooperative housing, Flat, Farm
Public enterprise	Mayoralty, Post office, Consulate, Fire station, Court house, Headman's office of a district, Chamber, Penal institution, Administration, Public enterprise
Industrial areas	Industrial site, Factory, Warehouse, Free zone, Market hall, Disafforestation and operation area, Maintenance and service area, Shipyard, Purification plant, Plantation
Health buildings	Dispensary, Tooth clinic, Hospital (commonwealth), Hospital (private), Hospital (University), Polyclinic
Social facility areas	Sport center, Swimming pool, Soccer field, Fair, Funfair, Cinema, Sport complex, Entertainment center, Official service area, Recreation area, Basketball court, Hippodrome, Stadium
Historical, cultural and natural asset or places	Monument, Historical artifact, Museum, Protected area
Commercial areas	Shopping center, Restaurant, Chain stores, Point of sale, Greengrocer, Shop, Bazaar, Media, Trade center, Warehouse
Tourism	Guesthouse, Touristic facility area, Turkish bath, Pension, Hotel
Transportation	Train station, Airport, Harbor, Terminal, Pier, Garage, Bus station, Subway station
Cooperation centers	Social cooperation centers, Charitable institution, Donation foundation
Recreation areas	Park, Afforestation area, Forest
Others	Power distribution unit, Cemetery (Muslim), Cemetery (Jewish), Cemetery (Christian), Martyrdom, Tomb, Cistern, Forcing house, Square, Car parking, Multilevel parking garage, Switchboard

3.3.3 Meteorology Data

Meteorological data which includes the year in which crime committed are obtained from Turkish State Meteorological Service (TSMS). Data name and types are listed in Table 3.2.

Table 3.2 Meteorological data types

Data Name	Meteorology Station Type	Time Range	Station Name
Local amount of rainfall	Climatic station	07:00 14:00 21:00	Menemen Seferihisar
Local dry bulb temperature	Climatic station	07:00 14:00 21:00	Menemen Seferihisar
Average temperature	Climatic station	Daily	Menemen Seferihisar
Total amount of rainfall	Climatic station	Daily	Menemen Seferihisar Kemalpaşa
Local temperature	Automatic station	07:00 15:00 22:00	İzmir Aliağa Menemen Seferihisar Ödemiş Selçuk
Local wind speed	Automatic station	07:00 15:00 22:00	İzmir Aliağa Menemen Seferihisar Ödemiş Selçuk

Temperature data is obtained from automatic stations. Working principle of automatic stations is recording the measure of temperature which taken in every 10 minutes. Local temperature data is obtained for İzmir, Aliağa, Menemen, Seferihisar, Ödemiş and Selçuk. Wind speed and direction of wind data are obtained from automatic stations for same districts. Data obtained from climatic stations are not used because of no rain had been observed during the study period.

Meteorology data are gathered in spreadsheet format including station names, date, time, temperature, wind speed and address information. The data is consisted of total number of 3,841 records. According to date and station name, pivot tables are composed to parse whole data to useful units for applying interpolation techniques.

3.3.4 Social Data

Social data which contributes of socio-cultural and demographic values of Turkey are obtained from Turkish Statistical Institute (TSI). District and neighborhood population data are obtained between years 2007 and 2011. Gender, age, education level and migration data are obtained between years 2009 and 2011.

Research area has 749 neighborhoods. 201 of total amount of neighborhoods has less than "250" population value. In population data, population data for these neighborhoods are not included. Standard value of "200" is accepted to these neighborhoods to prevent any loss of data. Accordingly, total population values of district and neighborhood are listed in Table 3.3.

Table 3.3 Demographic data

Year	Population of District (village + urban)	Population of Neighborhood (urban)
2007	3,282,231	2,963,894
2008	3,330,878	3,175,133
2009	3,400,716	3,227,008
2010	3,479,507	3,354,934
2011	3,492,494	3,366,947

3.4 Methodology

"Uncertainty of the future is the most important factor to become decision problem a significant and vital process for DMs" (Yaralıoğlu, 2010, p.157). For this research, senior executives of IPD are determined as DMs. DMs need lifelike spatial prediction systems to perform crime prevention efforts accurately. However, a study which computes future crime prediction spatially has not found in our country yet.

One of the reasons of this problem was explained by Öztemel (2006) as the lack of solving the problem with using specific algorithms or formulations.

ANN techniques are used to support learning the relations between different cases through heuristic methods applied on sample cases. Thus, the system would have ability to make decisions on cases which has never seen before according to previously learned information. Using ANN and GIS which have spatial analyzing and querying capabilities, together, could be an advantage on crime prevention studies to eliminate the risk of uncertainty of future and make SDSS. In Figure 3.2, desired SDSS is schematically showed.

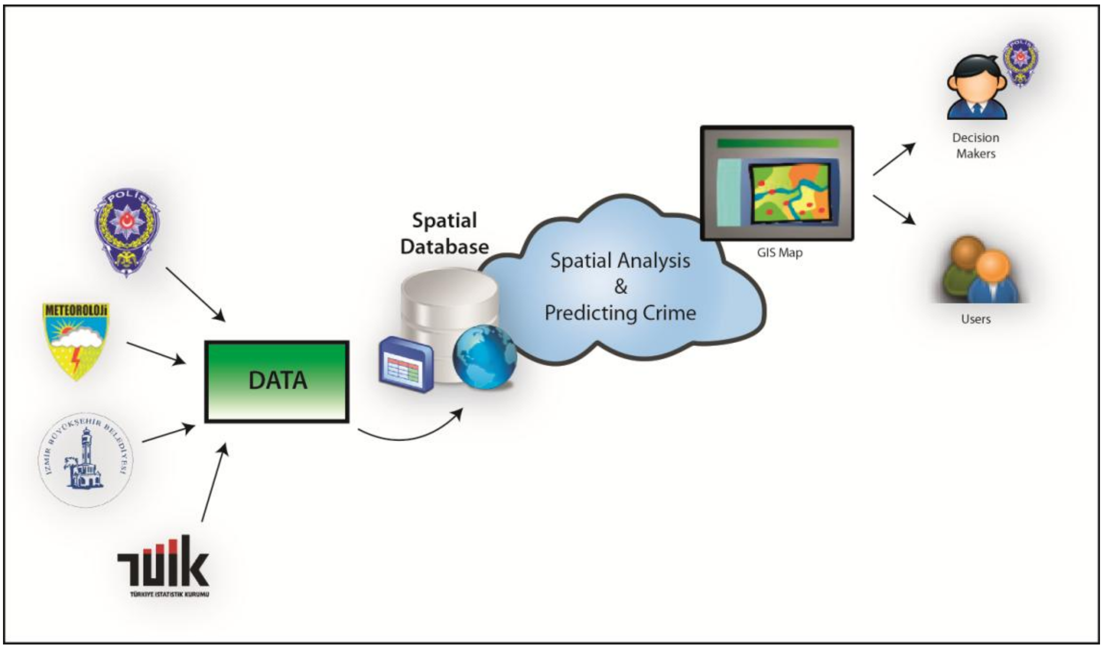


Figure 3.2 Spatial decision support system schema

In order to develop a SDSS, data is obtained from different data sources which can be seen in Figure 3.2. Methodology of this dissertation is consisted of editing and arranging processes of obtained data to apply them effectively in the research. Then, data obtained from various data sources are transferred into a spatial database with using organize, store and spatial visualization properties of GIS technology.

Data which transferred into spatial database is used to define factors affect on Theft crimes as an independent variables of this research with using spatial and non-spatial statistical methods. In order to identification of these factors, the data is used to make spatial future forecasting by applying ANN techniques.

Developed system has an ability to learn relations between events with the help of sample data (2009 and 2010 data). After sample data is trained to the system, test data (2011 data) is send to computer without any statistical process. Number of future Theft incidents are computed by ANN algorithms. Prediction results are compared with currently committed 2011 Theft incidents. If there is found more difference than expected levels, ANN algorithm is changed and test data is send to the system again. This process have been continuing until the difference between target and desired results dropped under the expected level. When desired result was achieved, the result would be presented to DMs by the help of GIS-based software. Thus, structure of a SDSS which can produce lifelike results with the integration of GIS and ANN methods is formed.

3.4.1 Framework of the Research

According to literature section, regression methods are often used in identifying the factors that lead to the formation of a crime as a research method in the last 20 years. However, it is important to determine the correct scale of the study for applying this method. For this reason, framework of the research is focused on finding the appropriate scale for this study.

Dependent variable which is consisted of Theft data and independent variables which are consisted of spatio-temporal, geographical and socio-cultural data are obtained from variety of data sources to determine the appropriate scale of the study. The data which can be adapted for two different scales are digitized and transferred into the spatial database. Then, regression methods are used for both two study scale to define the suitable study scale. After selecting the suitable scale, spatial prediction of future Theft occurrences is done.

In this context, meteorological data that differ from both time and space is grouped as spatio-temporal data. Land use, boundaries, building footprints and facility points are grouped as geographical data. Migration and age data which laid out the social structure, education level which laid out the cultural structure and population which laid out the demographic structure of a region are grouped as socio-cultural data as shown in Figure 3.3.

Spatio-temporal data is consisted of 3,841 individual temperature and wind speed values which were recorded by 6 different automatic stations in the study area. The data is eliminated based on information obtained by time periods (morning, noon, night) which critical changes occurred (Turkish State Meteorological Service [TSMS], (2012). The final data has 558 records.

Geographical data is consisted of environmental factors which were obtained from IMM with total number of 10,536. Environmental data with the number of 7,508 related facilities which includes 641 educational buildings, 470 religious structures, 5,904 transportation stations, 59 security units, 377 banks and 526 commercial areas, are used for the study.

Socio-cultural data is consisted of population, migration, education and age values of districts and neighborhoods which were obtained from TSI.

Crime data is classified in 9 groups which are Informatics, Economic, Narcotic, Sexual, Assault, Crime Against Property, Crime Against Person, Traffic and Other. In these categories, most affected type from the daily activities was Crime Against Property except Arson and Tangible Damages. Thus, Theft incidents are selected as a dependent variable of the research.

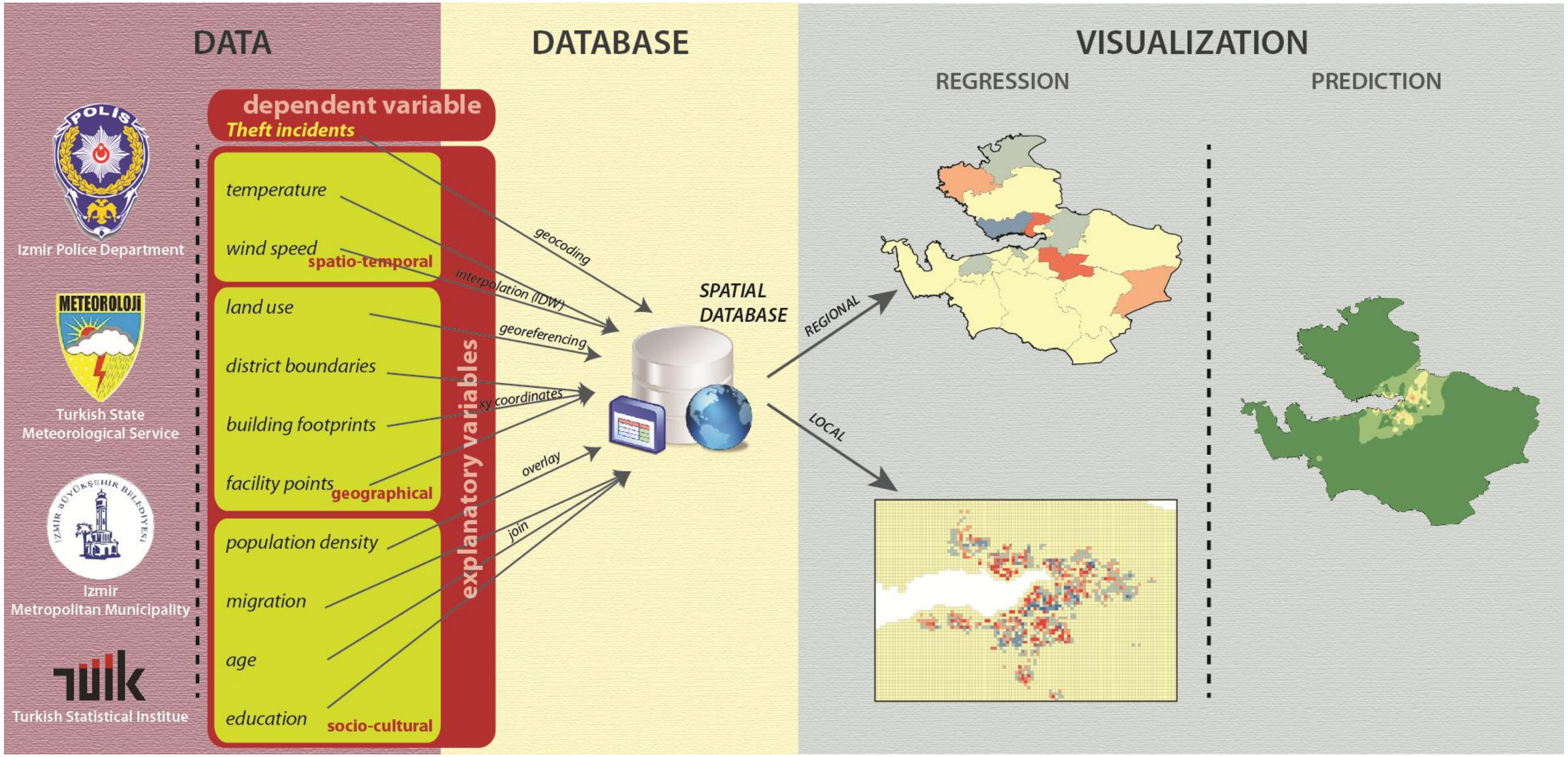


Figure 3.3 Methodology of the research

Two different study scale, named as regional and local scale, are used to measure the exchange of explanatory variables of Theft incidents by using regression methods. Regional and local scale terms are specific to this study. Regional scale is defined by district level administrative boundaries. For local scale, neighborhood level administrative boundaries and geographically restricted grid cells are used. Grid cells are defined by dividing the study area into 400x400 meters cells. Buffer analysis is applied on environmental factor points to determine the grid size as shown in Figure 3.4. Firstly, 50 meter in a diameter is applied on exact locations of environmental factors. Then, the buffer zone have been increased by the equal intervals of 50 meters. Increasing process is ended when buffer zone covers all the locations of Theft incidents. Therefore, 400 meters in a diameter had been found that Theft occurrences are committed in this zone. As a result, 0.16 km^2 is selected for grid size. Total number of 35,785 grid cells are comprised in the study area.

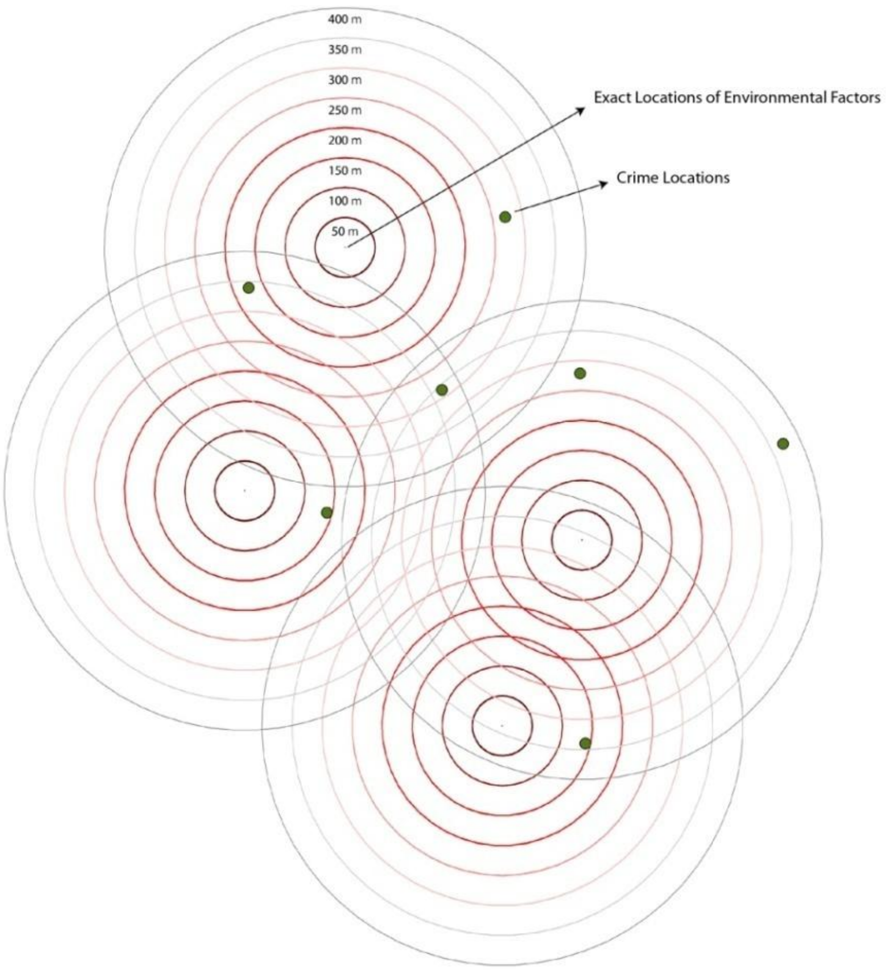


Figure 3.4 Grid size selection

Data which was obtained from variety of data sources, is required to be digitized primarily by using proper querying techniques as shown in Figure 3.5 to decide prediction scale correctly. Attribute data can be located on a map by converting attribute data to spatial with using spatial information in the data or joining with other spatial data. Thus, data which have different formats can be transferred into common spatial database. Spatial statistics are applied to these data to define the influenced factors on Theft occurrences separately in regional and local scales.

In this context, steps which were used in the operation method is described in Table 3.4.

Table 3.4 Steps which were used in spatial support system

Steps	**Description**
Crime Data	is data which spatially organized according to crime locations and date of occurrences.
Spatial Factors Affected on Crime	is a dataset of independent variables which compiled based on literature review in order to determine the factor affected on crime occurrences at a specific time and location.
Spatial Query	is a method which is applied to provide proper use of spatial data (crime data and spatial factors affected on crime).
Geographically Weighted Regression	is a spatial statistics method to provide visualization of geographical change of crime occurrence probability using stepwise variable selection method within a set of independent variables.
Spatial Data Transfer	is a transfer method using for locating crime data and spatial factors affected on crime which are obtained from various data sources in paper form.
Maps	is an environment to visualize the results of spatial statistics and spatial data.

Crime necessarily takes place in a space. This place could be determined by the factors affecting the crime occurrences. So, regression analysis methods are applied on independent variables to define factors affected on Theft incidents. The factors are determined by considering the high significance levels for regional and local study scales. Then, the appropriate scale of the study is selected for predicting the future Theft events. ANN techniques are used to provide computer learning from previous experiments of Theft incidents which have dynamic structure and predict future events. Finally, GIS is undertaken with ANN techniques together for mapping the results. A risk map is constructed for the study area. The accuracy of prediction is tested with comparing pre-crime locations with forecasting results on generated risk map.

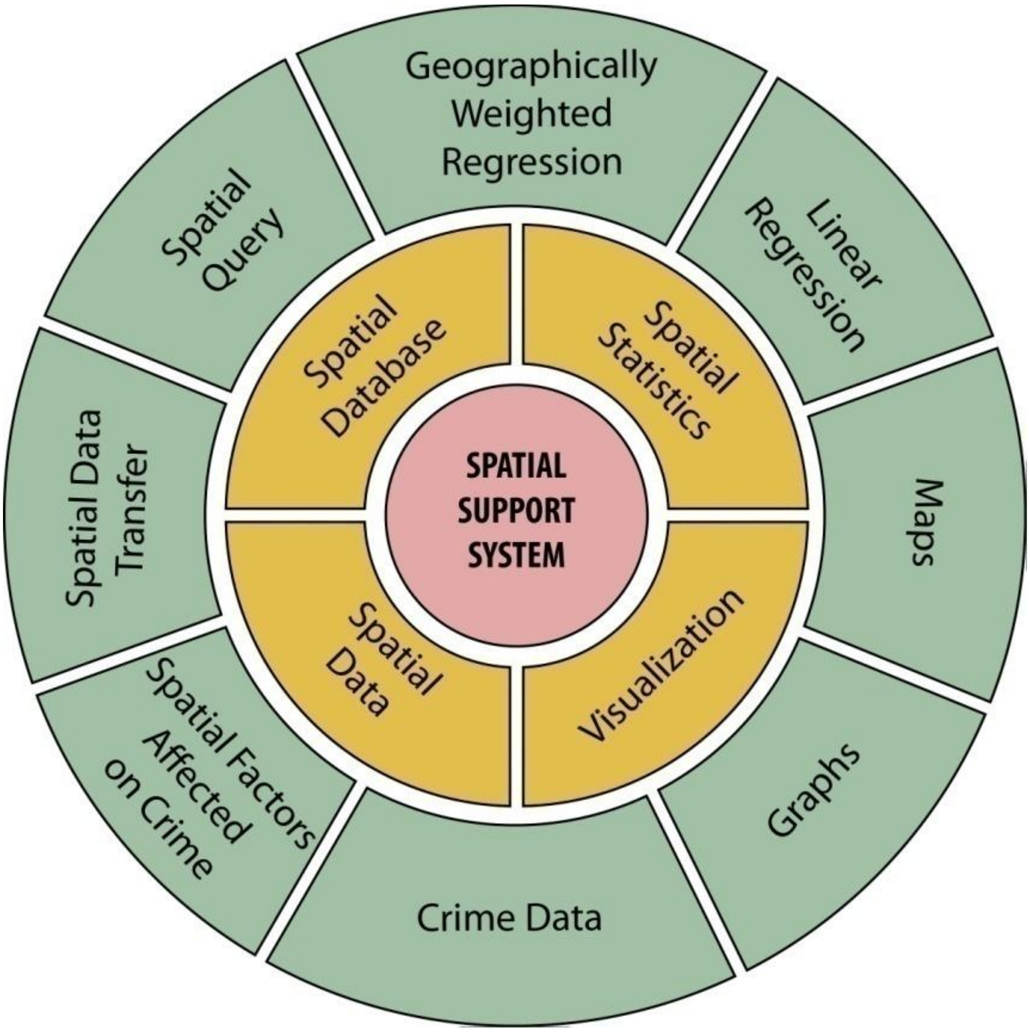


Figure 3.5 Data editing for spatial support system

Data should be organized to make accurate future predictions for Theft incidents in a systematic manner. The next section explains how data editing was performed.

3.4.2 Organization of Data

Spatial data transformations could be done for using the obtained data in both regional and local study scales. In this section, use of the data in accordance and analysis methods which were used in the study are described.

3.4.2.1 Positioning

Crime data which obtained as attribute table has spatial information. With using this information, the data were transferred into spatial data by applying geocoding method. However, x,y coordinate information had been entering with commas "," and dots "." together. So, it causes the right coordinate information converted to wrong ones like "999.999999902". When it is mapped, the crime points remains outside of the study area. These data had been adjusted individually by hand in spreadsheet and matched again with the current data. According to this process, 420, 200 and 1,050 recordings are recovered for years 2009,2010 and 2011 respectively. Hence, in this research, 1,083, 1,139 and 1,208 records are used as Theft incidents committed in August respectively years in 2009, 2010 and 2011.

Time of Theft occurrences are overlapped with meteorological data. According to 8 hour periods, the records were grouped as morning (04:00-12:00), noon (12:00-20:00) and night (20:00-04:00). Theft data are related with districts, neighborhoods and grids in spatial database to be used in regional and local scales according to time classifications.

Socio-cultural data which was obtained as attribute table has district and neighborhood names. The data is joined with geographic data of district and neighborhood boundaries by using common column type *names*.

3.4.2.2 Inverse Distance Weighted Interpolation Method

Meteorology stations consist of discrete locations in the study area. As Brunsdon, McClatchey & Unwin (2001) mentioned that although there was a point data over sparse networks, it is useful to interpolate these records as a continuous surface. "Inverse Distance Weighted (IDW) is a simple distance-weighted 'area average' estimate" of the value of temperature and wind speed at the target location which meteorology station does not exist (Eischeid, Pasteris, Diaz, Plantico & Lott, 2000, p. 1585). By applying IDW, continuous surface maps are created for temperature and wind speed using observations at meteorological stations according to Equation 3.1.

$$z_i = \frac{\sum_{j=1}^{n} \frac{z_j}{d_{ij}^k}}{\sum_{j=1}^{n} \frac{1}{d_{ij}^k}} \tag{3.1}$$

Where

z_i : the temperature or wind speed at location i

z_j : the temperature or wind speed at sampled location j

d_{ij} : the distance form i to j

k : the inverse distance weighting power (k=2).

Meteorology stations collect temperature and wind speed values in every one hour period. However, meteorological data have critical changes that occur at 07:00 (morning), 14:00 (noon) and 21:00 (night) (TSMS, 2012). So, IDW method is applied to temperature and wind speed values of every day between 1st and 31st of August 2009, 2010 and 2011 at morning, noon and night respectively.

The illustration of 1st August 2010 is shown in Figure 3.6. The output of IDW method is produced with raster based map as seen in Figure 3.6(a). Each pixel of raster map has temperature and wind speed values. Points are required to transfer these values to regional and local scale. For local scale, centers of grid cells are used as point data. Totally 35,785 points are found in study area for local scale (see Figure 3.6(b)). For regional scale, point data is consisted of 1,000 randomly generated points in districts (see Figure 3.6(c)). Thus, relevant temperature and wind speed values of each pixel are available to assign to each points (see Figure 3.6(d)). The assigned values are used just same as the grid cell values (see Figure 3.6(e)). The average of the assigned values are used as district value (see Figure 3.6(f)).

The meteorology data has 558 records that mentioned before. Applying IDW model to whole data is a time consuming process. Thus, a model is built to execute IDW model. The results are assigned to each point data generated for both districts and grid cells. The illustration of the model at 1st August 2010 for centroid of grid cells is shown in Figure 3.7.

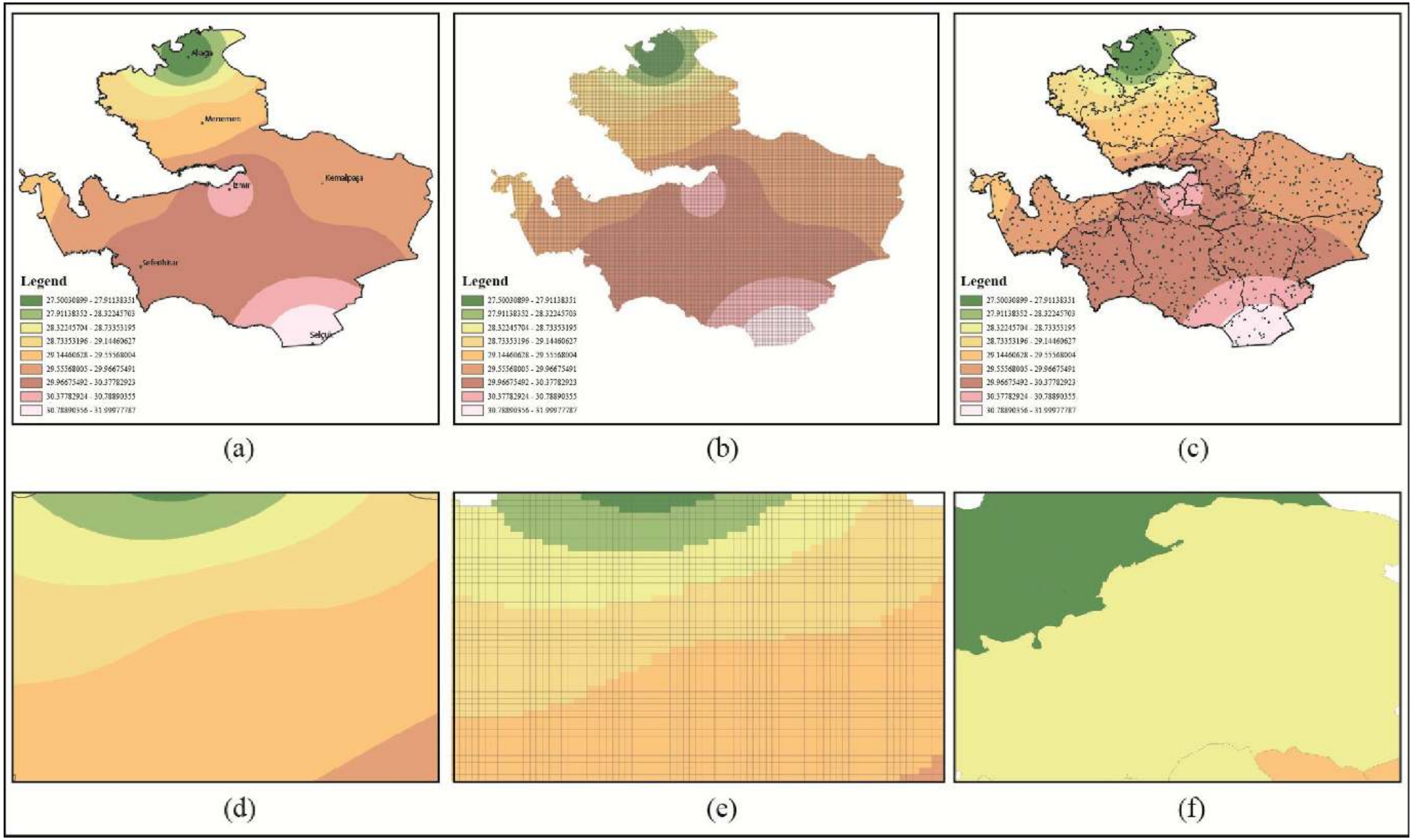


Figure 3.6 The interpolation method applied to temperature data

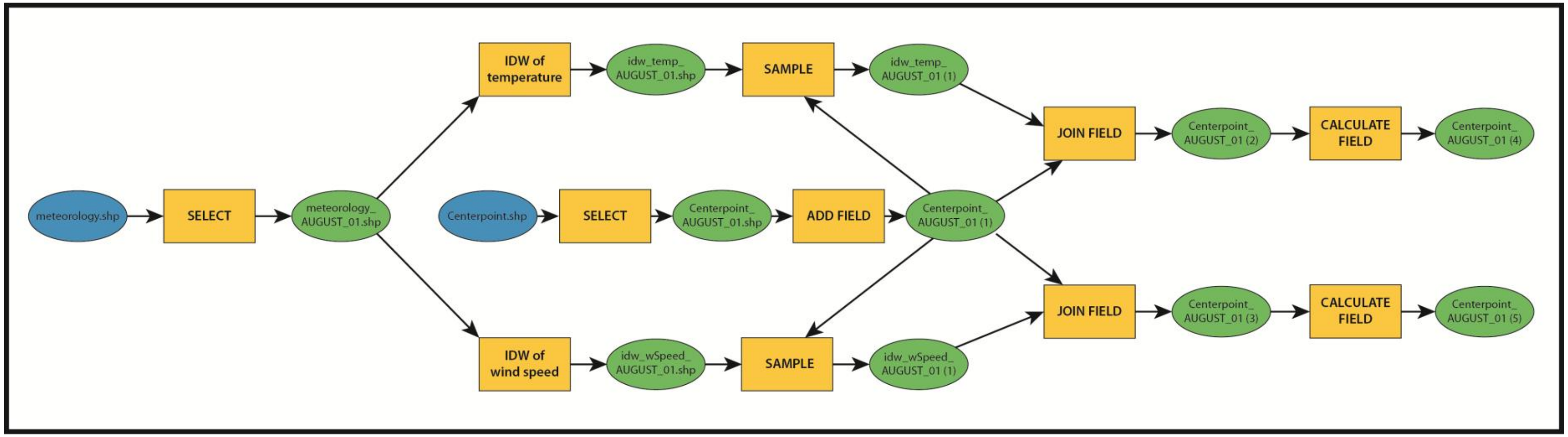


Figure 3.7 The model which developed to assign meteorology data to center points of grid cells

3.4.2.3 Computing Number of Households

Large surfaces would have more population. However, it is important to know the proportion of the population of the surface. Thus, population density is intended to be used as independent variable.

District areas are used to calculate population density at regional scale. At local scale, the fixed value of grid area which computed as 0.16 km^2 is used. Population data was obtained from TSI on the basis of district and neighborhood. District populations are included in computation of population density at regional scale. However, population data in smaller spatial units, is required such as buildings to calculate population density for grid cells (Yavuz & Tecim, 2013).

Population per building is calculated by multiplying number of apartments, building heights and number of households. Land use maps are crucial to identify residential areas in order to calculate individual building populations. Vector maps which include building footprints and heights were obtained from IMM. Land use maps were obtained with scale of 1/5000. Then, vector maps are overlaid onto land-use maps to define residential areas as shown in Figure 3.8. And other land use types are eliminated from the process.

Building footprint size is characteristic for extracting the number of apartments and determining the type of that building is also crucial to extract information about the apartment number in a building and usage of a building. For instance, some parcels include residential utility buildings such as garages, sheds and barns which are called as premises (Ural, Hussain & Shan, 2011).

Figure 3.8 Part of the vector map showing the residential areas and building footprints

Available land use maps show only land use at parcel level, the buildings which are used as premises inside a parcel, cannot be identified. Therefore, area thresholds are applied to classify residential building usages. The area threshold which was taken "60 m^2", is applied to identify premises (Ural, Hussain & Shan, 2011, p. 848). The threshold values for residential buildings are given in Table 3.5.

Table 3.5 Threshold values of residential buildings

Number of apartment on housing floor	Threshold value (m^2)	Number of buildings
Single apartments	60 – 200	360,950
Two apartments	200 – 300	28,249
Three apartments	300 – 400	8,681
Four apartments	400 – 550	5,712

Height information is necessary to calculate the population per building. This information is held in vector based maps. Thus, the number of households are calculated from mean values of average population per neighborhood and building (Ural et al., 2011). The average population density for neighborhoods is calculated as 0.26 people/100 m^2 and for buildings is 3.49. Mean value of these population densities, which was rounded to two, is taken as a constant value of a household number. Population of a building is calculated by multiplying number of households, number of apartments and height of a building. By this methodology the population of the included neighborhoods is calculated as 3,364,476 which overlaps with the independently provided neighborhood population of 3,479,507 at 96.7 percent level. Therefore, building population is used to calculate population density in each grid cell.

Socioeconomic variables were obtained from census data like district level population, migration, education and age provided by TSI. Data extraction is performed by querying the database for primary school graduate of male and 18-35 age male populations. These queries are adopted, because Theft events are encountered more frequent among this population group (Turkish Penal Institution [TPI], 2008).

3.4.2.4 Measuring Distance

Environmental factors are assessed by the distance from the location where crime occurred at regional scale. At local scale, they are analyzed by the distance to each grid cell. While calculating the distance, it was intended to answer the question: *which reinforcement is located to the closest location of Theft occurrences?* Proximity answers the question as *what is the distance between two locations?* Euclidean distance answers the question as *what is the closest town?*. Thus, distance between objects is measured by using closest proximity method with Equation 3.2.

$$d_2(x, y) = \sqrt{(x_1 - y_1)^2 + (x_2 - y_2)^2} \tag{3.2}$$

Where

$(x_1 - y_1)$: the x, y coordinates of the first object

$(x_2 - y_2)$: the x, y coordinates of the second object

$d_2(x, y)$: the measured distance between two object

Accordingly, total number of reinforcements in districts are calculated for regional scale. Total number of reinforcements in grid cells are calculated for local scale.

3.4.2.5 Geographically Weighted Regression Analysis

In this dissertation, it is necessary to determine the reasons of Theft incidents which were occurred in a location for predicting future possible Theft locations to support DMs. DSS, which is an interactive Computer Based Information System (CBIS), is being developed to provide making decisions and problem solving for DMs with using information, data, knowledge and communication technologies. For this research, decision making problem should be solved by taking steps spatially. Therefore, a SDSS must be effectively designed and managed to develop a system that might be useful for DMs.

The factors which were discussed in the previous section, are used as independent variables. The factors affected on previous Theft cases are determined geographically. Thus, if defined factors will came together in a location, it would possible that similar cases is going to be occur in that place. According to this, GWR analysis is used as regression method.

Unlike traditional regression analysis, spatial regression has 2 features:

- Events located spatially close to each other has high liability in order to remote ones.
- Data can produce different results in different regions because data is not static.

In order to examine the spatial relations between Theft events and independent variables, GWR is applied in the study area with Ordinary Least Squares (OLS) method. The spatial relationships between dependent and independent variables are calculated with Equation 3.3 for both regional and local scales.

$$y_i = \beta_0(u_i, v_i) + \sum_k \beta_k(u_i, v_i)x_{ik} + \varepsilon_i \tag{3.3}$$

Where

y_i : the i^{th} observation value of number of Theft occurrences which is the dependent variable of the study in each district or grid cell

β_0 : constant value

β_k : the estimation parameter of k^{th} variable

x_{ik} : covariation values of k^{th} variable

(u_i, v_i): the location of i

ε_i : the error term

3.4.2.6 Artificial Neural Networks

AI is concerned with several issues such as organization of information, learning, problem solving, prove a theorem and modeling of scientific discovery (Öztemel, 2006). Specially, AI systems are being developed for solving problems which cannot be solved by using specific formulation and algorithms.

There are more than 60 AI technology. The most well knowns are:

- Expert systems
- Artificial neural networks
- Genetic algorithms
- Fuzzy logic

ANN is an information processing system that inspired by biological neural networks and includes some performance characteristics similar to biological neural networks (Fausett, 1993). ANN is simply simulates the method of working of the human brain. ANN has several important features such as having ability to learn from data, making generalization, working an unlimited number of variables. Artificial neural cell or processing element is the smallest unit that constitute of fundamental of ANN. The common artificial neural cell consists of 5 main components which named inputs, weights, additive and activation functions and outputs illustrated in Figure 3.9 (Kaynar & Taştan, 2009).

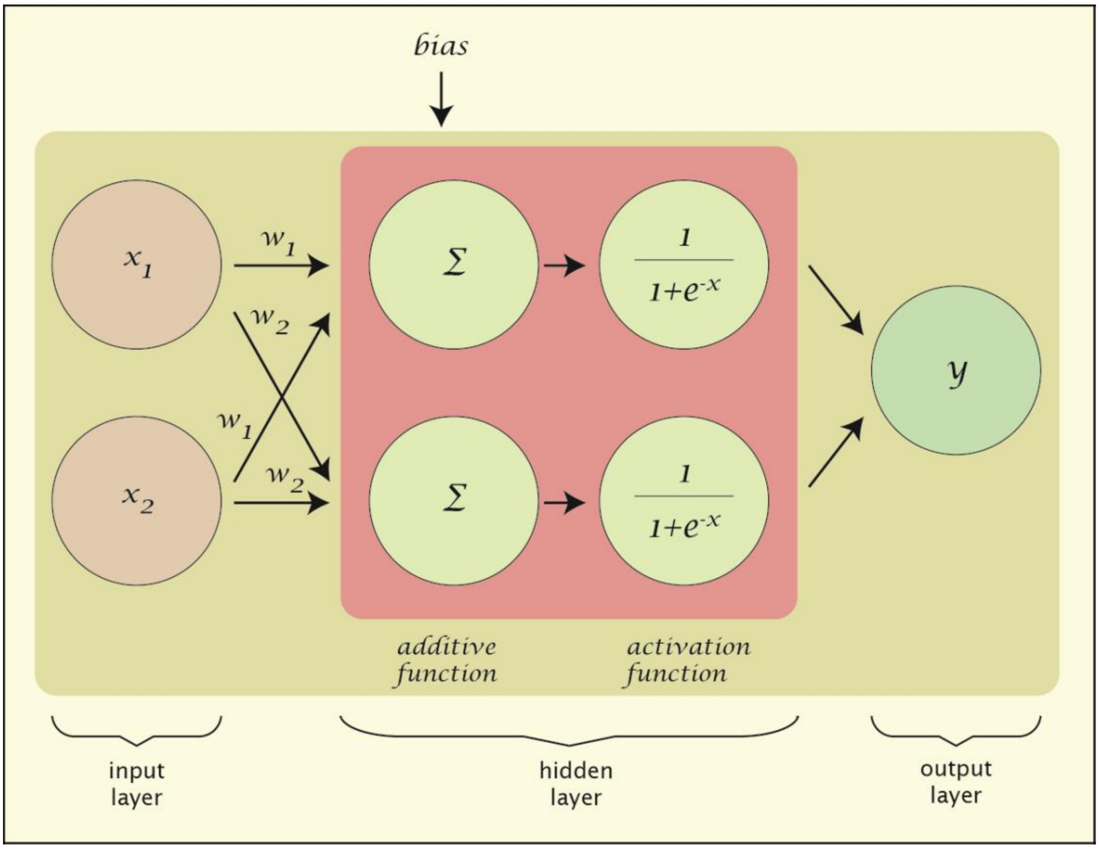


Figure 3.9 Common structure of ANN

The mathematics model of ANN is shown in Equation 3.4.

$$y = f(\sum_{i=1}^{n} w_i x_i - \theta^2) \quad (3.4)$$

Where

y	: the neuron output
f	: an activation function (nonlinear function) of neuron, which may be a step function
x	: the input vector of neuron
w	: the neuron's weight vector
θ	: the neuron's activation threshold (Wang, 2003).

First ANN studies had revealed in relation to field engineering in 1940 (Öztemel, 2006). At these years, ANN had been contributed to the solution of linear problems. ANN had started to solving non-linear problems by the presence of multilayer perceptron in 1982. ANN is also a simulation methodology of calculation that how the human brain works in spatial data problems (Thurston, 2002). ANN works on the basis of machine learning.

Even among machine learning practitioners, there is not a well accepted definition of what is and is not machine learning. Samuel (1959) was defined machine learning as the field of study that gives computers the ability to learn without being explicit programmed.

Mitchell (1999) defined machine learning by saying that, a neural network is the ability to learn from its environment in order to improve its performance (measured through a predefined performance measure) over time. Learning in an ANN stands for an iterative process of adjusting the synaptic weights and threshold values. There are several different types of learning algorithms. The main two types are supervised learning (teacher or target is available) and unsupervised learning (without teacher). Others: reinforcement learning (without target, but with reward), recommender systems.

In supervised learning, the idea is teaching the computer how to do something, whereas in unsupervised learning letting it learn by itself. Our research has Theft occurrences as a target value. Thus, supervised learning algorithm is applied to modeling research neural network. According to that learning algorithm, whole Theft data is divided into three dataset which named as training, validation and test set. Training set is formed with Theft occurrences and explanatory variables affected on Theft occurrences as a response to procedure desired outputs. Validation set is used to calculate input weights for carrying out the accuracy of forecasting that learned from training set. Purpose of test set is making them particularly well-suited to modeling and predicting future Theft events.

3.4.3 System Design

The design of the developed system is expressed as data storage, analysis and presenting to end-user which illustrated in Figure 3.10. Accordingly, PostgreSQL which interoperable with variety of GIS software is used as a database management system. PostgreSQL 9.3 is selected in order to be able to store and manage the data. The data is transferred into defined database management system with using data editing process which was described in the previous section.

Two GIS software which are MapInfo 10.0 and ArcMAP 9.3, are used together to implement spatial query and analysis functionally. Chosen database is provided easy data exchange between MapInfo and ArcMAP. Thus, dependent and independent variables are transformed into spatial database by using MapInfo software. The factors affecting Theft occurrences are determined by using ArcMAP software. These factors are transferred into a statistics software named as MATLAB 2014a in order to be used in ANN algorithms. Therefore, system had been learn affected factors from previously occurred Theft events by applying ANN algorithms. Then, prediction is performed. Finally, the outputs of the system are mapped into GIS software to provide spatial visualization of prediction results for DMs.

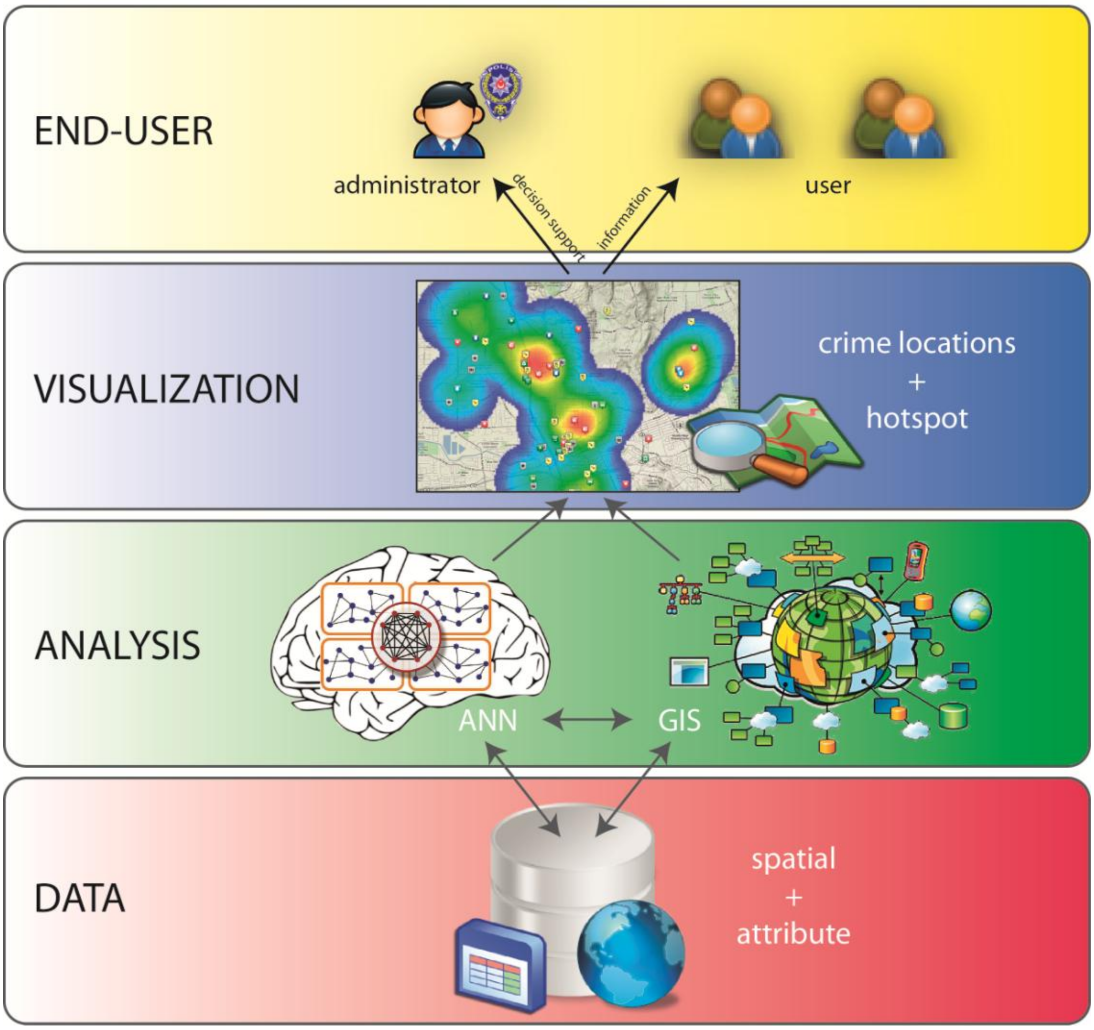


Figure 3.10 System design

Two different interfaces are setup to inform and support end-users. Senior managers of IPD are identified as DMs. They are supported to make crime preventions. Thus, the results of future forecasting of Theft events are visualized for them. And current crime locations are visualized to inform people who wanted to learn more about committed crimes.

CHAPTER FOUR
ANALYSIS

According to literature review, goal of this research was defined as developing a system to predict the potential locations of singular criminal activities before they occur according to examine the factors affecting Theft occurrences and support DMs in Police Department to make high accuracy crime prevention studies. In this chapter, spatial analysis and prediction methods which were allowed to achieve the goal are described.

Police Departments are agreed on the necessity of evaluating available data is emerging for taking precautionary measure against crime before they occurred (Demirci & Çoban, 2002). According to this opinion, crime analysis is performed to understand how crime events occurred in that location. If the factors affecting the crime will came together, that location would be the future crime scene.

Demirci & Çoban (2002) mentioned that crime analysis is done in 3 ways:

- Administrative crime analysis: Periodic reports that organized annually, monthly, etc.
- Tactical crime analysis: Mapping crime according to regions, time or groups and analyzing the relationships between crime and possible reasons of crime occurrence.
- Strategic crime analysis: Predicting crime that may occur in the future, on the basis of previous information.

Administrative crime analysis is the most commonly used technique in Turkey. But recently tactical crime analysis has been used to keep pace with the evolution of technology. Crime has a dynamic structure. Crime analysis which are suitable for this dynamic structure must be performed by using developing technologies. Therefore, this dissertation is intended to implement strategic crime analysis.

In order to execute the strategic crime analysis, firstly administrative and tactical crime analysis should be applied and the results of these must be used in strategic crime analysis. The following objectives should be performed sequentially to achieve the defined crime analysis.

- Mapping the previously occurred crime incidents spatially
- Temporally analyzing the distribution of Theft events of the province
- Exploring the effective of spatial or non-spatial factors in the formation of Theft events
- Determining the potential locations of future Theft incidents spatially with using suitable ANN algorithms

4.1 Spatial Visualization of Crime Incidents

It is important that the obtained data must include the information of province, district, neighborhood, street, door number, x,y coordinates, crime date, crime time and type of the crime. These information are arranged for 17,012 crime events which were totally occurred in years 2009, 2010 and 2011 at August. The arranged data were mapped and published on web to give an access to whom wants to be informed.

Thematic map is applied on district populations by using equal ranges. District population of the year 2009 is illustrated in Figure 4.1. And this is also used as a base map of visualizing crime incidents occurred in 2009. Crime data which was classified in 9 groups, is located spatially on this map. Each categories of crime incidents are marked with different colors. Map has the ability to zoom in-zoom out actions. Small window, located at the right bottom of the map, points out the selected location in the study area. The selection of the desired crime types is provided to be displayed on the map.

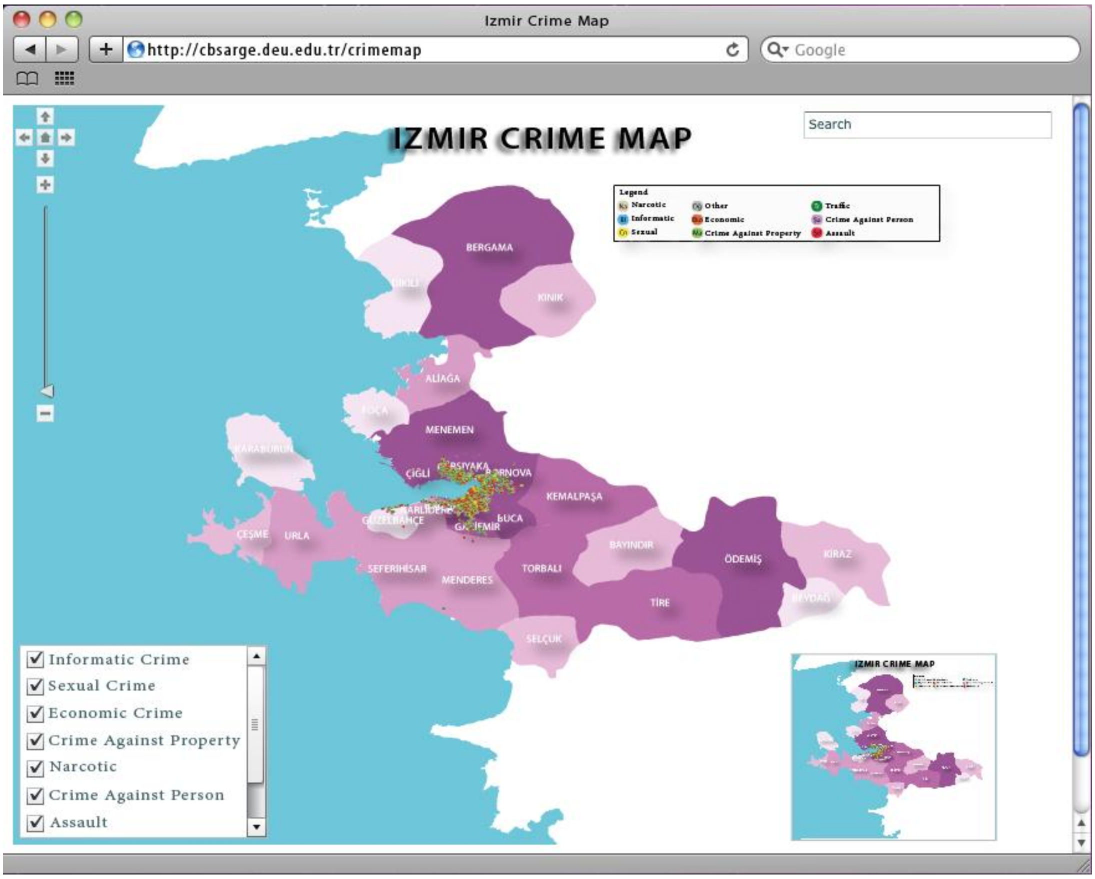


Figure 4.1 Spatial visualization of crime incidents between days in 1-31 August with the year of 2009

In order to obtain more detailed information, some features are added to the map which are shown in Figure 4.2 and 4.3. When a crime event is clicked on the map, a table which has limited information of crime incidents is shown. The table includes crime date, crime time, the location address of the crime and inferred unit to the crime information as shown in Figure 4.2.

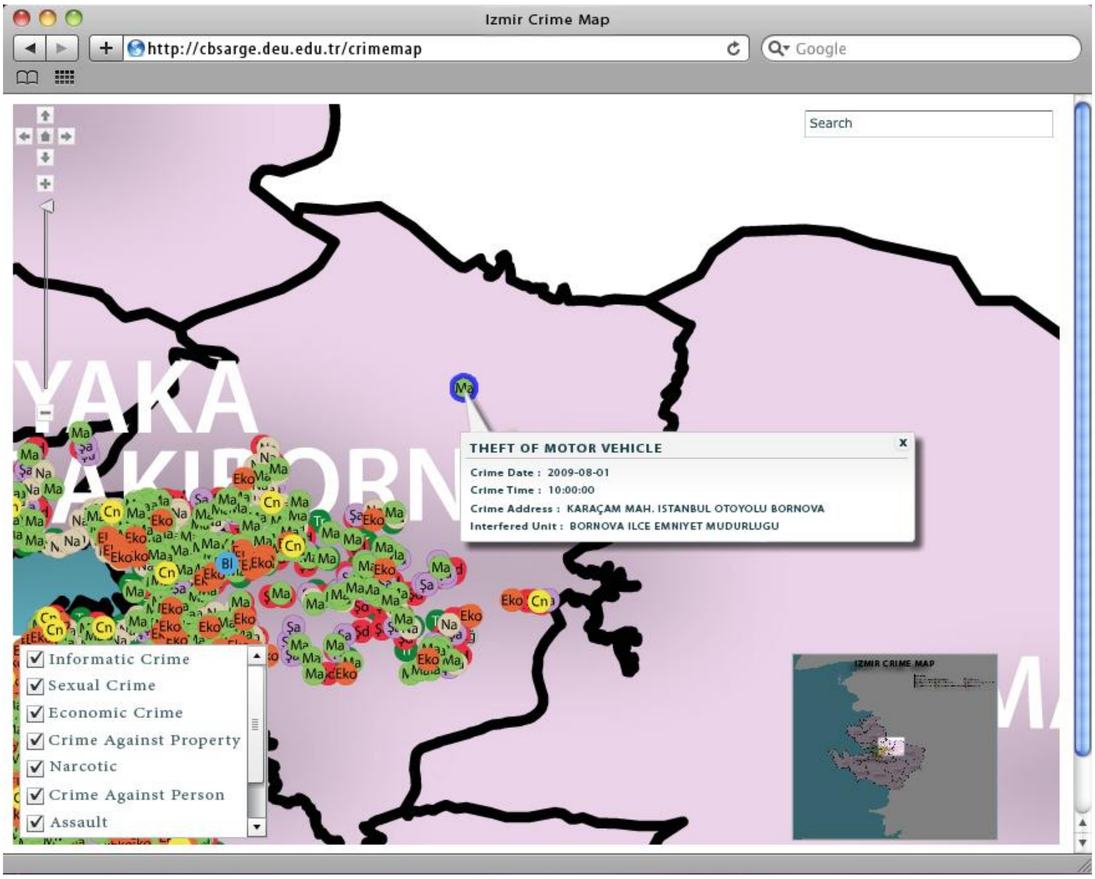


Figure 4.2 The information table of a crime incident

Some information are added for districts. When a district boundary is clicked on the map, a graph is visualized. The graph represents the pie chart of the distribution of different types of crime incidents for selected district. Thereby, DMs or people whom wanted to be informed will already know how the ratios of different types of crimes distributed in selected district. For instance, Assault has the biggest ratio in total crime in district Buca in 2009 as shown in Figure 4.3.

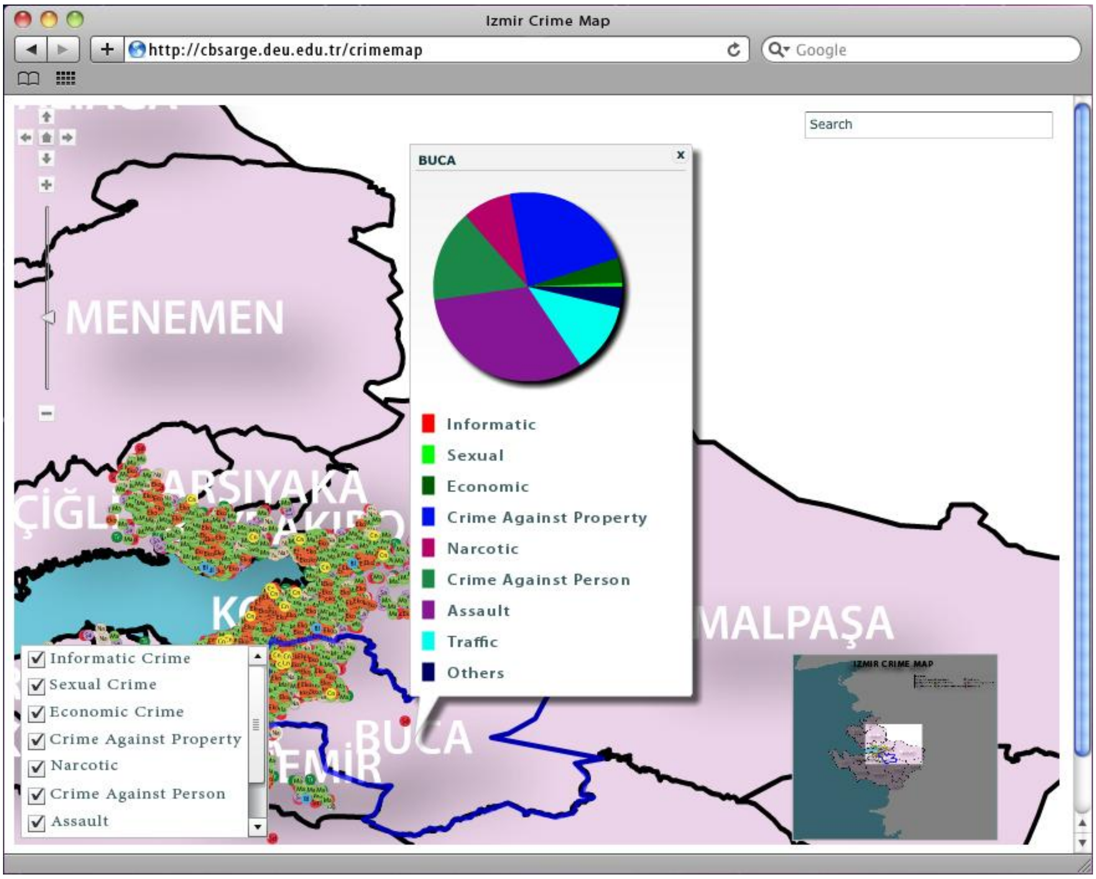


Figure 4.3 Graph of the distribution of different types of crime events in a district

In addition, search button is added at right top of the map. It is intended to allow people search police station or district names manually.

4.2 Temporal Analysis of Theft Incidents

Crimes are required to analyze with reporting them daily, weekly or monthly. Thus, crimes occurred in which time interval or days more frequent can be detected. Different types of Theft events are considered for making temporal analysis. All Theft incidents, which were found in years 2009, 2010 and 2011 with the number of 1,083, 1,139 and 1,208 respectively, are included in the analysis for month August. Totally, 3,430 number of Theft incidents are analyzed.

The analysis are applied on the basis of time and day of the Theft occurrences. According to Figure 4.4, the least Theft activities are seen at 2 and 4 o'clock in the morning and mid-day with the ratio between 3% and 6% in every day.

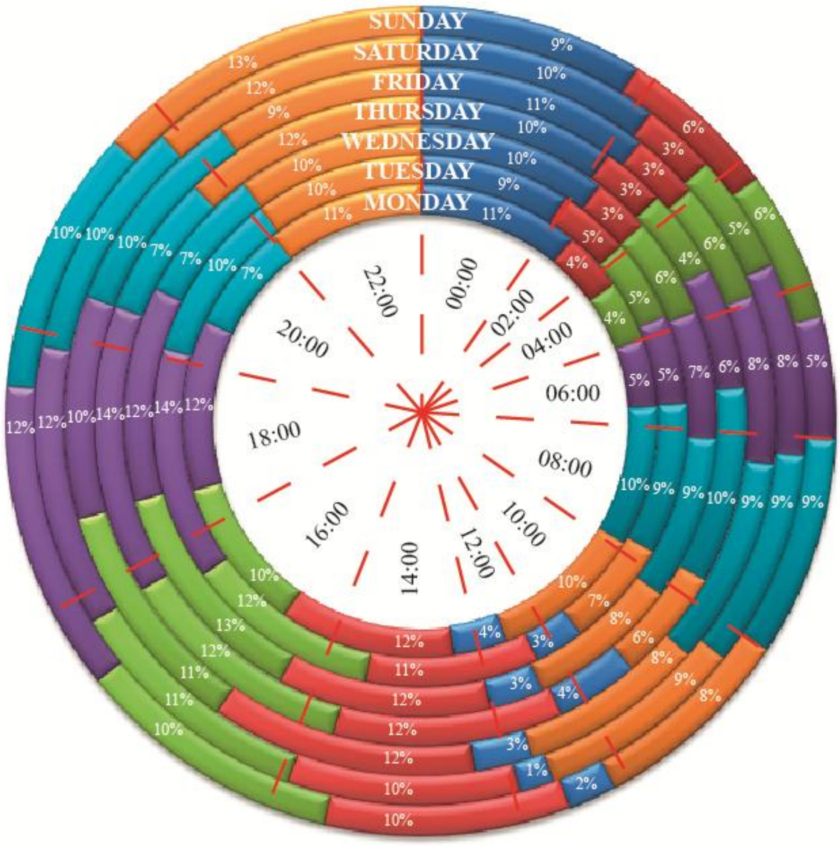


Figure 4.4 The analysis of Theft incidents by the times of the day

However, different types of Theft occurrences are analyzed by the days of the week as shown in Figure 4.5. According to graph, any significant change is not observed. Therefore, it can be said that time of the day is more important rather than the day of the week.

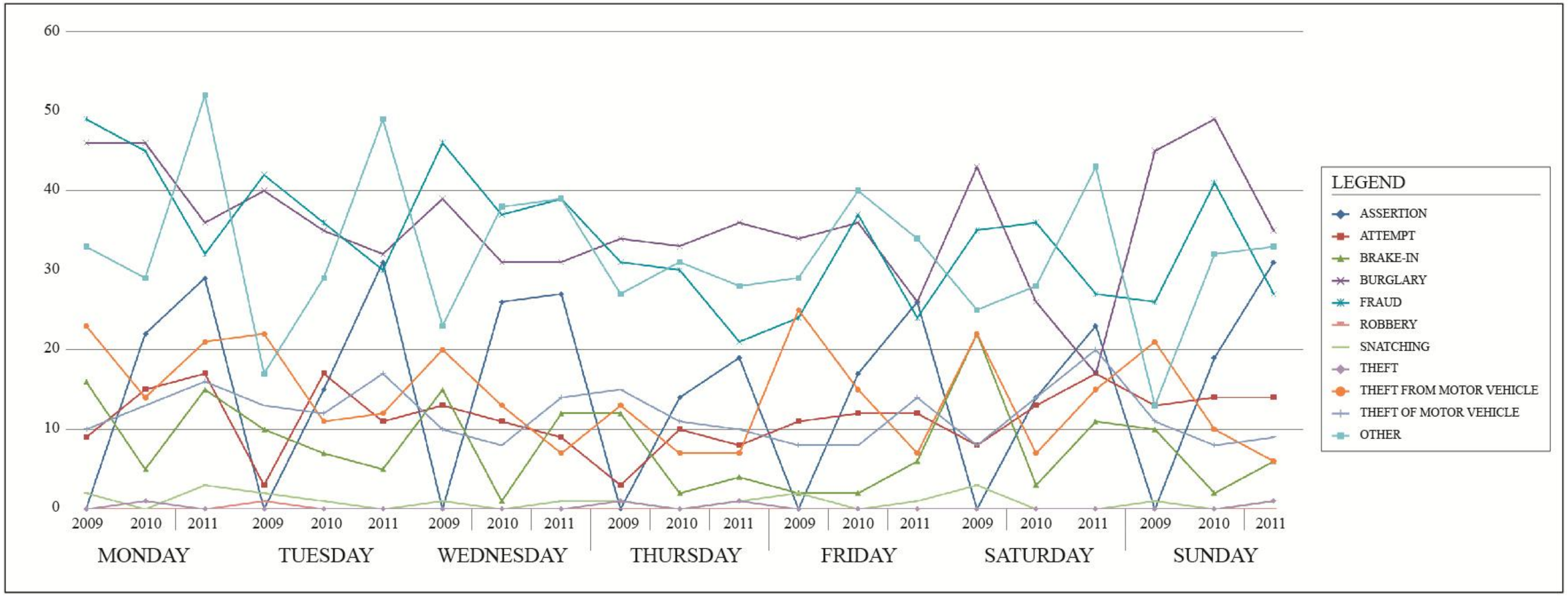


Figure 4.5 The analysis of Theft incidents by the days of the week

Days of the week are grouped by time intervals such as morning, noon and night. The selection of time intervals were described in the previous chapters. The graphs are visualized. It is seen from the Figure 4.6 that Theft occurrences are distributed approximately equal in days of the week.

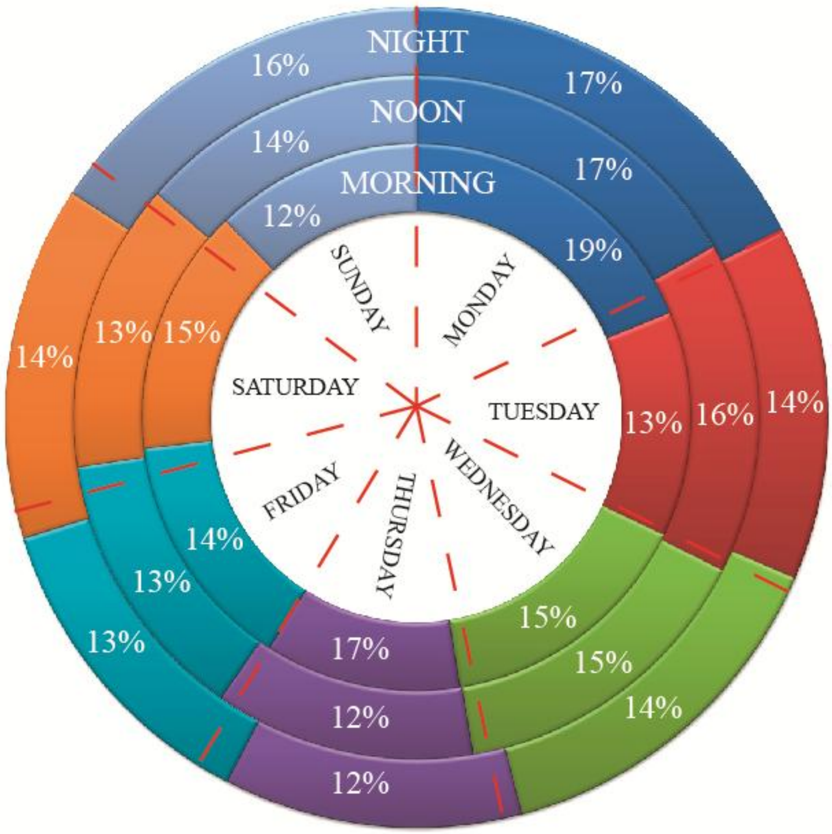


Figure 4.6 The analysis of Theft incidents by the time intervals of the day

The distribution of different types of Theft incidents is explored in Figure 4.7. The bar chart shows that Fraud, Burglary and Other type of Theft events are increased according to time intervals.

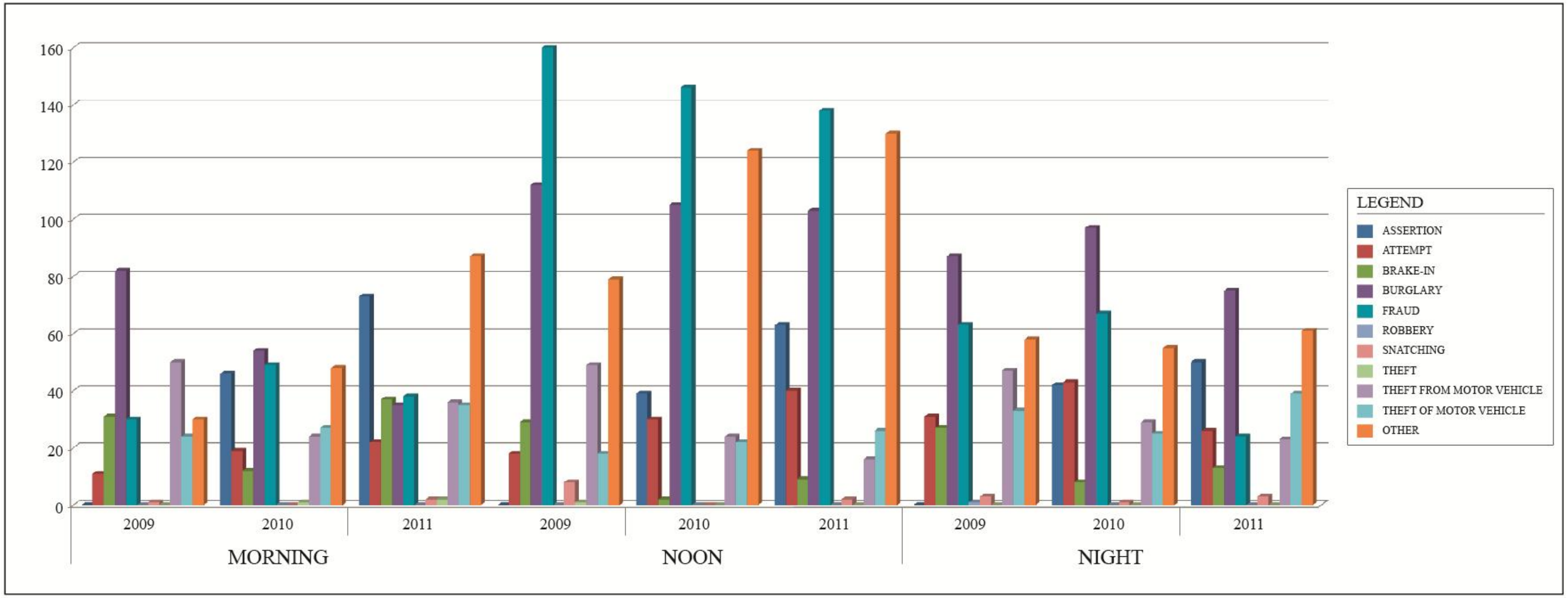


Figure 4.7 The analysis of Theft incidents by the time intervals yearly

Multiple regression analysis is applied to Theft incidents to explain that different types of Theft incidents are significantly changed according to time intervals or not. Thus, the relationship between one dependent variable (y) and multiple independent variables ($x_1, x_2, \ldots\ldots\ldots, x_n$) are explored. The relation is computed by using linear regression method as shown in Equation 4.1.

$$y = (a + b_1 x_1 + b_2 x_2 + \ldots + b_n x_n) \tag{4.1}$$

Where

y : dependent variable

a : intercept

$b_{1\to n}$: the coefficient number of the independent variable

$x_{1\to n}$: independent variable

The number of different types of Theft incidents which were committed in districts is used as dependent variable. Firstly, time intervals are used as independent variables of the equation. Then, days of the week are used with time intervals as independent variables. With this analysis, it is attempted to be determine whether any significant relationship between these two variables are exist or not.

Theft incidents which were occurred temporally are consisted of events committed in the morning (x_1), noon (x_2) and night (x_3). Dummy variable is used to denote the Theft incidents committed at morning, noon or night in a district. The results of the first linear regression analysis is shown in Table 4.1.

Table 4.1 The result of linear regression analysis applied on Theft incidents with time intervals

Type of Theft	Adjusted R^2	a	b_1	b_2	b_3	p value for b_1	p value for b_2	p value for b_3
Assertion	0.04	$1.39e^{-17}$	0.26	0.13	0.26	0.10	0.53	0.17
Attempt	0.40	$1.7e^{-16}$	0.05	0.25	0.48	0.77	0.11	0.01
Burglary	0.28	$-8.7e^{-17}$	0.02	0.36	0.14	0.93	0.02	0.46
Brake-in	0.39	$-1.39e^{-17}$	0.34	0.08	0.50	0.02	0.67	0.01
Fraud	-0.02	$8e^{-17}$	0	0.22	0	-	0.40	-
Robbery	0.85	0	0	0	0.8	-	-	$1.2\ e^{-222}$
Snatching	0.64	$6.94\ e^{-18}$	0	0.62	0.27	-	$2.92\ e^{-05}$	0.02
Theft	0.92	0	0.8	0.8	0	$6.7\ e^{-209}$	$3.9\ e^{-207}$	-
Theft form Motor Vehicle	0.50	$-2.08e^{-17}$	0.08	0.08	0.36	0.01	0.54	0.04
Theft of Motor Vehicle	0.02	-2.43	0.19	0.19	0.24	0.11	0.24	0.27
Other	0.14	$3\ e^{-17}$	0.25	0.25	0.60	0.82	0.31	0.09

Regression results are interpreted through the value of adjusted R^2 cited in the table. Because the coefficient of determination of R^2 is usually not sufficient for multiple models. Thus, adjusted R^2 is calculated to make significant tests in multiple models according to the Equation 4.2.

$$\bar{R}^2 = 1 - (1 - R^2)\frac{n-1}{n-k} \tag{4.2}$$

Where

$\bar{R}^2$: adjusted R^2

n : number of observation

k : number of variables in the model (dependent variables + independent variables)

It can be said that the model is significant if the coefficient of determination of adjusted R^2 is closed to 1. According to applied multiple linear regression model, Robbery, Snatching, Theft and Theft from Motor Vehicle are explained over the ratio of 50%. There is not found any significant relation between time intervals and the other types of Theft incidents.

In addition to time intervals, days of the week (Monday, Tuesday, etc.) are added as independent variables into the model. The regression results are shown in Table 4.2. According to the results, independent variables are explained 70% significantly only for Brake-in and Assertion types of Theft crimes.

While evaluating the results of both two regression analysis, it is seen that different types of Theft incidents are explained by different time intervals of a day. For instance, independent variable group which includes also days of the week are not be able to explain Theft crimes with acceptable levels. So, days of the week are not included from the next stage of the analysis. However, time intervals are used separately in GWR models to explore factors affecting the Theft events.

Table 4.2 The result of linear regression analysis applied on Theft incidents with both time intervals and days of the week

Type of Theft	Adjusted R^2	a	b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	p value for b_1	p value for b_2	p value for b_3	p value for b_4	p value for b_5	p value for b_6	p value for b_7	p value for b_8	p value for b_9	p value for b_{10}
Assertion	0.71	$-1.6\ e^{-17}$	0.38	0.5	0.31	-0.31	-0.22	-0.37	0	0.42	0.01	0.06	0.01	0.01	0.04	0.02	0.06	0.02	-	0.01	0.94	0.58
Attempt	0.31	$-8.3\ e^{-17}$	0.35	0.64	1.04	-0.29	0	-0.69	0	-0.57	0	-.056	0.19	0.01	0.001	0.19	-	0.02	-	0.02	-	0.02
Burglary	-0.13	$2.8\ e^{-17}$	-0.23	0.11	-0.14	0.25	0.22	0	0.4	0.02	0	0.35	0.58	0.68	0.68	0.41	0.50	-	0.26	0.96	-	0.23
Brake-in	0.70	$-1.4\ e^{-16}$	0.02	-0.62	-0.23	0.71	0.09	0.18	0.68	0	0.75	0	0.61	$1.2\ e^{-05}$	0.002	$8.4\ e^{-07}$	0.08	0.003	$1.6\ e^{-05}$	-	$5.9\ e^{-07}$	-
Fraud	-0.18	$9.02\ e^{-17}$	0	0.007	0	0.4	0	0	0	0.10	0.05	0.26	-	0.97	-	0.08	-	-	-	0.66	0.85	0.28
Robbery	0.36	0	0	0	0.8	0	0	0	0	0	0	0	-	-	$3.4\ e^{-222}$	-	-	-	-	-	-	-
Snatching	0.40	$-3.1\ e^{-17}$	0	0.6	0.13	0.2	0	0	0.2	0	-0.33	0	-	0.002	0.19	0.10	-	-	0.26	-	0.07	-
Theft	0.42	$-1.4\ e^{-17}$	$-2.8\ e^{-16}$	0	0	0.8	0	0	0.8	0	0	0	0.02	-	-	$2.1\ e^{-184}$	-	-	$3.8\ e^{-187}$	-	-	-
Theft form Motor Vehicle	-0.06	$-8.3\ e^{-17}$	0.13	-0.20	0	0.29	0.22	0	0	0.39	0	0.32	0.53	0.36	-	0.25	0.41	-	-	0.08	-	0.14
Theft of Motor Vehicle	0.21	$2.9\ e^{-16}$	1.21	1.22	0.44	-1.11	-1.04	-1.13	-0.94	0	-0.41	0	0.01	0.01	0.05	0.01	0.01	0.01	0.03	-	0.13	-
Other	-0.34	$1.5\ e^{-16}$	-0.24	0.021	0.31	0.29	0.06	0	0	0.34	0	0.25	0.55	0.95	0.50	0.31	0.83	-	-	0.25	-	0.40

4.3 Exploring Factors on Affecting Theft Incidents

In the previous section, it was explained that temporal factors are not have significant effect on the formation of Theft events. In this section, geographical, socio-cultural and/or spatio-temporal factors had been explored whether they are affected on Theft incidents in different study scales or not.

Influential factors cannot be determined based on historical information obtained from literature review. "Crimes can change from country to country, region to region, culture to culture or even for social and economic structure of a country" (Aksoy, 2004, p.3). Thus, explanatory factors of Theft incidents must be recalculated for each study. In this research, independent variables are investigated to compute the influencing levels of explanatory variables on Theft incidents with using event data occurred in August 2010 by using GWR method. GWR allows different relationships to exist at different points in space by calibrating a multiple regression model and investigate local trends in nonstationarity in regression models (Brunsdon, Fotheringham & Charlton, 1996). And also GWR has the ability to model the spatial relationships (Fotheringham, Brunsdon & Charlton, 2002).

Hence, this research is performed on two different scale of the study area to determine which scale is suitable for predicting potential locations of future Theft incidents. Number of Theft events and their locations are used as a dependent variable of the study. Population density, migration, male population which are in age between 18-35, male population which graduated from primary school, temperature, wind speed, number of facility areas, number of public transportation stations, number of religious buildings, number of commercial use of buildings, number of education buildings, number of police stations, number of banks, distance from facility areas, distance from transportation stations, distance from religious buildings, distance from commercial use of buildings, distance from education buildings, distance from police stations and distance from banks are used as independent variables.

Because of using variety of variables in the research, some of these have very large values. Thus, normalization is applied on independent variables.

Socio-cultural variables (population density, migration, male population which are in age between 18-35, male population which graduated from primary school) are normalized by using Equation 4.3.

$$\frac{quantity \;\; in \; i^{th} \; region}{popula \; tion \;\; in \; i^{th} \; region} \tag{4.3}$$

Demographic (population density), spatio-temporal and geographic variables are normalized by using Equation 4.4.

$$\frac{quantity \;\; in \; i^{th} \; region}{total \;\; value \;\; of \;\; study \;\; area} \tag{4.4}$$

Descriptive statistics of the independent variables per district and grid cells are represented in Table 4.3.

According to minimum and maximum values in the table, it can be said that population density is reached the maximum level at the inner areas of Gulf of Izmir. Moving away from the city center, population density is reduced at locations where coastline of Gulf of Izmir ends. The areas which implemented for agricultural activities are also areas has minimum population density. They are dispersed in the southern and eastern locations of the study area.

Coastal districts like Foça, Urla, Seferihisar where tourism activities executed, has low number of male population graduated from primary school. However, population density is increased in districts which are intensely deal with urban activities like Konak, Bayraklı, Karabağlar, Bornova and Buca. Male population which are in age between 18-35 and migration are also increase in these districts and their surrounding districts.

Table 4.3 Descriptive statistics of explanatory variables (regional scale n= 21, local scale n=35,785)

Variables	Regional Scale				Local Scale			
	min	max	variance	Std. deviation	min	max	variance	Std. deviation
Population density	0.002	0.306	0.006	0.08	0	2.681	0.016	0.13
Male population graduated from primary school	0.007	0.027	$2.765e^{-005}$	0.01	0	2.571	0.016	0.13
Male population which are in age between 18-35	0.101	0.522	0.160	0.09	0	4.252	0.017	0.13
Migration	0.138	7.29	2.08	1.44	0	1.151	0.001	0.02
Temperature	2.80	3.10	0.004	0.06	2.750	3.120	0.004	0.06
Wind speed	1.180	3.323	0.192	0.44	0.963	3.460	0.251	0.50
# facility areas	0.001	0.147	0.002	0.04	0	1.247	0.001	0.03
# transportation stations	0.002	0.111	0.001	0.03	0	0.675	0.000	0.02
# religious building	0.001	0.291	0.005	0.07	0	1.702	0.001	0.03
# commercial use	0.001	0.350	0.007	0.09	0	1.711	0.002	0.04
# education buildings	0.001	0.222	0.004	0.06	0	1.404	0.001	0.03
# police stations	0.002	0.397	0.008	0.09	0	3.390	0.005	0.07
# banks	0.001	0.416	0.009	0.09	0	4.775	0.004	0.07
Distance from facility areas	0	0.774	0.027	0.16	0.001	0.199	0.001	0.03
Distance from transportation station	0.004	0.221	0.005	0.07	0.001	0.199	0.001	0.03
Distance from religious building	0.001	0.160	0.003	0.06	0.001	0.458	0.011	0.11
Distance from commerce	0.002	0.184	0.004	0.06	0.001	0.447	0.012	0.11
Distance from education	0	0.725	0.023	0.15	0.001	0.448	0.010	0.10
Distance from police station	0.002	0.149	0.003	0.05	0.001	0.500	0.013	0.11
Distance from bank	0.002	0.163	0.003	0.05	0	0.477	0.013	0.11

In addition, number of whole facilities are increased when moving towards city center from periphery. Conversely, distance from these facilities are decreased at the city center.

Each independent variable is included in the GWR method with using add-drop technique. Adjusted R^2 values are computed for each process of add-drop technique.

Variables which calculated the adjusted R^2 values closest to 1, are selected as the explanatory variables that contributes to the formation of Theft incidents.

Unlike conventional regression, which produces single regression equation to summarize relationships among the explanatory and dependent variables, GWR generates spatial variation in the relationships among variables with producing multiple regression equation (Mennis, 2006). GWR method shows the existence of spatial relationships between different spatial units over space (Brunsdon et al., 1996).

As mentioned in the previous section, the factors influenced on Theft occurrences are computed at morning, noon and night respectively for regional and local scales of the study area separately. The outputs of GWR method which applied at morning in regional and local scales are shown in Figure 4.8.

According to Figure 4.8(a), Theft incidents which committed at morning are explained with the contribution of whole demographic and socio-cultural variables and besides these number of transportation stations, number of education buildings and distance from transportation stations of geographic variables by the rate of 94%. Because of the existence of educational units, which have great areal size such as university campuses, in the districts located around the Gulf of Izmir, transportation stations are positioned remote from each other. It causes the change of standard deviation between ± 2.5 in those areas.

According to the results of spatial statistics at the same time interval and in the same limited study area, the factors defined by using regional scale is not found sufficient to explain Theft incidents at local scale. However, Theft incidents are identified with the contribution of population density, temperature, distance from educational units, number of religious buildings and number of educational units by the rate of 50% at local scale (see Figure 4.8(b)).

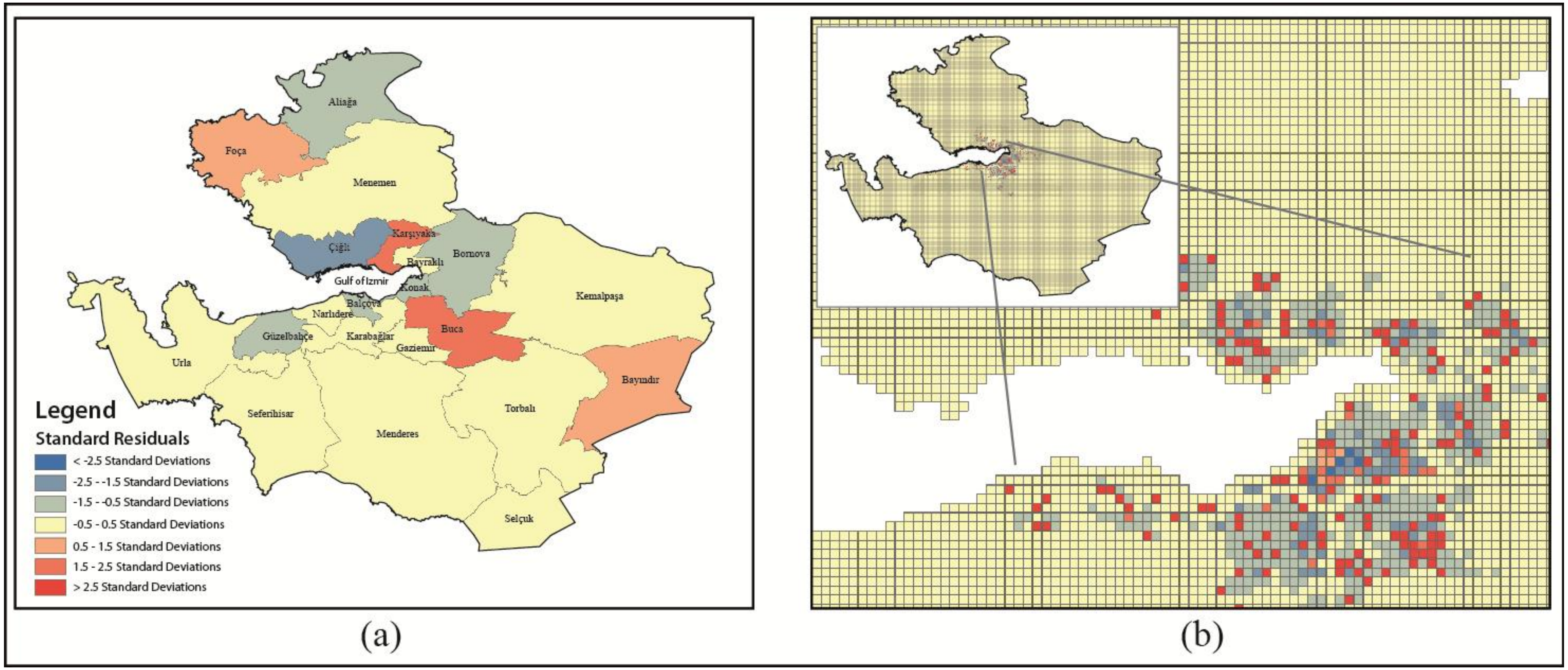


Figure 4.8 The output map of GWR method applied on Theft incidents at morning (a) Regional scale (district level administrative boundaries) (b) Local scale (geographically restricted 400x400 m grid sizes)

The results of the influencing factors of Theft incidents at morning, noon and night are summarized in Table 4.4.

Table 4.4 Relationship between crime events and explanatory variables at regional and local scale

Variable Type	Variable Name	Regional Scale			Local Scale		
		morning	noon	night	morning	noon	night
Demographic	Population density	X	X	X	X	X	
Cultural	Male population graduated from primary school	X					
Social	Male population which are in age between 18-35	X	X	X			X
	Migration	X					
Spatio-temporal	Temperature				X		
	Wind speed			X			
Geographic	# facility areas			X			
	# transportation stations	X				X	X
	# religious building		X		X		
	# commercial use		X				
	# education buildings	X			X	X	
	# police stations			X			
	# banks		X				
	Distance from facility areas						
	Distance from transportation stations	X				X	
	Distance from religious buildings						
	Distance from commercial use						X
	Distance from education buildings				X	X	
	Distance from police stations						X
	Distance from banks						

According to the results, Theft incidents, occurred at noon, are explained with the contribution of population density, male population which are in age between 18-35, number of religious buildings, number of commercial use of buildings and number of banks by the rate of 80% at regional scale. Theft incidents, occurred at night, are explained with the contribution of population density, male population which are in age between 18-35, wind speed, number of facility areas and number of police stations by the rate of 81% at regional scale.

At local scale, Theft incidents, occurred at noon, are explained with the contribution of population density, number of transportation stations, number of education buildings, distance from transportation stations and distance from education buildings by the rate of 60%. Theft incidents, occurred at night, are explained with the contribution of male population which are in age between 18-35, number of transportation stations, distance from commercial use of buildings and distance from police stations by the rate of 55% at local scale.

Responsibility areas of security units are defined by the boundaries of the neighborhoods as seen in Figure 4.9.

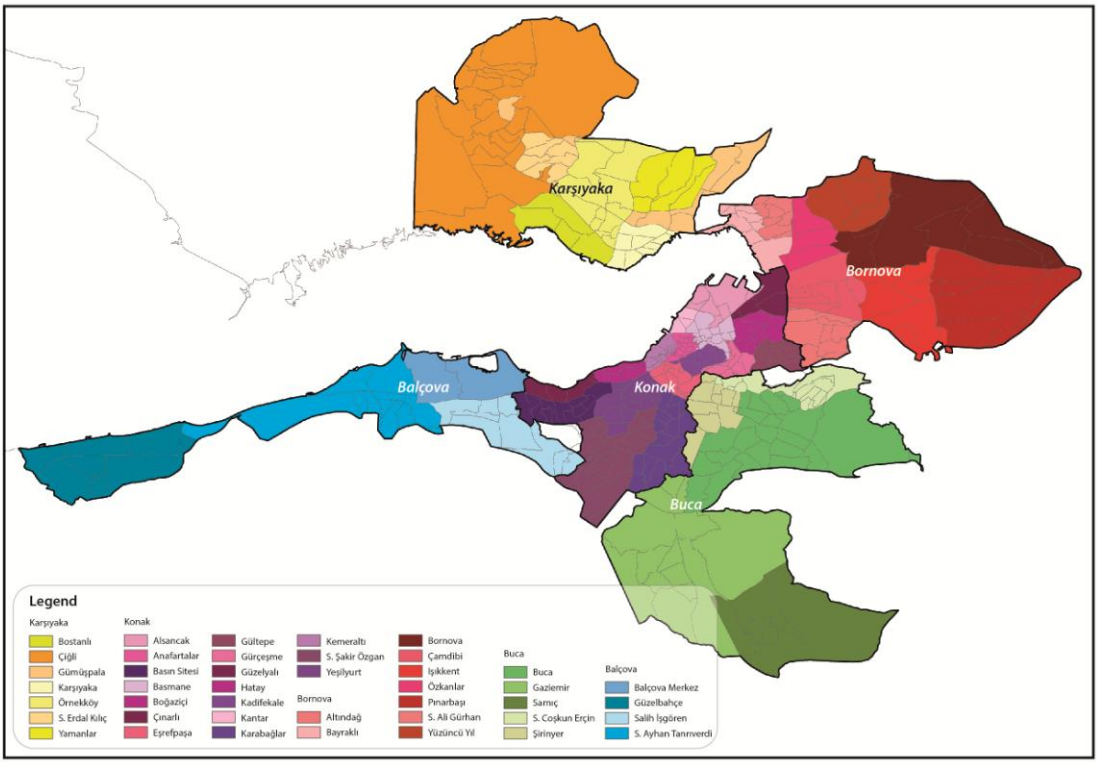


Figure 4.9 Responsibility areas of security units

There are 44 police stations which are belong to 5 major security units. So, another local scale is generated with using neighborhood boundaries for the research area. And GWR is repeated for this new local scale as shown in Figure 4.10.

This newly generated scale is described the Theft incidents with 68% significance level with using the contribution of population density, male population which are in age between 18-35, number of transportation stations, number of police stations, distance from education buildings, distance from commercial use of buildings and distance from transportation stations.

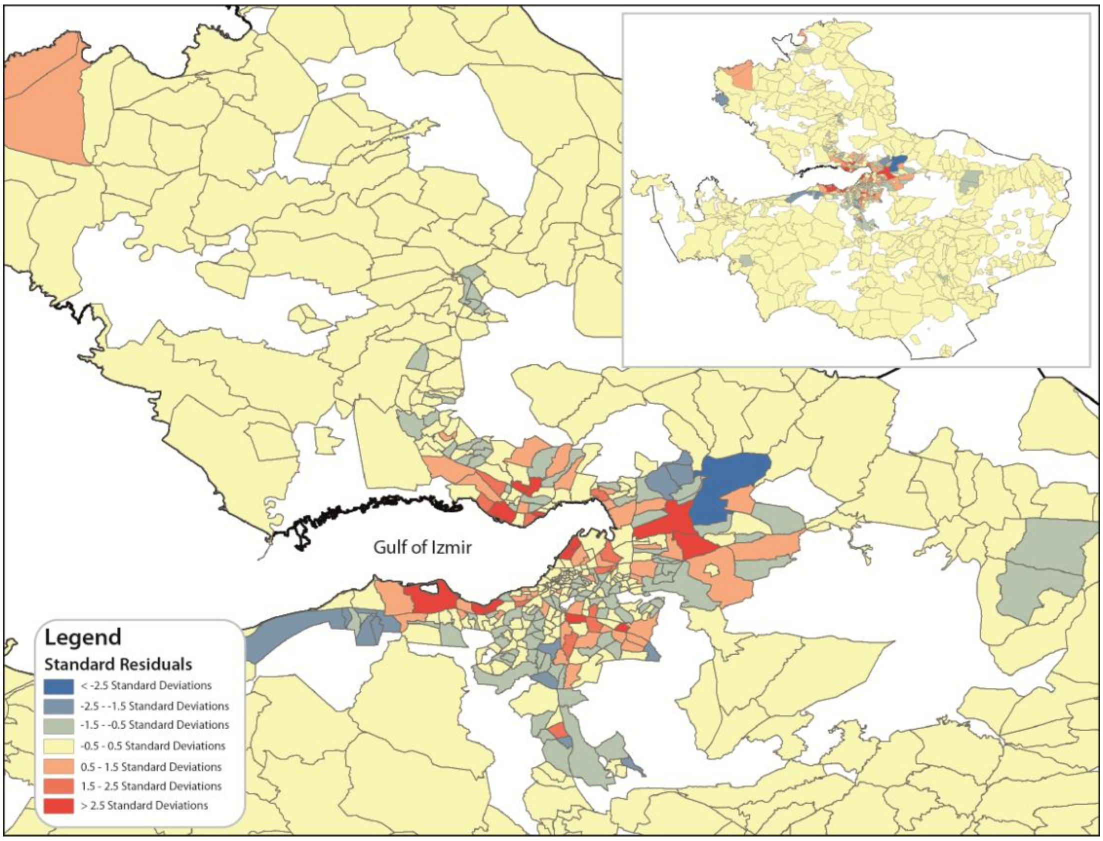


Figure 4.10 The output map of GWR method applied on Theft incidents with the limitation of neighborhood boundaries

4.4 Spatial Prediction

The integration of ANN and GIS techniques is needed to enable DMs for making prospective spatial analysis and visualizing the results spatially. It will also allow ease in decision-making. In this research, structure of a SDSS is created by constructing this integration.

Explanatory variables which obtained from GWR results are used in structure of ANN. Because supervised learning algorithm is a computation method that effectively used in cases where both information and samples are exist, it is applied as learning strategy in this research.

It is intended to estimate the approximate locations of future crime events. Despite crimes can be described better at regional scale, security units which is going to take measures of crime prevention activities has responsibility areas limited by neighborhood borders. Therefore, spatial prediction is performed at local scale.

In order to achieve this goal, crime data which has at least three period of time is necessarily needed. First two period of data is obtained for using as sample data of the study. The remaining data is allocated as test data to check the accuracy of prediction results. The data could consisted of 3 months of any season or it could be 3 different years of a month. In this study, spatial prediction is performed by using Theft data which occurred in three different year of the same month.

Prediction is carried out in two different output set. One of them is estimating the actual number of Theft incidents at local scale. The other one is estimating whether a Theft event committed in a location or not at local scale.

4.4.1 Prediction of Actual Number of Theft Incidents

Estimation of actual number of Theft incidents is performed by using feed-forward back propagation method. The network is trained with using Levenberg-

Marquardt learning algorithm. ANN architecture of this algorithm is visualized in Figure 4.11.

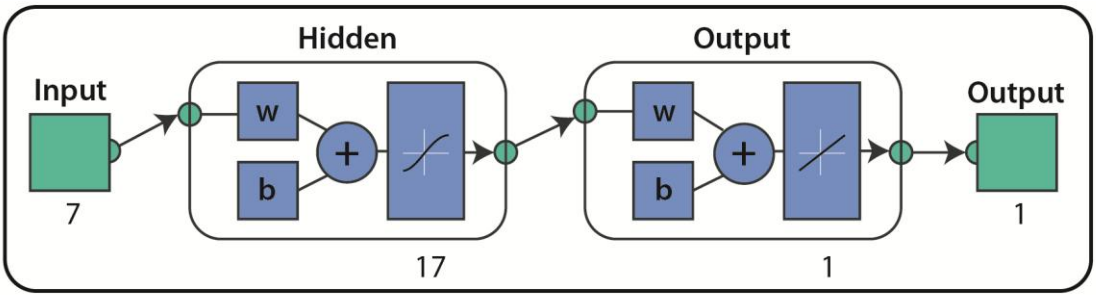


Figure 4.11 Architecture of Levenberg-Marquardt algorithm

Hidden layer has a sigmoid function which limits the minimum and maximum values of target data. Mean Square Error (MSE) is used for evaluating the network's performance. MSE is the average squared difference between targets and outputs. MSE is calculated by Equation 4.5.

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (4.5)$$

Where

y_i : individual observation (target) values for feature i

$\hat{y}_i$: the predicted (output) value for feature i

n : total number of features

Lower values are better (it is desired to be close to "0"). Zero means no error occurred.

Input layer of this architecture is included scaled values of population density, male population which are in age between 18-35, number of transportation stations, number of police stations, distance from transportation stations, distance from commercial use of buildings, and distance from education buildings which were defined as factors affected on Theft incidents by GWR analysis. Output layer is consisted of number of Theft events.

Hidden layer size is chosen as experimental. Experimental method is based on exploring the performance of the network by increasing the number of hidden neuron while all other parameters keep constant (Aras, 2013). The aim is to achieve the optimum hidden layer size. The experiment is completed when best performance is obtained in validation set. At this moment, the number of hidden neuron is set as number of hidden layer size.

Table 4.5 Error results of validation set for different hidden layer sizes

Number of hidden neurons	average mse	average mae	average R
1	12.16	1.94	0.73
2	10.15	1.72	0.60
3	9.59	1.75	0.65
4	9.82	1.75	0.65
5	9.55	1.74	0.65
6	9.42	1.75	0.70
7	9.49	1.75	0.69
8	9.29	1.74	0.66
9	9.38	1.75	0.71
10	9.49	1.75	0.68
11	9.28	1.75	0.69
12	9.48	1.75	0.70
13	9.44	1.76	0.71
14	9.67	1.76	0.71
15	9.27	1.74	0.71
16	9.31	1.74	0.70
17	**9.25**	**1.75**	**0.69**
18	9.29	1.75	0.71
19	9.43	1.75	0.70
20	9.40	1.75	0.70

In this study, hidden layer size is determined experimentally, not to exceed 20. The number of hidden neurons is defined through a total of 200 trials conducted over 10 different input weight value. Learning of the network is provided by dividing the dataset 50% training, 17% validation, and 33% test with block. The results of the experiments are carried out according to the different number of hidden neurons are shown in Table 4.5.

Average MSE of validation set is computed in experiments which have different input weights in each validation set. Hidden layer size is chosen as the number of hidden neurons which has the lowest value of average MSE. According to computation, number of hidden neurons is determined as 17.

10 different input weights had been tried to minimize the MSE of validation set. The minimum average is taken in which hidden layer size was 17. The results of different weights for chosen hidden layer size is shown in Table 4.6.

Table 4.6 Results for different weights of hidden layer size 17

Hidden layer size	Number of trial of initial weight	Val mse	Val mae	epoch	Test R	Test mse
17	1	9.22	1.73	20	0.70	6.50
	2	8.68	1.75	7	0.71	6.62
	3	8.99	1.69	14	0.73	6.20
	4	9.15	1.76	16	0.70	6.49
	5	9.16	1.71	11	0.69	6.55
	6	9.18	1.74	18	0.70	6.72
	7	9.41	1.73	11	0.59	9.70
	8	**9.51**	**1.77**	**25**	**0.73**	**5.92**
	9	9.49	1.79	11	0.70	6.77
	10	9.71	1.78	12	0.68	6.71

Prediction results of output are obtained with stopping the algorithm by validation check at 25th epoch. Accordingly, training of the algorithm is explained the target set with the accuracy of 77% and validation set was explained the target set with the accuracy of 75% as shown in Figure 4.12. Thus, test set is explained the target set with the accuracy of 73%.

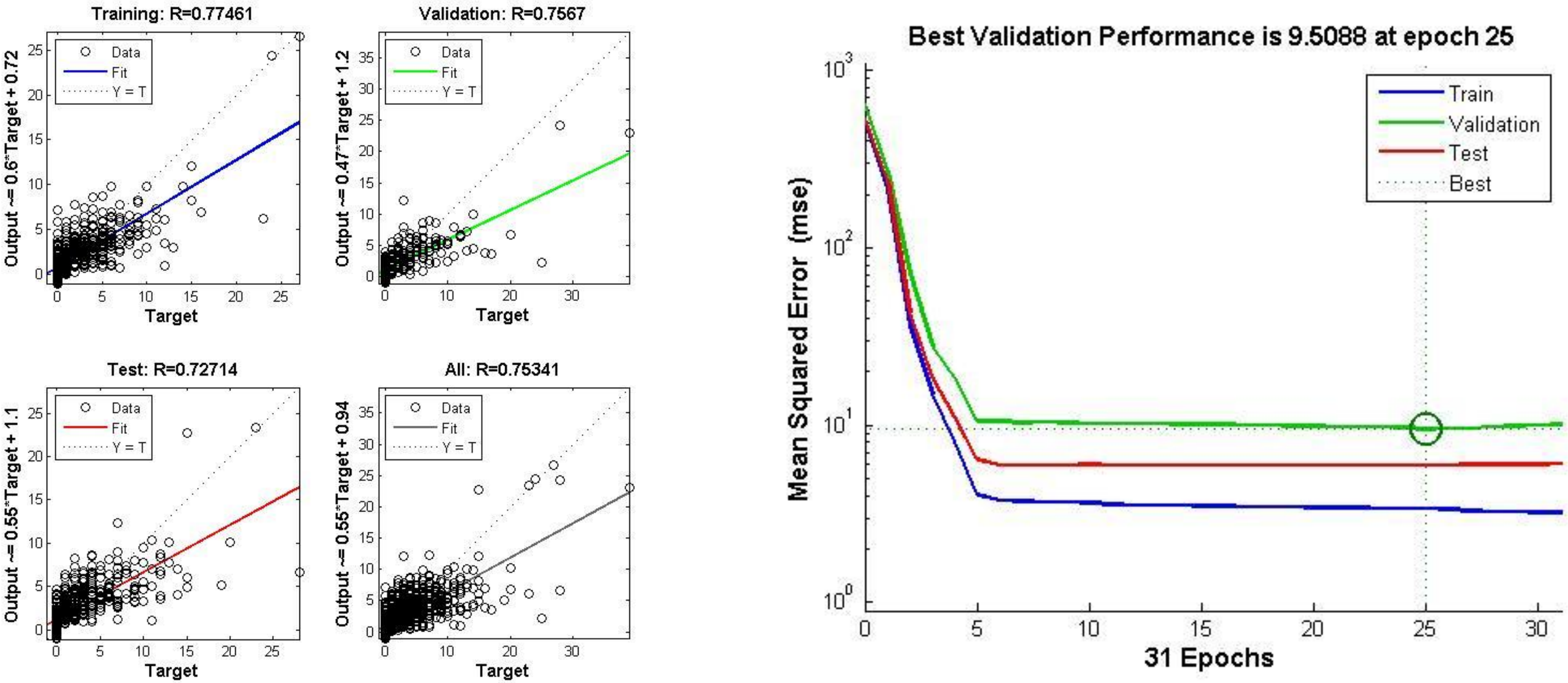


Figure 4.12 Regression and performance results of selected prediction algorithm

Output set is the number of Theft incidents occurred within the boundaries of each neighborhood. Totally, 200 trials are conducted to define optimal hidden layer size. At the end of experimental method hidden layer size is chosen as 17. According to prediction, differences between target and output sets is shown in Figure 4.13.

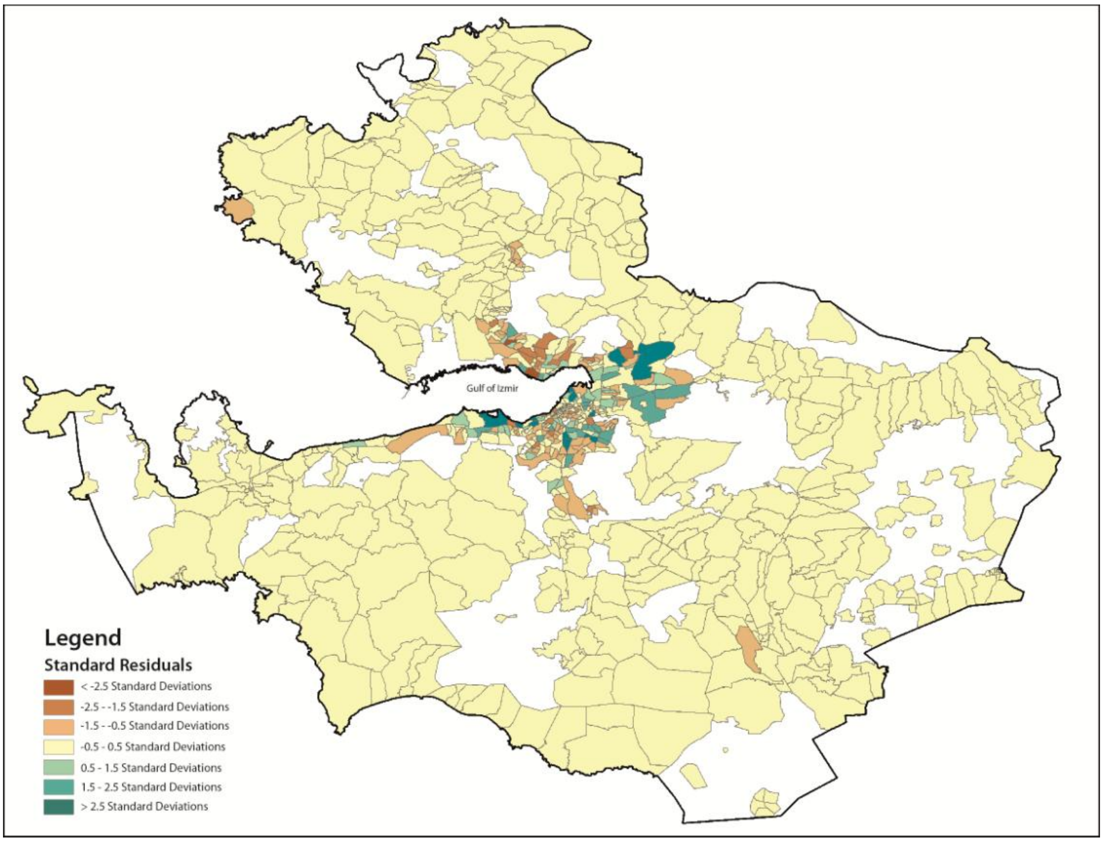


Figure 4.13 Map of standard deviations

According to map of standard deviations, it is observed that prediction results are more accurate farther from the city center. Coexistence of more than one activity and complex social relationships in the city center causes the divergence from target value near the city center.

Distributions of current and predicted Theft incidents are shown in Figure 4.14.

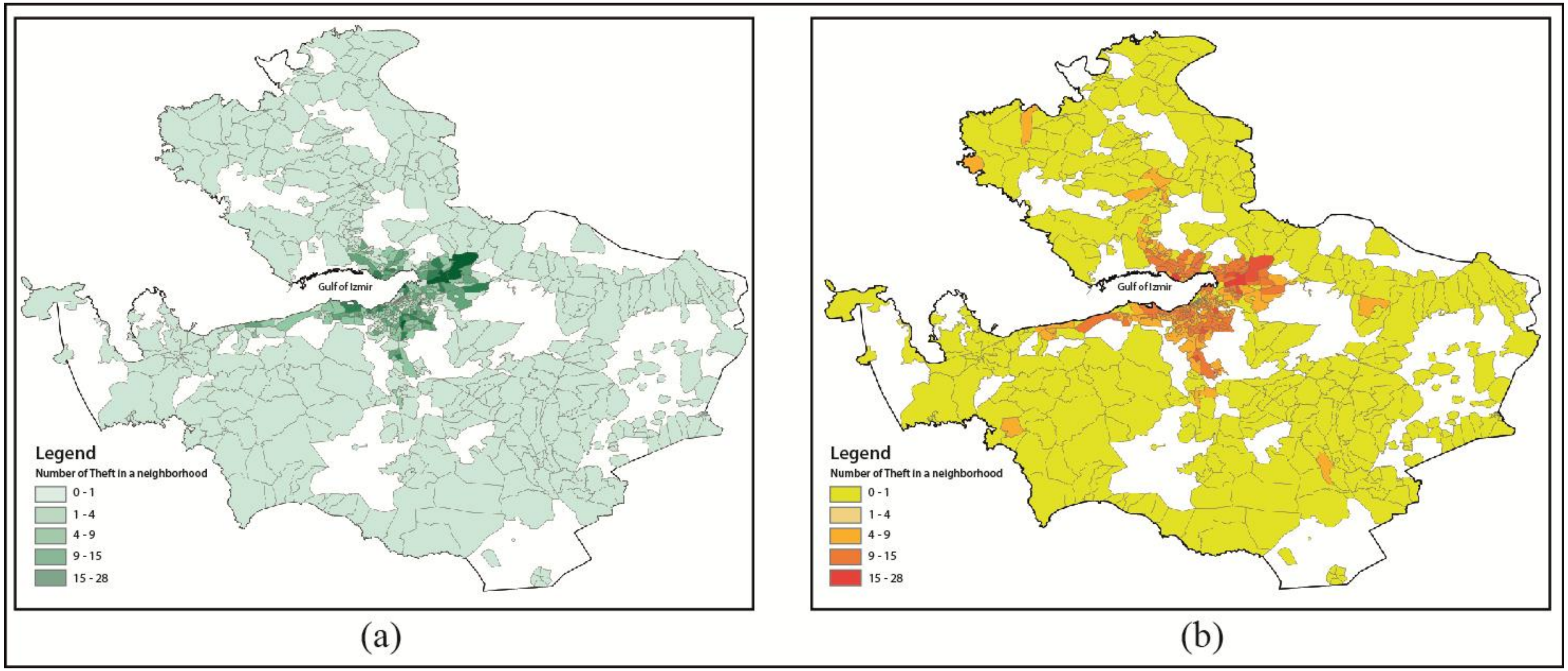


Figure 4.14 Map of target and output sets of the study (a) Number of Theft incidents occurred in 2011 (b) Number of predicted Theft incidents which probably occurred in 2011

Same period of dataset is also predicted by using linear regression method. Prediction results of ANN and regression method are compared in Table 4.7.

Table 4.7 Results of linear regression and ANN

Regression		**ANN**	
MSE	**R**	**MSE**	**R**
6.54	0.65	5.92	0.73

According to Table 4.7, it is observed that MSE of the output data is decreased by using ANN method. R values are calculated with using Equations 4.6, 4.7 and 4.8 respectively. According to results, it can be said that ANN method is explain target values with the accuracy of 32.6% better than regression methods.

$$S_x = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(x_i - \bar{x})^2} \quad (4.6)$$

$$S_y = \sqrt{\frac{1}{n-1}\sum_{i=1}^{n}(y_i - \bar{y})^2} \quad (4.7)$$

$$R = \frac{1}{n-1}\sum_{i=1}^{n}(\frac{x_i - \bar{x}}{S_x})(\frac{y_i - \bar{y}}{S_y}) \quad (4.8)$$

Where

x_i : individual observation values for feature i

y_i : individual target values for feature i

$\bar{x}$: mean value of observed features

$\bar{y}$: mean value of target features

S_x : standard deviation of observation values

S_y : standard deviation of target values

4.4.2 Prediction of Theft Occurrences in a Neighborhood Boundary

In order to estimate whether a Theft incident committed in that location or not, classification process is conducted. Accordingly, the existence of an incident is expressed by binary digits (1-0). Pattern Recognition (PR) is used as the classification method. PR is a two layer feed forward network with a sigmoid hidden and output neurons, can classify vectors arbitrary well, given enough neurons in its hidden layer. The network is trained with Scaled Conjugate Gradient back propagation. MSE is used for evaluating the network's performance. ANN architecture of this algorithm is visualized in Figure 4.15.

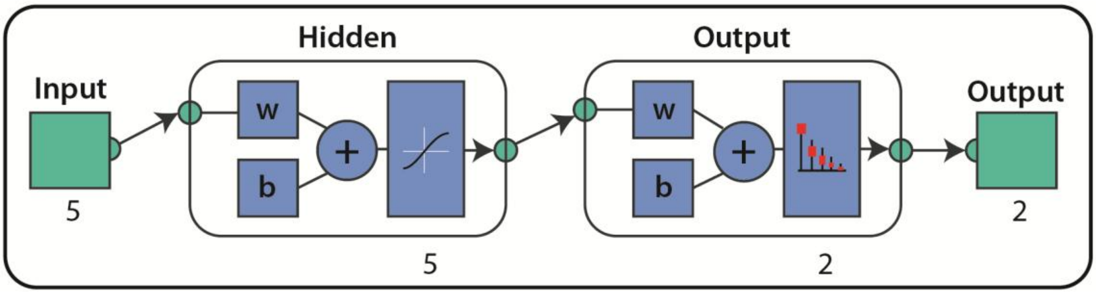


Figure 4.15 Architecture of Scaled Conjugate Gradient back propagation algorithm

The data which includes population density, male population which are in age between 18-35, number of transportation stations, number of police stations, distance from transportation stations, distance from commercial use of buildings, and distance from education buildings which were defined as factors affected on Theft incidents by GWR analysis are used as input variables. Principle component analysis is applied on these variables to convert the correlation between each variable into linearly uncorrelated. Thus, input layer had 5 input variables which also scaled. Output of dataset is featured as “1,0” for existence of Theft events and “0,1” for non-existence of Theft events.

Hidden layer size is chosen as experimental. Again, the aim is to achieve the optimal hidden layer size. The experiment is completed when best performance is obtained in validation set. The best performance of hidden layer size is taken in 5 after 30 attempts. Learning of the network is provided by dividing the dataset 50%

training, 17% validation, and 33% test with block. The results of the experiments are carried out according to the different number of hidden neurons are shown in Table 4.8.

Table 4.8 Experiment results of validation set for different number of hidden neurons

Number of hidden neuron	mse	mae	R	epoch	time	Test mse
1	0.11	0.22	0.81	27	1.0	0.09
2	0.11	0.21	0.82	19	0.5	0.08
3	0.11	0.23	0.82	21	2.0	0.08
4	0.11	0.22	0.82	31	0.2	0.08
5	**0.10**	**0.21**	**0.84**	**68**	**0.3**	**0.07**
6	0.11	0.23	0.81	23	0.2	0.09
7	0.11	0.23	0.80	14	0.1	0.09
8	0.11	0.22	0.81	16	0.5	0.09
9	0.11	0.21	0.82	34	0.4	0.08
10	0.11	0.22	0.83	24	0.4	0.08
11	0.11	0.22	0.81	7	0.1	0.09
12	0.11	0.22	0.81	13	0.1	0.09
13	0.11	0.22	0.82	30	0.2	0.08
14	0.10	0.21	0.84	36	0.2	0.08
15	0.11	0.21	0.82	14	0.1	0.08
16	0.10	0.22	0.84	43	0.6	0.07
17	0.10	0.21	0.83	37	0.3	0.08
18	0.10	0.21	0.83	25	0.6	0.08
19	0.11	0.21	0.83	37	0.5	0.08
20	0.10	0.21	0.83	36	0.5	0.08
21	0.11	0.22	0.82	22	1.0	0.08
22	0.11	0.24	0.80	19	0.3	0.09
23	0.11	0.22	0.83	23	0.4	0.10
24	0.39	0.51	-0.08	2	0.1	0.42
25	0.11	0.22	0.81	11	0.2	0.09
26	0.11	0.23	0.80	12	0.3	0.09
27	0.11	0.22	0.81	14	0.2	0.09
28	0.11	0.23	0.82	17	0.3	0.08
29	0.11	0.22	0.83	37	0.4	0.08
30	0.10	0.21	0.84	58	0.5	0.07

Error histogram of the results and performance of the learning algorithm is shown in Figure 4.16. According to Figure 4.16(a), it can be said that error distribution of training, validation and test datasets had incrementally decreased.

Distribution of standard deviations of differences between existence of current Theft incidents and predicted Theft incidents is shown in Figure 4.17. Prediction results are decreased at farther away from the city center. Although complex social relationships are existed in the city center, Theft crime was committed. Prediction algorithm is run to calculate the existence of Theft incidents in each neighborhood. So results of the prediction had been correctly worked in the city center.

Farther away from the city center, dataset is exposed to similar social and spatial relationships as in the city center. This situation is caused that Theft incidents are predicted as exist in those areas. Therefore, the error rate is increased at the periphery.

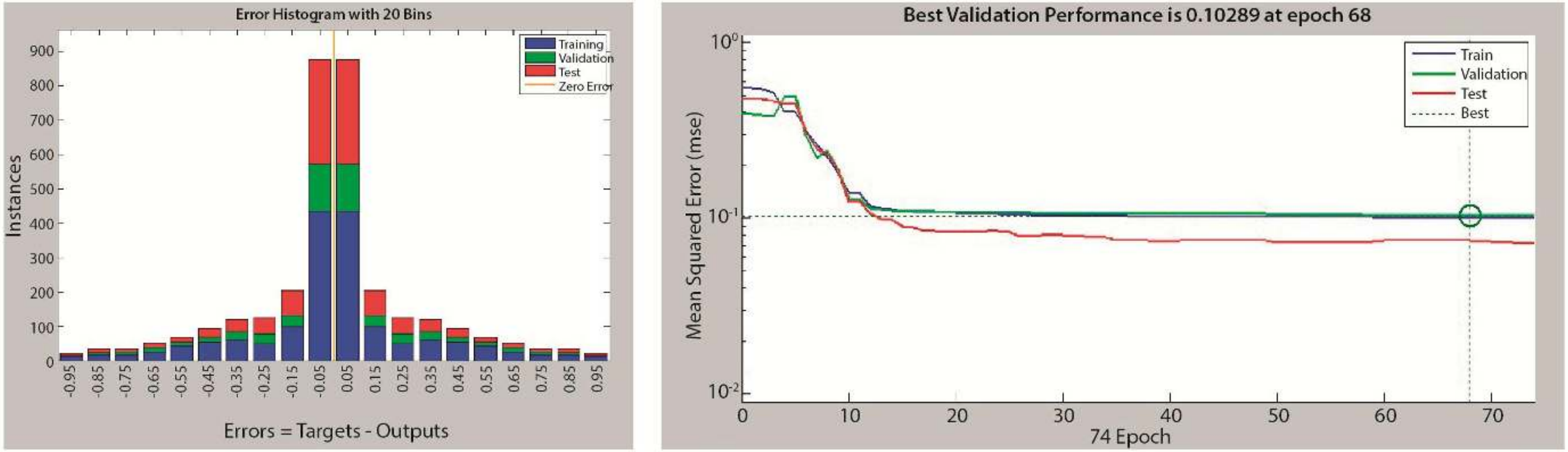


Figure 4.16 Graphs of learning algorithm (a) Error histogram (b) Performance

As a result, prediction algorithm is explained target values with the ratio of 84%. And success rate is determined by comparing the estimated values with the actual values with each other after rounded the fractional numbers to binary numbers. If these two values are equal to each other, it can be said that the prediction was performed correctly. Accordingly, it can be said that prediction is performed 91% successfully.

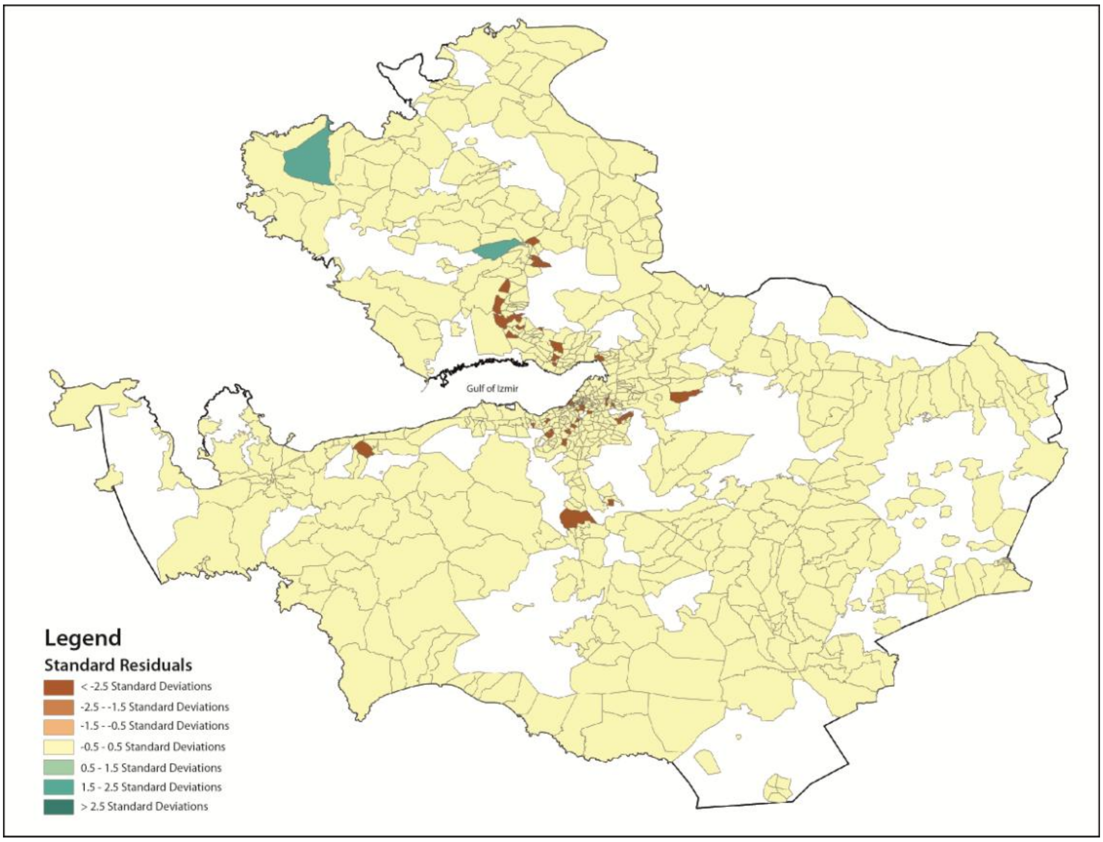


Figure 4.17 Distribution of standard deviations of differences between current Theft existence and predicted Theft existence

Finally, distribution of current and predicted Theft existence is shown in Figure 4.18.

Prediction process was run on HP Z420 workstation with Intel Xeon E5 4C CPU, 3.60 GHz, 8 GB RAM and 64-bit processor. Prediction of number of Theft incidents was done in 0.1 second at the end of the 25 epoch. Prediction of existence of Theft incidents was done in 0.3 second at the end of the 68 epoch.

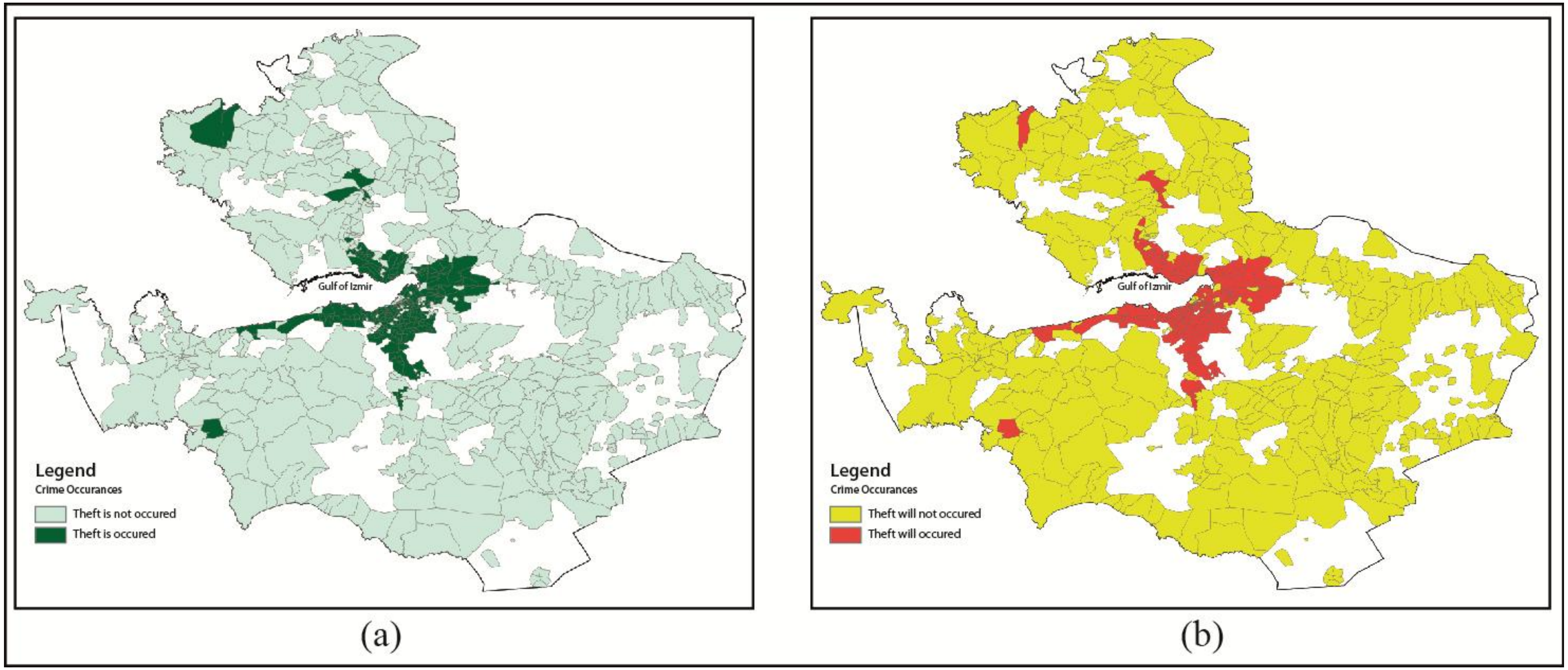


Figure 4.18 Distribution of current and predicted Theft existence (a) Current Theft occurrences in 2011 (b) Predicted Theft occurrences in 2011

CHAPTER FIVE
CONCLUSION AND DISCUSSION

According to the literature review, it was determined that numerous studies had been done about identification of factors affecting crime occurrences, accessing criminal profiles or locations of criminals by investigating crime scenes and police databases. Nevertheless, the results did not include computer aided future prediction efforts to prevent singular crime events. If repeated formation of same and/or similar conditions comes together, similar crime events can also be committed in that location. Because of this reason, it is important to define factors affecting crime occurrences and train them to an intelligent system. Thus, innovative steps were taken by this study which offers a methodology for making spatial future predictions by using ANN and GIS techniques together.

Although the combination of these two techniques (ANN and GIS) are still very new in literature for crime prevention activities, successful results were obtained in prediction of serial crime events. Olligschlaeger (1997) had gained the accuracy of 70% for prediction of crime series. Prediction of actual number of Theft incidents (non-serial crimes) are achieved with the accuracy of 73% by using described methodology in this thesis. And prediction of whether a Theft event occurred or not in a neighborhood boundary is achieved with the accuracy of 91%. Thus, it can be said that this research provides support to DMs for making crime prevention activities.

In order to compare the results of the statistical analysis, performed in two different level, data which can be used in both study scales must be obtained from different data sources. In this thesis, data about social, cultural, demographic and spatio-temporal variables were obtained from institutions in table format. These data were joined with using attribute data in geographical data obtained as GIS maps from IMM including district and neighborhood boundaries. Crime data was geocoded with the help of GIS techniques using coordinate information in attribute data. Data which was completely geocoded was transferred to a spatial database to measure the spatial relationships between dependent and independent variables.

It is known that objects which are located close to each other have more similarities than those distant from each other. Therefore, spatial statistic methods could be useful in examining the interactions between two or more objects. Spatial statistical method offers a general model of variables by applying the least squares methods in linear regression equation, including the information about locations of objects. In this thesis, factors affecting the formation of Theft incidents had been identified by using spatial statistics methods at regional and local scales.

It was found that demographic and socio-cultural factors are mainly effective on the occurrence of Theft incidents with the support of geographical factors at regional scale. Another fact was identified, geographical factors are more important than socio-cultural factors at the local scale.

This thesis aimed to provide a SDSS for supporting senior managers in Police Departments. Future prediction ANN algorithms were performed by using explanatory variables which were found to be significantly contributing to the formation of Theft events at local scale. Two different output sets (point estimation and clustering) were used for this purpose. One of the output sets had number of Theft incidents in each neighborhood. The other one had binary numbers as indicators of Theft occurrences (exist or not exist).

5.1 Research Limitations

Different sized areal units were used to identify scale effect in this dissertation. District level administrative boundaries were used as a regional scale, neighborhood level administrative boundaries and geometric boundaries which sized as 400x400 m (0.16 km^2) grid size maps were used as local scale. The definition of scales used in this study can be misunderstood by traditional urban planning perspective. Regional and local scale terms are specific to this study.

This study was started in 2009. Because of difficulties at obtaining previous data and time consuming process of data editing, the data were gathered from 2009 till 2011.

Socio-economic, spatio-temporal, geographic and crime data were used to explore factors affecting Theft incidents. In these dataset socio-economic, demographic, cultural, meteorological and crime data were obtained by years 2009, 2010 and 2011. Geographical data is consist of public transportation stations, religious buildings, commercial use of buildings, education buildings, police stations and banks. Each subgroup of geographical data are recorded in paper forms by different foundations. It is hard to transform the paper data to GIS maps with using just the address information of the constructions. Due to the lack of obtaining these data in sequence by years, only the year of 2009 geographical data, which mapped from IMM, was used.

5.2 Research Results

In research examining, findings indicated different results for each factor affecting crime occurrences. Each research had its own specific results in the domain of their study area. Researchers explain ineffectiveness of some factors which were effective only in their study in this way. While explaining the situation, it is seen that the differences of spatial magnitude and scale of the study area are ignored. Therefore, this dissertation tried to compare factors affecting Theft incidents using two different scales in same study area by applying GWR methods. Regional and local scales were used for this purpose. Although the research was conducted in the same spatial area, the results of affecting factors differ from each other. Hence, in addition to the opinion that using different geographic locations may influence the results of a research, it is determined that using different study scales would also have an effect on the results.

Researchers usually use only one factor group (social environment, physical environment, etc.) while determining the factors affecting the formation of crime. In the first stage of the study, it is observed that crimes are affected by socio-cultural environment with the contribution of physical environment factors at regional scale. Likewise, physical environment with the contribution of socio-cultural environment were affected on crime occurrences at local scale studies. The important point is to obtain appropriate data according to the scale of study area.

In the second stage of the study, it has been attempted to predict potential locations of future crime events by using defined factors which affect the formation of crime, determined by different study scales. For this purpose local scale, which includes neighborhood boundaries covering the area of responsibility of the security units, was used. Two different prediction results were developed by using explanatory variables defined from spatial regression as the input layer in ANN algorithm.

The first prediction was developed to compute the probability of whether Theft occurrences are going to be exist in the next year, or not, for each neighborhood boundary. The second prediction was estimating the number of Theft incidents in each neighborhood boundary for the next year. Prediction results were mapped geographically. Based on the results, it was observed that accuracy of test outputs decreases in city center, which has intensive urban activities close together. Singular Theft incidents can be predicted by using the methodology described in this thesis. Therefore, it can be said that geographically mapped prediction results may support DMs in crime prevention activities.

Risk maps about future Theft incidents were generated for senior managers in Police Departments to provide their crime prevention activities with Hotspot analysis techniques, as shown in Figure 5.1. Hotspot means statistically significant clusters of high values. Coldspot means statistically clusters of low values. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. Getis- Ord statistics is used for computing hot and cold spots by using the Equation 5.1.

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \frac{\sum_{j=1}^{n} x_j}{n} \sum_{j=1}^{n} w_{i,j}}{\sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left(\frac{\sum_{j=1}^{n} x_j}{n}\right)^2} \sqrt{\frac{\left[n \sum_{j=1}^{n} w_{i,j}^2 - \left(\sum_{j=1}^{n} w_{i,j}\right)^2\right]}{n-1}}} \tag{5.1}$$

Where

x_j : the attributed value of feature j

$w_{i,j}$: the spatial weight between feature i and j

n : total number of features

According to Hotspot analysis, it can be said that city center is under high risk on Theft events which will be committed in next year August. The periphery of the study area has low risk about Theft incidents. The areas located near the Aegean Sea and the external border of the Gulf of Izmir should be considered because these areas are under possible risk.

A risk map created by using Hotspot analysis techniques contains general information for the study area. In order to provide decision support locally for DMs, density map of risky areas was generated in addition to risk map which has limited information. Mid-points of the neighborhoods with weighting the number of Theft incidents are used to process interpolation. Distribution of predicted Theft incidents is drawn on the map as shown in Figure 5.2.

Current locations of Theft events are overlaid with the prediction output map as shown in Figure 5.3. Accordingly, it can be said that the prediction of future events are estimated in acceptable levels.

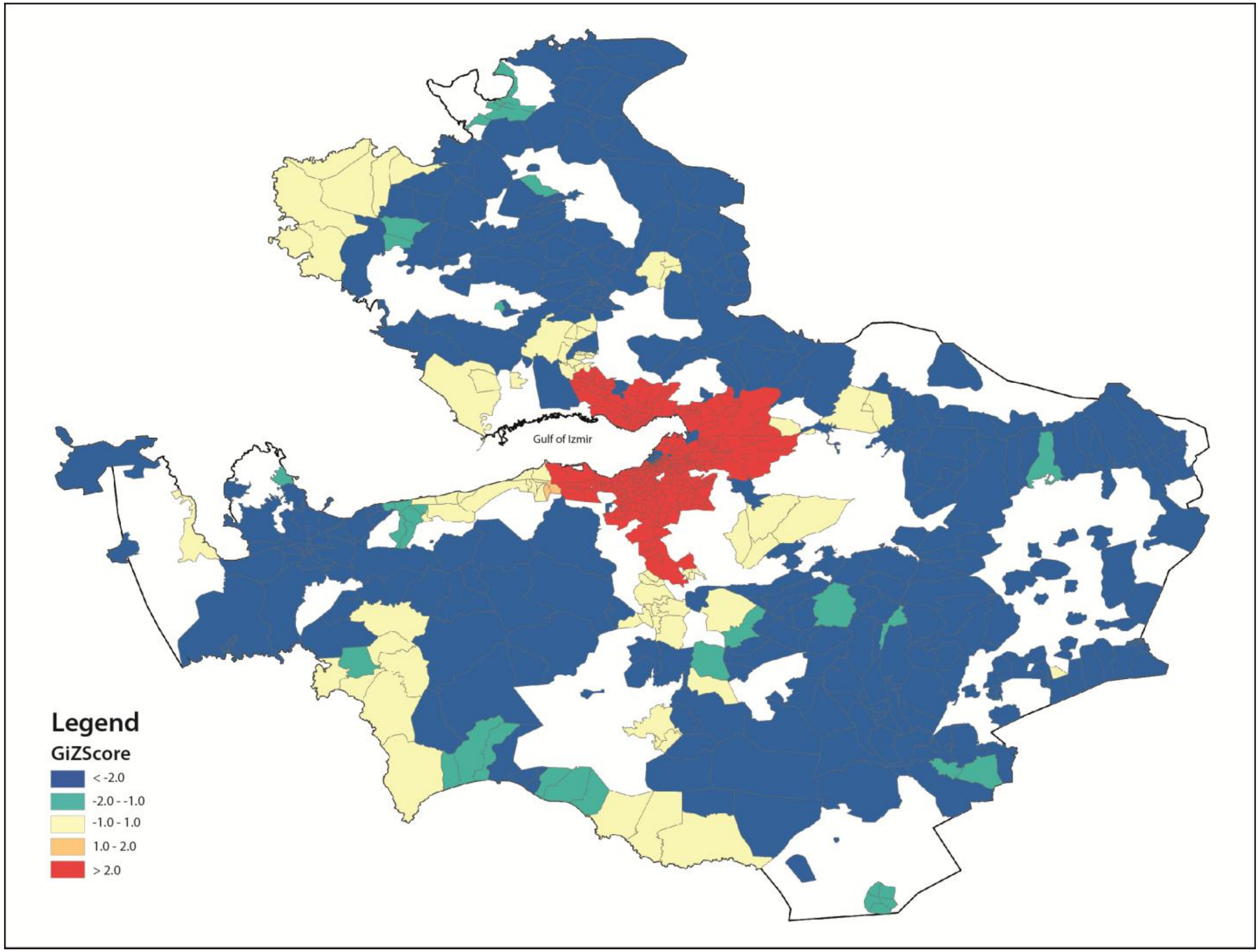


Figure 5.1 Risk map

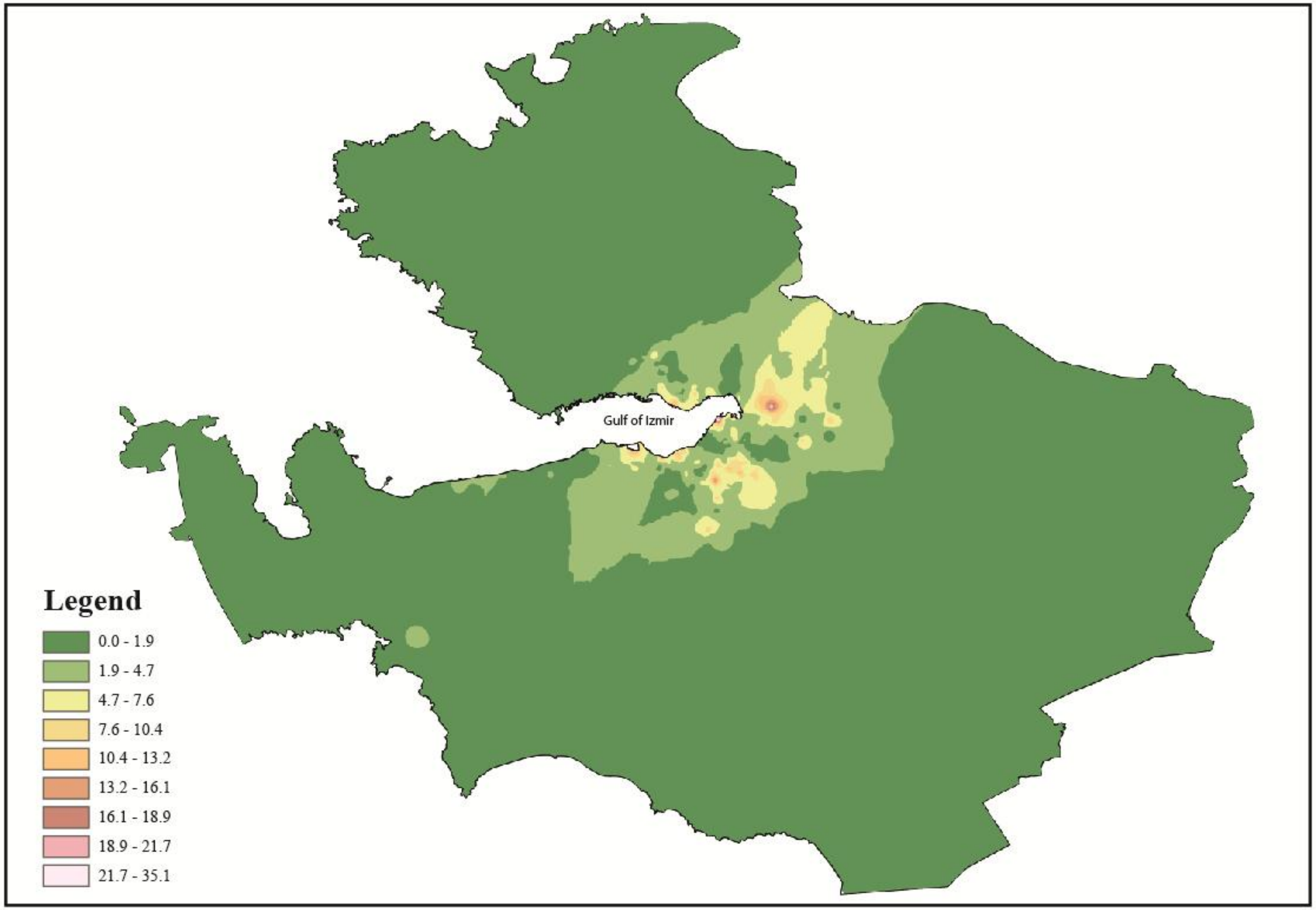


Figure 5.2 Density map of risky areas of future Theft events

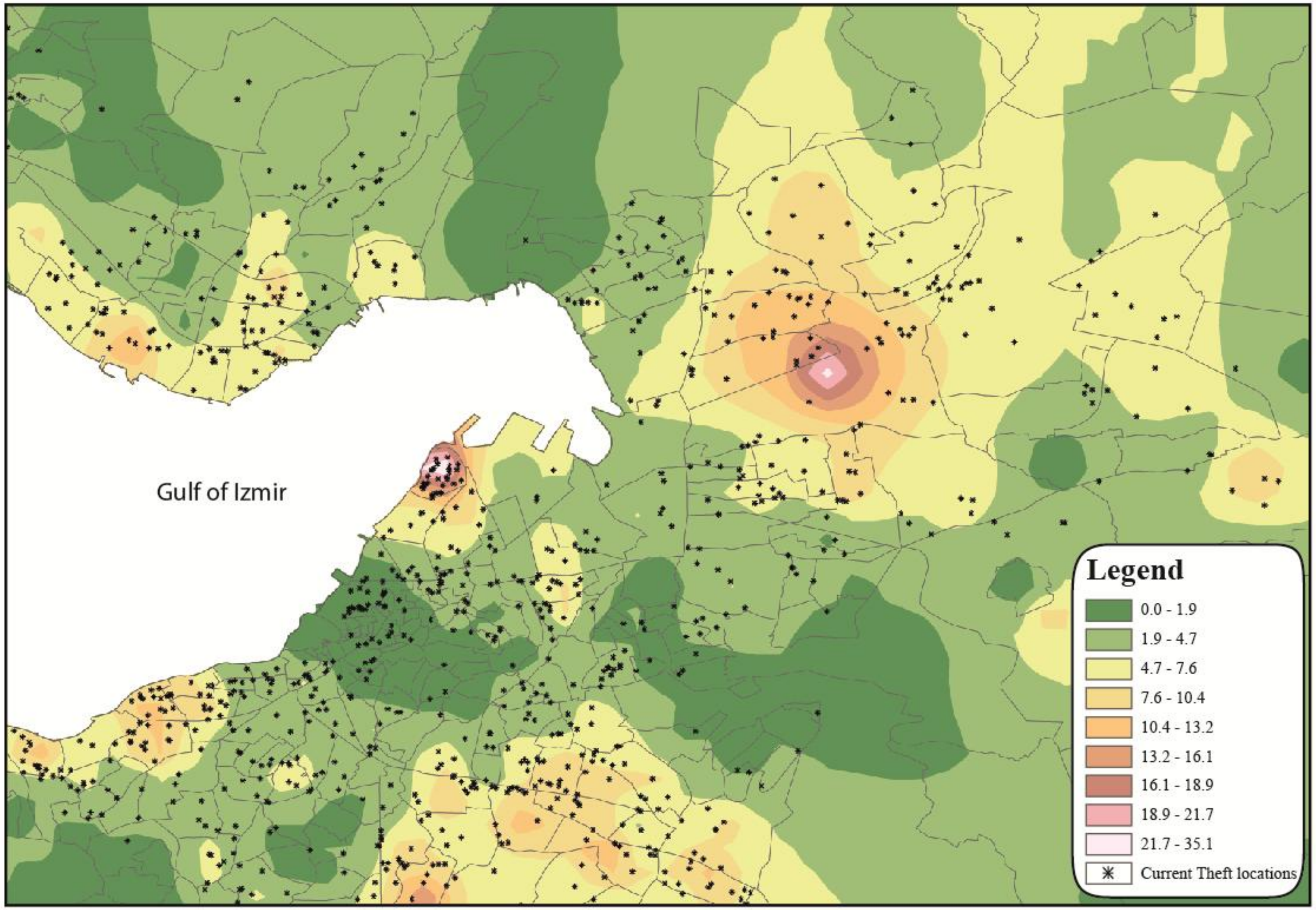


Figure 5.3 Density map of risky areas with current Theft locations

Prediction results of ANN were compared with prediction results of linear regression. According to the comparison, it is found that ANN algorithm explains future Theft events better than regression methods.

The data obtained for the study, the prediction algorithm was run again without being detected with spatial statistical methods. It was observed that the accuracy of the predictions had decreased. Accordingly, it can be said that spatial statistics, when applied for determining optimal study scale, improve the accuracy of prediction algorithms.

Finally, this research has results for three different issues:

- Study scale has been identified as a factor which affecting the formation of Theft incidents.
- The formation of Theft incidents, which is a type of non-serial crime, can be predicted at the neighborhood level successfully. Thus, a risk map of future Theft incidents could be mapped.
- This research is contributed to Turkish Literature as an application which uses ANN and GIS techniques in combination.

5.3 Further Studies

This research was performed on a single spatial database with using two different GIS software. Two software was used to convert the attribute data into spatial for making spatial statistical analysis successfully. If independent data will have such properties which mentioned in methodology, there won't be need any conversion process for data. Therefore, the data editing process would not be time consuming and prediction will start earlier.

Prediction results was reported both statistically and spatially at neighborhood level. If study on larger scales is requested, it would be necessary to use much detailed data, such as street attributes. Due to the lack of such data, prediction has not been carried out on grid scale.

Predicted Theft incidents were explained target values 73% successfully. More successful results can be achieved with this methodology by using different prediction algorithms and additional variables.

Finally, experience of integrating ArcGIS and MATLAB was found challenging because of difficulties on interoperability of packages of these softwares developed by different companies for this research (Roberts, Best, Dunn, Treml & Halpin, 2010). Thus, the integration of GIS and ANN software was performed manually. It is planned to develop a tool for GIS and ANN integration in further studies.

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APPENDICES

List of Abbreviations

ANN **:** Artificial Neural Networks

CBIS **:** Computer based Information Systems

DMs **:** Decision Makers

DSS **:** Decision Support Systems

GIS **:** Geographical Information Systems

GWR **:** Geographical Regression Analysis

IDW **:** Inverse Distance Weighted Interpolation

IMM **:** Izmir Metropolitan Municipality

IPD **:** Izmir Police Department

OLS **:** Ordinary Least Squares

SDSS **:** Spatial Decision Support Systems

TSI **:** Turkish Statistics Institute

TSMS **:** Turkish State Meteorological Service

Glossary of Terms

Artificial Neural Networks are computational models inspired by biological neural networks (the central nervous systems of animals, in particular the brain) and are used to estimate or approximate functions that can depend on a large number of inputs and are generally unknown. Artificial neural networks are generally presented as systems of interconnected neurons which can compute values from inputs, and are capable of machine learning as well as pattern recognition thanks to their adaptive nature.

ArcMAP is the main component of ESRI's ArcGIS suite of geospatial processing programs, and is used primarily to view, edit, create and analyze geospatial data.

Avenza MAPublisher is a powerful suite of plug-in tools for Adobe Illustrator, leveraging its superior graphics capabilities for high-quality map creation (www.avenza.com). It has ability to import the most widely used GIS data formats, such as Esri, MapInfo, FME Desktop, AutoCAD, Google and the US government with all attributes and georeferencing intact.

Geographical Information Systems is a computer based system which contains latitude, longitude and altitude information from a satellite positioning system and geological, biological and climatic data entries (Oxford University). GIS link the spatial information (people and addresses, buildings to parcels, species to habitat) to give a better understanding of how it all relates (ESRI). GIS is an integrated system of computer hardware, software and trained personnel linking topographic, demographic, utility, facility, image and other resource data that is geographically referenced (NASA).

Geographically Weighted Regression is the method which is mapping the existence spatial relationships between different spatial units over space by calculating statistics (Brunsdon et al., 1996). GWR is one of several spatial regression techniques, increasingly used in geography and other disciplines. GWR provides a local model of the variable or process you are trying to understand/predict by fitting a regression equation to every feature in the dataset. When used properly, these methods are powerful and reliable statistics for examining/estimating linear relationships.

Hot Spot Analysis is the method to calculate the Getis-Ord Gi* statistic (pronounced G-i-star) for each feature in a dataset. The resultant z-scores and p-values tell you where features with either high or low values cluster spatially. This tool works by looking at each feature within the context of neighboring features. A feature with a high value is interesting but may not be a statistically significant hot spot. To be a statistically significant hot spot, a feature will have a high value and be surrounded by other features with high values as well. The local sum for a feature and its neighbors is compared proportionally to the sum of all features; when the local sum is very different from the expected local sum, and that difference is too large to be the result of random chance, a statistically significant z-score results.

MapInfo helps GIS analysts and professionals gain new insights by sharing information with maps and graphs to improve strategic decision-making. It allows importing existing data from spreadsheets and databases, and publishing content to high-quality maps. It is useful to manage location based assets, such as human resources and property (Pitney Bowes).

MATLAB is the high-level language and interactive environment used by millions of engineers and scientists worldwide. It lets you explore and visualize ideas and collaborate across disciplines including signal and image processing, communications, control systems, and computational finance. It also allows for developing control and prediction algorithms (Mathworks).

Ordinary Least Squares Regression is the best known of all regression techniques. It is also the proper starting point for all spatial regression analyses. It provides a global model of the variable or process you are trying to understand or predict (early death/rainfall); it creates a single regression equation to represent that process.

p value is the probability that you have falsely rejected the null hypothesis. Both statistics are associated with the standard normal distribution. This distribution relates standard deviations with probabilities and allows significance and confidence to be attached to z-scores and p-values.

Regression Analysis allows you to model, examine, and explore spatial relationships, and can help explain the factors behind observed spatial patterns. Regression analysis is also used for prediction. You may want to understand why people are persistently dying young in certain regions, for example, or may want to predict rainfall where there are no rain gauges.

Thematic Map is a type of map, which uses a variety of graphic styles (e.g., colors or fill patterns) to display information about the map's underlying data (MapInfo User Guide Version 8.0, 2005).

z score is a test of statistical significance that helps you decide whether or not to reject the null hypothesis. Z scores are measures of standard deviation. For example, if a tool returns a Z score of +2.5 it is interpreted as +2.5 standard deviations away from the mean. Both statistics are associated with the standard normal distribution. This distribution relates standard deviations with probabilities and allows significance and confidence to be attached to z-scores and p-values.

Error result table for different hidden layer sizes of predicting actual number of Theft incidents

Number of hidden neuron	initial weights	mse	mae	Test R	epoch	Test mse	average mse
1	1	12.12	1.95	0.73	8	7.31	12.161
	2	12.10	1.93	0.73	16	6.98	
	3	12.14	1.94	0.73	8	7.02	
	4	12.17	1.94	0.73	25	6.74	
	5	12.18	1.94	0.73	35	6.76	
	6	12.18	1.94	0.73	28	6.57	
	7	12.18	1.94	0.73	27	6.68	
	8	12.18	1.94	0.73	11	6.40	
	9	12.18	1.94	0.73	20	6.38	
	10	12.18	1.94	0.73	26	6.42	
2	1	9.89	1.76	0.50	28	11.42	10.146
	2	11.14	1.81	0.74	243	6.20	
	3	9.60	1.08	0.50	22	11.36	
	4	11.95	1.88	0.74	21	6.42	
	5	9.12	1.70	0.28	19	34.49	
	6	9.40	1.74	0.41	21	16.42	
	7	10.39	1.78	0.71	20	6.78	
	8	9.96	1.83	0.70	14	6.54	
	9	10.03	1.81	0.73	70	6.32	
	10	9.98	1.80	0.73	66	6.41	
3	1	9.54	1.75	0.52	54	12.67	9.585
	2	9.54	1.75	0.72	19	6.49	
	3	10.63	1.82	0.73	16	6.41	
	4	9.91	1.77	0.72	28	6.52	
	5	9.75	1.79	0.71	231	6.64	
	6	9.34	1.73	0.71	38	6.61	
	7	9.45	1.72	0.72	24	6.58	
	8	9.16	1.71	0.71	12	6.65	
	9	9.46	1.76	0.31	18	31.28	
	10	9.07	1.70	0.60	26	9.02	
4	1	14.75	1.95	0.68	32	7.13	9.819
	2	9.97	1.79	0.72	30	6.42	
	3	8.66	1.69	0.71	21	6.47	
	4	9.44	1.76	0.69	37	7.18	
	5	8.99	1.72	0.71	65	6.38	
	6	9.18	1.69	0.28	26	34.45	
	7	9.37	1.76	0.72	22	6.57	
	8	9.24	1.71	0.64	16	7.26	
	9	9.47	1.74	0.68	34	7.21	
	10	9.12	1.72	0.70	19	6.98	

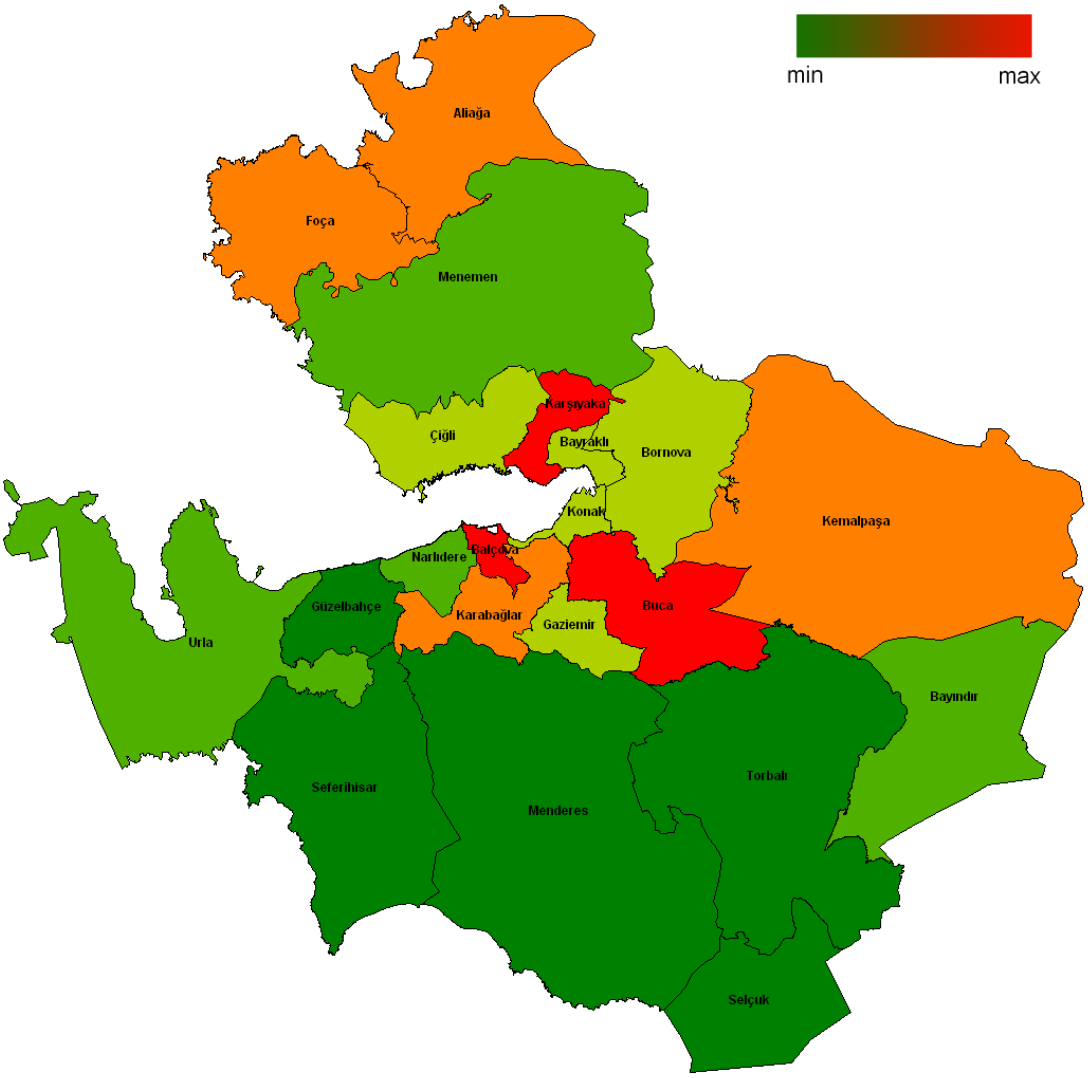
Number of hidden neuron	initial weights	mse	mae	Test R	epoch	Test mse	average mse
5	1	8.94	1.73	0.04	149	42.53	9.553
	2	9.63	1.73	0.72	12	6.25	
	3	9.50	1.72	0.72	27	6.32	
	4	9.42	1.77	0.71	11	6.54	
	5	9.00	1.66	0.71	25	6.51	
	6	9.60	1.76	0.73	38	6.21	
	7	11.04	1.84	0.72	44	6.30	
	8	10.37	1.82	0.73	16	6.22	
	9	9.33	1.73	0.71	12	6.49	
	10	8.70	1.66	0.71	44	6.51	
6	1	9.24	1.74	0.72	30	6.31	9.422
	2	9.46	1.76	0.69	41	6.99	
	3	9.86	1.82	0.71	30	6.53	
	4	9.40	1.69	0.71	40	6.49	
	5	9.33	1.72	0.70	11	6.72	
	6	9.08	1.68	0.66	37	7.02	
	7	9.13	1.73	0.67	19	7.00	
	8	9.63	1.79	0.73	15	6.24	
	9	9.70	1.77	0.73	18	6.23	
	10	9.39	1.78	0.71	16	6.51	
7	1	9.52	1.77	0.73	48	6.21	9.488
	2	9.62	1.79	0.72	37	6.32	
	3	11.69	1.89	0.74	17	5.81	
	4	9.63	1.78	0.71	16	6.41	
	5	9.27	1.73	0.71	24	6.53	
	6	9.34	1.77	0.70	23	6.39	
	7	8.94	1.67	0.70	37	6.73	
	8	8.95	1.68	0.53	32	11.38	
	9	8.90	1.71	0.70	16	7.31	
	10	9.02	1.70	0.69	23	6.92	
8	1	8.86	1.67	0.68	62	6.91	9.286
	2	9.28	1.75	0.71	26	6.35	
	3	9.11	1.75	0.69	16	7.13	
	4	10.49	1.87	0.71	30	6.42	
	5	9.60	1.77	0.72	30	6.34	
	6	9.19	1.69	0.71	9	6.39	
	7	9.17	1.74	0.66	11	7.19	
	8	9.07	1.69	0.69	18	6.70	
	9	8.98	1.75	0.72	33	6.24	
	10	9.11	1.70	0.34	81	29.61	

Number of hidden neuron	initial weights	mse	mae	Test R	epoch	Test mse	average mse
9	1	9.68	1.80	0.69	8	6.85	9.375
	2	9.62	1.76	0.70	28	6.37	
	3	9.10	1.72	0.71	29	6.41	
	4	9.59	1.82	0.74	33	6.15	
	5	8.93	1.72	0.67	29	7.40	
	6	9.56	1.75	0.71	49	6.60	
	7	9.65	1.74	0.72	17	6.25	
	8	9.12	1.72	0.71	19	6.39	
	9	9.01	1.71	0.70	37	6.44	
	10	9.49	1.75	0.72	21	6.03	
10	1	9.43	1.71	0.72	17	6.40	9.491
	2	9.25	1.72	0.72	15	6.12	
	3	9.71	1.79	0.71	17	6.16	
	4	9.27	1.72	0.71	20	6.27	
	5	8.96	1.70	0.70	13	6.74	
	6	8.73	1.72	0.71	24	6.42	
	7	9.51	1.72	0.72	12	6.11	
	8	9.03	1.74	0.33	27	34.30	
	9	9.37	1.76	0.71	16	6.30	
	10	11.65	1.91	0.73	100	5.80	
11	1	9.57	1.78	0.61	30	10.36	9.275
	2	9.26	1.69	0.71	25	6.20	
	3	9.17	1.71	0.68	20	6.90	
	4	9.21	1.72	0.71	23	6.38	
	5	9.33	1.76	0.70	20	6.43	
	6	9.48	1.82	0.71	11	6.24	
	7	9.27	1.74	0.70	15	6.34	
	8	9.26	1.81	0.71	7	6.22	
	9	9.17	1.71	0.69	28	6.81	
	10	9.03	1.72	0.70	19	6.40	
12	1	11.42	1.86	0.73	14	5.95	9.481
	2	9.64	1.76	0.71	23	6.16	
	3	8.86	1.68	0.69	12	6.70	
	4	9.24	1.73	0.71	13	6.22	
	5	9.08	1.78	0.67	30	7.29	
	6	9.23	1.74	0.68	17	7.07	
	7	9.41	1.75	0.71	23	6.18	
	8	9.64	1.75	0.71	10	6.13	
	9	9.17	1.75	0.71	13	6.51	
	10	9.12	1.72	0.69	22	7.27	

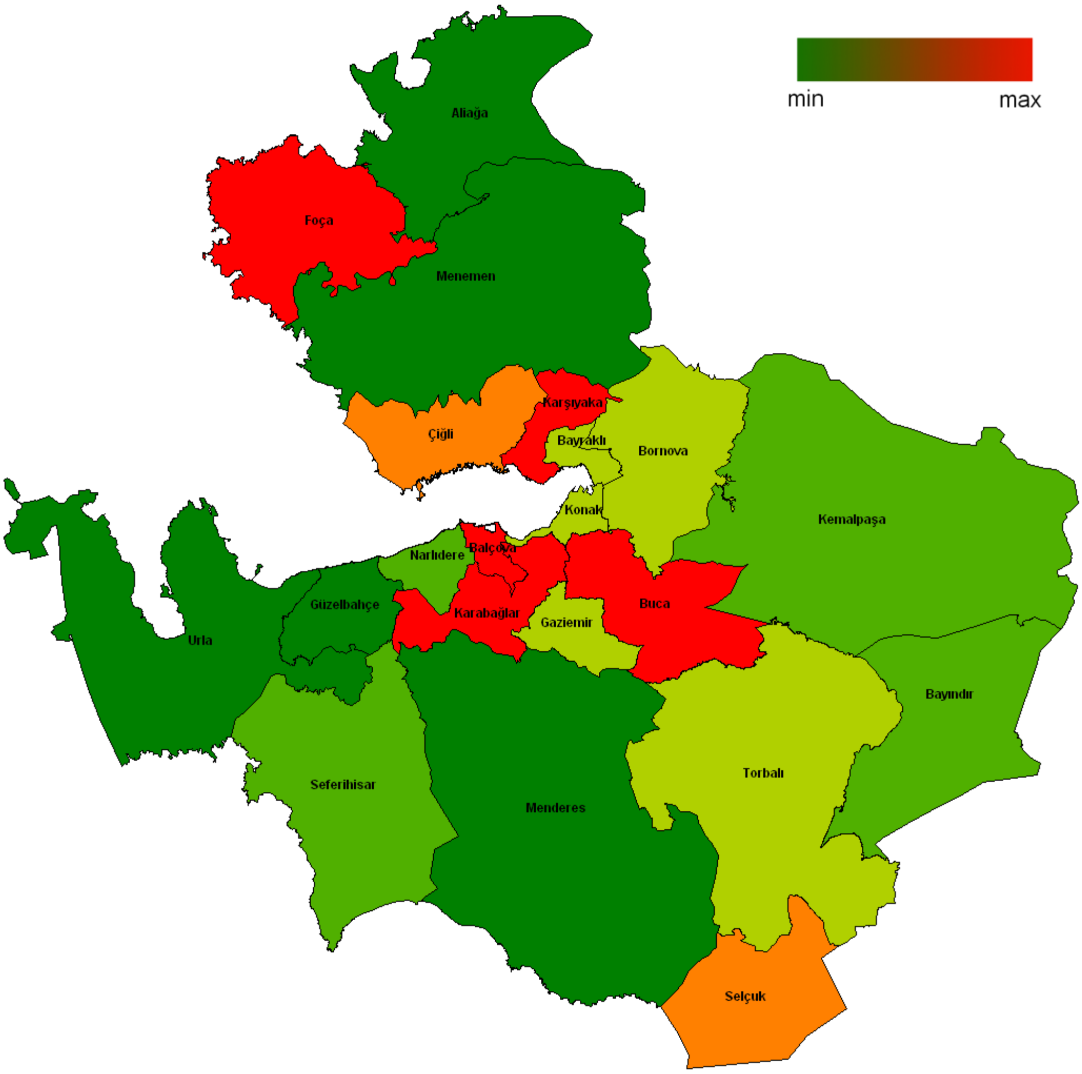
Number of hidden neuron	initial weights	mse	mae	Test R	epoch	Test mse	average mse
13	1	9.26	1.74	0.70	9	6.50	9.44
	2	9.93	1.87	0.68	6	6.99	
	3	9.75	1.77	0.71	43	6.33	
	4	9.04	1.73	0.71	19	6.48	
	5	9.44	1.73	0.71	23	6.19	
	6	9.13	1.76	0.71	13	6.61	
	7	9.03	1.71	0.71	10	6.34	
	8	9.50	1.75	0.71	9	6.65	
	9	9.83	1.74	0.73	11	5.95	
	10	9.49	1.75	0.69	13	6.68	
14	1	8.84	1.72	0.68	16	6.74	9.673
	2	9.17	1.69	0.70	23	6.80	
	3	9.85	1.77	0.71	31	6.29	
	4	9.04	1.75	0.71	15	6.48	
	5	9.35	1.74	0.69	25	6.58	
	6	9.21	1.73	0.71	9	6.28	
	7	13.62	2.02	0.70	14	6.51	
	8	9.27	1.72	0.72	37	6.23	
	9	9.42	1.76	0.72	35	6.78	
	10	8.96	1.73	0.71	14	6.48	
15	1	9.12	1.74	0.70	15	6.81	9.27
	2	8.90	1.70	0.72	39	6.29	
	3	9.10	1.69	0.71	31	6.24	
	4	9.20	1.73	0.71	8	6.20	
	5	9.75	1.75	0.68	9	6.73	
	6	9.15	1.70	0.71	9	6.32	
	7	9.49	1.74	0.71	8	6.26	
	8	8.89	1.75	0.72	11	6.27	
	9	9.47	1.79	0.70	17	6.64	
	10	9.63	1.82	0.72	17	6.20	
16	1	9.28	1.74	0.71	13	6.28	9.306
	2	9.11	1.69	0.70	12	6.48	
	3	10.10	1.77	0.72	15	6.02	
	4	9.20	1.74	0.69	17	7.18	
	5	9.41	1.72	0.71	12	6.38	
	6	9.45	1.78	0.71	12	6.20	
	7	9.70	1.80	0.70	11	6.36	
	8	9.33	1.76	0.70	15	6.95	
	9	8.44	1.66	0.67	40	7.31	
	10	9.04	1.70	0.71	26	6.32	

Number of hidden neuron	initial weights	mse	mae	Test R	epoch	Test mse	average mse
17	1	9.22	1.73	0.70	20	6.50	9.25
	2	8.68	1.75	0.71	7	6.62	
	3	8.99	1.69	0.73	14	6.20	
	4	9.15	1.76	0.70	16	6.49	
	5	9.16	1.71	0.69	11	6.55	
	6	9.18	1.74	0.70	18	6.72	
	7	9.41	1.73	0.59	11	9.70	
	8	9.51	1.77	0.73	25	5.92	
	9	9.49	1.79	0.70	11	6.77	
	10	9.71	1.78	0.68	12	6.71	
18	1	9.63	1.79	0.71	11	6.31	9.293
	2	9.07	1.71	0.70	18	6.68	
	3	8.86	1.72	0.71	30	6.77	
	4	9.27	1.74	0.72	15	6.14	
	5	9.46	1.75	0.68	25	6.75	
	6	9.34	1.78	0.72	17	6.42	
	7	9.23	1.74	0.70	10	6.53	
	8	9.32	1.74	0.71	8	6.24	
	9	9.32	1.77	0.70	11	6.53	
	10	9.43	1.75	0.70	12	6.49	
19	1	10.19	1.79	0.70	8	6.46	9.429
	2	9.37	1.75	0.70	7	6.32	
	3	9.25	1.81	0.70	11	6.97	
	4	9.61	1.72	0.71	10	6.24	
	5	8.82	1.70	0.65	14	7.65	
	6	9.45	1.72	0.71	11	6.29	
	7	9.45	1.76	0.72	14	6.12	
	8	9.26	1.76	0.71	16	6.34	
	9	9.26	1.73	0.71	11	6.22	
	10	9.63	1.72	0.70	13	6.43	
20	1	9.53	1.80	0.71	7	6.23	9.404
	2	9.27	1.77	0.70	5	6.31	
	3	9.36	1.77	0.67	12	6.97	
	4	9.68	1.74	0.70	8	6.44	
	5	9.10	1.71	0.69	16	6.68	
	6	9.82	1.76	0.72	7	6.14	
	7	9.20	1.75	0.71	16	6.36	
	8	9.74	1.77	0.70	8	6.44	
	9	9.11	1.70	0.68	12	6.94	
	10	9.23	1.77	0.70	6	6.45	

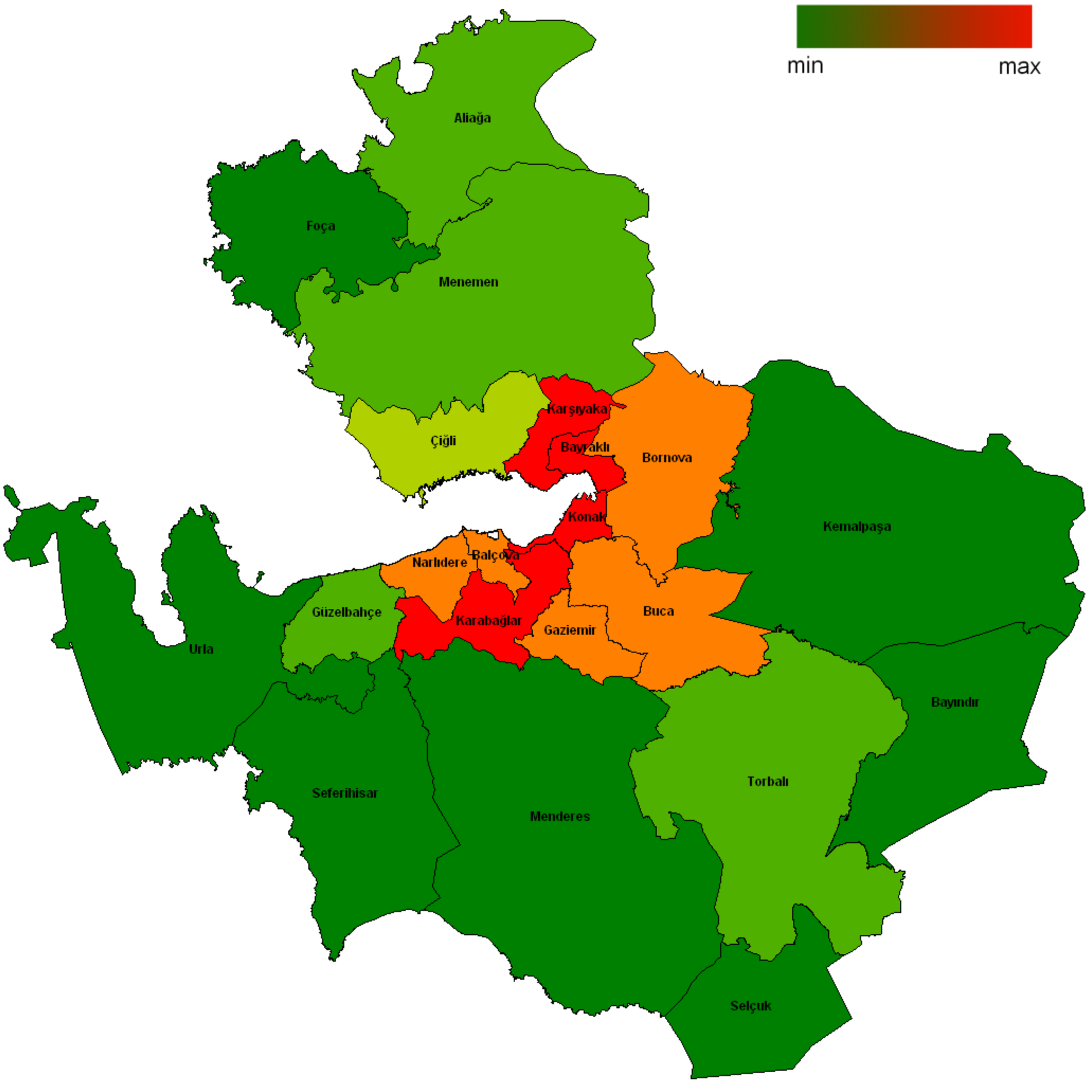
Density maps of explanatory variables



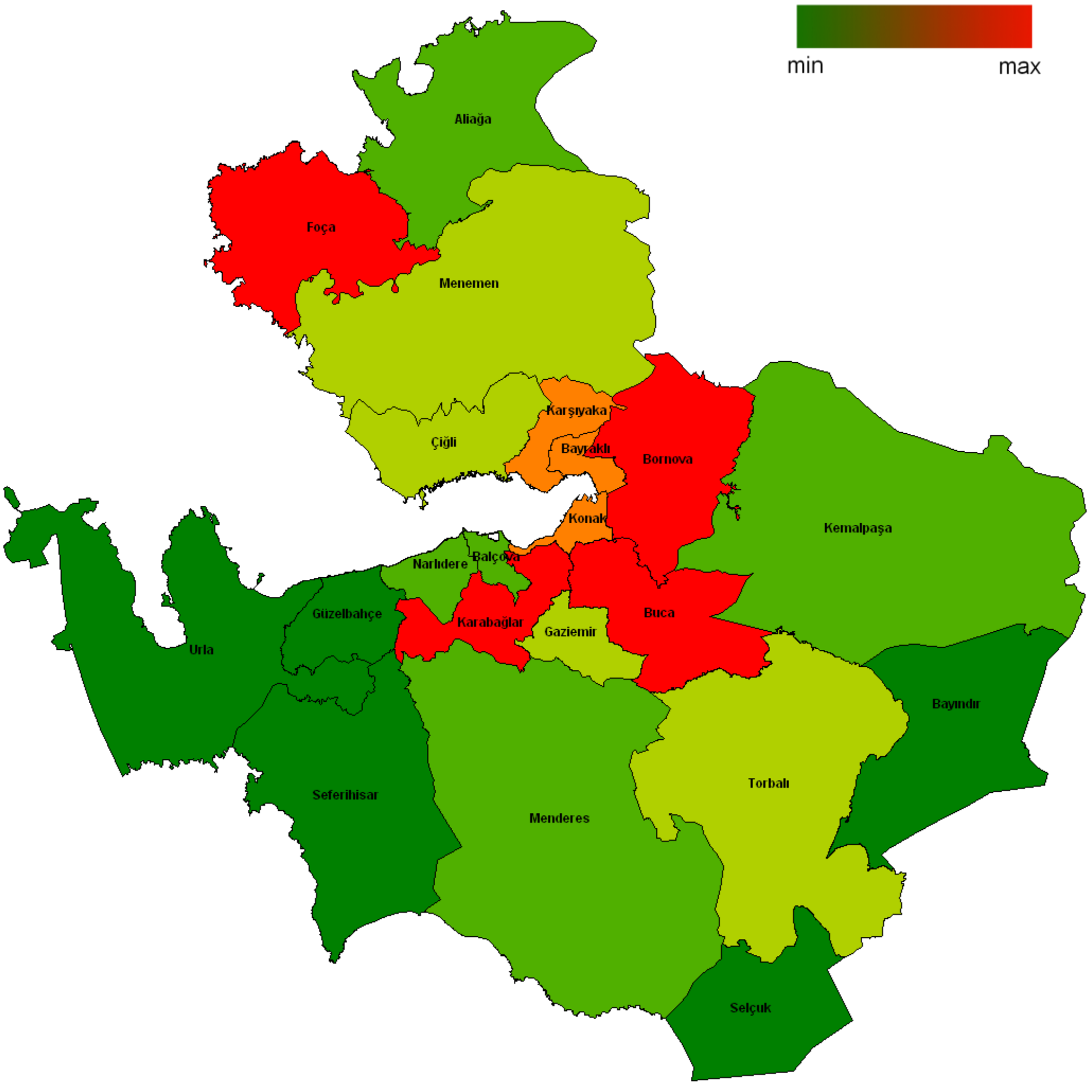
Average wind speed



Average temperature



Population density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max
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Foça
Menemen
Karşıyaka
Bayraklı
Bornova
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Konak
Kemalpaşa
Balçova
Narlıdere
Güzelbahçe
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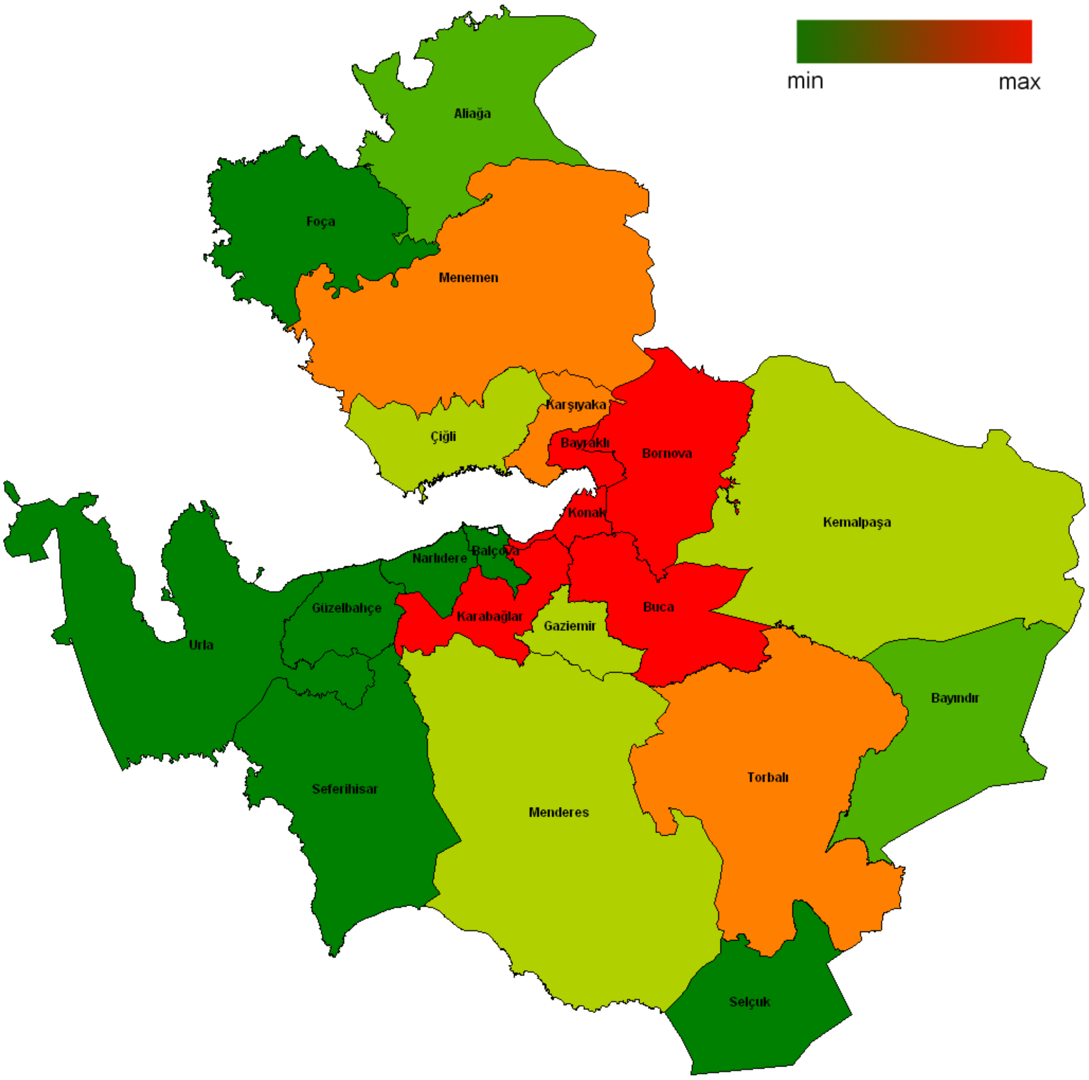
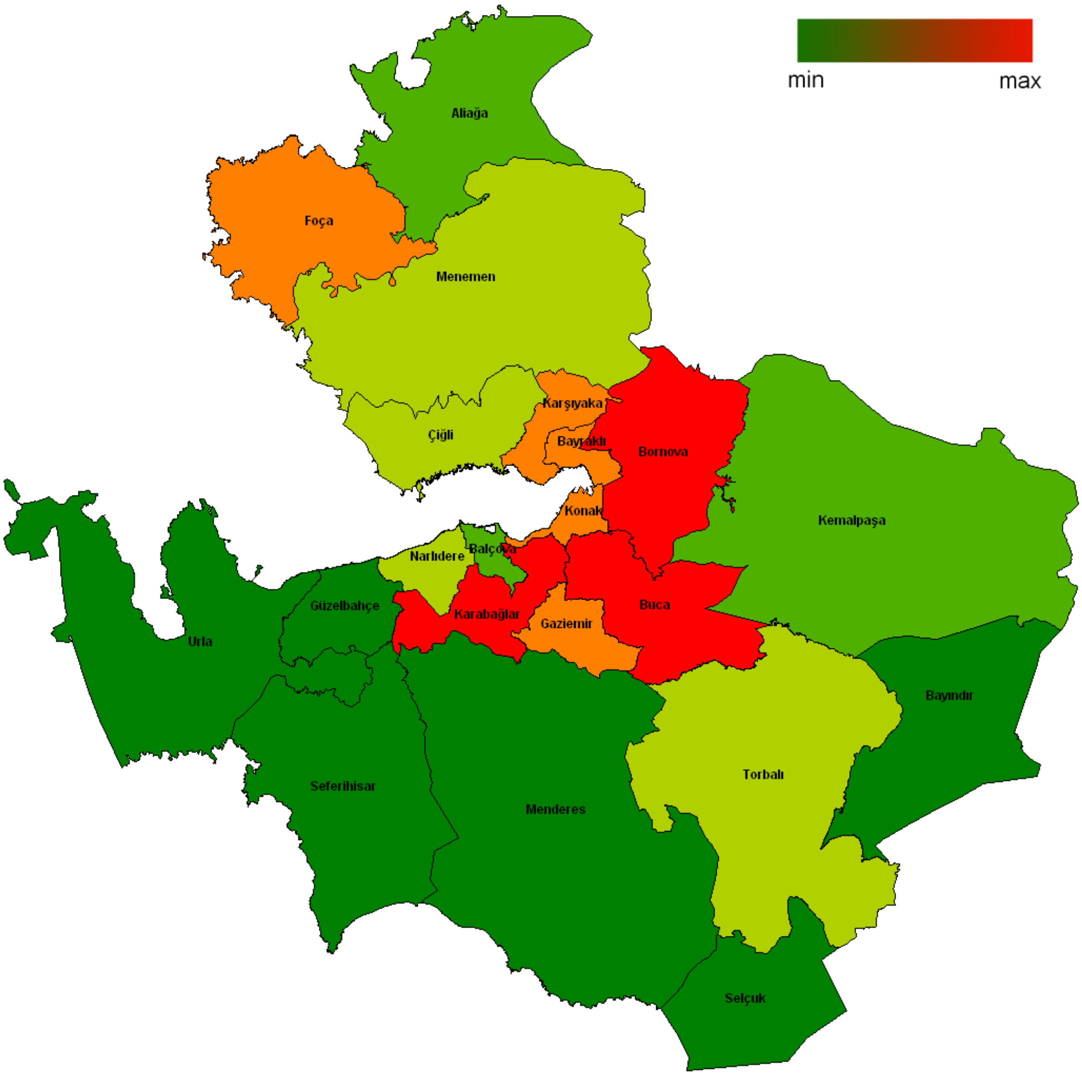
Gaziemir
Buca
Urla
Bayındır
Seferihisar
Torbalı
Menderes
Selçuk

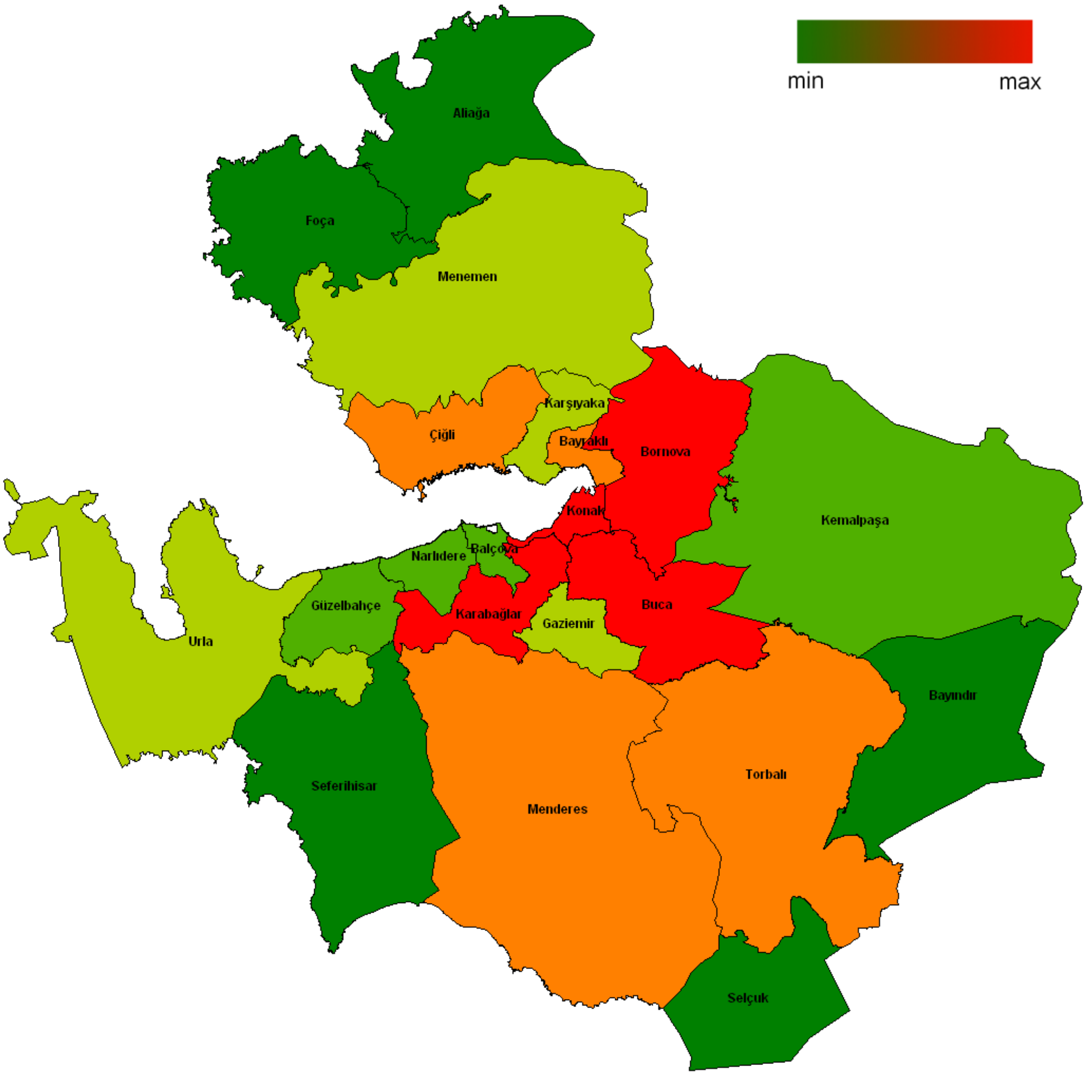
Migration



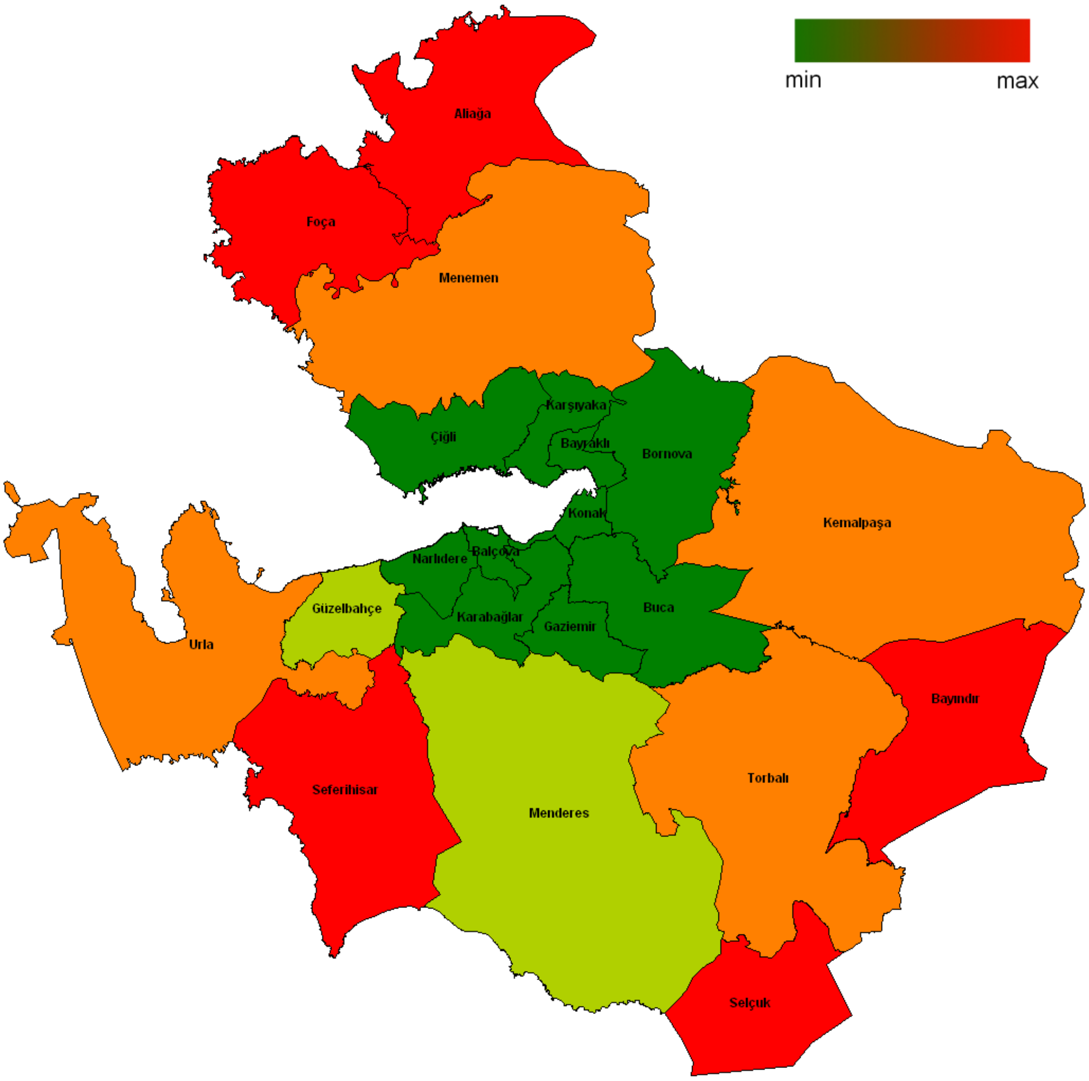
Male population which graduated from primary school



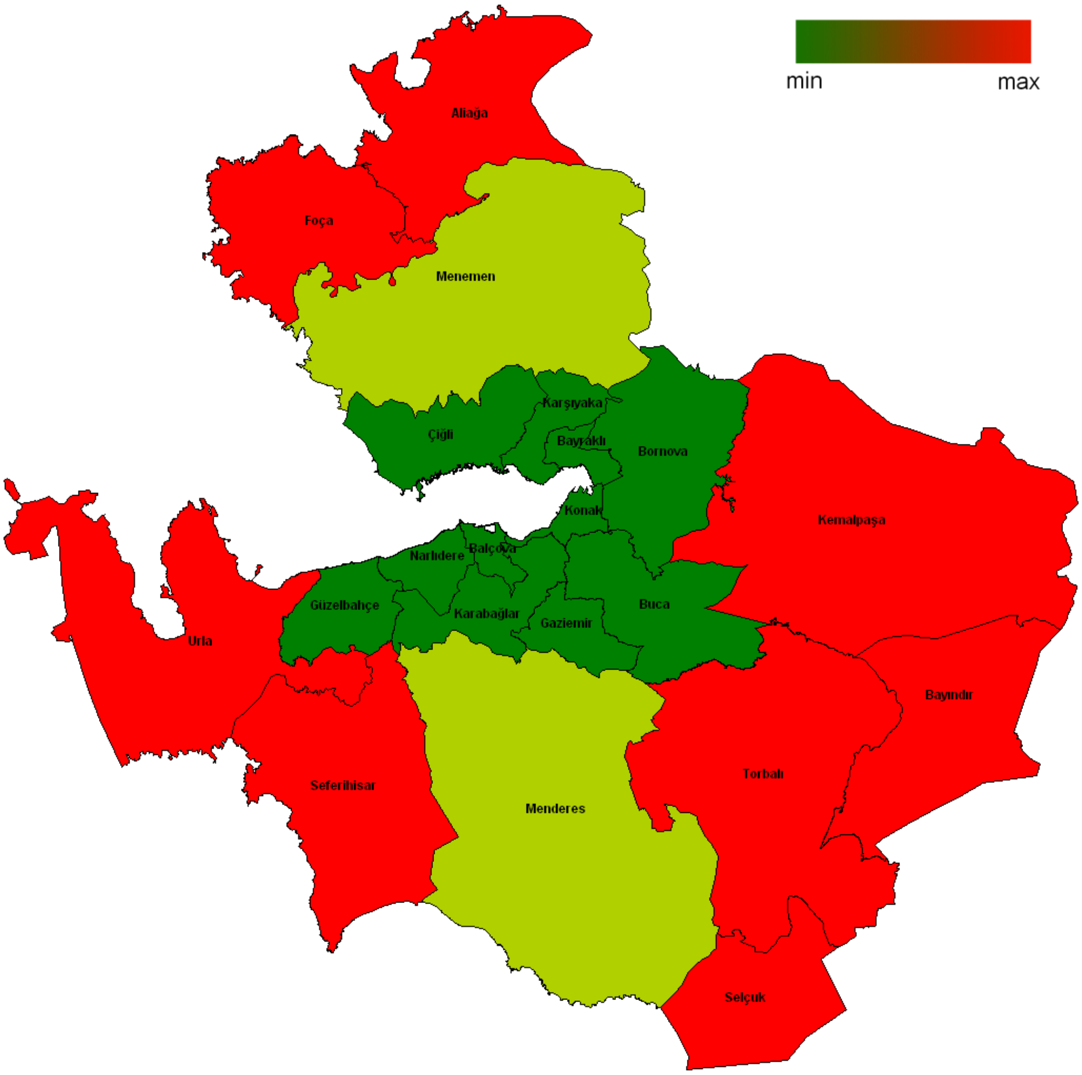
Male population which are in age between 18-35



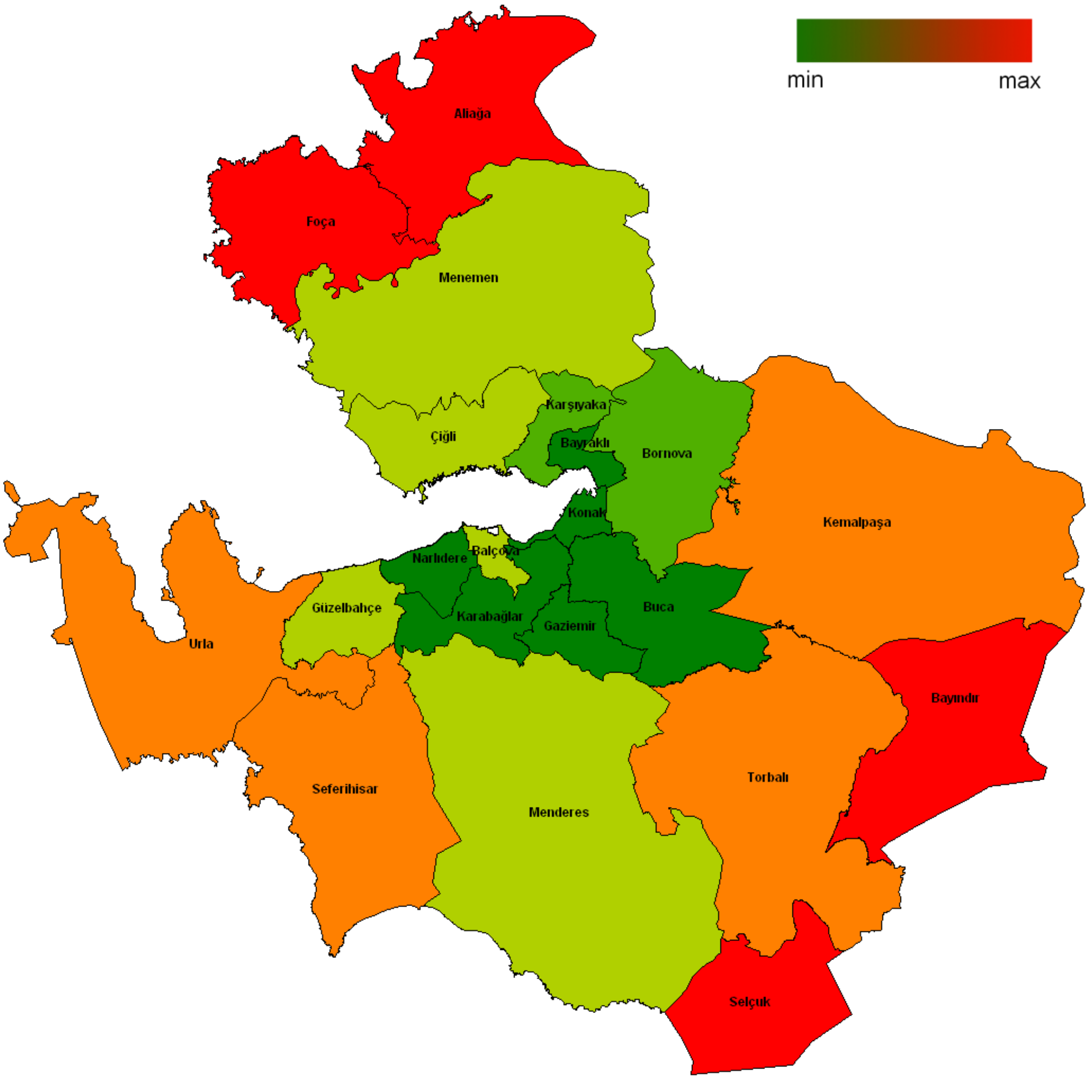
Number of public transportation stations



Distance from education buildings



Distance form commercial use of buildings



Distance from police stations