



**T.C.
SELÇUK UNIVERSITY
THE GRADUATE SCHOOL OF NATURAL AND APPLIED SCIENCES**

**AIR POLLUTION MODELING OF TURKEY WIDE BY GEOGRAPHIC
INFORMATION SYSTEM**

NAHIDA HAMEED HAMZA AL-QAYSI

**Ph.D. of Science
Environmental Engineering Department**

**Supervisor of Thesis
Prof. Dr. ŞÜKRÜ DURSUN**

**August, 2019
Konya
All rights reserved**



**T.C.
SELÇUK ÜNİVERSİTESİ
FEN BİLİMLERİ ENSTİTÜSÜ**

**TÜRKİYE GENELİNDE MEVCUT HAVA KİRLİLİĞİNİN COĞRAFİ BİLGİ
SİSTEMİYLE MODELLENMESİ**

NAHIDA HAMEED HAMZA AL-QAYSI

**DOKTORA TEZİ
Çevre Mühendisliği Anabilim Dalı**

**Danışman
Prof. Dr. ŞÜKRÜ DURSUN**

**Ağustos, 2019
KONYA
Her Hakkı Saklıdır**

THESIS ACCEPTANCE AND APPROVAL

Thesis namely “Air Pollution Modeling of Turkey Wide by Geographic Information System” prepared by **Nahida Hameed Hamza Al-Qaysi** was accepted as Ph. D. Thesis by below jury members with unanimity/plurality on the date of 26/08/2019 at Environmental Engineering Department, the Graduate School of Natural and Applied Sciences Selçuk University.

Supervisor

Prof. Dr. Şükrü DURSUN

Jury Members

Chair

Prof. Dr. Ali TOR

Member

Prof. Dr. Şükrü DURSUN

Member

Prof. Dr. Tayfun ÇAY

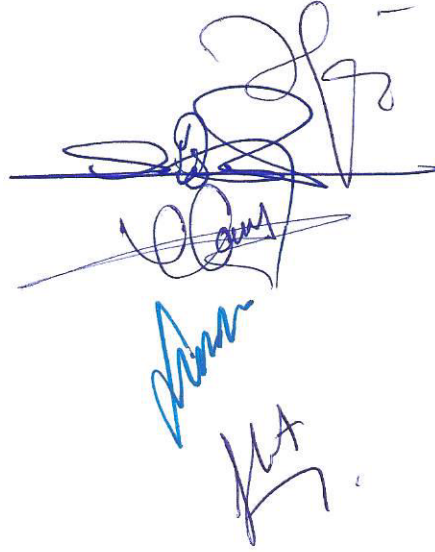
Member

Asst. Prof. Dr. Sezen KÜÇÜKÇONGAR

Member

Asst. Prof. Dr. Fatma KUNT

Signature



I approve the result above.

Prof. Dr. Mustafa YILMAZ
Head of Science Institute

This thesis has been supported by Selçuk University-BAP with 16201091 numbered project.

TEZ KABUL VE ONAYI

Nahida Hameed Hamza Al-Qaysi tarafından hazırlanan “Türkiye Geneline Mevcut Hava Kirliliğinin Coğrafi Bilgi Sistemiyle Modellenmesi” adlı tez çalışması 26/08/2019 tarihinde aşağıdaki jüri tarafından oy birliği / oy-çokluğu ile Selçuk Üniversitesi, Fen Bilimleri Enstitüsü, Çevre Mühendisliği Anabilim Dalı’nda DOKTORA TEZİ olarak kabul edilmiştir.

Jüri Üyeleri

Başkan

Prof. Dr. Ali TOR

Danışman

Prof. Dr. Şükrü DURSUN

Üye

Prof. Dr. Tayfun ÇAY

Üye

Dr. Öğr. Üyesi Sezen KÜÇÜKÇONGAR

Üye

Dr. Öğr. Üyesi Fatma KUNT

İmza



Yukarıdaki sonucu onaylarım.

Prof. Dr. Mustafa YILMAZ
FBE Müdürü

Bu tez, 16201091 sayılı proje ile Selçuk Üniversitesi-BAP tarafından desteklenmiştir.

DECLARATION PAGE

I hereby declare that all information in this document has been obtained and presented in accordance with academic rules and ethical conduct. I also declare that, as required by these rules and conduct, I have fully cited and referenced all material and results that are not original to this work.

TEZ BİLDİRİMİ

Bu tezdeki bütün bilgilerin etik davranış ve akademik kurallar çerçevesinde elde edildiğini ve tez yazım kurallarına uygun olarak hazırlanan bu çalışmada bana ait olmayan her türlü ifade ve bilginin kaynağına eksiksiz atıf yapıldığını bildiririm.



Signature/ İmza

Nahida Hameed Hamza Al-Qaysi

Tarih: 29/ 07/2019

ABSTRACT

Ph. D. THESIS

AIR POLLUTION MODELING OF TURKEY WIDE BY GEOGRAPHIC INFORMATION SYSTEM

Nahida Hameed Hamza Al-Qaysi

**SELÇUK UNIVERSITY, THE GRADUATE SCHOOL OF NATURAL AND
APPLIED SCIENCE, ENVIRONMENTAL ENGINEERING DEPARTMENT**

Supervisor: Prof. Dr. Şükrü DURSUN

2019, 154 pages

Jury

Prof. Dr. Şükrü DURSUN

Prof. Dr. Ali TOR

Prof. Dr. Tayfun ÇAY

Assist. Prof. Dr. Sezen KÜÇÜKÇONGAR

Assist. Prof. Dr. Fatma KUNT

The air pollution in the urban atmosphere is rising gradually as a result of the increase in population density, rapid urbanization, industrial growth, fossil fuels consumed in manufacture and home heating processes. The objectives of this research are producing the spatial distribution maps of the monthly average of PM₁₀ and SO₂ that covered all Turkey regions for the period 2015–2018 by applying Inverse Distance Weighted (IDW) technique within the ArcGIS software environment. In addition to the spatial distribution maps of seasonal AQI and annual NO_x values, Cokriging was then applied to estimate the contribution of different covariates when assessing the spatial distribution of PM₁₀ concentration, the different covariates utilized in this study are SO₂ and NO_x, and developing several modules to visualize air pollution data. The correlation between concentrations of air pollutant and meteorological elements was analyzed applying multiple regression method. The results were showing generally, the concentrations of PM₁₀ and SO₂ increasing in winter months in most provinces of Turkey and approximately at the same stations especially in January, February, November and December because of using the fossil fuels in domestic heating in winter months, and decreasing in the summer months during periods from 2015-2018, except in southeastern part of some Turkey cities where the concentrations of PM₁₀ was increasing during the months July to October, may be due to occurring of desert dust. The maximum value of SO₂ emissions reached to 932.4 µg/m³ in Edirne-Keşan station. The most NO_x concentrations exceeding (30 µg/m³) the annual allowable limit value, about 77.4%, 79% and 65.5% during 2016, 2017 and 2018 respectively, especially in the central parts of Turkey. The high levels of nitrogen oxides can happen damage to the person respiratory tract and rise a person's vulnerability to, and the seriousness of, respiratory diseases and

asthma. According to AQI for PM_{10} and SO_2 , the results shown the most parts of the southeastern, central and west parts of country occurs within unhealthy, very unhealthy and hazardous classification during 2015-2018 especially in winter seasons, therefore must find solutions for the emission sources of PM_{10} in these parts. Simple CoKriging method had been applied during winter 2017-2018, the best semivariogram modeling for PM_{10} was Exponential semivariogram modeling that applied as dependable variable, for SO_2 and NO_x was J-Bessel and Gaussian semivariogram modeling, respectively that applied as undependable variable, based on this method the distribution of pollution spread more than other Kriging methods.

Keywords: Air pollution, Air quality Index, Turkey, GIS, Kriging, Cokriging, Geostatistical analysis, Semivariogram modelling.



ÖZET

DOKTORA TEZİ

TÜRKİYE GENELİNDE MEVCUT HAVA KİRLİLİĞİNİN COĞRAFİ BİLGİ SİSTEMİYLE MODELLENMESİ

Nahida Hameed Hamza AL-Qaysi

SELÇUK ÜNİVERSİTESİ, FEN BİLİMLERİ ENSTİTÜSÜ,
ÇEVRE MÜHENDİSLİĞİ ANABİLİM DALI

DANIŞMAN: Prof. Dr. Şükrü DURSUN

2019, 154 pages

Juri

Prof. Dr. Şükrü DURSUN

Prof. Dr. Ali TOR

Prof. Dr. Tayfun ÇAY

Dr. Öğr. Üyesi Sezen KÜÇÜKÇONGAR

Dr. Öğr. Üyesi Fatma KUNT

Kentsel atmosferdeki hava kirliliği, nüfus yoğunluğu, hızlı kentleşme, sanayi gelişme, üretimde kullanılan fosil yakıtlar ve evsel ısınma süreçleri nedeniyle günden güne artmaktadır. Bu çalışmanın amacı, ArcGIS yazılım ortamında Invers Distance Weighted (IDW) yöntemini kullanarak 2015-2018 dönemi için Türkiye'nin tüm bölgelerini kapsayan aylık ortalama PM₁₀ ve SO₂ dağılım haritalarını oluşturmaktır. Ayrıca mevsimsel AQI ve yıllık NO_x değerlerinin mekansal dağılım haritalarına ek olarak, PM₁₀ konsantrasyonunun mekansal dağılımını değerlendirirken farklı değişkenlerin katkısını tahmin etmek için Cokriging uygulanıp, bu çalışmada kullanılan farklı değişkenler PM₁₀, SO₂ ve NO_x, Hava kirliliği verilerini görselleştirmek için modüller oluşturmaktır. Bu çalışmada hava kirlileti konsantrasyonları ve meteorolojik faktörler arasındaki ilişki çoklu regresyon analiz yöntemi kullanılarak analiz edilmiştir. Sonuçlar, genel olarak, Türkiye'nin çoğu ilinde kış aylarında ve özellikle Kasım, Aralık Ocak ve Şubat, aylarında aynı istasyonlarda, kış aylarında evsel ısınmada fosil yakıtların kullanılması nedeniyle kış aylarında artan PM₁₀ ve SO₂ konsantrasyonlarının, ve 2015-2018 dönemlerinde yaz aylarında azaldığı, PM₁₀'un konsantrasyonlarının ise bazı illerde Temmuz - Ekim ayları arasında arttığı, bunun Türkiye'nin güneydoğu şehirlerinin kesiminde Sahra tozundan dolayı oluştuğu tahmin edilmektedir. Edirne-Keşan ölçüm istasyonunda maksimum SO₂ emisyon değeri 932.4 µg/m³ değerle en yüksek ulaşmıştır. Türkiye İç Anadolu bölgesinde ölçümlerin büyük bir kısmında NO_x konsantrasyonları izin verilen yıllık sınır değerini (30 µg/m³) geçmekte, özellikle sırasıyla 2016, 2017 ve 2018 yıllarında sırasıyla % 77,4,% 79 ve% 65,5'dir. Yüksek azot oksit seviyeleri, insan solunum sistemine zarar verebilir ve insanların ciddi solunum hastalıklarına ve astıma karşı duyarlılığını artırabilmektedir. AQI'ye göre PM₁₀ ve SO₂ için, ülkenin güneydoğu, orta ve batı bölgelerinin çoğunun hava kalitesi yönünden sağlıklı, çok sağlıklı ve tehlikeli sınıflandırma içinde gerçekleştiğini gösteren sonuçlar ortaya çıkmış, PM₁₀ için de özellikle kış mevsiminde, 2015-2018 yılları arasında emisyon kaynakları için çözümler bulmalıdır. 2017-2018 kış ayları verileri için Basit CoKriging metodu uygulanmış,

bağımlı değişken olarak uygulanan PM_{10} için en iyi model Exponential semivariogram çıkmış, SO_2 ve NO_x için bağımlı değişken modellemesinde sırasıyla J-Bessel ve Gaussian semivariogram modellemesi uygun çıkarken, kirlilik dağılımında bağımsız değişken olarak uygulandığında diğer Kriging yöntemlerinden daha uygun çıkmıştır.

Anahtar Kelimeler: Hava kirliliği, Türkiye, CBS, Kriging, Cokriging, Jeostatiksel analiz, Semivariogram modellemesi.



ACKNOWLEDGMENTS

In the Name of Allah the Merciful

This study was prepared within the scope of the Ph.D. thesis in the Institute of Science, Department of Environmental Engineering, Selçuk University, Konya, Turkey.

I am honored and happy to find the opportunity to work together with **Prof. Dr. Şükrü DURSUN** to his guidance and to share his experiences and scientific contributions in the period from the determination of the subject to the final stage, and thank very much to my jury members who contributed with their important comments and evaluations **Prof. Dr. Tayfun ÇAY** and **Assist. Prof. Dr. Sezen KÜÇÜKÇONGAR**. I also would like thank to Selcuk University-BAP to financial supporting of this study with project number of 16201091. Especial thanks for the Ministry of Environment and Urbanization for taking advantage to getting air pollution data.

Thanks to all my family and friends who assisted me in every way during the thesis, especially my husband **Dr. Mushtaq Abdulameer Alwen AlMuslehi**, I would like to thank my mother and my father, who never gave up supporting me during my thesis.

This study was financially supported by the Iraqi Ministry of Higher Education and Scientific Research, Special thanks to Representative of the Iraqi Ministry of Higher Education and Scientific Research (MOHESR) in Turkey, Ankara for their continuous materially support and motivation.

Nahida Hameed Hamza Al-Qaysi

Konya 2019

TABLE OF CONTENTS

ABSTRACT	1
ÖZET	i
ACKNOWLEDGMENTS	iii
TABLE OF CONTENTS.....	iv
LIST OF TABLES	vi
LIST OF FIGURES	ix
INDEX OF SYMBOLS AND ABBREVIATIONS	xiii
I. INTRODUCTION	1
1.1 Introduction.....	1
1.2 Objectives and scopes of the study	5
II. LITERATURE REVIEW	6
2.1 Introduction.....	6
2.2 Sources and Impacts of Air Pollutants	7
2.3 Control Equipment of Air Pollution.....	11
2.4 Air Quality in Turkey	11
2.5 Air pollution in Turkey.....	15
2.6 Air pollution modelling	17
2.7 Definition and data types of Geographic Information Systems	18
2.8 Geostatistics analysis.....	19
2.9 Kriging methods in spatial statistics.....	20
2.10 Inverse Distance Weighting (IDW)	21
2.11 CoKriging method	22
2.12 Semivariogram model.....	23
2.13 Applications of Geographic Information System in air pollution	26
III. MATERIALS AND METHOD	30
3.1 General information	30
3.2 Study area (Turkey).....	30
3.3 Data collection	31
3.4 Methodology	34
3.5 Traffic and industrial maps of Turkey	37
3.6 Land cover data	38
3.7 Statistical and data analysis.....	39

3.8	Air quality standards	41
3.9	The wind speed and wind direction maps	43
IV.	RESULTS AND DISCUSSION.....	45
4.1	Results and discussion	45
4.2	The spatial analysis of PM ₁₀ during 2015-2018 by using IDW interpolation method	46
4.3	The Spatial analysis of SO ₂ during 2015-2018 by using IDW interpolation method	67
4.4	The Spatial analysis of NO _x during 2015-2018 by using IDW interpolation method	87
4.5	The Statistical Analysis by SPSS program.....	90
4.6	The Spatial analysis of air quality Index (AQI) for PM ₁₀ during winter and summer season 2015-2018 by using IDW interpolation method.....	104
4.7	The Spatial analysis of air quality Index (AQI) for SO ₂ during winter and summer season 2015-2018 by using IDW interpolation method.....	111
4.8	The Cokriging modelling.....	117
V.	CONCLUSION AND RECOMMENDATION	125
5.1	Conclusions.....	125
5.2	Recommendations	127
	REFERENCES.....	129
C.V.		153

LIST OF TABLES

Table 2. 1: Sources, health and ecological impact of air pollutants reproduced from (Heinsohn and Kabel 1999, Coşkun 2008, Gurjar, Molina et al. 2010, Trivedy and Goel 2010).....	10
Table 2. 2: Standards of Air Quality Index for health trouble (EPA Air Quality Index)	14
Table 2. 3: Experimental semivariogram models types	24
Table 3. 1: The names of stations and their coordinates.....	31
Table 3. 2: Air Quality Limit Values for the Protection of Human Health and Ecosystem (Odası 2018).....	42
Table 3. 3: The EU and WHO guideline values of air pollution (Krzyzanowski and Cohen 2008, Özden, Döğeroğlu et al. 2008, Abdul-Wahab, En et al. 2015)	42
Table 3. 4: EPA Air Quality Index (Al-Saadi, Szykman et al. 2005, Dimitriou, Paschalidou et al. 2013, Abdul-Wahab, En et al. 2015, Gopalaswami 2016)	43
Table 4. 1: Average annual Concentration of PM ₁₀ during period 2009-2018.....	51
Table 4. 2: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2014-2015 in Iğdir station	90
Table 4. 3: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2015 in Iğdir station.....	91
Table 4. 4: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2015-2016 in Iğdir station	91
Table 4. 5: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2016 in Iğdir station.....	92
Table 4. 6: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2016-2017 in Iğdir station	92
Table 4. 7: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2017 in Iğdir station.....	93
Table 4. 8: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2017-2018 in Iğdir station	93
Table 4. 9: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2018 in Iğdir station.....	94
Table 4. 10: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2018-2019 in Iğdir station	94

Table 4. 11: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during winter 2014-2015 in Edirne-Keşan.....	95
Table 4. 12: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during summer 2015 in Edirne-Keşan	95
Table 4. 13: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during winter 2015-2016 in Edirne-Keşan.....	96
Table 4. 14: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during summer 2016 in Edirne-Keşan	96
Table 4. 15: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during winter 2016-2017 in Edirne-Keşan.....	97
Table 4. 16: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during summer 2017 in Edirne-Keşan	97
Table 4. 17: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during winter 2017-2018 in Edirne-Keşan.....	98
Table 4. 18: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during summer 2018 in Edirne-Keşan	98
Table 4. 19: Investigation of regression coefficients between SO ₂ and meteorological measurements according to multiply regression analysis during winter 2018-2019 in Edirne-Keşan.....	98
Table 4. 20: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2014-2015 in İstanbul - Esenyurt-MTHM station	99
Table 4. 21: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2015 in İstanbul - Esenyurt-MTHM station	99
Table 4. 22: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2015-2016 in İstanbul - Esenyurt-MTHM station	100
Table 4. 23: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2016 in İstanbul - Esenyurt-MTHM station	100
Table 4. 24: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2016-2017 in İstanbul - Esenyurt-MTHM station	101
Table 4. 25: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2017 in İstanbul - Esenyurt-MTHM station	101

Table 4. 26: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2017-2018 in İstanbul - Esenyurt-MTHM station	102
Table 4. 27: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during summer 2018 in İstanbul - Esenyurt-MTHM station	102
Table 4. 28: Investigation of regression coefficients between PM ₁₀ and meteorological measurements according to multiply regression analysis during winter 2018-2019 in İstanbul - Esenyurt-MTHM station	103
Table 4. 29: Summarize of statistical analysis of multiple linear regression of PM ₁₀ in Iğdir station	103
Table 4. 30: Summarize of statistical analysis of multiple linear regression results of SO ₂ in Edirne_ Keşan station	103
Table 4. 31: Summarize of statistical analysis of multiple linear regression of PM ₁₀ in İstanbul - Esenyurt-MTHM station	104
Table 4. 32: Semivariogram modelling for PM ₁₀ during winter 2017-2018	122
Table 4. 33: The best fitted factors of the theoretical semivariogram model for PM ₁₀ depending on prediction errors during winter 2017-2018	123
Table 4. 34: Descriptive Statistics of pollutants and regression equation of PM ₁₀	123

LIST OF FIGURES

Figure 2. 1: Air Pollution Sources (Dubois, Novak et al. 2012).....	11
Figure 2. 2: Feature types and their representations in two spatial data models.	19
Figure 2. 3: The shape of conventional semivariogram and semivariance function.....	24
Figure 3. 1: National geographical map of Turkey, stations locations	34
Figure 3. 2: procedures of manual data entry diagram.....	36
Figure 3. 3: Procedures of Cokriging method modeling of PM ₁₀ -SO ₂ -NO _x	37
Figure 3. 4: State Traffic Volume Map in 2018 (Uraloğlu 2019).....	37
Figure 3. 5: Turkey industry density (Tuk 2010, Kılıç, Kum et al. 2016)	38
Figure 3. 6: Land Cover and Land Use of Turkey	39
Figure 3. 7: Wind direction and wind speed map during January 2016.....	44
Figure 3. 8: Wind direction and wind speed map during January 2017	44
Figure 3. 9: Wind direction and wind speed map during January 2018.....	44
Figure 4. 1: Spatial analysis of PM ₁₀ in January 2015 by using IDW method.	47
Figure 4. 2: Spatial analysis of PM ₁₀ in January 2016 by using IDW method.	48
Figure 4. 3: Spatial analysis of PM ₁₀ in January 2017 by using IDW method.	48
Figure 4. 4: Spatial analysis of PM ₁₀ in January 2018 by using IDW method.	48
Figure 4. 5: Average concentration of PM ₁₀ _January 2015 in the all Stations.....	49
Figure 4. 6: Average concentration of PM ₁₀ _January 2016 in the all Stations.....	49
Figure 4. 7: Average concentration of PM ₁₀ _January 2017 in the all Stations.....	50
Figure 4. 8: Average concentration of PM ₁₀ _January 2018 in the all Turkey Stations..	50
Figure 4. 9: Average annual Concentration of PM ₁₀ during period 2009-2018	51
Figure 4. 10: Spatial analysis of PM ₁₀ in February 2015 by applying IDW model	52
Figure 4. 11: Spatial analysis of PM ₁₀ in February 2016 by applying IDW model	52
Figure 4. 12: Spatial analysis of PM ₁₀ in February 2017 by applying IDW model	53
Figure 4. 13: Spatial analysis of PM ₁₀ in February 2018 by applying IDW model	53
Figure 4. 14: Spatial analysis of PM ₁₀ in March 2015 by applying IDW model.....	53
Figure 4. 15: Spatial analysis of PM ₁₀ in March 2016 by applying IDW model.....	54
Figure 4. 16: Spatial analysis of PM ₁₀ in March 2017 by applying IDW model.....	54
Figure 4. 17: Spatial analysis of PM ₁₀ in March 2018 by applying IDW model.....	54
Figure 4. 18: Spatial analysis of PM ₁₀ in April 2015 by applying IDW model.....	55
Figure 4. 19: Spatial analysis of PM ₁₀ in April 2016 by applying IDW model.....	55
Figure 4. 20: Spatial analysis of PM ₁₀ in April 2017 by applying IDW model.....	55
Figure 4. 21: Spatial analysis of PM ₁₀ in April 2018 by applying IDW model.....	56
Figure 4. 22: Spatial analysis of PM ₁₀ in May 2015 by applying IDW model.....	56
Figure 4. 23: Spatial analysis of PM ₁₀ in May 2016 by applying IDW model.....	56
Figure 4. 24: Spatial analysis of PM ₁₀ in May 2017 by applying IDW model.....	57
Figure 4. 25: Spatial analysis of PM ₁₀ in May 2018 by applying IDW model.....	57
Figure 4. 26: Spatial analysis of PM ₁₀ in June 2015 by applying IDW model.....	57
Figure 4. 27: Spatial analysis of PM ₁₀ in June 2016 by applying IDW model.....	58

Figure 4. 28: Spatial analysis of PM ₁₀ in June 2017 by applying IDW model.....	58
Figure 4. 29: Spatial analysis of PM ₁₀ in June 2018 by applying IDW model.....	58
Figure 4. 30: Spatial analysis of PM ₁₀ in July 2015 by applying IDW model.....	59
Figure 4. 31: Spatial analysis of PM ₁₀ in July 2016 by applying IDW model	59
Figure 4. 32: Spatial analysis of PM ₁₀ in July 2017 by applying IDW model	59
Figure 4. 33: Spatial analysis of PM ₁₀ in July 2018 by applying IDW model	60
Figure 4. 34: Spatial analysis of PM ₁₀ in Augusts 2015 by applying IDW model	60
Figure 4. 35: Spatial analysis of PM ₁₀ in Augusts 2016 by applying IDW model	60
Figure 4. 36: Spatial analysis of PM ₁₀ in Augusts 2017 by applying IDW model	61
Figure 4. 37: Spatial analysis of PM ₁₀ in Augusts 2018 by applying IDW model	61
Figure 4. 38: Spatial analysis of PM ₁₀ in September 2015 by applying IDW model	61
Figure 4. 39: Spatial analysis of PM ₁₀ in September 2016 by applying IDW model	62
Figure 4. 40: Spatial analysis of PM ₁₀ in September 2017 by applying IDW model	62
Figure 4. 41: Spatial analysis of PM ₁₀ in September 2018 by applying IDW model	62
Figure 4. 42: Spatial analysis of PM ₁₀ in October 2015 by applying IDW model.....	63
Figure 4. 43: Spatial analysis of PM ₁₀ in October 2016 by applying IDW model	63
Figure 4. 44: Spatial analysis of PM ₁₀ in October 2017 by applying IDW model	63
Figure 4. 45: Spatial analysis of PM ₁₀ in November 2018 by applying IDW model.....	64
Figure 4. 46: Spatial analysis of PM ₁₀ in November 2015 by applying IDW model.....	64
Figure 4. 47: Spatial analysis of PM ₁₀ in November 2016 by applying IDW model.....	64
Figure 4. 48: Spatial analysis of PM ₁₀ in November 2017 by applying IDW model.....	65
Figure 4. 49: Spatial analysis of PM ₁₀ in November 2018 by applying IDW model.....	65
Figure 4. 50: Spatial analysis of PM ₁₀ in December 2015 by applying IDW model	65
Figure 4. 51: Spatial analysis of PM ₁₀ in December 2016 by applying IDW model	66
Figure 4. 52: Spatial analysis of PM ₁₀ in December 2017 by applying IDW model	66
Figure 4. 53: Spatial analysis of PM ₁₀ in December 2018 applying IDW model.....	66
Figure 4. 54: Spatial analysis of SO ₂ in January 2015 by applying IDW model.....	68
Figure 4. 55: Spatial analysis of SO ₂ in January 2016 by applying IDW model.....	68
Figure 4. 56: Spatial analysis of SO ₂ in January 2017 by applying IDW model.....	69
Figure 4. 57: Spatial analysis of SO ₂ in January 2018 by applying IDW model.....	69
Figure 4. 58: Spatial analysis of SO ₂ in February 2015 by applying IDW model.....	69
Figure 4. 59: Spatial analysis of SO ₂ in February 2016 by applying IDW model.....	70
Figure 4. 60: Spatial analysis of SO ₂ in February 2017 by applying IDW model.....	70
Figure 4. 61: Spatial analysis of SO ₂ in February 2018 by applying IDW model.....	70
Figure 4. 62: Spatial analysis of SO ₂ in March 2015 by applying IDW model.....	71
Figure 4. 63: Spatial analysis of SO ₂ in March 2016 by applying IDW model.....	71
Figure 4. 64: Spatial analysis of SO ₂ in March 2017 by applying IDW model.....	71
Figure 4. 65: Spatial analysis of SO ₂ in March 2018 by applying IDW model.....	72
Figure 4. 66: Spatial analysis of SO ₂ in April 2015 by applying IDW model.....	72
Figure 4. 67: Spatial analysis of SO ₂ in April 2016 by applying IDW model.....	72
Figure 4. 68: Spatial analysis of SO ₂ in April 2017 by applying IDW model.....	73
Figure 4. 69: Spatial analysis of SO ₂ in April 2018 by applying IDW model.....	73
Figure 4. 70: Spatial analysis of SO ₂ in May 2015 by applying IDW model.....	73
Figure 4. 71: Spatial analysis of SO ₂ in May 2016 by applying IDW model.....	74
Figure 4. 72: Spatial analysis of SO ₂ in May 2017 by applying IDW model.....	74
Figure 4. 73: Spatial analysis of SO ₂ in May 2018 by applying IDW model.....	74
Figure 4. 74: Spatial analysis of SO ₂ in June 2015 by applying IDW model.....	75

Figure 4. 75: Spatial analysis of SO ₂ in June 2016 by applying IDW model.....	75
Figure 4. 76: Spatial analysis of SO ₂ in June 2017 by applying IDW model.....	75
Figure 4. 77: Spatial analysis of SO ₂ in June 2018 by applying IDW model.....	76
Figure 4. 78: Spatial analysis of PM ₁₀ in July 2015 by applying IDW model	76
Figure 4. 79: Spatial analysis of SO ₂ in July 2016 by applying IDW model	76
Figure 4. 80: Spatial analysis of SO ₂ in July 2017 by applying IDW model	77
Figure 4. 81: Spatial analysis of SO ₂ in July 2018 by applying IDW model	77
Figure 4. 82: Spatial analysis of SO ₂ in Augusts 2015 by applying IDW model	77
Figure 4. 83: Spatial analysis of SO ₂ in Augusts 2016 by applying IDW model	78
Figure 4. 84: Spatial analysis of SO ₂ in Augusts 2017 by applying IDW model	78
Figure 4. 85: Spatial analysis of SO ₂ in Augusts 2018 by applying IDW model	78
Figure 4. 86: Spatial analysis of SO ₂ in September 2015 by applying IDW model	79
Figure 4. 87: Spatial analysis of SO ₂ in September 2016 by applying IDW model	79
Figure 4. 88: Spatial analysis of SO ₂ in September 2017 by applying IDW model	79
Figure 4. 89: Spatial analysis of SO ₂ in September 2018 by applying IDW model	80
Figure 4. 90: Spatial analysis of SO ₂ in October 2015 by applying IDW model	80
Figure 4. 91: Spatial analysis of SO ₂ in October 2016 by applying IDW model	80
Figure 4. 92: Spatial analysis of SO ₂ in October 2017 by applying IDW model	81
Figure 4. 93: Spatial analysis of SO ₂ in October 2018 by applying IDW model	81
Figure 4. 94: Spatial analysis of SO ₂ in November 2015 by applying IDW model.....	81
Figure 4. 95: Spatial analysis of SO ₂ in November 2016 by applying IDW model.....	82
Figure 4. 96: Spatial analysis of SO ₂ in November 2017 by applying IDW model.....	82
Figure 4. 97: Spatial analysis of SO ₂ in November 2017 by applying IDW model.....	82
Figure 4. 98: Spatial analysis of SO ₂ in December 2015 by applying IDW model.....	83
Figure 4. 99: Spatial analysis of SO ₂ in December 2016 by applying IDW model.....	83
Figure 4. 100: Spatial analysis of SO ₂ in December 2017 by applying IDW model	83
Figure 4. 101: Spatial analysis of SO ₂ in December 2018 by applying IDW model	84
Figure 4. 102: Average monthly SO ₂ Concentrations during winter season March 2013- April 2019 in Edirne City.	85
Figure 4. 103: Average annual SO ₂ Concentrations during 2013-2018 in Edirne City.	86
Figure 4. 104: Average annual SO ₂ Concentrations during January 2010-April 2019 in some cities of Turkey as maximum values chosen.	86
Figure 4. 105: Spatial analysis of NO _x during 2016 by applying IDW model	88
Figure 4. 106: Spatial analysis of NO _x during 2017 by applying IDW model	88
Figure 4. 107: Spatial analysis of NO _x during 2018 by applying IDW model	88
Figure 4. 108: Spatial analysis of NO _x during 2018 by using Ordinary Kriging prediction method.	89
Figure 4. 109: The relation between measured and prediction values of NO _x , OK method.	89
Figure 4. 110: Spatial analysis of AQI for PM ₁₀ , winter 2015 by applying IDW model	106
Figure 4. 111: Spatial analysis of AQI for PM ₁₀ , summer 2015 by applying IDW model	107
Figure 4. 112: Spatial analysis of AQI for PM ₁₀ , winter 2015-2016 by applying IDW model	108
Figure 4. 113: Spatial analysis of AQI for PM ₁₀ , summer 2016 by applying IDW model	108

Figure 4. 114: The spatial distribution of AQI for PM ₁₀ , winter 2016-2017 by applying IDW model.....	109
Figure 4. 115: Spatial analysis of AQI for PM ₁₀ , summer 2017 by applying IDW model	110
Figure 4. 116: Spatial Analysis of AQI for PM ₁₀ , winter 2017-2018 by applying IDW model	111
Figure 4. 117: Spatial analysis of AQI for PM ₁₀ , summer 2018 by applying IDW model	111
Figure 4. 118: Spatial Analysis of AQI for SO ₂ , winter 2015 by applying IDW model	112
Figure 4. 119: Spatial analysis of AQI for SO ₂ , summer 2015 by applying IDW model	113
Figure 4. 120: Spatial Analysis of AQI for SO ₂ , winter 2015-2016 by applying IDW model	114
Figure 4. 121: Spatial analysis of AQI for SO ₂ , summer 2016 by applying IDW model	114
Figure 4. 122: Spatial Analysis of AQI for SO ₂ , winter 2016-2017 by applying IDW model	115
Figure 4. 123: Spatial analysis of AQI for SO ₂ , summer 2017 by applying IDW model	115
Figure 4. 124: Spatial Analysis of AQI for SO ₂ , winter 2017-2018 applying IDW model	116
Figure 4. 125: Spatial analysis of AQI for SO ₂ , summer 2018 by applying IDW model	117
Figure 4. 126: Spatial analysis of PM ₁₀ , simple Kriging method during winter 2017-2018	118
Figure 4. 127: Semivariogram modeling of PM ₁₀ simple Kriging method	118
Figure 4. 128: Spatial analysis of PM ₁₀ -SO ₂ , CoKriging method during winter 2017-2018	119
Figure 4. 129: Semivariogram modeling of PM ₁₀ -SO ₂ , simple CoKriging method	119
Figure 4. 130: Cross-validation comparison between CoKriging (PM ₁₀ -SO ₂) and Kriging (PM ₁₀) that had been selected as the best methods during winter 2017-2018.....	120
Figure 4. 131: Spatial analysis of PM ₁₀ -NO _x , CoKriging method during winter 2017-2018	120
Figure 4. 132: Semivariogram modeling of PM ₁₀ -NO _x , simple CoKriging method....	121
Figure 4. 133: Spatial analysis of PM ₁₀ -SO ₂ -NO _x , CoKriging method during winter 2017-2018	121
Figure 4. 134: Semivariogram modeling of PM ₁₀ -SO ₂ -NO _x , simple CoKriging method	122
Figure 4. 135: Relation between PM ₁₀ and SO ₂	124
Figure 4. 136: Relation between PM ₁₀ and NO _x	124

INDEX OF SYMBOLS AND ABBREVIATIONS

WHO: World Health Organization

PM: Particulate Matter

SO₂: Sulfur Dioxide

CO: Carbon Monoxide

O₃: Ozone

NO_x: Nitrogen Oxides

AQI: Air Quality Index

EEA: European Environment Agency

GIS: Geographic Information System

IDW: Inverse Distance Weighted

US EPA: United States Environmental Protection Agency

OK: Ordinary Kriging

SK: Simple Kriging

UK: Universal Kriging

RMS: Root-Mean-Square

MS: Mean Standardized

RMSS: Root-Mean-Square Standardized

ASE: Average Standard Error

T: Temperature

WD: Wind Direction

WS: Wind Speed

RH: Relative Humidity

AP: Air Pressure

R²: Correlation coefficient

µg/m³: microgram per cubic meter

I. INTRODUCTION

1.1 Introduction

Air pollution is the change in the natural structure of the air for different reasons, which may adversely affect human and environmental health. Air pollution has become a universal environmental trouble in most towns in the world, during the evolutions causal to air pollution in the towns are incorrect urbanization for the topographical and climatological conditions, incorrect partition of urban land , bad types of fuel and inappropriate burning methods, an insufficiency of green regions, an excess in the numeral of motor vehicles and unsuitable discarding of wastes ([Tuncel, Baykal et al. 1994](#), [Evcı 2009](#), [Grsic, Dramlić et al. 2014](#), [Partigöç and Çubukçu 2017](#), [Partigöç 2019](#)). Different types of pollution in the atmosphere come from anthropological activities and natural happenings such as desert storms and forest fires ([Hamzelo, Gharagozlou et al. 2015](#)), over the years air pollution problems have converted into a more serious form because of increasing release of dangerous and toxic contaminants into the environment ([Gurjar and Ojha \(2016\)](#)), because of dense energy consumption, economic development beside population growth and urbanization, the air pollutants quantities have increased and releases of many pollutants are rising principally in metropolitan areas. Air pollution affects the quality of life, public health directly and negatively affect the environment ([Ozcan and Cubukcu \(2016\)](#), [Shareef, Husain et al. 2016](#)), and it is also a main environmental danger to a social cost: WHO noises that in 2010 the amount yearly financial cost of health influences and death-rate from air pollution, consist of disease costs, equalize to 1.575 trillion US dollars for the states of the WHO European ([Bruno, Cameletti et al. 2016](#)). The WHO recognized outdoor air pollution as a human carcinogen ([Loomis, Huang et al. 2014](#)). Actual air quality administration should be depend on a complete realizing of local air contamination troubles and resolution in an extensive Public Health context ([Brunt, Barnes et al. 2016](#)). So a growing need for accurate report on the effect of air pollution on human health necessary as a foundation for designing scientific, effective and purposeful strategies for decreasing these influences, taking into consideration temporary health influences in ecological time-series researches on atmosphere pollution and death-rate, it look-alike sensible to suppose such a spatially uniform temporal height or decrease concentration of air pollution for they are reliant on the fundamental climatological conditions ([Hennig,](#)

[Sugiri et al. 2016](#)). Atmospheric pollution problems in urban areas are often combined with the products of burning in manufacturing, vehicles and for domestic purposes ([Ahmad and Aziz 2013](#)). Excessive levels of these contaminants are displayed by most of the urbanite cities around the world air pollutants are released from a range of both artificial sources involving: industries, manufacturing facilities, motor vehicles, heating, tobacco smoking, fossil fuels burning in electricity generation, agriculture, waste treatment and from many natural sources including fires of wild land, dust storms, volcanic activity also give a share in gases and particulates to the atmosphere and emissions of volatile organic composites from plants ([Khan and Ali 2013](#), [Ali, Mustafa et al. 2016](#), [Sim 2016](#)). Air pollution occurs inside the boundary layer of the planet's atmosphere under the combined influence of weather elements, topographic characteristics of land surface and emission of air pollutants from different sources. Weather elements for example temperature, wind direction, wind speed and relative humidity are efficient factors to the blend of air pollutants ([Ocak and Turalioglu 2008](#)). There is a requirement to comprehend much around the geographical differences of atmospheric contaminants. This demands the capability to generalize from observing stations in the locations have not been sampled. The goal was to evaluate ways to improve careful and high resolution maps of the air pollution ([Beelen, Hoek et al. 2009](#)). Air pollutants comprise a wide range of substances including carbon monoxide (CO), particulate matter, nitrogen oxides (NO_x), sulfur dioxide (SO₂), ozone (O₃), hydrogen sulfide (H₂S), hydrogen fluoride (HF), volatile organic composites (VOC) and various gaseous forms of metals, volatile organic matter and other air pollutants which usually existing together that vary by site, source activity, season, weather and year ([Yerramilli, Dodla et al. 2011](#), [Ahmad and Aziz 2013](#), [Adedeji, Oluwafunmilayo et al. 2016](#)). PM_{2.5} and PM₁₀ for diameter smaller than 2.5 mm and 10 mm respectively, they are ordinarily measured by air quality index (AQI) ([Du and Varde 2016](#), [Li, Fan et al. 2016](#)). From amongst the factors that play a significant role in eliciting health impacts are the size and the surface of the particles, their number and constituents. PM formation is different because it can absorb and transfer many of the pollutants ([Kampa and Castanas 2008](#)). Atmospheric pollution can have a destructive influence on health of human and animal; losses plants; causes the damage of building materials, fabrics and decoration; and causes climatic change ([Abdul Wahab, Shukri et al. 2013](#)). Delineation of urban areas and land use strategies can have significant effects for local concentrations of air pollution ([Larkin, van Donkelaar et al. 2016](#)).

Turkey appears as a country with one of the greatest amounts of early mortalities produced by air pollution in Europe. Unfortunately, 99.7% of the urban people in Turkey is unprotected to particulate matter in much more than the "normal" values prepared by the World Health Organization (WHO) in the outdoor environment ([Bertrams 2017](#)), according to latest estimates, 28,924 persons in Turkey died early from exposure to ambient PM and ozone in 2010, and consistent with the European Environment Agency (EEA), more than 97 percent of Turkey's urban population is revealed to insecure quantities of particulate matter contamination ([Indicators 2004](#)). In 2014, the quantity of the coal industry has increased or are planning to construct in Turkey to nearly 80 new plants to produce electricity, which means that the risk from adding planned projects has risen to 39,000 years of life lost, where 72.3 % of the population of Turkey (58,172,652 people in 2017 of 80,107,821 people) lives in urban areas with ambient particulate matter levels (PM) beyond WHO Air Quality Standards and Turkish Air Quality Index. Urban growth breeds decline of the urban environment, increases air and water pollution and decreases the amount of vegetation cover and the high levels of diseases ([Han, Hayashi et al. 2009](#), [Mohammady and Delavar 2016](#)). Lignite, one of the largely essential energy sources and heavily used to generate electrical energy in Turkey since the 1950s and it is quarried in Turkey with low quality, the increasing usage of fossil fuels causes air pollution in the nearness of thermal power plants, where lignite (coal) standby of Turkey was described to be over 8 billion metric tons, the Turkish lignite have minimal calorific value and consist of comparatively higher quantities of ash, moisture and sulfur. ([Kaygusuz and KAYGUSUZ 1996](#), [Say 2006](#), [Köne and Büke 2012](#), [Kayabasi, Turer et al. 2016](#)), gas consumption accounts today about 10 percent of the power supply in Turkey. Most major cities and inhabited areas, particularly in the eastern portion of Turkey, have set up natural gas pipeline to be used in heating systems and in industries for decreasing air pollution in Turkey ([Karaca 2012](#)). The rising urban population, population intensity, manufacturing and the fossil fuels using, atmospheric pollution has made a dangerous environmental problem in urban parts in Turkey ([Özcan and Çubukçu 2013](#)). Since the second half of the 20th century, environmental concerns linked to air pollution have heartened broader oncoming to natural gas (NG) amongst other premier energy sources. Mobile and stationary fossil fuel burning is well identified as a chief source of anthropogenic gaseous contaminants such as particulate matter ([Kampa and Castanas 2008](#), [Taşpınar 2015](#)). Mobile sources like traffic releases are a subcategory of the area source ([Dobie 1992](#), [Khafaie, Ojha et al. 2016](#)). In environmental management

laws, important emissions of air pollutants, essentially in industrial regions have continually been a worry for factory workers and people who live near industrial areas and this is due to the complication of emission sources, pollutants' function and the type of pollutants ([Kho, Sentian et al. 2007](#), [Nadoushan, Mansouri et al. 2016](#)). Amendments to technology, and strategies to limit air pollution emitters can be slow to perform or they may not be line up with to the values of the government ([Adams and Kanaroglou 2016](#)). The health dangers of air pollution producing from public transports could be lessened by improvements to the vehicle fleet, this can be bettered by modernizing, maintaining, or replacing engines of motor vehicle. Sophisticated states have made considerable efforts to upgrade air quality during the implementation of clean air projects that have involved processes for instance: demanding emission and guidelines of air quality, incessant air quality observing in urban and industrial positions, and use of clean fuel like natural gas ([Baldasano, Valera et al. 2003](#)). Exposure to atmospheric pollution has been linked to different health outcomes. Consequently, data analyzing of air pollution and reporting associated statistics have become significant jobs for governments and non-governmental organizations ([Ahn 2015](#)). A combination of pollutants in the outdoor air varies significantly through time and place, showing not only the variety of sources, but the impact of atmospheric operations, including oxidation and climate. Geographic Information System tools play a distinguished role in developing efforts in modelling of place-time, GIS must assist to better data combination and consistency ([Briggs 2005](#)). The spatial analysis and overlay methods existing in GIS are powerful tools for pollution mapping, with the advancement of GIS and geostatistical methods in latest years, an extensive range of spatial interpolation methods have become accessible ([Briggs, Collins et al. 1997](#)). Interpreting and comprehending air pollution data commonly needs taking into consideration a suitable spatial context: most information come with geographic information, and several investigations utilize a geographical framework for analysis, the usage of GIS in air pollution modeling can be furthermore widened to deal with the surface data ([Jerrett, Burnett et al. 2005](#), [Matejcek 2005](#)). GIS-based pollution mapping has evidenced effectual in the evaluation of urban air pollution, applying interpolation techniques, like inverse distance weighting and Kriging methods ([Adedeji, Oluwafunmilayo et al. 2016](#)). Interpolation of fixed- location air pollution observing data has usually been used to predict concentrations of pollutants across wide regions ([Beelen, Hoek et al. 2009](#), [Hystad, Setton et al. 2015](#)). Abilities of the GIS comprise primarily administration of spatial data in the form of map layers that can envision real aims by

vector and raster data formats together with graphs and multimedia presentations. A numeral of definitions illustrate susceptibility of the GIS to resolve an extensive range of ecological problems that are associated to urban areas ([Banja, Como et al. 2010](#)). The spatial distribution of ambient pollutant can be gained using spatial interpolation of monitoring data.

1.2 Objectives and scopes of the study

The objectives of this study are:

- To describe spatial patterns of air pollutants by analyzing and visualizing Turkey air pollution data for the period 2015–2019.
- To produce the spatial distribution maps of the monthly average of PM₁₀ and SO₂ that covered all Turkey regions for the period 2015–2019 by using Inverse Distance Weighted (IDW) method within the ArcGIS software environment.
- To produce the spatial distribution maps of seasonal AQI and annual NO_x values that covering the full study area Turkey.
- Cokriging was then applied to estimate the contribution of different covariates when assessing the spatial distribution of PM₁₀ concentration, the different covariates utilized in this study are SO₂ and NO_x, and developing several modules to visualize air pollution data.
- The relationship between air pollutant concentrations and meteorological factors was analyzed applying multiple regression method.
- In this study, GIS has been used for investigating air quality research using various air pollutants, examination several modelling to illustrate distribution of pollution and level which has not been applied before by using Cokriging geostatistical method.

II. LITERATURE REVIEW

2.1 Introduction

One of the major problems of the last period the health problems that result from air pollution. Most partial of the world's people lives in cities and is increasingly exposed to air pollution. The increased result of industrialization is the rising demand for energy from fossil fuels for instance oil and coal, and motor vehicles are the main causes of increased pollution. Those living in rural areas are exposed to the fumes of solid fuels (wood, charcoal, animal feces, etc.) used for lighting, heating and cooking ([Salvi and Barnes 2009](#), [Po, FitzGerald et al. 2011](#), [Çilingir 2016](#)). Air pollution; can be described as pollutants like sulfur dioxide (SO_2), particulate matter (PM), nitrogen oxides (NO_x) and ozone (O_3) that we breathe are at levels that will negatively influence the environment and health. This pollution disrupts the natural procedures in the atmosphere and have an effect on the health of the community negatively and though the level of air pollution has been consistently watched and fought in the last 30 years in the world, the pollution levels, particularly in the big cities, are still exceeding the secure limits. Until the 1980s, 1.3 billion people in the world are living in cities with contamination beyond air quality levels. Air pollution is caused by exhaust releases from motor vehicles, industrial facilities, fuel utilization for heating in residences. In the world, a fivefold rise in air pollutant releases is predictable by 2030. Specifically in growing regions, pollution increases with quick urbanization and increases in energy utilization ([Organization 1992](#), [Bayram, Dörtbudak et al. 2006](#)). Sulfur and nitrogen emissions from the usage of fossil fuels, together with other pollutants, cause air pollution by altering the structure of the air. The first effects of these emissions that cause air pollution are felt in their own regions. However, with the help of the dominant winds and the long chimneys built after the 1960s, there is a potential to affect farther regions of air pollution. In addition, when these pollutants combine with moisture in the air and fall to the earth as rainfall, they have an adverse effect on the living environment and the physical environment. This is actually the result of the reaction of nitrogen and sulfur emissions with water vapor, which can be termed as acid rain. When it goes down to earth, it affects both human health and the natural and artificial environment ([Orhan 2012](#)). With the purpose of solve increasing air pollution problems in Turkey, it is essential to provide healthy and up-to-date inventory data showing the sources of air pollutants and the types and amounts of

these sources. However, with such inventories, it is possible for administrators to see which sources of pollutants should be reduced in regional air quality management programs, and as a result, how much improvement in air quality can be achieved as a result. In this respect, the first step in managing air quality is to have a good inventory. The air that inhaled must be characterized by some kind of balance; it is a reason to save human life. Dry air is composed of several gases are 78.1% nitrogen, 20.9% oxygen, 0.9% argon, 0.04% carbon dioxide, 0.002% neon, 0.0005% helium.

2.2 Sources and Impacts of Air Pollutants

The sources of air pollution may be from natural activities or human activities, natural activities such as forest fires and lightning, which may cause an increase in the nitrogen ratio in the atmosphere. On the other hand, fires that are ignited for different purposes which cause fumes from factories, home facilities, and exhaust gases from compounds that cause air to mix with toxic gases such as carbon monoxide, sulfur dioxide and nitric acid in abundant quantities. Hence, natural gas emissions or human-induced gas emissions can cause pollution by changing gas rates in the atmosphere ([Kardeşoğlu, Yalçın et al. 2011](#)). Concentrations of air pollutants differ spatially considerably with artificial emissions and weather conditions, because they are influenced by various sources such as fixed sources (manufactories, power plants, and dry cleaners), mobile sources (fuel combustion from vehicles), and natural sources (windblown dust and volcanic eruptions). The greater part of electricity produces by fossil fuels combustion in thermal power plants (TPP). The burning of a large amount of fossil fuels such as coal and oil, diesel and kerosene in the TPP for the production of electricity, would have caused a large amount of air pollution ([Malik, Mohideen et al. 2016](#)). Primary pollutants are expressed as pollutants emitted directly from the source to the atmosphere. There are five primary pollutants in terms of importance and resources in air pollution, they account for almost 90% of all pollutants like carbon monoxide (CO), sulfur oxides (SO_x), nitrogen oxides (NO_x), hydrocarbons (HC), and particulate matter (PM). Secondary pollutants are formed as a result of chemical reactions that occur with the help of natural components and atmospheric properties, such as sulfur compounds (SO₃, H₂SO₄, SO₄ compounds), organic compounds (ketones, aldehydes, acids), nitrogen compounds (NO₂, NO₃ compounds), photo chemicals formations and ozone (O₃) ([Incecik 1994](#), [Thad 1997](#), [Gustafson 2009](#), [Godish, Davis et al. 2014](#)). Photochemical

reactions play an important role in the formation of secondary pollutants. The amount of substance that is altered in photochemical reactions is proportional to the amount of absorbed solar radiation. The photochemical smog that occurs in the summer is due to vehicle emissions and effective solar radiation.

Mobile sources release immediate greenhouse gas emissions of carbon dioxide (CO₂), methane (CH₄) and nitrous oxide (N₂O) from the burning of different fuel species, as well as some other pollutants like carbon monoxide (CO), sulfur dioxide (SO₂), particulate matter (PM) and nitrate oxides (NO_x), that cause or participate to local or provincial atmosphere pollution ([Change 2006](#)). The aerosols of atmospheric sulfate released from industrial emissions absorb or squander solar radiation, producing a decreasing in the rate of sunlight coming to the earth surface. Emissions are subject to a number of kinds of physical and chemical conversions and contribute to an extensive scope of health and ecological effects, as well as the worsening of air quality, stress toxic to human health and environments, and the forming of a photo-oxidant (smog), and depletion of stratospheric ozone (O₃), variation of climate, and decline of air sources, noise and other ([Gurjar, Molina et al. 2010](#)). The effect of air pollution on human health, especially children and pregnant women, old and patients with chronic diseases of the respiratory system in various ways, including decreased lung function, and raised morbidity and mortality among children ([Tecer, Tomac et al. 2009](#)). There is a big probable cause of the Air problems is population growth in urban areas and increase in land use because of urban and industrial zones along with the changes in disease and death-rate during the harsh climate conditions. the major sources of air pollution In urban areas are domestic heating, transportation, and manufacturing, whereas in rural areas pollution sources usually come from burning of solid fuel, the influences of PM₁₀ on human health are recognized at least to decrease cardiopulmonary mission and excess mortality from cardiovascular disease, the happening of asthma in children, and the danger of lung cancer and even death ([Kabatas, Unal et al. 2014](#), [Hou, An et al. 2016](#), [Jørgensen, Johansen et al. 2016](#)). Where children are the population most susceptible to the air pollutants because they are in the development of pulmonary function and physical growth phase ([Guo, Liu et al. 2016](#)). Results for the carcinogenicity of outdoor air pollution on a combination form of particle especially, are remarkably significantly in epidemiological research ([Loomis, Huang et al. 2014](#)), particles with diameters less than 10 mm, can reason weakness in the long term to human health because they can

permeate deep and deposit on the wall of the respiratory system ([Holst, Mayer et al. 2008](#)). The lately published studies show, founded on the available information, the major sources of particulate matter causing to towns, air pollution are traffic (25%), burning and agriculture (22%), home fuel burning (20%), natural dust and salt (18%), and industrial facilities (15%), in spite of this, there are important variations between diverse areas of the world ([Karagulian, Belis et al. 2015](#)). Atmospheric processes that command to the creation of the particles because of gaseous traffic, heating and agriculture releases look to be most significant in Turkey. Nitrogen oxides (NO_x) have an ability to react with ammonia, wetness and other composites to compose little particles which can enter deeply into sensible portions of human lungs ([Sillaparassamee, Tantrakarnapa et al. 2016](#)). NO₂ exposure near the roads are of specific concern for persons at risk, including people who suffer from asthma, children and the elderly, and carbon monoxide can rise toxic health influences by decreasing oxygen distribution to the body's organs (such as the heart and brain) and tissues. The widespread use of natural gas, the decrease in fuel consumption due to domestic heating in summer and the decrease in population and vehicle density in urban centers are the factors that reduce sulfur dioxide (SO₂) levels ([Özaslan 2008](#), [Evcı 2009](#), [Lin, Xu et al. 2013](#), [Partigöç and Çubukçu 2017](#)). In addition, dust and aerosols, chemical reactions in the atmosphere and the use of incomplete or incorrect combustion techniques are among the factors that increase sulfur dioxide (SO₂) concentrations ([Ahmed, Kim et al. 2015](#)). There is a high indication that exposure to atmosphere pollution influences the brain, for example, by inflammation of the nerves and stimulates oxidative stress, cognitive impairment and stroke ([Poulsen, Sørensen et al. 2016](#)). There are another impacts of atmosphere pollution like global warming, depletion of ozone, acid rain, and the wildlife extinction ([Ari, Özköse et al. 2016](#)). For protecting the atmosphere, governments reinforced policies and programs in the energy fields, ecologically sound, effective transportation, and industrial pollution limitation and administration of hazardous waste and other toxic. Many countries and various international regulations such as the United States Environmental Protection Agency (US EPA), and the World Health Organization (WHO), the Occupational Safety and Health Administration (OSHA) etc., issued their own standards for this purpose ([Özden, Döğeroğlu et al. 2008](#)).

The major sources of pollutants in Turkey are traffic, housing heating, industrial facilities, particularly power plants and surface mining activities. Brown coal (Lignite)

the most common fuel utilized in both domestic areas and industrial plants. Vehicles are one of the major sources of dynamic pollution in urban centers, transportation vehicles are also about 14% of global greenhouse gas releases and to symbolize a big trouble in growing countries ([Wright and Fulton 2005](#), [Slovic, de Oliveira et al. 2016](#)). Table 2.1 shows sources, health and environmental impact of air pollutants and figure 2.1 shows air pollution sources

Table 2. 1: Sources, health and ecological impact of air pollutants reproduced from ([Heinsohn and Kabel 1999](#), [Coşkun 2008](#), [Gurjar, Molina et al. 2010](#), [Trivedy and Goel 2010](#))

Pollutants	Sources	Health and ecological impacts
Particulate Matter (PM) dusts, fumes, mists, smoke, or spray	Natural sources such as volcanoes, forest fires, and desert land, artificial sources like incomplete combustion, road traffic, energy production, power plants, and construction, agricultural activities	Damage of lung, irritation of eye, asthma, reproductive problems and cancer, decrease visibility, discolor buildings and figurines, crops damage, acid deposition that may cause damaged trees, soils and aquatic life in lakes.
Sulfur dioxide (SO ₂)	Power plants, industrial sources that burn coal or fuel, fossil fuels incomplete combustion, or burning any material containing sulfur, heaters, natural sources like volcanoes	Eye irritation, lung damage, breathing problems, harmful effect on aquatic life, reacts in the atmosphere resulting in acidic rain, deteriorate buildings and figurines, destruction forests
Carbon Monoxide (CO)	Smoking, traffic emissions, incomplete combustion sources, manufacturing industries, solid waste disposal	Decreasing blood oxygen concentrations and reducing blood carboxyhemoglobin concentrations, increase the risk of arrhythmias and death, low birth weight, headache, weakens bones, causes bronchitis and lowers resistance to influenza, heart damage, smog
Nitrogen Oxides (NO _x)	Exhaust from vehicles, burning fossil fuels in industries and power plants.	Can unite with water to produce acid rain, react in the atmosphere creating ozone and other pollutants, or be dangerous by themselves as a gas in the air.
Ozone (O ₃)	Secondary pollutant where is formed during reaction between volatile organic compounds (VOCs) and nitrogen oxides or through photochemical smog in the atmosphere.	Breathing problems, eye irritation, lung damage

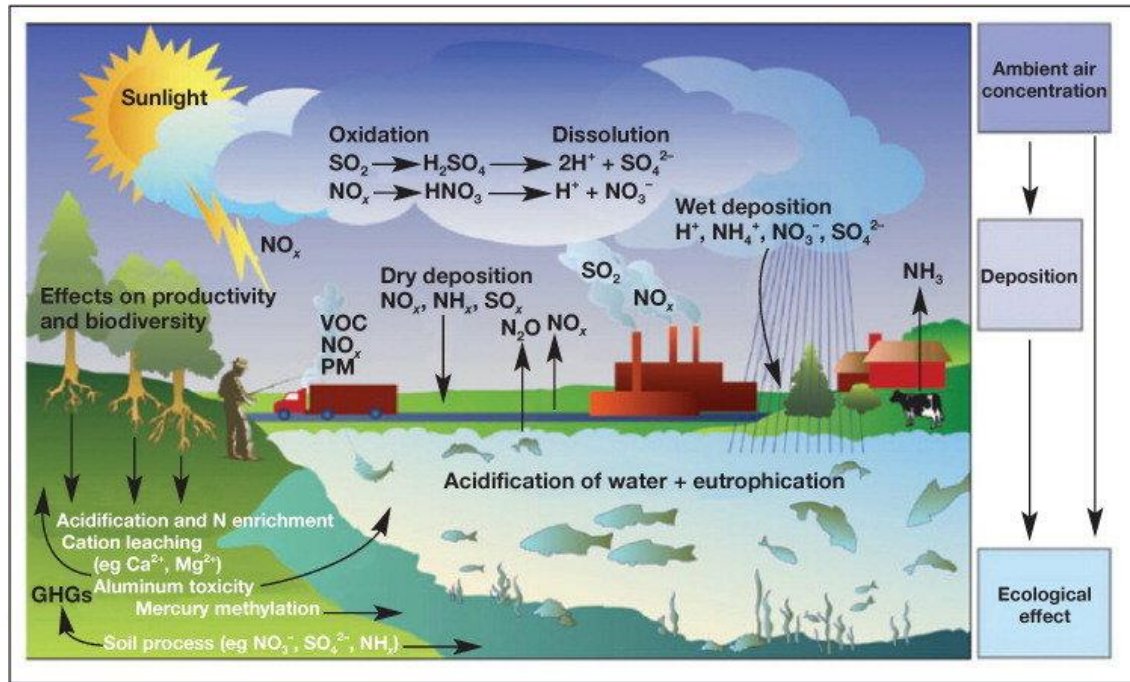


Figure 2. 1: Air Pollution Sources ([Dubois, Novak et al. 2012](#))

2.3 Control Equipment of Air Pollution

Safeguarding sufficient supply of oxygen to the burning chamber and enough temperature so that the combustion is complete and thus eliminate a lot of smoke that composed of partially burned ashes and dust. Using control devices such as packed towers, scrubbers (used for removing some particulates and/or gases from industrial exhaust), Bag filter (used to collect dry free flowing dust) electro-static precipitators in industrial processes (for eliminating soot and ash from exhaust fumes before they exit the chimney), all devices retain dangerous materials which should be disposed of safely. Wet washing can reduce the sulfur dioxide emissions. Air pollutants that have been collected should be disposed with caution ([Harrison 2001](#), [Mussatti, Srivastava et al. 2002](#)).

2.4 Air Quality in Turkey

The air pollution in Turkey, especially after 1950 has become a public health problem. Epidemiological researches and air quality observing data, the air pollution index in Turkey, SO_2 , NO_2 , CO, CO_2 , PM_{10} and $\text{PM}_{2.5}$ levels, especially in winter, illustrates that over the acceptable level. On the other hand, although efforts to reduce air

pollution in metropolitan cities, particularly in Istanbul, Ankara and Izmir, have been successful, further efforts are required to get better air quality in medium and small cities ([Incecik 1994](#), [Tuncel 2008](#)).

The goal of the regulation on the safeguard of air quality is to domination on the smoke, dust, fog and aerosols that are emitted into the air as a consequence of any type of activities, emissions, and guard the rights of human and the ecosystem from any danger that might arise from environmental contamination in the atmosphere ([Aydin Coskun, Türker et al. 2011](#)). Variations in weather and emissions of air pollutants influence the air quality in the future from the global to the urban boundary ([Sá, Martins et al. 2016](#)), where chemical interactions depends on climate conditions around, because they are affected by short-wave radiation, air temperature, air humidity and rainfall ([Katsoulis and Kassomenos 2004](#)). A mixture of contaminant releases and climatology have important implications for the management of air quality levels., where strategies of air quality observation further must be transacted with a combination of gases and particles which is highly changing in place and time ([Theunis, Peters et al. 2017](#)). Additionally the atmospheric dispersion, chemical conversion and topographic position have an effect on air quality in urban regions ([Tecer, Tomac et al. 2009](#)). To build an ecosystem with minimal pollutants, there must be a technique to measure it in real time, and also to forecast the level of pollution in the future, regardless of the size of the accumulated data ([Mehta, Pai et al. 2016](#)). High-precision monitoring and mapping can be involved to a large extent in the air quality administration in names of reducing pollution and exposure to pollution, and danger evaluation ([Krasnov, Kloog et al. 2016](#)). Planting vegetation has an essential impact on reducing of air pollution, benefit from planting trees in the city is not only to decrease air pollution, but also to meet other social requirements (for example, entertainment, cultural, aesthetic, etc.) without additional cost ([Selmi, Weber et al. 2016](#)). A precise and inclusive emissions inventory have been assisted governments to take on board active strategies with consideration to air pollution and qualify them to plan efficient strategies in terms of cost ([Shahbazi, Reyhanian et al. 2016](#)). Moreover, the inventory of emissions are the basic data for the predict air quality models ([Houyoux, Vukovich et al. 2000](#)). Population and vehicle skills, industrial processes, and urban infrastructure are continuously changing. Therefore, it must be updated the emissions inventory on a regular basis in order to express the current situation ([Miller, Hidy et al. 2006](#)), where must be developing appropriate tool able to

contribute to elevating the awareness of citizens about pollution levels in a sufficient and understandable manner ([Büke and Köne 2016](#))

The AQI is an index for reporting daily air quality, since 1970's, air quality watching activities were began in some main cities by investigators in Turkey. In 1990's, continual air pollution observing program started in main district centers and large cities ([Özdilek 2006](#)). Air quality estimation is the collection, management, calculation, analysis, and display of data desired to comprehend the air pollution problem of a specific region ([Koren 2016](#)). The increasing public worries lately raised the role of air quality policies, air pollution is the biggest threat to the environmental health, and traffic is the main factor in this regard ([Dias, Tchepel et al. 2016](#)). Many local policies pursuing to limit the emissions of traffic in cities by encouraging active transport, consolidating physical activity and developing public transport ([Ramos, Wolterbeek et al. 2016](#)), there is a need for further research to better assess and understand the dangers and benefits of the shift to active transport. The observing of the air pollution in urban environments achieved through a certain number of monitoring stations in various locations that represent the public exposure to pollution in terms of population ([Banja, Como et al. 2010](#)). AQI values can differ from season to another. In winter, carbon monoxide may be elevated in several regions due to the low temperature makes it complicated for car emission control systems to work efficiently. SO₂ keeps the downward trend all over the world, except for some Central American countries and Asian cities. NO₂ preserves very close to the levels of the standard value WHO worldwide. In summer, ozone can be main air pollutant because it forms in the existence of high temperature and sunlight, indicating that it is a global problem appears. While particulate matter may be high at any time of the year, it is a main problem in almost all of Asia, which exceeds 300 µg/m³ in several cities. The objective of the AQI is to assistance realize what local air quality means to your health. The major sources of atmospheric contamination in Turkey are urbanization and manufacturing, and the most significant pollutants in Turkey PM, despite SO₂ and NO levels are elevated. Table 2.2 shows air quality index levels of health worry. The elevated the air quality index, the higher the air contamination. As soon as the air quality index is above 100, we can say that the air quality is serious for health, whereas the air quality index is above 300, air quality is harmful to health ([Bıyık 2010](#)). The national air quality index was created by adapting the EPA air quality index to Turkey national legislation and limit values, the air quality index is calculated for 5 major pollutants

these; particulate matter (PM₁₀), carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂) and ozone (O₃).

Table 2. 2: Standards of Air Quality Index for health trouble (EPA Air Quality Index)

([Bishoi, Prakash et al. 2009](#), [Dominici, Peng et al. 2010](#))

Air Quality Index Levels of Health Concern	Numerical Value	Meaning
Good	0 to 50	Air quality is considered satisfactory, and air pollution poses little or no risk.
Moderate	51 to 100	Air quality is acceptable; however, for some pollutants there may be a moderate health concern for a very small number of people who are unusually sensitive to air pollution.
Unhealthy for Sensitive Groups	101 to 150	Members of sensitive groups may experience health effects. The general public is not likely to be affected.
Unhealthy	151 to 200	Everyone may begin to experience health effects; members of sensitive groups may experience more serious health effects.
Very Unhealthy	201 to 300	Health alert: everyone may experience more serious health effects.
Hazardous	301 to 500	Health warnings of emergency conditions. The entire population is more likely to be affected.

Good: When the air quality index is between 0-50, we can say that air quality is safe for health and atmosphere contamination has slight influence.

Medium: At what time the air quality index is ranged among 51- 100, air quality is within acceptable limits. A number of pollutants have adverse impacts for some persons. Respiratory symptoms occur in persons who are very responsive to ozone.

Unhealthy for Vulnerable Groups: At what time the air quality index is ranged among 101 and 150, there is a negative impact on the health of vulnerable group members. Persons with lung illnesses unprotected to particle pollution are at greater danger. While the air quality index is in this range, commonly healthy people are not influenced much.

Unhealthy: When the air quality index is ranged among 151 and 200, health influences begin to be seen in any person. Sensitive persons start to have more dangerous health influences.

Very Unhealthy: The air quality index 201-300, the Air Quality Index, indicates the health alarm sign. Dangerous health impacts can occur in any human.

Harmful: When the air quality index exceeds 300, emergency health warnings begin. All the people are negatively affected.

2.5 Air pollution in Turkey

Air pollution is one of the most polluted kinds of contamination; atmospheric pollution is a change in the air due to the existence of solid, liquid or gaseous substances in amounts that cause damage to humans, animals and plants, as well as things. Air pollution is considered to be one of the nastiest air contaminants, The population in the region has increased pollution, especially with the spread of the industrial revolution in the world, the increase in transport and development and its dependence on oil and petroleum as fuel; it emits large quantities of polluting gases in the atmosphere, such as poisonous carbon monoxide, sulfur dioxide, and ozone gas. The Black Sea and Eastern Mediterranean regions are under the effect of industrialized regions in both Western and Eastern Europe. This geography causes polluters to move to the region ([Nicolás, Chiari et al. 2011](#), [Tokgöz, Balcılar et al. 2017](#)).

In Turkey, coal is widely used in domestic heating. The sulfur content of commonly used lignite coal is high. SO₂ emissions from the combustion gases that emitted to the atmosphere are hurtful to human health and the natural environment. Approximately 36% of the total energy consumed in Turkey is used to heat buildings in the housing sector. Emissions from the fuels combustion used in the heating system constitute 85% of the exhaust gases emitted by the end-effector such as CO₂ and 15% of the emissions are sulfur dioxide (SO₂), carbon monoxide (CO) particulate matter (PM₁₀ and PM_{2.5}) and nitrogen oxides (NO_x) ([Yasemin and Kırmacı 2015](#), [Elshahat, Soliman et al. 2019](#), [Genereux 2019](#), [Yin, Cui et al. 2019](#)). As has been pointed out in numerous surveys to date, the major source of air pollutants is the use of fossil fuels like coal, lignite and petroleum and their by-products for various purposes. The duration of air contaminants in the air due to the burning of these fossil fuels is the main reason that increases the adverse effects of the air pollution process in terms of person health and living conditions. Therefore, in order to solve the problem of air pollution, firstly topographic and meteorological parameters that control the persistence of pollution need to be presented ([Keser 2002](#)). To reduce air pollution must:

- i. Minimize the consumption of electricity, through the construction of new plants, qualified with electrical equipment, with little damage and limited.
- ii. Minimizing logging and forest burning, as well as minimizing the burning of toxic waste in the atmosphere.
- iii. Restoring the environment to its green color by encouraging agriculture, thereby restoring the overall ecological balance. Preserving vegetation that helps filter the air and purify it.
- iv. Minimize the use of ordinary gasoline, and use unleaded gasoline to eliminate toxic lead.
- v. Reduce greenhouse gas emissions, particularly carbon dioxide, which is a state mission.
- vi. To obligate factories and laboratories to place filters on their chimneys to avoid the release of contaminants into the outside air, and to use advanced technologies to reduce air pollution, such as sediment chambers or rotary precipitators that decrease the emission of solids in the air. Change the type of fuel used or the mechanism of use, or it can be converted to other forms less harmful to the environment or forms that can be used.
- vii. Develop laws and legislation that include deterrent penalties for violators who contaminate the air through factories or vehicles.
- viii. Dispose of waste properly and keep away from burning near residential sites.
- ix. Encourage people to live in rural areas in order to alleviate the pressure and overcrowding of cities.
- x. Encouraging people to stop smoking and fight it. Maintenance of soil moisture and spraying of water on the surface of streets and roads, especially in the summer days in order to reduce the volatilization of dust.
- xi. Educating citizens, through giving courses and lectures that relate to air pollution and its dangers, so that the person is more aware of this subject.

The follow of all these and other processes bring about the decrease of air pollution inhaled by persons and other living organisms, therefore, getting a healthy ecosystem free of any type of pollutants that threaten the continuance of life on Earth.

2.6 Air pollution modelling

Modeling of air quality is a mathematical tool to assess surroundings concentrations of air pollution centered on climatological and emissions data, and it is beneficial for atmospheric research where can assistance to illustrate a number of atmospheric processes and to analyze the source and fate of pollutants and help to apply policies of emission decline and the knowledge around aerosol effect through cloud interaction and human health ([Kumar, Patil et al. 2016](#), [Mendez, Lebègue et al. 2016](#)). A number of conditions must be accomplished for performing the modeling of air quality and workflow evaluation. Commonly, air quality models should be simple to usage and the possibility of interpreting the results, where choosing of the appropriate models and modeling strategies pose a chief challenge ([Wiemann, Brauner et al. 2016](#)). Modeling of air pollution or epidemiological research paper needs modeling of concentration by way of land use, transportation, and weather conditions with temporal and spatial resolutions appropriate. Each of these in turn affecting standards involves several predictors of weather conditions such as relative humidity, temperature and wind speed that prevent air pollution modeling to the problem of high-dimensional ([Tashayo and Alimohammadi 2016](#)). With modern developments in geographic information systems, spatial modeling techniques and improvement of models to estimate exposure to air pollution in environmental epidemiology researches at the urban scale have been considered in the first rank ([Ribeiro, Pinho et al. 2016](#)).. Monitor and predict future values of the concentrations of pollutants is a very significant subject, as it provides an early caution for the population, and it gives the opportunity for governments to take the necessary precautions. In determining the possibility of air pollution, both air pollution sources and parameters of meteorological should be taught together, therefore, it is clear that there is a requirement for better information on the levels of these operators, and not just for time trends but also on geographical variation and spatial distribution by using GIS ([Karimi, Soffianian et al. 2016](#)). GIS software also saves time taken for collecting geographical data during both preprocessing and post processing stages that is required for air pollution modeling. There are many modelling techniques applied for air pollution modelling: extrapolation from the nearest monitoring site, air quality model, interpolation method and geostatistical analysis existing in GIS techniques, Land Use Regression (LUR) and dispersion modelling ([Hoek, Beelen et al. 2008](#), [Chen, Bai et al. 2010](#), [Gulliver, de Hoogh et al. 2011](#)).

2.7 Definition and data types of Geographic Information Systems

Geographic Information Systems (GIS) is a computer system that established for the storage, restoration, capturing, checking, and analysis of geographically referenced data and understand patterns and relationships ([Longley, Goodchild et al. 2005](#), [Kurland 2016](#)), and it is a digital database administration system designed to manage large quantities of spatially distributed data from a diversity of sources ([Torabi-Kaveh, Babazadeh et al. 2016](#)), the elements required for the establishment of GIS; Software, hardware, databases, methods, and users, in GIS, Data can be collected from many sources, include; corrected maps, digital maps, aerial photographs, satellite images, terrain measurements, land registry and cadastral records, computer-aided design drawings, database logs, text files and other resources ([Bank and Taştan 1994](#), [Boyda, Holzman et al. 2019](#)), where GIS is an advanced system used for the management of urban, environmental and other planning data suitable for monitoring data, planning and preparation, decision making and implementation of decisions ([Cowen 1988](#), [Parker 1988](#), [Campbell and Wikstrom 2019](#), [Yasobant, Vora et al. 2019](#)). GIS techniques have been utilized by different researchers mainly to analyze the spatial and temporal distribution of contaminants ([Kumar, Gupta et al. 2016](#)). Basic feature of using GIS is to regulate the geographic data, where decision making process becomes easy and it offers many of the advanced statistical management and spatial data ([Shareef, Husain et al. 2016](#), [Thill 2019](#)) and supporting decision makers through environmental dangers assessment ([Valdor, Gómez et al. 2016](#), [de Albuquerque, Horita et al. 2019](#)). The expansion of geographical information systems, that have acquired extensive assessment during the past 20 years, offers the scope to predict pollutant concentrations, more geographical data with high accuracy are being collected by public organizations ([Hochadel, Heinrich et al. 2006](#)).

GIS data models founded in three forms are vector, raster and tabular as shown in figure 2.2. Vector and raster data are the two essential data kinds used in GIS, they have a latitudes and longitudes that determine location on Earth. Vector include three categories are polygon, line and point data as Shape file or Coverage, each one of them shows a various role in displaying of geographical topographies. Point data used to characterize non-adjacent and discrete data point, where don't have dimension, used to represent point location such as school, monitoring stations, city center etc. Line data

used to clarify linear features, a combination of many points such as electricity lines, telephone lines, roads, water and sewer networks, rivers, it only have one dimension. A polygon or area data used to signify areas such as forest and lake. Also, it measures the area and perimeter of geographic characteristics and take a two dimensional form ([Behr 1995](#), [Tecim 2008](#), [Huisman and De By 2009](#), [Johnson 2016](#)).

Whereas raster (cells or grid) represent any type of digital image, satellite images, or exemplification of surfaces like elevation, that are used to represent the continuing geographical areas ([Chang 2006](#), [Kurland 2016](#)), raster data can be split into two groups, a continuous and separate, separate raster data such as the population density while continuous data such as temperature and height measurements ([Huisman and De By 2009](#)). Digital models used to count values for land features at any location, for example a digital elevation model used for elevation calculation, based on values that found by surveying ([Bossomaier and Hope 2015](#))

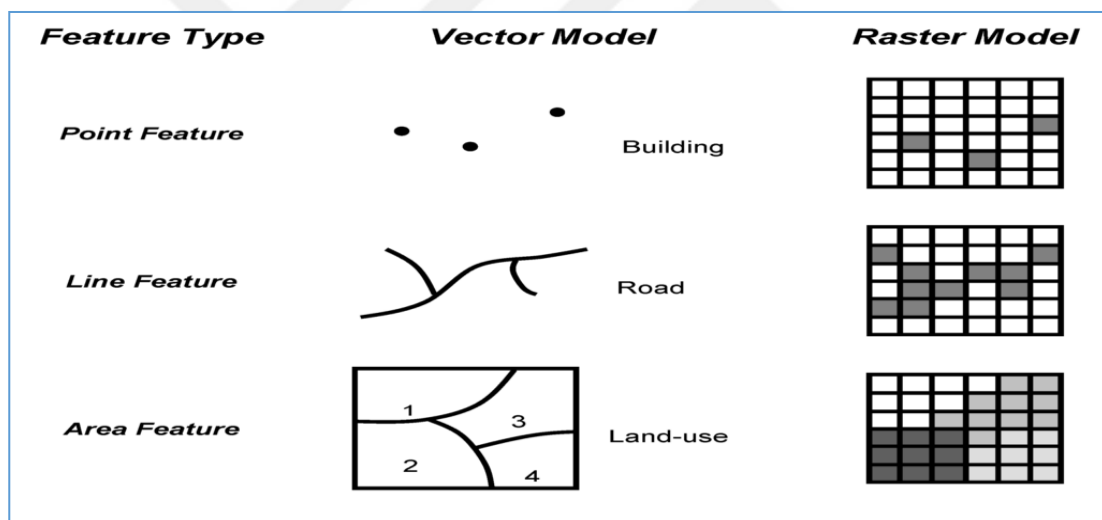


Figure 2. 2: Feature types and their representations in two spatial data models.

2.8 Geostatistics analysis

Geostatistical analyst existing in ArcGIS provides a cost active, rational solutions to analyze a diversity of datasets that need further cost and time to accomplish ([Krivoruchko and Gotay 2003](#)), and offers employers with the ability for predicting the optimal conditions for effective and more dependable production ([Analyst 2001](#)). Geostatistical Analyst used to estimate probable environmental dangers by investigating, visualizing, and producing surfaces for developed spatial analysis. Numerous more

advanced spatial interpolation methods, comprising geostatistical methods such as Kriging in different forms have been advanced ([Vienneau, De Hoogh et al. 2009](#)), geostatistical methods have ability to provide accurate forecasts and more efficient rationally, compared with the application of traditional physical-existing models for the complex natural system ([Yu, Ku et al. 2016](#)), measure the fineness of surface models by determining the statistical error of predicted surfaces ([Johnston 2004](#)). Geostatistics depends on both statistical and mathematical methods include autocorrelation, that possible to be utilized for produce surfaces and estimate the suspicion of the predictions ([Ribeiro Jr and Diggle 2001](#)). Geostatistical analysis happens in two stages are Semivariogram modeling or covariance for analyzing surface characteristics, and various kinds of Kriging such as ordinary, simple, universal Kriging ([Johnston, Ver Hoef et al. 2001](#)). Semivariogram analysis description of spatial correlation, whereas Kriging (optimum interpolation) produce better linear unbiased evaluate at each site; utilizes Semivariogram model ([Bohling 2005](#)).

2.9 Kriging methods in spatial statistics

One of the largely employed methods for the interpolation of spatial data are Kriging methods. There are diverse kinds of Kriging methods, like Ordinary Kriging (OK), Universal Kriging (UK), Simple Kriging (SK), Indicator Kriging, Co-Kriging and others, the selection of Kriging method to be used builds on the characteristics of the data. Kriging expands the solution to a problem on the basis of continuous model assessment of the spatial variation stochastic. Kriging provides standard predictions errors of the model. It makes optimal usage of present information by taking into consideration the method wherein different property in the space through model variogram. Kriging has been advanced to the problems that become increasingly complex in the areas of mining, petroleum engineering, pollution control and reduction, and public health. This term is now common, implementation several distinct types of Kriging, both linear and non-linear ([Stein and Corsten 1991](#), [Nalder and Wein 1998](#), [Webster and Oliver 2007](#), [Wang and Kockelman 2009](#), [Lichtenstern 2013](#), [Kiš 2016](#), [Arabameri, Pradhan et al. 2019](#), [Ghorbanzadeh, Salehi et al. 2019](#)).

Ordinary Kriging model shown in the equation (2.1):

$$Z(s) = \mu + \varepsilon(s), \quad (2.1)$$

μ is an unknown constant

Simple Kriging model shown in the equation (2.2):

$$Z(s) = \mu + \varepsilon(s), \quad (2.2)$$

μ is a known constant.

Universal Kriging model shown in the equation (2.3):

$$Z(s) = \mu(s) + \varepsilon(s), \quad (2.3)$$

$\mu(s)$ is some deterministic function.

For example, the mathematical model of the Universal Kriging is shown in the equation (2.4)

$$Z(s) = \beta_0 + \beta_1 x_1(s) + \beta_2 x_2(s) + \delta(s) \quad (2.4)$$

$Z(s)$ is a random variable indicating pollutants concentration at the site s , $x_1(s)$ is longitude and $x_2(s)$ is the altitude at site s , β_0 , β_1 and β_2 are coefficients of the linear trend, $\delta(s)$ is an intrinsic stationary random process with present variogram $2\gamma(h)$, where $h = s_i - s_j$ is a distance vector between sites s_i and s_j ([Johnston 2004](#), [Calcagno, Chilès et al. 2008](#), [Cressie and Johannesson 2008](#), [Goodchild, Longley et al. 2013](#)). Generally, kriging method is more advanced than other deterministic interpolation methods because it uses a positional structure based algorithm instead of simple distance approach when determining weight in intermediate value estimation. It may also be preferred as a better estimation method in environmental applications where observation points are few.

2.10 Inverse Distance Weighting (IDW)

Inverse distance weighting interpolation method is one of the easiest and more common interpolation methods. It unites the perception of proximity with the piecemeal change of the surface trend ([Lu and Wong 2008](#), [Babak and Deutsch 2009](#)), the strength and easiness of inverse distance interpolation method stimulate its continuous usage ([Babak and Deutsch 2009](#)), where Inverse Distance Weighting (IDW) and Ordinary Kriging (OK) are the most generally utilized spatial interpolation methods ([Jeong, St-Hilaire et al. 2017](#), [Qian, Qingliang et al. 2017](#), [Arabameri, Pradhan et al. 2019](#), [Ma, Longley et al. 2019](#)).

Inverse Distance Weighting interpolation method clearly performs the assumption that things that are near one another are more alike than those that are faraway far. IDW will be employed for predicting a value for any unsampled site, where the calculated values nearest to the forecast site will have more effect on the predicted value

than those further far. Consequently, IDW supposes that each sampled point has a local effect that reduces with distance, the weights are inversely commensurate to power of the distances for the data points ([Smith, Smith et al. 2017](#)). It weights the points nearer to the prediction site larger than those further far, therefore is named inverse distance weighted. The general formula is shown in the equation (2.5) ([Bon, Aoudou et al. 2019](#), [Falaize, Liberge et al. 2019](#), [Nevruz and Yildirak 2019](#)):

$$\hat{Z}(s_0) = \sum_{i=1}^N \lambda_i Z(s_i) \quad (2.5)$$

$Z(s_i)$ = the gauged value at the i th site

λ_i = an anonymous weight for the gauged value at the i th site, where the weight, λ_i , based just on the distance to the prediction site.

s_0 = the prediction location

N = the number of measured values

2.11 CoKriging method

CoKriging usages information on many variable types. The major variable of attention is Z_1 , and both autocorrelation for Z_1 and cross-correlations between Z_1 and all other variable types are utilized to produce better predictions. It is interesting to utilize information from other variables to assist produce predictions. CoKriging requires much more valuation, comprising evaluating the autocorrelation for each variable besides all cross-correlations. In theory, we can do no worse than Kriging because if there is no cross-correlation, we can fall back on autocorrelation for Z_1 . CoKriging is the assessment of one variable depending on gauged values of two or more variables to generalize best gridding results, is the multivariate extension of Kriging. CoKriging assessments the cross-variogram of several changed variables that is a function associated with their distance variances ([Rossi, Lavelle et al. 1995](#), [Dirks, Hay et al. 1998](#), [Goovaerts 1999](#), [Sarangi, Cox et al. 2005](#), [Forrester, S6bester et al. 2007](#), [Nerini, Monestiez et al. 2010](#), [Park, Haftka et al. 2017](#)). The simple cokriging evaluator based on the mean m_{i0} of the variable of interest, to which is added a sum of weights w_i , each multiplied by the difference of a sample $Z_{i0}(x_0)$ with respect to the mean m_i shown in the equation (2.6):

$$Z_{i0}^*(x_0) = m_{i0} + \sum_{i=1}^N \sum_{\alpha=1}^n w_{\alpha}^i (Z_i(x_{\alpha}) - m_i) \quad (2.6)$$

The CoKriging system is $A_C \lambda_C = b_C$, where A_C is created from the direct and cross-semivariances of the sample points (both target and co-variable) ([Furrer and Genton 2011](#), [Park, Haftka et al. 2017](#)):

$$A_C = \begin{bmatrix} \Gamma_{ZZ} & \Gamma_{ZW} & \mathbf{1} & \mathbf{0} \\ \Gamma_{WZ} & \Gamma_{WW} & \mathbf{0} & \mathbf{1} \\ \mathbf{1}^T & \mathbf{0}^T & 0 & 0 \\ \mathbf{0}^T & \mathbf{1}^T & 0 & 0 \end{bmatrix} \lambda_C = \begin{bmatrix} \lambda_1 \\ \dots \\ \lambda_{n_z} \\ \mu_1 \\ \dots \\ \mu_{n_w} \\ \psi_z \\ \psi_w \end{bmatrix} \quad b_C = \begin{bmatrix} \gamma_{zz}(\vec{x}_1, \vec{x}_0) \\ \vdots \\ \gamma_{zz}(\vec{x}_{n_z}, \vec{x}_0) \\ \gamma_{wz}(\vec{y}_1, \vec{x}_0) \\ \vdots \\ \gamma_{wz}(\vec{y}_{n_w}, \vec{x}_0) \\ 1 \\ 0 \end{bmatrix}$$

The vectors of 1's and 0's control which of the semivariances are included in each equation. The Γ are the matrices of semivariances (next slide). The cokriging prediction variance is then shown in the equation (2.7):

$$\hat{\sigma}_z^2(\vec{x}_0) = \mathbf{b}_C^T \lambda_C \quad (2.7)$$

2.12 Semivariogram model

The modeling of Semivariogram is the basis for geostatistical analysis, and can also be the most difficult and time consuming part of the analysis. The semivariogram is assessed by the sample semivariogram that is calculated from the input point dataset. Semivariance is a measurement of the grade of spatial reliance between values of attribute Z at two diverse positions or points in space. The division distance between the spatial points is the lag h . The semivariance $\gamma(h)$ is a function of lag h between two observations $Z(x)$ and $Z(x + h)$ of attribute Z ([Webster and Oliver 2007](#), [Goovaerts 2008](#), [Biswas and Si 2013](#), [Montero and Mateu 2015](#), [Obroślak and Dorozhynskyy 2017](#)). The experimental cross-semivariance equation can be calculated as shown in the equation (2.8):

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i=1}^{N(h)} [Z(x_i) - Z(x_i + h)]^2, \quad (2.8)$$

Cokriging and kriging method is graphically modeled with 3 values are partial sill, range and nugget as shown in figure 2.3, partial sill is the difference between the total sill ($C_0 + C_1$) and the nugget (C_0), range (a_1) is the distance at which the sill first flattens out and the nugget effect describes measurement error and microscale variation,

and illustrates the expected difference between samples when the separation distance is almost zero (Çolak 2010, Akyürek, Arslan et al. 2013, Sadoti, Pollock et al. 2014).

Geostatistical Analyst supplies the many semivariogram/covariance equations to model the experimental semivariogram are Circular, Spherical, Tetraspherical, Pentaspherical, Exponential, Gaussian, Rational Quadratic, Hole Effect, K-Bessel, J-Bessel and Stable as summarized in the table 2.3:

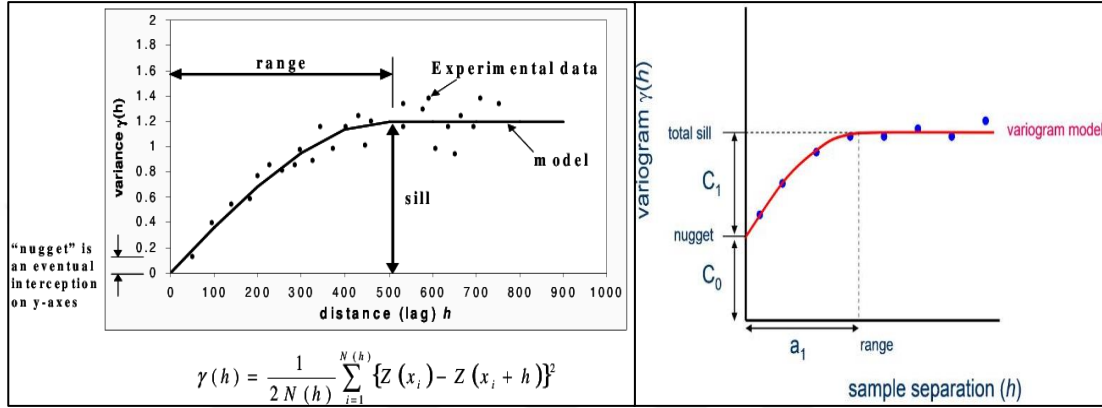


Figure 2. 3: The shape of conventional semivariogram and semivariance function

Table 2. 3: Experimental semivariogram models types

Model Type	Functions of the empirical semivariogram models
Stable	$\gamma(h) = C_0 + C_1 \left[1 - e^{\left(-3\left(\frac{h}{a}\right)^{\theta} e\right)} \right]$
Exponential	$\gamma_z(\mathbf{h}) = \begin{cases} 0 & \text{if } \mathbf{h} = 0 \\ c_n + \sigma_0^2 \left[1 - \exp\left(-\frac{ \mathbf{h} }{a_0}\right) \right] & \text{if } 0 < \mathbf{h} \end{cases}$
Gaussian	$\gamma_z(\mathbf{h}) = \begin{cases} 0 & \text{if } \mathbf{h} = 0 \\ c_n + \sigma_0^2 \left[1 - \exp\left(-\frac{ \mathbf{h} ^2}{a_0^2}\right) \right] & \text{if } 0 < \mathbf{h} \end{cases}$
Spherical	$\gamma_z(\mathbf{h}) = \begin{cases} 0 & \text{if } \mathbf{h} = 0 \\ c_n + \sigma_0^2 \left[\frac{3}{2} \frac{ \mathbf{h} }{a_0} - \frac{1}{2} \left(\frac{ \mathbf{h} }{a_0}\right)^3 \right] & \text{if } 0 < \mathbf{h} \leq a_0 \\ c_0 & \text{if } a_0 < \mathbf{h} \end{cases}$
Pentaspherical1b	$\gamma_z(\mathbf{h}) = \begin{cases} 0 & \text{if } \mathbf{h} = 0 \\ c_n + \sigma_0^2 \left[\frac{15}{8} \frac{ \mathbf{h} }{a_0} - \frac{5}{4} \left(\frac{ \mathbf{h} }{a_0}\right)^3 + \frac{3}{8} \left(\frac{ \mathbf{h} }{a_0}\right)^5 \right] & \text{if } 0 < \mathbf{h} \leq a_0 \\ c_0 & \text{if } a_0 < \mathbf{h} \end{cases}$

Sine Hole Effect	$\gamma_z(\mathbf{h}) = \begin{cases} 0 & \text{if } \mathbf{h} = 0 \\ c_n + \sigma_0^2 \left[1 - \frac{\sin(\pi \mathbf{h} /a_0)}{\pi \mathbf{h} /a_0} \right] & \text{if } 0 < \mathbf{h} \end{cases}$
K-Bessel	$\gamma(h) = C_0 + C_1 \left[1 - \frac{\left(\frac{\Omega_{\theta_k} h}{a} \right)^{\theta_k}}{2^{\theta_k-1} \Gamma(\theta_k)} K_{\theta_k} \left(\frac{\Omega_{\theta_k} h}{a} \right) \right]$
J-Bessel	$\gamma(h) = C_0 + C_1 \left[1 - \frac{2^{\theta_d} \Gamma(\theta_d+1)}{\left(\frac{\Omega_{\theta_d} h}{a} \right)^{\theta_d}} J_{\theta_d} \left(\frac{\Omega_{\theta_d} h}{a} \right) \right]$

The Mean Standardized prediction error ($\bar{E}$) estimated by using the equation (2.9):

$$\bar{E} = \frac{\sum_{i=1}^n [\hat{Z}(s_i) - z(s_i)]}{n}, \quad (2.9)$$

Where z is the noticed value and $\hat{z}$ is the evaluated value.

The standard deviation of the prediction error (SD) measured by using the equation (2.10):

$$SD = \sqrt{\frac{\sum_{i=1}^n \{[\hat{Z}(s_i) - z(s_i)] - \bar{E}\}^2}{n-1}}. \quad (2.10)$$

The mean prediction absolute error ($\bar{AE}$), determined by using the equation (2.11):

$$\bar{AE} = \frac{\sum_{i=1}^n |[\hat{Z}(s_i) - z(s_i)]|}{n} \quad (2.11)$$

The Root Mean Square prediction error (RMS) measured by the using equation (2.12):

$$RMS = \sqrt{\frac{\sum_{i=1}^n [\hat{Z}(s_i) - z(s_i)]^2}{n}} \quad (2.12)$$

The best model is realized when this factor be nearer to zero.

The root-mean-square standardized prediction error (RMSS) evaluated by the using equation (2.13):

$$RMSS = \sqrt{\frac{\sum_{i=1}^n [(\hat{Z}(s_i) - z(s_i)) / \sigma(s_i)]^2}{n}}, \quad (2.13)$$

e best model is realized when RMSS get nearer to 1 ([Box and Cox 1964](#), [Goovaerts 1997](#), [Johnston, Ver Hoef et al. 2001](#), [Webster and Oliver 2007](#), [Farias, Barbosa et al. 2008](#), [Smith, Smith et al. 2017](#)).

2.13 Applications of Geographic Information System in air pollution

The scientific studies on atmosphere pollution and variation of weather requires long-term dependable data of air, soil, water, and plant. Geographic Information Systems is one of the most significant tool that is utilized to evaluated air pollution and its distribution. GIS is employed as a tool in several researches in worldwide because of its functions of analyzing values readily and high mapping dexterities with developed spatial statistics. Utilizing of the geographic information systems is necessary in supplying border conditions to models of air quality. A cross-validation procedure uses to estimate the model performance. Geographic information systems in the field of air pollution modeling can further expand the scope of treatment of surface data ([Matejicek 2005](#)). Several studies in air pollution have concentrated on urban areas, and pollution caused by vehicle in particular, also off road vehicles is one of the major sources of air pollution in most parts of the world, [Shareef, Husain et al. \(2016\)](#) suggested an easy technique of improving the air quality observing network utilizing geographical information system, interpolation methods and historic data of Riyadh, Saudi Arabia. Whereas [Adedeji, Oluwafunmilayo et al. \(2016\)](#) used Kriging interpolation method (GIS) for mapping of several concentration of air pollutants like SO₂, NO, NO₂ and CO in Nigeria, according to AQI the air quality is highly unhealthy in most regions that requires for the requirement to organize and support the health depended on limited for air contaminants, and [Memarianfard, Aghdam et al. \(2016\)](#) utilized Radial Basis Functions (RBF) spatial prediction model existing in Geostatistical wizard-ArcGIS to develop maps of zoning air quality and assessment health dangers of PM_{2.5} concentrations emission over Tehran city. While [Abass, Ziboon et al. \(2016\)](#) created air pollution maps by ArcGIS to analyze and visualize the gasses such as SO₂, VOCs, H₂S and NO₂ in AL-Nahrawan-suburban, where the concentration of these gasses was exceeding the WHO and Iraqi limits in the most tested sites. [Tashayo and Alimohammadi \(2016\)](#) used a three-step approach for growing a linguistic fuzzy model to air pollution

prediction depended on land use, transport, and climatological conditions, using GIS. [Cheewinsiriwat \(2016\)](#) [Wang, Henderson et al. \(2013\)](#) introduced Land Use Regression (LUR) model that describe the relationship between land use and air pollution level and added to Geographic Information System, additionally use the multiple regression analysis which can inserts another significant determining factors like traffic volume, land use and chosen meteorological parameters. Wind direction is an important factor impacting the quality of the environment in the atmosphere, where the traditional LUR models built-in geographic information system have trouble in taking the wind direction into account, therefore [Li, Liu et al. \(2015\)](#) promoted a semicircular-buffer-based LUR model to estimate the effect of wind direction on model execution. [Ujang, Anton et al. \(2015\)](#), [Uznir, Francois et al. \(2013\)](#) showed the applicability of the achievement of the 3D city model in ArcGIS for air quality modeling in urban areas, where visualization in 3D improves the visual analysis to comprehend the manner of the dispersion of air pollutants at street level. [Bertazzon, Johnson et al. \(2015\)](#) studied the spatial influences for instance spatial non-fixed and spatial autocorrelation that enable decreasing of the exactitude of LUR assessments by rising regression errors and non-sureness, then use statistical methods to solve these impacts like spatially auto-regression (SAR) and geographically weighted regression models, whereas [Tuna and Buluç \(2015\)](#) analyzed the spatial distribution of PM₁₀ between 2003 and 2012 in Istanbul city by using GIS methods such as Inverse Distance Weighting and Kriging methods. Analysis and visualization of the linear relationship between atmospheric pollutants and meteorological features in the Kirkuk city investigated by [Salah, Bahaa et al. \(2014\)](#) where ArcGIS air pollution maps used to acceptable distribution of suitable locations of air pollution. [Adam-Poupart, Brand et al. \(2014\)](#) compared the reliability of three space-time models that including Bayesian maximum entropy (BME), Land Use Regression mixed model (BME-LUR) and Kriging method model (BME Kriging) to predict summer O₃ in Quebec, Canada where found The BME-LUR was the better model of predictive. [Fu, Jiang et al. \(2014\)](#) investigated the spatial variation of forest litter carbon density, which plays a main part in estimating carbon sequestration potentials, in the forests in southeastern China using Spatial autocorrelation analyses (Moran's I), Geostatistical analysis and a geographical information system. [Karaca \(2012\)](#) identified the air quality areas applying geographic information system (GIS) method, then compared the air quality zones with Turkish National Clean Air Regions and discussed the influences of several considerations for example urbanization, geographical position, and local factors.

The provision of such statistical information through GIS maps lead to assess the risks and gives an concept of not only the areal extent of the effect of pollutants, but also its influence on demographic information lines ([Yerramilli, Yerramilli et al. 2011](#)). [Gulliver and Briggs \(2011\)](#) developed dispersion model of air pollution in GIS system and utilized in London for daily and annual PM₁₀ modelling. It was seen as a model for the production of good predictions of the observed abundances for dissimilar time intervals and in dissimilar sites. Several advancements have been organized on the model and trends for future work. A decision support system was advanced based on CALMET/CALPUFF dispersion modeling system, digital maps, and related databases for the administration of air quality in urban areas of the Istanbul city and to evaluate the releases and spatial allocation of air contaminants within a GIS software. [Elbir, Mangir et al. \(2010\)](#), [Vlachokostas, Nastis et al. \(2010\)](#) provided a merged air quality with modeling of geographic information systems procedural approach to assess crop destruction from photo-chemical air pollution, imaging spatial resolution and an assessment of the size of the interview about the economic damage. [Beelen, Hoek et al. \(2009\)](#) compared the authenticity of ordinary Kriging, universal Kriging and regression mapping in the European Union maps of air pollution, the results show the Universal Kriging performance best than both regression models and ordinary Kriging. [Tang and Wang \(2007\)](#) combined prototype system include a noise model of road traffic, an operational model of air pollution, digital maps, model of urban landscape and a GIS for noise and air pollution modelling. Whereas [Jerrett, Burnet et al. \(2006\)](#) reported the influences of chronic health are related with exposure to PM_{2.5} and found model connected between atmospheric pollution and death-rate, while [Matejcek \(2005\)](#) combined a large range of data in the GIS database for Spatial modelling of air quality which developed by the LIDAR data that characterizes measurements of components over the surface situated by 3D coordinates. [Bayraktar and Turalioglu \(2005\)](#) used Kriging method for drawing contours to represent the city (Erzurum, Turkey) based on the smoke data measurements of long years, [Gulliver and Briggs \(2005\)](#) explained the advancement and experimenting of a GIS system for modeling human travel-time exposures to traffic-linked air pollution. The model merges data on source activity, dispersion of pollutant, and trip conduct to devise individual or group level exposure standards for air pollution, and was designed for simulating exposures of populaces because they move during a variable air pollution scope, and [Elbir \(2004\)](#) developed the decision support system to manage air quality for big Turkish towns, the system is centered on CALPUFF dispersion model, digital maps

and linked databases to evaluate the releases and spatial distribution of air contaminants, then mapping of air quality by GIS and situation analysis for air pollution reduction. [Brauer, Hoek et al. \(2003\)](#) used a GIS regression models prediction for assessing long-term exposure to average annual of particulate material emission from traffic in the Netherlands, Germany; and in Sweden. It seems that regression mapping based on geographic information systems provides successful technique for mapping traffic-linked contaminants, and constantly offers good predictions of pollution levels at non-sampled points [Briggs, Collins et al. \(1997\)](#). In a study conducted by [Dalyan and Incecik \(2002\)](#), the relations between average SO₂ concentrations, land use and population increasing during the heating seasons in Istanbul were investigated using Geographic Information Systems (GIS). In the 1992-2000 period, the temporal variation of SO₂ concentrations in heating seasons was examined and a decreasing trend was observed. High SO₂ concentration levels were determined by using spatial analysis with GIS in the regions covering large settlements and business centers. The distributions of SO₂ concentrations measured in 5 stations in Istanbul (2 on European side, 3 on Anatolian side) in 1995-1996 and 1999-2000 heating seasons were compared and SO₂ levels were decreased. Despite this reduction in SO₂, it was determined that higher concentrations occurred mostly on the European side. In a study done by [Aydın, Durduran et al. \(2007\)](#), the air quality in Konya was evaluated, SO₂ and PM₁₀ values and pollution maps were created for the years 2004, 2005 and 2006 with the help of Geographical Information System (GIS). By examining the change in the level of pollution over time, the results were compared with the Turkish Air Quality Control Regulation (EQCR), European Union (EU), World Health Organization (WHO) and American Environmental Protection Agency (US EPA) air quality standards. In 2004, 2005 and 2006, the average annual SO₂ values at the five measured points of the city had been found that it exceeds 20 µg/m³ which is the European Union's Long-Term Boundary Value (UVS), and the average annual PM₁₀ values in the four regions outside the Meram Region exceed the EU-determined UVS value of 40 µg/m³. [Ocak and Demircioğlu \(2002\)](#) find the relationship between air pollutants and meteorological data; in the first approach (with airborne pollutants only meteorological factors, which are temperature, wind speed and relative humidity), the coefficient of determination is 52% and 51% for SO₂ and PM; second approach (pollutants temperature, wind speed and relative humidity and the concentration of the pollutant the previous day) were found to be 72% and 68% for SO₂ and PM.

III. MATERIALS AND METHOD

3.1 General information

With the purpose of resolve increasing air pollution problems, it is essential to provide healthy and up-to-date inventory data showing the sources of air contaminants and the types and amounts of these sources. Air pollution is directly associated to change of climate, the chief driver of climate change is combustion of fossil fuel that is also a main contributor to air contamination and efforts to lessen one can better the other. The relative database management system has been formed depending on the geographical coordinates, as well as measuring the results of air pollution and climatological data in the field of work has been added to the GIS. In the study, firstly the data about the air pollution to be constructed by GIS (air pollutants and meteorological data), by using the analysis system, prepare tables and charts for monthly air quality data, analyze these data statistically, and create air quality spatial maps using GIS program based on several standard. A GIS software package ArcGIS 10.5.1 and Arc Map's geostatistical analyst was used in this research for the examination of change in air quality, also for the solution suggestions. Where data of air pollutants in Turkey have been used for spatial interpolation by using different interpolation techniques of ArcGIS such as Inverse Distance Weight (IDW), Kriging techniques and Geostatistical analysis for this study.

3.2 Study area (Turkey)

Turkey is positioned in Southwestern Asia and Southeastern Europe, therefore, Turkey Republic is a linking between Asia and Europe. Turkey is bounded sea on three sides, from the south The Mediterranean, from the north the Black Sea, and from the west the Aegean. From the northwest The Marmara Sea that involves the Istanbul and Dardanelles Straits and is a regional water of Turkey. The capital of Turkey is Ankara, Turkey is sited between 36-42° N and between 26-45° E. The total area of Turkey is about 783,562.35 km², the latest population of Turkey is 82,750,391 as of Saturday, April 20, 2019, depending on the newest United Nations assesses, and the annual rate of population growth in 2019 was 1.28 %. Turkey is located in a geographical position wherever climatologic conditions are relatively moderate, there are considerable variations in climatologic conditions from one district to the other. Whereas the coastal districts enjoy temperate weathers, the internal Anatolia plateau involvements a dryer

weather, hot summers and cold winters beside limited rainfall ([Sensoy 2004](#), [Ispat 2006](#), [Sensoy, Demircan et al. 2008](#), [Toros, Erdun et al. 2013](#), [Tuik 2012](#)). Additionally, topographic properties related with the hilly terrain considerably confuse the weather variability. As well as the topography and other geographical issues for instance landscape and altitude ([Akman and Ketenoğlu 1986](#), [Türkeş 1996](#), [Kadioğlu 2000](#), [Tayanç, İm et al. 2009](#)). Air pollution is a very significant trouble today in Turkey and research on this area are rising ([Unal, Toros et al. 2011](#), [Yılmaz, Keşaf et al. 2019](#)). Problems of air pollution perhaps differ notably with the geography, demography, and social appearance of the area. The weather and topography of a county also effect the distribution and atmospheric processes of contamination and its influences on environment and/or human health. The major source of air pollution in Turkey is emissions of residential heating, in addition to other activates.

3.3 Data collection

Hourly PM₁₀, SO₂ and NO_x concentrations for 2015-2018 were obtained from about 210 air quality observing stations. Air Pollution Data are collected from the Ministry of Environment and Urbanization "Air Quality Monitoring Stations" website (<http://www.havaizleme.gov.tr>). The names of measurement stations belonging to the Ministry and their coordinates are given in table 3.1. Monthly and seasonal mean measurements were computed utilizing this hourly basis. Figure 3.1 illustrates the national geographical map of Turkey, locations of the observing stations and urban areas.

Table 3. 1: The names of stations and their coordinates.

ID	Name	Lat.	Long.	ID	Name	Lat.	Long.
1	Adana_Catalan	36.85444	35.34889	106	Istanbul_Alibeykoy	41.0575	28.94556
2	Adana_Dogankent	37.18639	35.26194	107	Istanbul_SileMTHM	41.17028	29.56333
3	Adana_Meteoroloji	37.00389	35.34389	108	Istanbul_SultangaziMTHM	41.10194	28.87194
4	Adana_Valilik	36.99917	35.31222	109	Istanbul_Goztepe	40.99417	29.06944
5	Adiyaman	37.76056	38.27806	110	Istanbul_Kandilli	41.06306	29.06444
6	Afyon	38.75167	30.54278	111	Istanbul_Kumkoy	41.25111	29.03806
7	Agri	39.72111	43.03944	112	Istanbul_SultanbeyliMTHM	40.98444	29.26861
8	Agri_Patnos	39.23639	42.85278	113	Istanbul_Büyükada	40.85778	29.12083
9	Agri_Dogubeyazit	39.5475	44.08333	114	Istanbul_Maslak	41.10111	29.02444
10	Aksaray	38.36778	34.01306	115	Izmir_Alsancak	38.43194	27.14417
11	Amasya	40.6675	35.83528	116	Izmir_Bayrakli	38.46194	27.16667
12	Amasya_Merzifon	40.87417	35.45722	117	Izmir_Bornova	38.46917	27.22139

13	Amasya_Suluova	40.49222	35.38528	118	Izmir_Cigli	38.49806	27.06778
14	Amasya_Sehzade	40.65722	35.83778	119	Izmir_Gaziemir	38.31444	27.13722
15	Ankara_Bahçelievler	39.91806	32.82278	120	Izmir_Güzelyali	38.39556	27.08278
16	Ankara_Cebeci	39.93694	32.87806	121	Izmir_Karsiyaka	38.45417	27.10944
17	Ankara_Demetevler	39.9675	32.79556	122	Izmir_Sirinyer	38.3825	27.14806
18	Ankara_Dikmen	39.89639	32.84056	123	Kahramanmaras	37.58472	36.89833
19	Ankara_Kayaş	39.92528	32.92667	124	Kahramanmaras_Elbistan	38.20361	37.19833
20	Ankara_Keçioren	39.96722	32.86278	125	Karabük	41.19667	32.62278
21	Ankara_Sihhiye	39.92722	32.85917	126	Karabük_Kardemir1	41.19194444	32.62722
22	Ankara_Sincan	39.97194	32.585	127	Karabük_Kardemir2	41.17972	32.63083
23	Antalya	36.8875	30.70278	128	Karaman	37.11639	33.1325
24	Ardahan	41.11056	42.70083	129	Kars_istasyonMah	40.605	43.10444
25	Artvin	41.17528	41.81806	130	Kars_trafik	40.60083	43.09667
26	Artvin_Hopa	41.46667	41.49056	131	Kastamonu	41.36722	33.76472
27	Aydin	37.84028	27.83667	132	Kayseri_Hürriyet	38.72333	35.46944
28	Balikesir	39.63361	27.89583	133	Kayseri_Melikgazi	38.72472	35.51556
29	Balikesir_BandirmaMTHM	40.34778	27.97472	134	Kayseri_OSB	38.74	35.37528
30	Balikesir_ErdekMTHM	40.48944	27.97833	135	Kilis	36.715	37.12694
31	Bartın	41.62444	32.35639	136	Kirikkale	39.84306	33.51806
32	Batman	37.90056	41.12889	137	Kirklareli	41.72444	27.21444
33	Bayburt	40.25889	40.22417	138	Kirklareli_LimankoyMTHM	41.885	28.05583
34	Bilecik	40.14083	29.9775	139	Kirklareli_LüleburgazMTHM	41.39833	27.34583
35	Bilecik_BozoyukMTHM	39.90389	30.05278	140	Kirsehir	39.14833	34.15917
36	Bingol	38.88361	40.50361	141	Kocaeli	40.76556	29.95111
37	Bitlis	38.41167	42.11222	142	Kocaeli_AlikahyaMTHM	40.77083	30.0075
38	Bolu	40.73306	31.60167	143	Kocaeli_Dilovasi	40.78861	29.53694
39	Burdur	37.72278	30.29444	144	Kocaeli_DilovasiIMESOSB1MTHM	40.82611	29.56111
40	Bursa	40.23417	29.03806	145	Kocaeli_DilovasiIMESOSB2MTHM	40.83806	29.58028
41	Bursa_BeyazitCadMTHM	40.18556	29.08028	146	Kocaeli_GolcükMTHM	40.72583	29.79444
42	Bursa_InegolMTHM	40.08083	29.5	147	Kocaeli_izmitMTHM	40.76806	29.93806
43	Bursa_KestelMTHM	40.19528	29.20528	148	Kocaeli_KandiraMTHM	41.13056	30.00639
44	Bursa_KültürParkMTHM	40.19556	29.04583	149	Kocaeli_KorfezMTHM	40.74583	29.78861
45	Bursa_UludagiUnivMTHM	40.22333	28.87139	150	Kocaeli_OSB	40.78806	29.52444
46	Canakkale	40.13667	26.40556	151	Kocaeli_YenikoyMTHM	40.70417	29.88444
47	Canakkale_Bigaiçdas	40.41722	27.10722	152	Konya_Meram	37.86	32.47528
48	Canakkale_CanMTHM	40.02917	27.04972	153	Konya_Selçuklu	37.94444	32.50806
49	Canakkale_LapsekiMTHM	40.40306	26.77056	154	Konya_KaratayBelediye	37.86806	32.51611
50	Cankiri	40.59972	33.61694	155	Konya_SelçukluBelediye	37.91583	32.5
51	Corum	40.55611	34.95639	156	Kütahya	39.41861	29.98583
52	Corum_Bahabey	40.54639	34.96722	157	Malatya	38.35	38.34167
53	Corum_MimarSinan	40.53167	34.94472	158	Manisa	38.61528	27.40472
54	Denizli_Bayramyeri	37.76639	29.09694	159	Manisa_Soma	39.18139	27.61278
55	Denizli_Merkezefendi	37.78139	29.08694	160	Mardin	37.32083	40.72389

56	Diyarbakir	37.91528	40.22472	161	Mugla_Musluhittin	37.21556	28.35694
57	Düzce	40.84556	31.14806	162	Mugla_Yatagan	37.34111	28.13417
58	Edirne	41.65917	26.585	163	Mus	38.74833	41.50944
59	Edirne_KaraagaçMTHM	41.65889	26.53722	164	Nevsehir	38.61583	34.70222
60	Edirne_KesanMTHM	40.85111	26.63528	165	Nigde	37.96639	34.68333
61	Elazig	38.67444	39.21167	166	Ordu_Fatsa	41.02694	37.5
62	EMEP_Ankaracubuk	40.29056	33.01722	167	Ordu_Karsiyaka	40.97361	37.9075
63	EMEP_IzmirSeferihisar	38.20333	26.83278	168	Ordu_Stadyum	40.98333	37.87833
64	EMEP_KirklareliVize	41.56333	27.7775	169	Ordu_unye	41.12139	37.28
65	Erzincan	39.74278	39.495	170	Osmaniye	37.07306	36.24111
66	Erzincan_Trafik	39.74639	39.49694	171	Rize	41.02167	40.53278
67	Erzurum	39.89806	41.2725	172	Rize_Ardesen	41.19167	40.98972
68	Erzurum_Aziziye	39.91861	41.0525	173	Sakarya	40.76667	30.39361
69	Erzurum_Palandoken	39.8675	41.275	174	Sakarya_MerkezMTHM	40.76917	30.40972
70	Erzurum_Pasinler	40.03333	41.57194	175	Sakarya_OzanlarMTHM	40.79056	30.39667
71	Erzurum_Tashan	39.90833	41.27306	176	Samsun_Atakum	41.32528	36.29639
72	Eskisehir	39.78056	30.50083	177	Samsun_Bafra	41.56222	35.90722
73	Gaziantep	37.05833	37.35083	178	Samsun_Canik	41.26306	36.35222
74	Giresun	40.90694	38.36194	179	Samsun_ilkadamHastane	41.27778	36.33806
75	Giresun_Gemilercekegi	40.91444	38.39833	180	Samsun_Tekkekoy	41.22333	36.455
76	Gümüşhane	40.46083	39.48083	181	Samsun_Yüzüncüyil	41.28722	36.32917
77	Hakkari	37.57417	43.73861	182	Sanliurfa	37.16028	38.78694
78	Hatay_Antakya	36.20778	36.15222	183	Siirt	37.93167	41.935
79	Hatay_iskenderun	36.71389	36.22389	184	Sinop	42.02944	35.15472
80	Içel	36.80583	34.635	185	Sinop_Boyabat	41.46111	34.77694
81	Igdir	39.92583	44.05333	186	Sirnak	37.51972	42.45972
82	Igdir_Aralik	39.79528	44.62556	187	Sivas_BasOgretmen	39.74861	37.02556
83	Isparta	37.77694	30.54694	188	Sivas_istasyonkavsagi	39.74722	37.01306
84	Istanbul_EsenyurtMTHM	41.02028	28.66944	189	Sivas_Meteoroloji	39.74361	37.00167
85	Istanbul_Kagithane	41.0875	28.9825	190	Tekirdag_MerkezMTHM	40.97722	27.50306
86	Istanbul_Selimiye	41.00361	29.02667	191	Tekirdag	40.97639	27.5125
87	Istanbul_Catladikapi	41.00222	28.97528	192	Tekirdag_CerkezkoymTHM	41.31833	27.98
88	Istanbul_Yenibosna	40.99889	28.82667	193	Tokat	40.32611	36.555
89	Istanbul_BasaksehirMTHM	41.09528	28.78972	194	Tokat_Erbaa	40.67167	36.56139
90	Istanbul_UmraniyeMTHM	41.02417	29.09972	195	Tokat_Meydan	40.31861	36.55194
91	Istanbul_Esenler	41.03806	28.88806	196	Tokat_Turhal	40.38556	36.08278
92	Istanbul_Kadikoy	40.99167	29.03333	197	Trabzon_Akçaabat	41.01417	39.59222
93	Istanbul_Aksaray	41.01444	28.95444	198	Trabzon_Besirli	40.99361	39.66806
94	Istanbul_MecidiyekoyMTHM	41.06583	28.99444	199	Trabzon_Fatih	40.99917	39.69417
95	Istanbul_Sariyer	41.12889	29.04944	200	Trabzon_Meydan	41.00444	39.73167
96	Istanbul_SirinevlerMTHM	41.00222	28.83861	201	Trabzon_Valilik	41.00583	39.71222
97	Istanbul_KagithaneMTHM	41.09222	28.97472	202	Tunceli	39.10083	39.54667
98	Istanbul_Karatal	40.89	29.20722	203	Uzak	38.6725	29.40556

99	Istanbul_Avcilar	40.98722	28.72972	204	Van	38.50722	43.37056
100	Istanbul_Besiktas	41.05389	29.01	205	Yalova	40.65306	29.26
101	Istanbul_KandilliMTHM	41.07444	29.05889	206	Yalova_AltinovaMTHM	40.70056	29.50778
102	Istanbul_SiliveriMTHM	41.07306	28.25528	207	Yalova_ArmutluMTHM	40.52917	28.78444
103	Istanbul_UskudarMTHM	41.02694	29.02472	208	Yozgat	39.81861	34.80556
104	Istanbul_Uskudar	41.01528	29.02472	209	Zonguldak	41.45056	31.78333
105	Istanbul_Umraniye	41.01333	29.16194	210	Zonguldak_KaradenizEregli	41.27639	31.43333



Figure 3. 1: National geographical map of Turkey, stations locations

3.4 Methodology

In this thesis, the PM_{10} , SO_2 and NO_x parameters of air pollutants are determined by T.C. within the scope of the Air Quality Monitoring Network by the T. C Ministry of Environment and Urbanization, data measured between the years 2015-2018 were used by stations located in 81 provinces. Within the scope of the National Air Quality Monitoring Network Project, initiated by the Ministry of Environment and Urbanization in 2005, meteorological parameters are measured in addition to pollutant parameters. In the ongoing studies within the scope of the project, it is possible to access the historical data of the stations easily. In Turkey country, the primary factors affecting the PM_{10} level observed in urban and rural areas are the primary sources of pollutants such as industry, traffic and domestic heating activities, in addition to climatological factors like temperature, wind, humidity, pressure, rain, and long-distance pollutant transport.

In ArcGIS 10.5.1 GIS software, a point layer was created using the coordinates of the measurement stations and the monthly average concentration were added to this point layer as attribute data. All maps have been converted to the country coordinate system (UTM). Using the "Inverse Distance Weighted (IDW)" method in the ArcGIS GIS software, the monthly average PM₁₀ and SO₂ distribution maps of the Turkey regions were produced. In order to be used in interpretation of distribution maps winds belonging to the region have been formed. For this purpose, wind speed and wind direction data of meteorological stations in the provincial centers were obtained from the data in the metering stations and from the meteorological data archive system of the general directorate of meteorology.

GIS was employed for achieving the spatial modelling with the spatial analysis tool extension, the commercial GIS software ESRI ArcGIS version 10.5.1 was utilized for determining the spatial distribution of air pollution maps, spatial interpolation techniques like Inverse Distance Weight (IDW) was used. Through this period air contamination data were collected from ([National Air Quality Observation Network, d. http://www.havaizleme.gov.tr/Default.ltr.aspx.](http://www.havaizleme.gov.tr/Default.ltr.aspx)) for more than 200 stations during 2015-2018. The observation network usages beta Gauge instruments that permits an exact assessment of the particulate mass under all conditions. For the available stations were had analyzed PM₁₀ and SO₂ measurements for Turkey areas, and the analysis of the spatial distribution of atmosphere pollution depended on monthly average air pollutants data in Turkey had been done by using IDW in ArcGIS environment. Additionally, nitrogen oxides pollution was investigated, the air pollution data had been collected from 137 air observing stations during 2016, 2017 and 2018 in Turkey, the spatial distribution maps of the annual average concentrations of nitrogen oxides were created with the help of spatial analyst tools, interpolation (inverse Distance Weighted method) within ArcGIS environment. The process of collecting data and entering the graphical data is as follows in figure 3.2A, while the semivariogram procedures shown in the figure 3.2B. Kriging and cokriging analysis were achieved to create prediction maps of PM₁₀ concentrations in Turkey. Kriging depend on the supposition that autocorrelation be present among the data.

The experimental semivariogram was applied to predict the spatial autocorrelation of datasets. The optimum model was chosen depending on cross-

validation and prediction errors are Root-Mean-Square (RMS), Mean Standardized (MS), Root-Mean-Square Standardized (RMSS) and Average Standard Error (ASE) that utilized to evaluate the performance of the improved model. A best fitted model has the smallest change between RMS and ASE, MS is near to 0 and RMSE is near to 1.

Cokriging was then applied to estimate the contribution of different covariates when assessing the spatial distribution of PM_{10} concentration, the different covariates utilized in this study are SO_2 and NO_x as shown in figure 3.3.

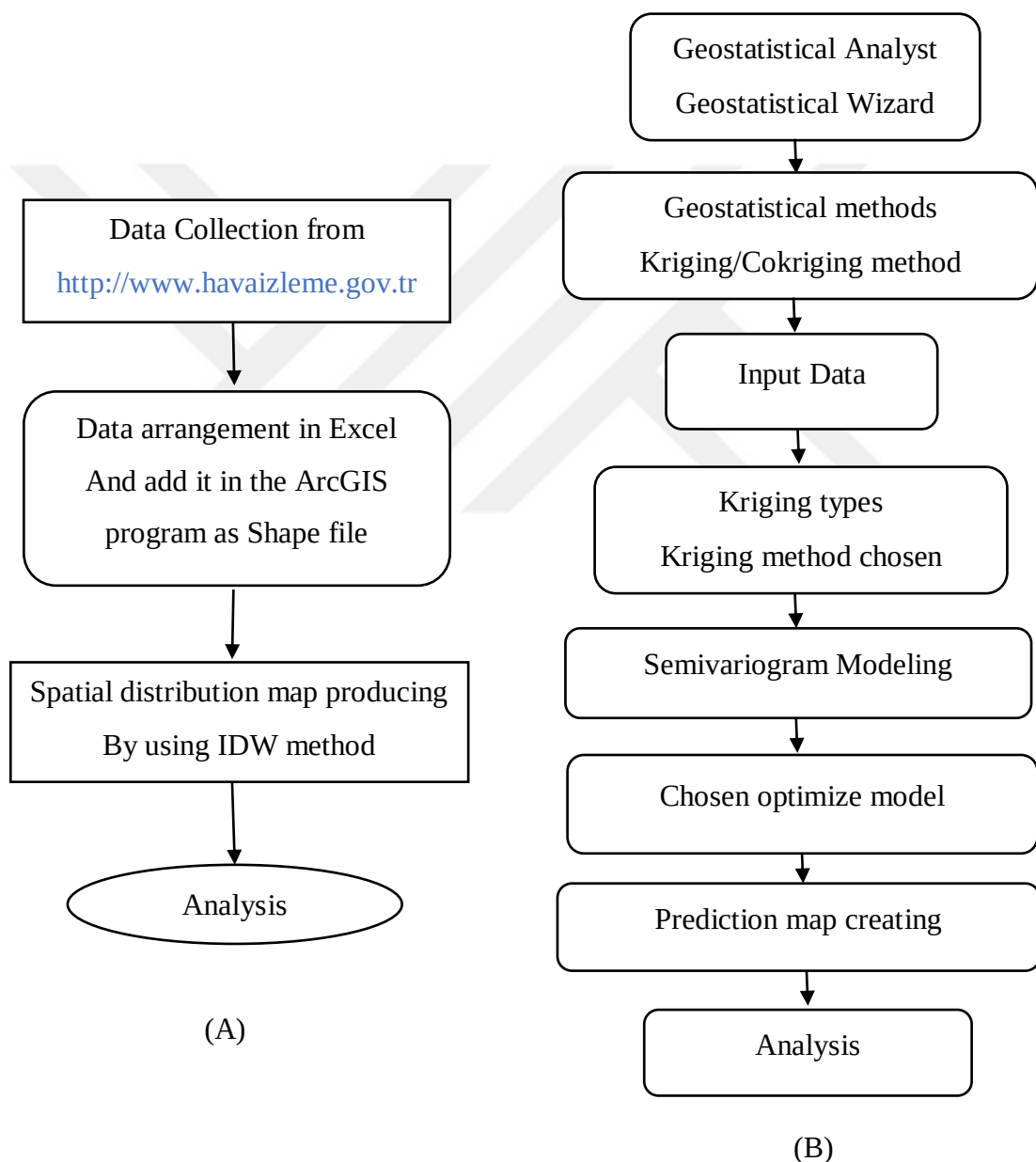


Figure 3. 2: The procedures of manual data entry diagram

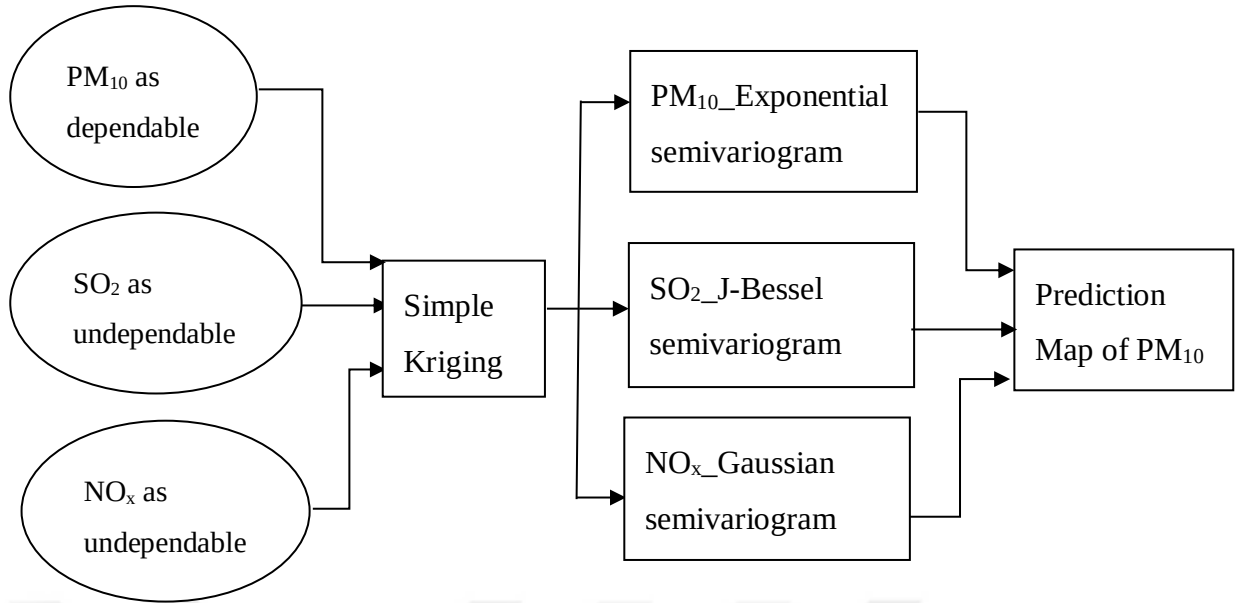
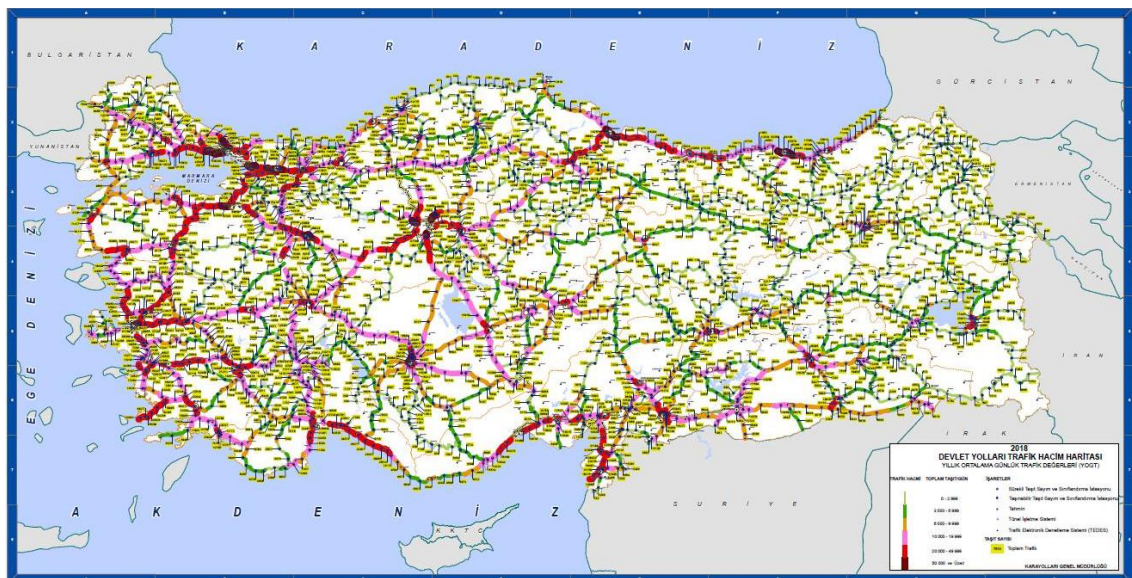


Figure 3. 3: The Procedures of Cokriging method modeling of PM_{10} - SO_2 - NO_x

3.5 Traffic and industrial maps of Turkey

Traffic survey data can be accessed through the internet at: www.kgm.gov.tr, figure 3.4 shows the state traffic volume map in 2018, annual average daily traffic values of Turkey (Yıllık Ortalama Günlük Trafik Değerleri-YOGT), from this figure we can know the the traffic volume for any region in Turkey



Whereas Turkey's industrial density is observed in figure 3.5 that shows the industrial density of Turkey districts. Through these figures we can know whether pollutants are caused by traffic or industries. Turkey's coastline is 8,333 km, 70% of the industry is located on the coastline ([Karaca and Nicholls 2008](#)). Marmara Region is Turkey's most developed regions; industry, trade, tourism and agriculture sectors have an important place compared to other regions. Energy consumption is the region with the highest. Turkey's electrical energy consumed in industry amount to 46% of total consumption in 2008's when creating; these rates are 80% in Bilecik, Kocaeli, Tekirdağ and Çanakkale. Turkey's 39% of the total electrical energy, while total industrial electricity 43% is consumed in this region ([Kılıç, Kum et al. 2016](#)). Istanbul is a large city with high population density and international air and sea traffic on highways connecting Asia and Europe. Turkey's industrial employment of 20% of 38% of industrial facilities.

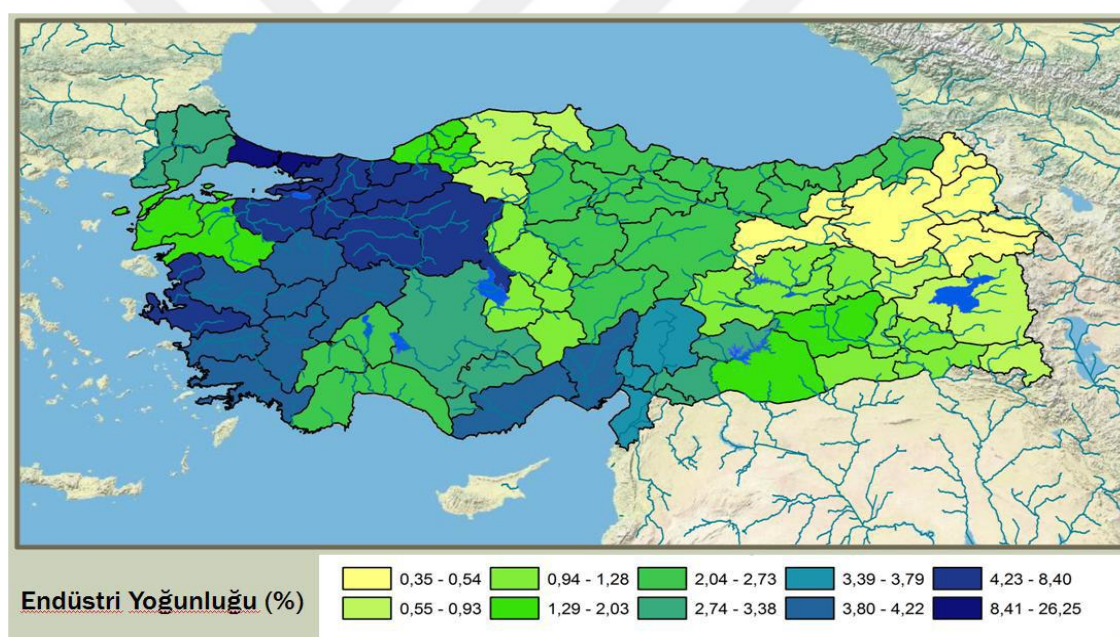


Figure 3. 5: Turkey industry density ([Tuok 2010](#), [Kılıç, Kum et al. 2016](#))

3.6 Land cover data

Turkey is a country with biodiversity according to extent of its geographical position. Forest and herbaceous plants form the main vegetation formations and host many other types. Different plant formations have varied across the country under the influence of climate and topographic conditions. Human activities (agriculture, settlement) cause these areas to be at risk of deterioration. Determining the ecological

structure of the plant species in these natural and semi-natural areas, determining the effects of changes in land use and demonstrating how these areas can be used and protected in the future is an essential requirement for a sustainable future ([Atalay 1994](#), [Turoğlu 2000](#), [Karabulut 2006](#), [Önder, Aydin et al. 2009](#)). Monitoring rapid changes in land use is of considerable significance in terms of generating a sustainable-planned land use pattern ([Gülersoy 2014](#)).

Figure 3.6 provides dynamic access to data from the Corine Land Cover 2006 inventory. Data are available as 100 meter pixel raster images at small scales up to 1:800.000 and at higher scales as vectors.

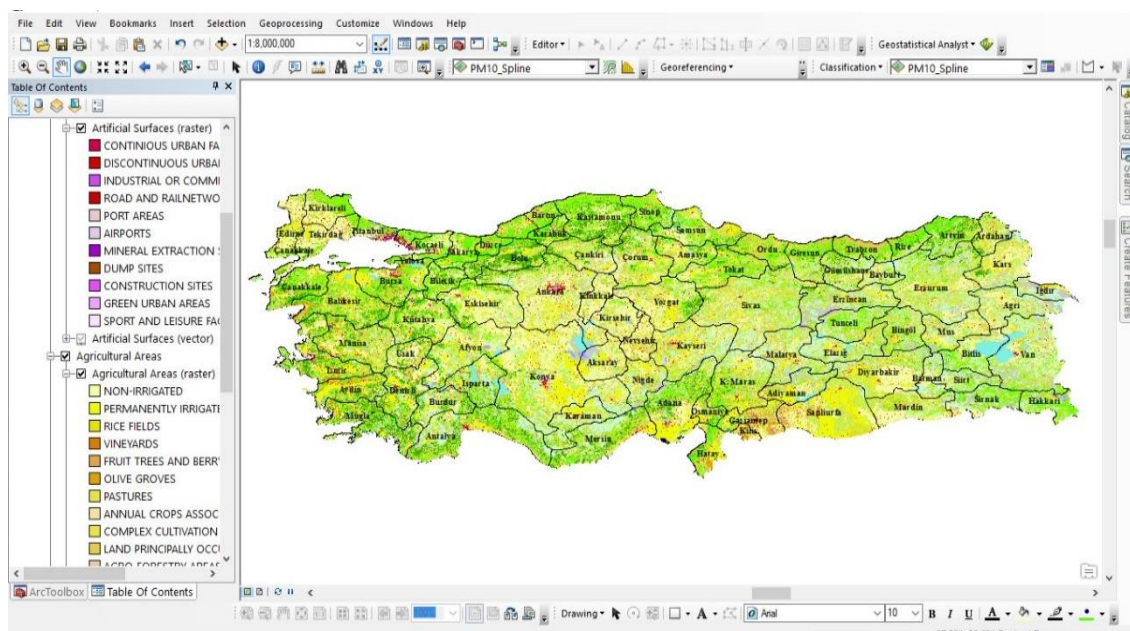


Figure 3. 6: Land Cover and Land Use of Turkey

3.7 Statistical and data analysis

Regression analysis means that the relationship between two or more variables (dependent and independent variables) which are found to be related is explained by mathematical equation (the relationships between the variables are analyzed statistically by regression analysis). If there is one dependent and one independent variable in the regression analysis, this type of analysis is named simple regression analysis. If there is one dependent variable and two or more independent variables in the analysis, it is named multiple regression analysis ([DeFries and Fulker 1985](#), [Mason and Perreault Jr 1991](#), [Büyüköztürk 2003](#), [Ge and Wu 2019](#), [Günlü, Ercanli et al. 2019](#), [Lee, Kim et al. 2019](#), [Little and Rubin 2019](#)). The method used in this study is linear multiple regression

analysis since it is not possible to mention a single independent variable in the investigation of cause - effect relationship in case the dependent variable is urban air pollution and simple regression analysis is inadequate. SPSS and ArcMap software were used in this study. By means of these softwares, it has been tried to prove how and in what way the independent variables that are estimated to affect urban air pollution are statistically effective on the air pollution. Linear multiple regression analysis was used for the variables. Empirical relations are established for the relationships between them in order to understand how the parameters that are effective in any event affect each other. These relations can be linear, non-linear or logarithmic structures. In the selection of the relations between the variables, it is essential to know the structure of the changes roughly and make a choice according to the change. In this way, it is possible to approach the truth ([Akçay 2000](#)). The statistics results were calculated using IBM SPSS statistics version 24. The relationship between air pollutant concentrations and climatological parameters like temperature (T), wind direction (WD), wind speed (WS), relative humidity (RH) and air pressure (AP) in this study was analyzed applying multiple regression method. Linear multiple regression equations shown in equation (3.1): ([Andrews 1974](#), [Hatiboğlu 1994](#), [Preacher, Curran et al. 2006](#), [Sousa, Martins et al. 2007](#), [Prieto, Silva et al. 2017](#), [Lee, Jung et al. 2019](#), [McCullagh 2019](#))

$$Y = \beta + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \dots + \beta_k X_k + \varepsilon \quad (3.1)$$

Y: Dependent variable, X_i : Independent variables, β regression constant, β_i : regression coefficient for variable i (a unit in X_i indicates how much the change will change the Y), ε : Error term. In terms of variables, the value of determination coefficient (R^2) is computed to measure whether the observational values in the linear multiple regression model are compatible with the established model. In statistics, the values of determination coefficient R^2 under 50% indicates to poor relationship between the variables, 50% -70% indicates to intermediate level of relationship and it shows a strong relationship at 70%- 100% ([Gökgöz 2009](#), [Astivia and Zumbo 2019](#), [Marko Sarstedt and Mooi 2019](#), [van Ginkel 2019](#)), t and Sig. – These are the t-statistics and their related 2-tailed p-values utilized in checking whether a given coefficient is considerably various from zero. Utilizing an alpha of 0.05. The intercept is considerably various from 0 at the 0.05 alpha level.

3.8 Air quality standards

As of 1 January 2014, limit values are tolerant values until the EU limit values are valid. It is reduced annually by an equal amount every 12 months so that the tolerance margins are reset to the dates that the EU limit values will apply as shown in table 3.2 <http://www.havaizleme.gov.tr>. The European air quality database (Airbase), air quality measurements and all air quality data flows are collected on the central database. Airbase comprises data from around 35 European countries, 140 pollutants, more than 6,000 stations and 25,000 time series, hourly and daily for more than 30 years ([Tosun 2017](#)). The European Union (EU) and the World Health Organization (WHO) standards are abbreviated in the table 3.3. Apply at different time intervals because the noted health effects related with the different pollutants happen at different times of exposure. The values of WHO limits are regulating for the protection of health, and are mostly stricter than the similar politically agreed EU limits ([EC 1996](#), [EC 1999](#), [Organization 2006](#), [Organization 2013](#), [Yilmaz 2018](#), [EEA 2019](#)). The Air Quality Guide, prepared by the World Health Organization, provides universal guidance on the risks and limits of major air contaminants that cause health dangers. According to World Health Organization limits, only 1 out of 10 people breathe reliable air. Comprehension the range and effect of atmosphere pollution is the initial step in preserving air secure. The National Air Quality Index was created by adapting the air quality index developed by the United States Environmental Protection Agency (US EPA) to national legislation and limit values. The air quality index is computed for 5 major pollutants are; particulate material (PM₁₀), carbon monoxide (CO), sulfur dioxide (SO₂), nitrogen dioxide (NO₂) and ozone (O₃). The National Air Quality Index is calculated and published on the main page of www.havaizleme.gov.tr ([Kara and Tezel 2017](#), [Olgun 2017](#)). The data obtained from the stations in the form of hourly averages are examined and verification studies are conducted and monthly and annual reports are prepared and published with these data. Air pollution in Turkey country is generally make happen by heating, industry and motor vehicles. In addition, factors such as crooked urbanization in Turkey's big cities, topographic structure of the cities, atmospheric conditions (inversion) and meteorological parameters (wind speed etc.), building and population density also contribute to the increase of pollution in winter season ([CSB 2017](#)).

The majority of the 210 stations installed in Turkey country are installed in urban areas and represent a type of station representing heating sources and a limited number of stations represent traffic and industrial resource types. However, according to European Union norms, the stations represent urban, urban environment and rural; according to the resource types, traffic, heating and industry should be established to represent the number of stations to be established, the number of stations that are effective in determining the number of existing stations should be increased. According to September 2017 data, PM₁₀ and SO₂ are measured at 228 stations, PM_{2.5} at 21 stations, NO_x at 112 stations, O₃ at 77 stations and CO at 60 stations ([ÇŞB 2016](#), [CSB 2017](#)).

Table 3. 2: Air Quality Limit Values for the Protection of Human Health and Ecosystem ([Odası 2018](#))

KİRLLETİCİ	Türkiye-Limit Değerler													Türkiye için AB Limit Değerlerin Geçerli Olacağı
	Süre	2014 Sınır Değer	2015 Sınır Değer	2016 Sınır Değer	2017 Sınır Değer	2018 Sınır Değer	2019 Sınır Değer	2020 Sınır Değer	2021 Sınır Değer	2022 Sınır Değer	2023 Sınır Değer	2024 Sınır Değer		
		(µg/m3)												
SO ₂	saatlik	350+150	350+120	350+90	350+60	350+30	350	350	350	350	350	350	1 Ocak 2019	
	24 saat	125+125	125+100	125+75	125+50	125+25	125	125	125	125	125	125		
	yıl ve kış	20	20	20	20	20	20	20	20	20	20	20		
NO ₂	saatlik	200+100	200+90	200+80	200+70	200+60	200+50	200+40	200+30	200+20	200+10	200	1 Ocak 2024	
	yıl	40+20	40+18	40+16	40+14	40+12	40+10	40+8	40+6	40+4	40+2	40		
NO _x	yıl	30	30	30	30	30	30	30	30	30	30	30	1 Ocak 2014	
PM10	24 saat	50+50	50+40	50+30	50+20	50+10	50	50	50	50	50	50	1 Ocak 2019	
	kış dönemi	40+50	40+40	40+30	40+20	40+10	40	40	40	40	40	40		
	yıl	40+20	40+16	40+12	40+8	40+4	40	40	40	40	40	40		
Pb	yıl	0.5+0.5	0.5+0.4	0.5+0.3	0.5+0.2	0.5+0.1	0,5	0,5	0,5	0,5	0,5	0,5	1 Ocak 2019	
C6H6	-	5+5	5+5	5+5	5+5	5+3.75	5+2.5	5+1.25	5	5	5	5	1 Ocak 2021	
CO	8 saat	10000+6000	10000+4000	10000+2000	10000	10000	10000	10000	10000	10000	10000	10000	1 Ocak 2017	
O ₃	8 saat	hedef değer								120	120	120	1 Ocak 2022	
	saatlik	bilgi eşiği								180	180	180		
		uyarı eşiği								240	240	240		
Arsenik	yıl	Bir yılda PM10 fraksiyonundaki toplam içerik için hedef değer						0,006	0,006	0,006	0,006	0,006	1 Ocak 2020	
Kadmiyum	yıl							0,005	0,005	0,005	0,005	0,005		
Nikel	yıl							0,02	0,02	0,02	0,02	0,02		
Benzo(a)piren	yıl							0,001	0,001	0,001	0,001	0,001		
NOT: 1 Ocak 2014'ten itibaren AB limit değerlerinin geçerli olacağı tarihe kadar limit değer toleranslı değerlerdir. AB Limit Değerlerinin geçerli olacağı tarihlere kadar tolerans payları sıfırlanacak şekilde her 12 ayda bir eşit miktarda yıllık olarak azaltılır														

NOT: 1 Ocak 2014'ten itibaren AB limit değerlerin geçerli olacağı tarihe kadar limit değerler toleranslı değerlerdir. AB Limit Değerlerin geçerli olacağı tarihlere kadar tolerans payları sıfırlanacak şekilde her 12 ayda bir eşit miktarda yıllık olarak azaltılır

Table 3. 3: The EU and WHO guideline values of air pollution ([Krzyzanowski and Cohen 2008](#), [Özden, Döğeroğlu et al. 2008](#), [Abdul-Wahab, En et al. 2015](#))

EU Air Quality Directive				WHO Guidelines	
Pollutant	Averaging Period	Objective and legal nature and concentration	Comments	Concentration	Comments
PM _{2.5}	Hourly			25 µg/m ³	99th percentile (3 days/year)
PM _{2.5}	Annual	Limit value, 25 µg/m ³		10 µg/m ³	
PM ₁₀	Hourly	Limit value, 50 µg/m ³	Not to be exceeded on more than 35 days per year	50 µg/m ³	99th percentile (3 days/year)
PM ₁₀	Annual	Limit value, 40 µg/m ³		20 µg/m ³	
O ₃	Maximum daily 8-hour mean	Target value, 120 µg/m ³	Not to be exceeded on more than 25 days per year, averaged over three years	100 µg/m ³	
NO ₂	Hourly	Limit value, 200 µg/m ³		200 µg/m ³	
NO ₂	Annual	Limit value, 40 µg/m ³		40 µg/m ³	

Values Air quality index (AQI) are obtained from air quality data readings of pollutants influencing air quality. The index is derived applying the formula (3.2):

$$AQI_{\text{pollutant}} = \frac{\text{Pollutant data reading}}{\text{Standard}} * 100 \quad (3.2)$$

EPA computes the AQI for five main air pollutants legalized by the Clean Air Act are ozone, particulate matter, carbon monoxide, sulfur dioxide, and nitrogen dioxide as given in table 3.4. For every of these contaminants, EPA has recognized national air quality guidelines to safeguard public health, ozone and particulate matter are the two pollutants that pose the greatest danger to human health in this country.

Table 3. 4: EPA Air Quality Index ([Al-Saadi, Szykman et al. 2005](#), [Dimitriou, Paschalidou et al. 2013](#), [Abdul-Wahab, En et al. 2015](#), [Gopalaswami 2016](#)), ([Saad et al., 2017](#))

O ₃ (ppm)	PM ₁₀ (ug/m ³)	PM _{2.5} (ug/m ³)	CO (ppm)	SO ₂ (ppm)	NO ₂ (ppm)	AQI Values	Level of Health Concern
0.000 – 0.059	0 – 54	0.0 – 15.4	0.0 – 4.4	0.000 – 0.034	–	0 – 50	Good
0.060 – 0.075	55 – 154	15.5 – 40.4	4.5 – 9.4	0.035 – 0.144	–	51 – 100	Moderate
0.076 – 0.095	155 – 254	40.5 – 65.4	9.5 – 12.4	0.145 – 0.224	–	101 – 150	Unhealthy for Sensitive Groups
0.096 – 0.115	255 – 354	65.5 – 150.4	12.5 – 15.4	0.225 – 0.304	–	151 – 200	Unhealthy
0.116 – 0.374	355 – 424	150.5 – 250.4	15.5 – 30.4	0.305 – 0.604	0.65 – 1.24	201 – 300	Very Unhealthy
–	425 – 504	250.5 – 350.4	30.5 – 40.4	0.605 – 0.804	1.25 – 1.64	301 – 400	Hazardous
–	505 – 604	350.5 – 500.4	40.5 – 50.4	0.805 – 1.004	1.65 – 2.04	401 – 500	Hazardous

3.9 The wind speed and wind direction maps

Figure 3.7, 3.8 and 3.9 illustrate maps of wind direction and wind speed during January 2016, 2017 and 2018, respectively that created within ArcGIS environment by using IDW method for producing map of wind direction and speed that may effects on the distribution of air pollutants, we can see from these figures that there are some different between these maps during these periods in Turkey.

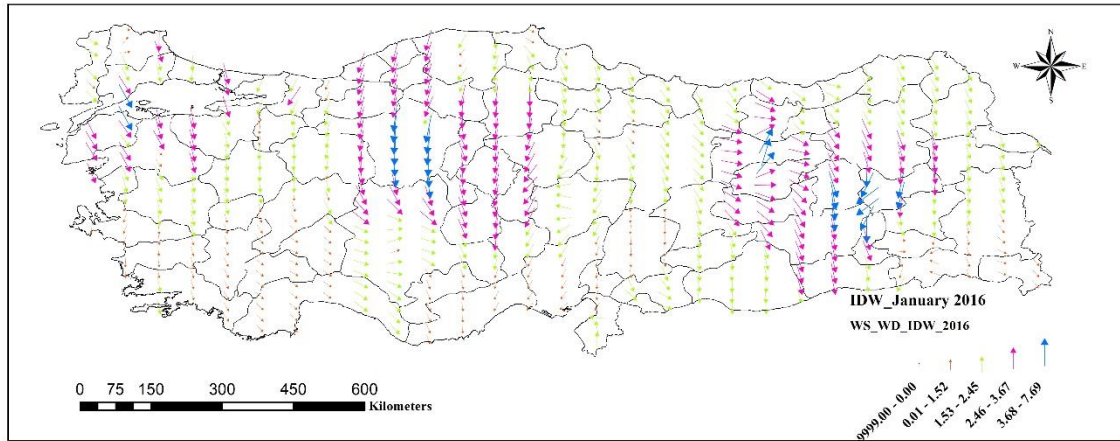


Figure 3. 7: Wind direction and wind speed map during January 2016

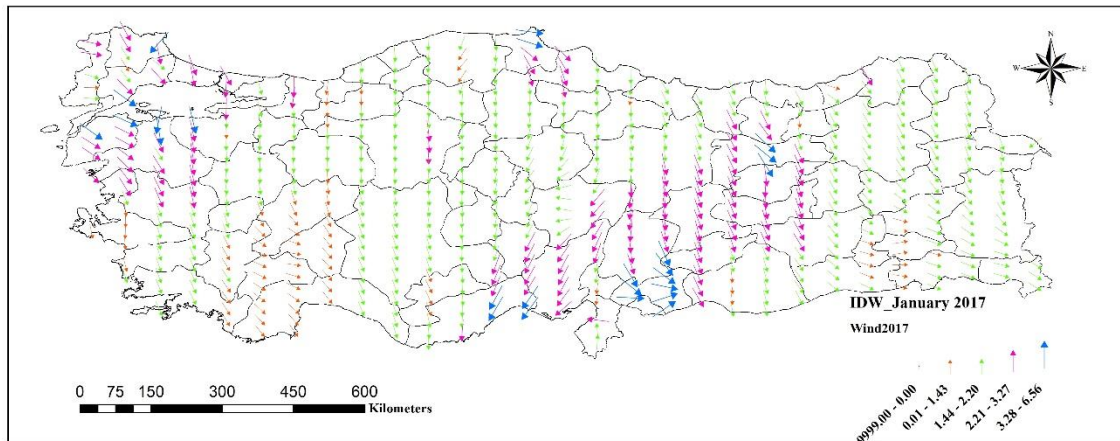


Figure 3. 8: Wind direction and wind speed map during January 2017

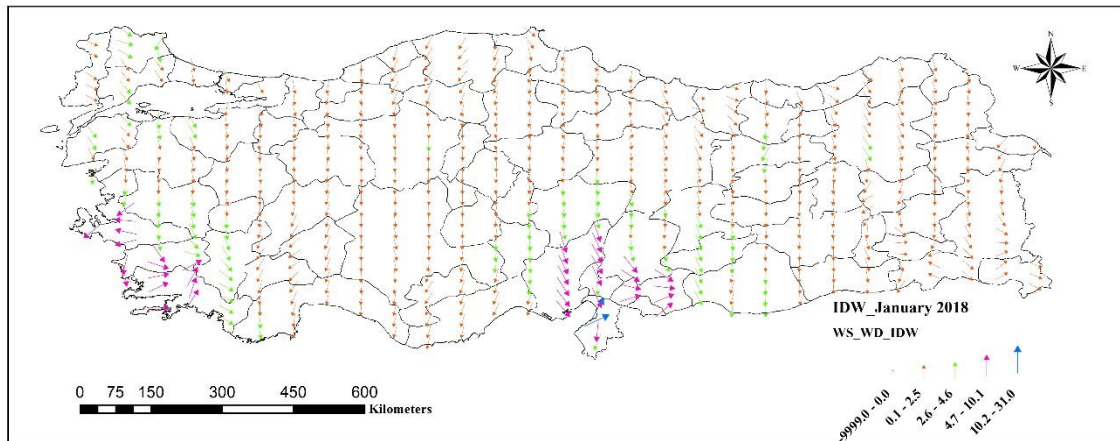


Figure 3. 9: Wind direction and wind speed map during January 2018

IV. RESULTS AND DISCUSSION

4.1 Results and discussion

Human-induced emissions (gas emissions) lead to significant air pollution, causing adverse impacts on the ecosystem and human health in dangerous dimensions. Air pollution is the result of pollutants in the form of solid, liquid and gaseous air that damage the normal life of the creatures and the natural balance of the environment. The pollutant is a chemical substance that disrupts the natural composition of the air and also has adverse environmental and health effects ([Kılıç, Kum et al. 2016](#)).

In recent years, geographic information systems and remote sensing have often been applied in the field of air quality, as well as in many branches of environmental engineering. Geographical information systems are used especially in the preparation of high spatial resolution emission inventories, air quality modeling and air pollution mapping. Geographical Information Systems (GIS) are very important in air quality modeling because pollutant sources have coordinates. In this study, it is explained how geographic information systems are used in air quality model. ArcGIS (version 10.5.1) is used as geographic information system software. The spatial distribution of pollution should be known in order to determine how air pollution affects cities. Air quality modeling is an efficient tool for assessing how pollution released from a source is distributed based on atmospheric conditions and topography. In latest years, air quality modeling has become a repeatedly used method, particularly because of developments in computer skills. Inputs of air quality models are emissions inventories, meteorological data and topographic data. The air quality models employing this data can evaluation the pollutant concentrations be based on the coordinates. Two of the most significant air contaminants are particulate matter and sulfur dioxide. The most principal source of sulfur dioxide in the air of the city is the combustion of sulfur- comprising fossil fuels for energy purposes ($S + O_2 \rightarrow SO_2$). The most essential effects of Sulfur dioxide are the damage caused to the environment by the formation of acid oil and the damage to the respiratory system. As a result of the advancements in both the field of statistics and in the ecosystem of Geographical Information Systems (GIS) and Remote Sensing, spatial analysis methods are a widely used method of analysis, which includes the data related to the space in the statistical study, providing highly useful information about the space.

Spatial analyzes are needed where classical statistics are insufficient to explain many changes taking place in the space ([Başbozkurt 2015](#), [Çubukçu 2015](#), [Özcan 2016](#)).

4.2 The spatial analysis of PM₁₀ during 2015-2018 by using IDW interpolation method

Particulate matter (PM) is expression of a combination of solid particles and liquid droplets existing in the atmosphere and the most important source of PM₁₀ in the city air is the heating activities. Because PM is a very diverse group of pollutants, its effects are also very broad, count on its physical and chemical characteristics. The most important effects are the important damage to the respiratory system and the shorter vision distance in the atmosphere. The major sources of particulate matter are vehicles, urban transformation, dust and industry. When we look at air pollution in 2003 as opposed to Turkey's air pollution by only 5.6 percent was higher in Europe, we get to 2018, we see that this rate go to 33.4 percent. So it allows the reduction of particulate matter ratio measures taken in Europe, but we have been facing the problem of dust pollution fast enough due to the measures not taken in Turkey, air pollution causes respiratory infection, cancer, early infant deaths, disrupted births and mass deaths ([Pope III, Burnett et al. 2002](#), [Brook, Rajagopalan et al. 2010](#), [Turner, Krewski et al. 2011](#), [Anderson, Thundiyil et al. 2012](#), [Burns, Boogaard et al. 2019](#), [Cetin, Onac et al. 2019](#), [Chen, Yin et al. 2019](#), [Cromie, Saef et al. 2019](#), [KoşanI, Kavuncuoğlu et al. 2019](#), [Onay, Coptly et al. 2019](#), [Sari, Tasdemir et al. 2019](#), [Tsiflikiotou, Kostenidou et al. 2019](#)).

Figures 4.1, 4.2, 4.3 and 4.4 show the spatial distribution of PM₁₀ through the periods of January 2015, 2016 2017 and 2018 respectively, as can be observed from these figures, the monthly mean PM₁₀ concentrations in most of the regions are above 50 µg/m³. The long-term limit given in the Turkish Air Quality Protection Regulation is 50 µg/m³ as hourly limit and 40 µg/m³ in winter season. As can be seen from these figures, the maximum concentrations were observed in the cities of Ordu, Igdir, Kahramanmaras, Kocaeli, Manisa, Bursa, Mus, Adana, Afyon and etc. about 73%, 54%, 56% and 58% of PM₁₀ concentrations, during January 2015, 2016, 2017 and 2018, respectively, are above the Turkish Regulation limit of 50 µg/m³. The PM concentrations around these cities are fundamentally as a result of home heating activities in the winter season. The lowest PM₁₀ values were observed in the Black Sea Region of the country, except in some stations like Ordu, Amasya and Tokat, and in the northwestern parts of East Anatolia

Region, the minimum particulate matter (PM₁₀) values are 6.28 µg/m³ in Rize_Ardesen, 5 µg/m³ in Istanbul_Catladikapi, 7 µg/m³ in Mardin and 4 µg/m³ in Samsun_Bafra, whereas the maximum particulate matter (PM₁₀) values are 224.94 µg/m³ in Ordu_fatsa, 202 µg/m³ in Ağrı_Dogubeyazit, 248 µg/m³ in Iğdir and 210 µg/m³ in Iğdir during periods 2018, 2017, 2016 and 2015, respectively. Additionally we can see from these figures the pollution distribution are in the same regions during these periods this mean the sources of PM₁₀ pollution are the same that may be from domestic heating activities, and when compare the results with the industrial map figure 3.4 we can observe the source of PM₁₀ may be come from industrial facilities specially in the western parts of country where the industrial density increase. Large particles; generally, crustal materials include powders from the road and industries to the atmosphere. [Hakan Erdun, Ali Öztürk et al. \(2015\)](#) studied the spatial distribution of annual PM₁₀ values for all regions of Turkey, the more polluted parts was Southeastern area of Turkey and the less polluted was middle region of Black Sea during the periods of 2008-2012. Changes in PM₁₀ pollution in December and January between 2009 and 2017 in Manisa were investigated. Although it is aimed to gradually reduce the PM₁₀ values to the EU limit value of 50 µg/m³ until 01.01.2019 with the EC which came into force in 2008, there has not been a significant decrease in PM₁₀ pollution in the city in the past years. As of 2017, PM₁₀ pollution values are still more than twice the EU limit values and it is almost impossible to reach the air quality values planned for 2019 within the remaining two years. The reason for this situation is that the target limit values between 2009 and 2013 are higher than the current pollution values observed in those years [Yılmaz \(2018\)](#).

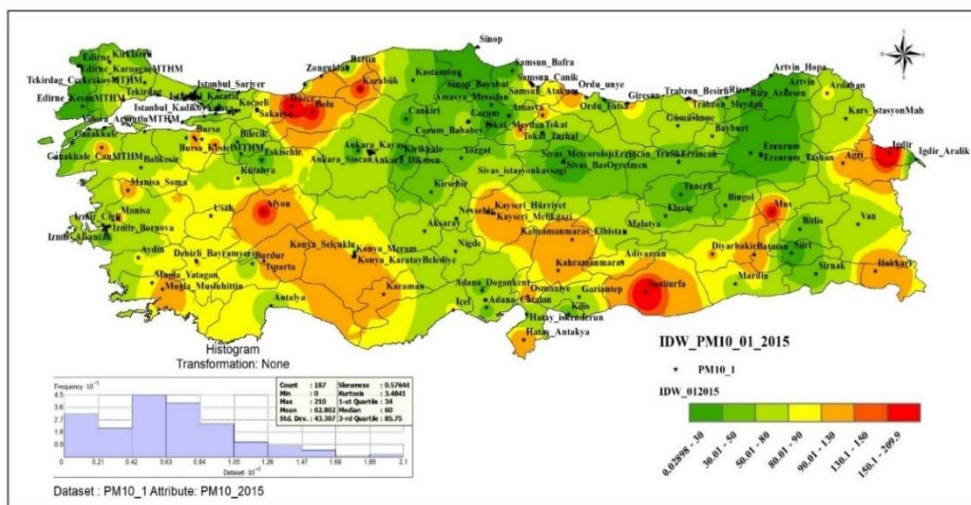


Figure 4. 1: Spatial analysis of PM₁₀ in January 2015 by using IDW method.

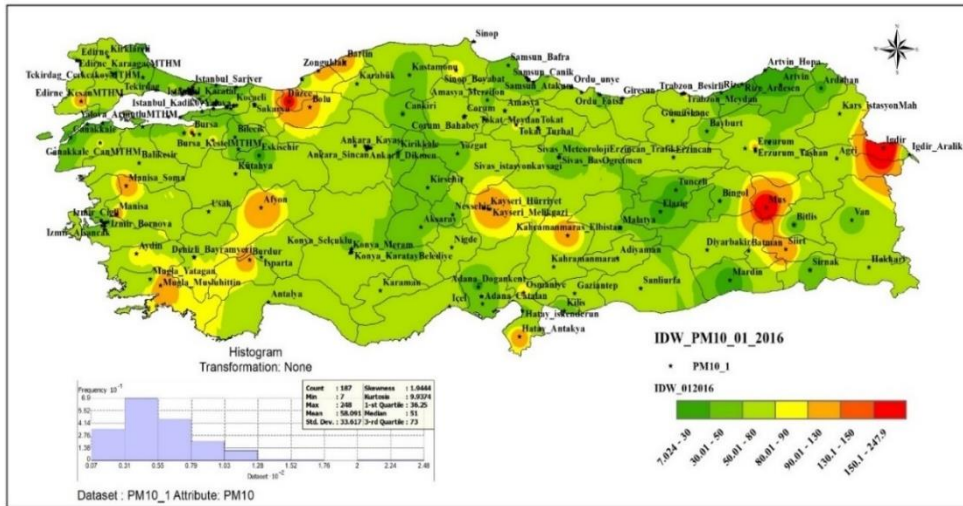


Figure 4. 2: Spatial analysis of PM₁₀ in January 2016 by using IDW method.

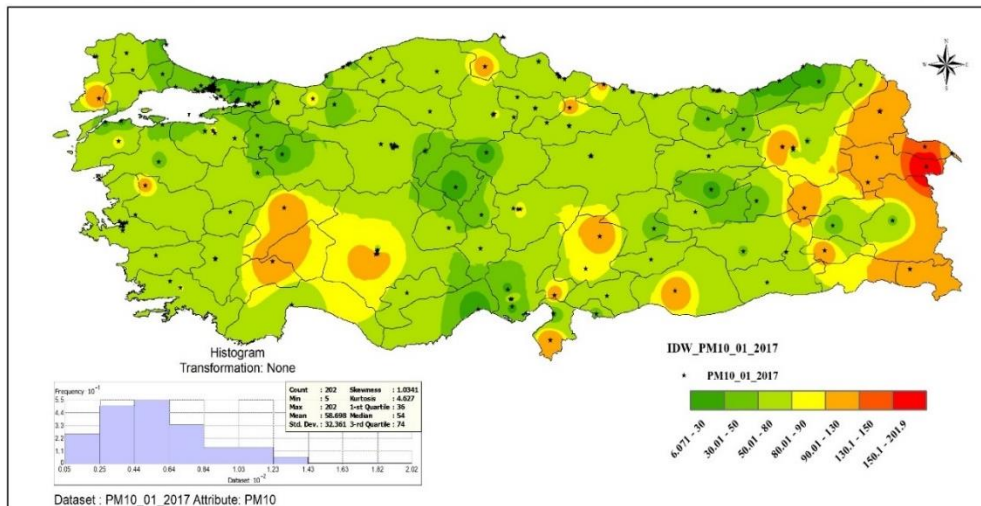


Figure 4. 3: Spatial analysis of PM₁₀ in January 2017 by using IDW method.

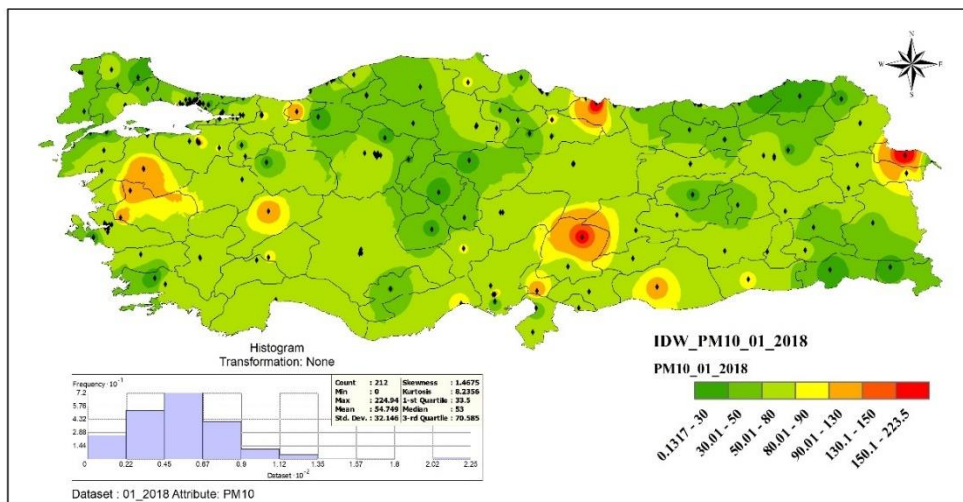


Figure 4. 4: Spatial analysis of PM₁₀ in January 2018 by using IDW method.

[illegible][illegible]

49

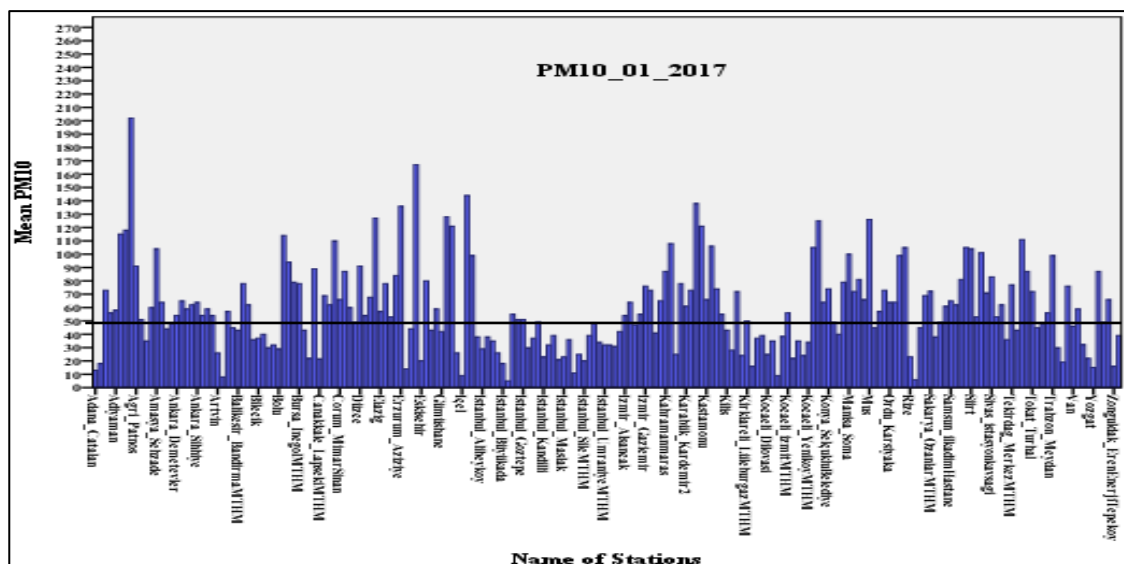


Figure 4. 7: Average concentration of PM₁₀_January 2017 in the all Stations

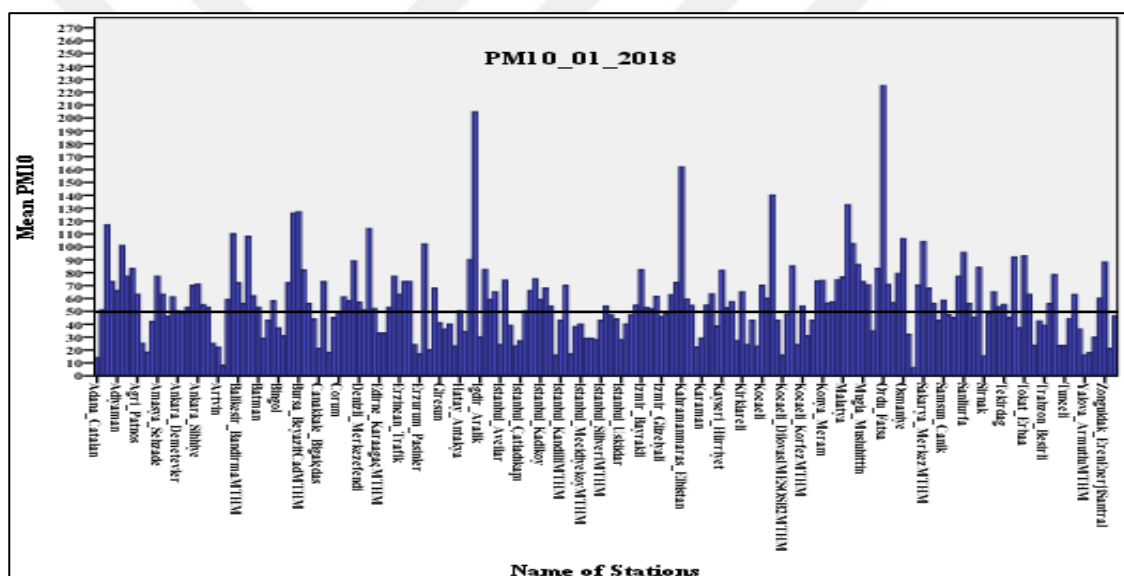


Figure 4. 8: Average concentration of PM₁₀_January 2018 in the all Turkey Stations

As can be noticed from the annual average emission values of the PM₁₀ during periods measured between 2009 and 2018 (Table 4.1 and Figure 4.9) it has been seeing in these cities to exceed the standard limit of (40 µg/m³) as annual allowable limit. PM₁₀ is compounds that can seriously threaten human health and cause death. The values of these compounds, which seriously threaten living and human health consequently efforts to avoid air pollution, can be brought to the values of the World Health Organization.

Table 4. 1: Average annual Concentration of PM₁₀ during period 2009-2018

Date	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018
PM ₁₀ (µg/m ³)_Adana	81	96.16	79.73	94.92	63.54	64.87	80.52	55.47	63.31	62.46
PM ₁₀ (µg/m ³)_Bursa	103.3	63.64	90.11	37.89	59.34	95.09	105.4	93.45	99.61	99.36
PM ₁₀ (µg/m ³)_Bolu	99.27	93.33	58.74	80.08	84.26	75.46	91.09	36.66	28.91	75.92
PM ₁₀ (µg/m ³)_Karabuk	115.8	96.39	55.93	49.87	49.15	47.65	76.57	35.36	39.37	52.01
PM ₁₀ (µg/m ³)_Kocali Izmit	74.34	64.68	55.85	54.12	63.62	58.24	57.03	55.49	59.19	61.19
PM ₁₀ (µg/m ³)_Mus	173.74	125.77	52.43	85.05	121.86	108.3	135.54	131.15	83.88	75.61
PM ₁₀ (µg/m ³)_Siirt	122.97	126.1	132.2	108.3	93.33	115.2	105	92.58	65.66	44.81
PM ₁₀ (µg/m ³)_Konya Meram	87.14	74.11	81.62	73.77	63.44	61	57.92	54.21	67.9	48.67
PM ₁₀ (µg/m ³)_Konya Selcuklu	64.55	58.23	58.61	50.34	52.94	49.31	51.05	49.37	62.17	55.04
PM ₁₀ (µg/m ³)_Sanliurfa	143.86	84.37	102.3	87.03	70.82	52.96	46.5	34.46	73.69	60.19
PM ₁₀ (µg/m ³)_Igdir	160.71	137.8	209.2	88.65	91.22	108.8	121.9	107.7	151.4	148.7
PM ₁₀ (µg/m ³)_Afyon	113.71	101.9	131.1	104.3	96.17	80.84	88.05	79.75	74.46	75.15

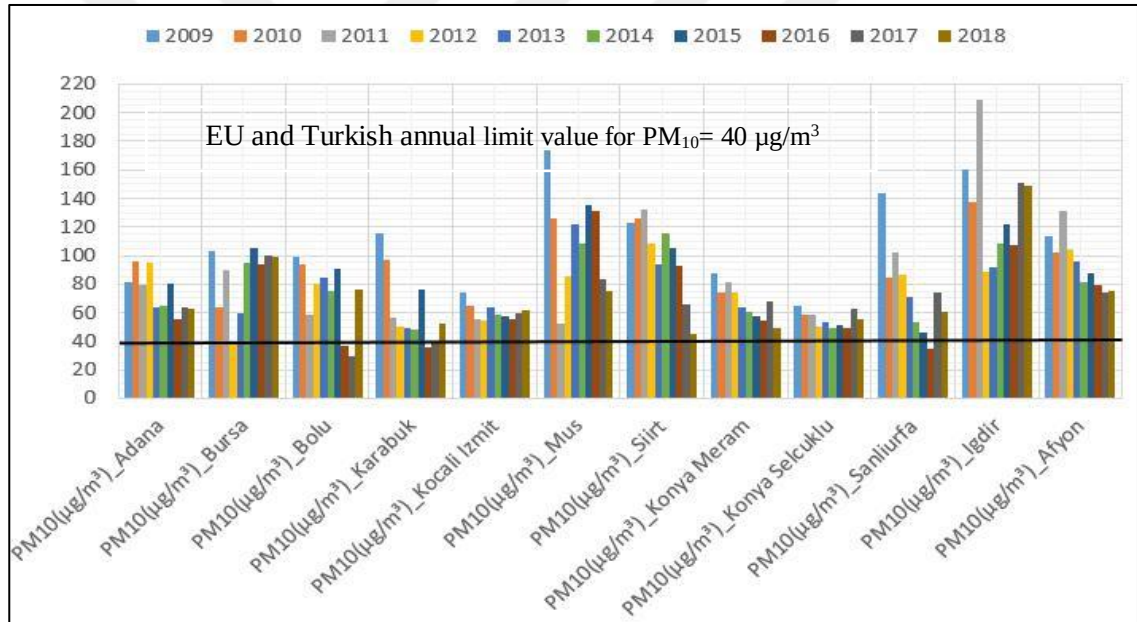


Figure 4. 9: Average annual Concentration of PM₁₀ during period 2009-2018

The results were showing generally, the concentrations of PM₁₀ increasing in winter months in most provinces of Turkey and approximately at the same stations especially in January, February, November and December because of using the fossil fuels in domestic heating in winter months, and decreasing in the summer months during periods from 2015-2018 as shown in the figures 4.10 - 4.53, except in southeastern part of some Turkey cities where the concentrations of PM₁₀ was increasing during the months July (7) to October (10), may be due to occurring of desert dust. According to these figures, the highest monthly average PM₁₀ concentration for 2015-2018 was 429.4,

422.4 and 767.5 $\mu\text{g}/\text{m}^3$ in April, June and November 2018, respectively. Different factors are important contributors to decrease of urban air quality like the reliance on fossil fuels in warming, industrial activities and traffic, dependence on the private automobiles, incompetent usage of energy in buildings and public transport, and the utilization of improper and incomplete burning methods, the degradation of open and green areas. In Karabuk city [Özer \(2013\)](#) shows the PM_{10} pollutant was the highest in the 2006-2007 season, but serious decreases in value occurred in 2010, when natural gas was used. While [\(Çapraz 2014\)](#) investigated the average particulate matter values have always been above 40 $\mu\text{g}/\text{m}^3$, which is the limit value of European Union between 2007 and 2012 in Istanbul city.

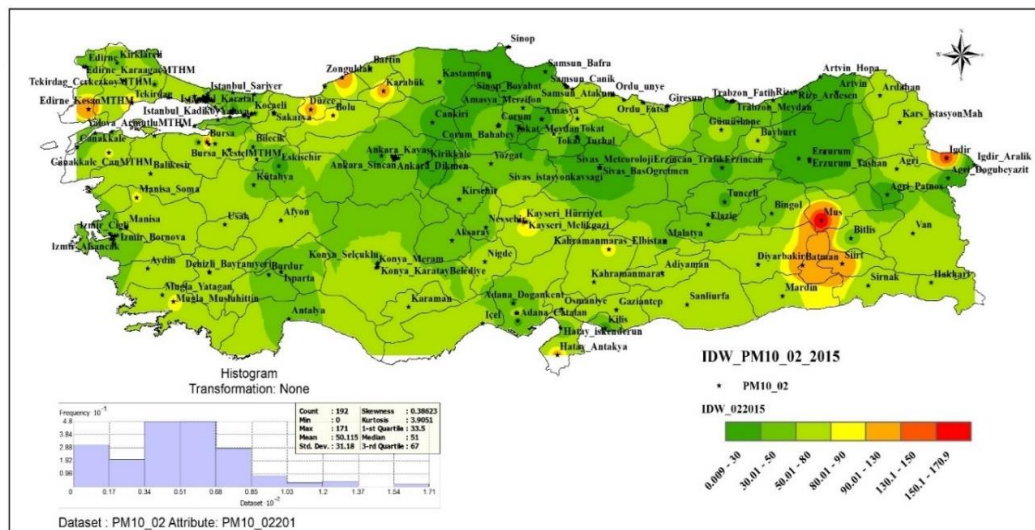


Figure 4. 10: Spatial analysis of PM_{10} in February 2015 by applying IDW model

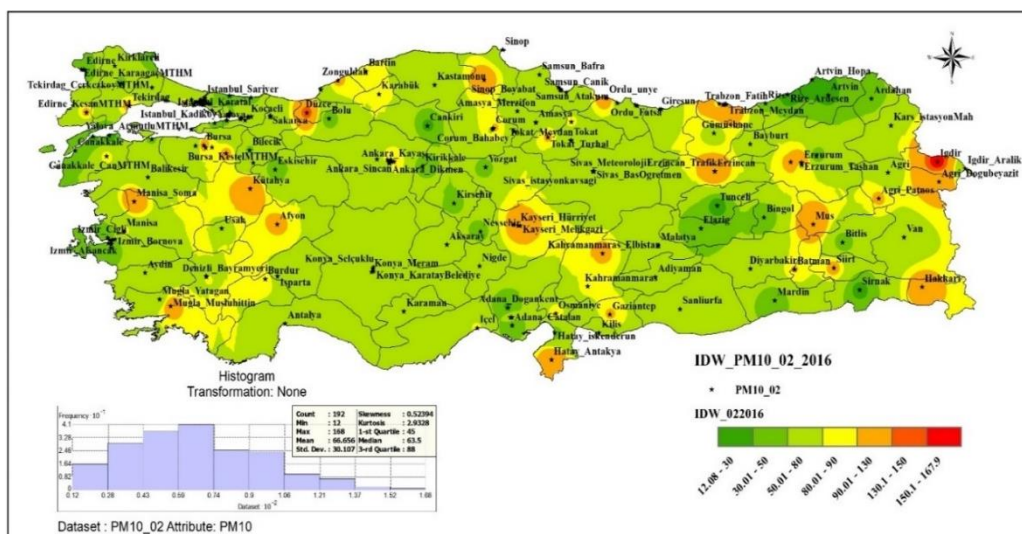


Figure 4. 11: Spatial analysis of PM_{10} in February 2016 by applying IDW model

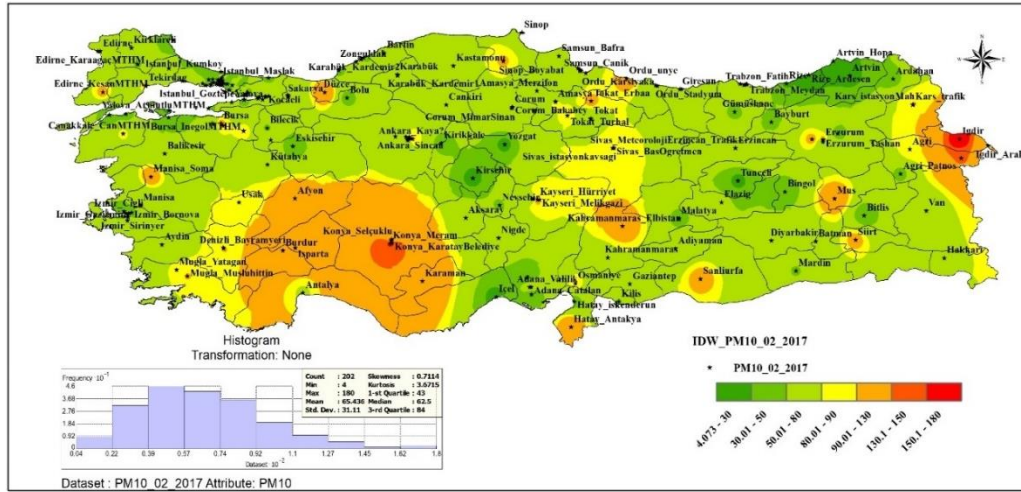


Figure 4. 12: Spatial analysis of PM₁₀ in February 2017 by applying IDW model

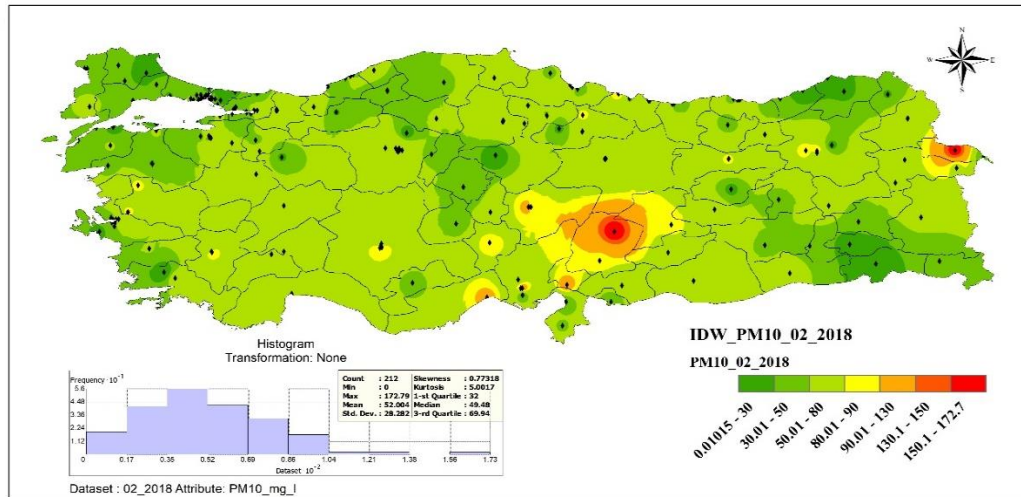


Figure 4. 13: Spatial analysis of PM₁₀ in February 2018 by applying IDW model



Figure 4. 14: Spatial analysis of PM₁₀ in March 2015 by applying IDW model

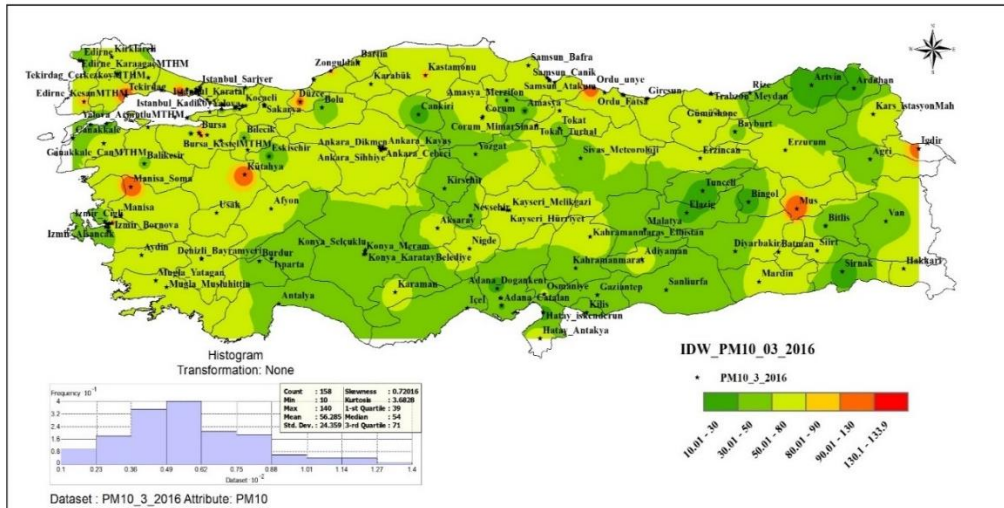


Figure 4. 15: Spatial analysis of PM₁₀ in March 2016 by applying IDW model

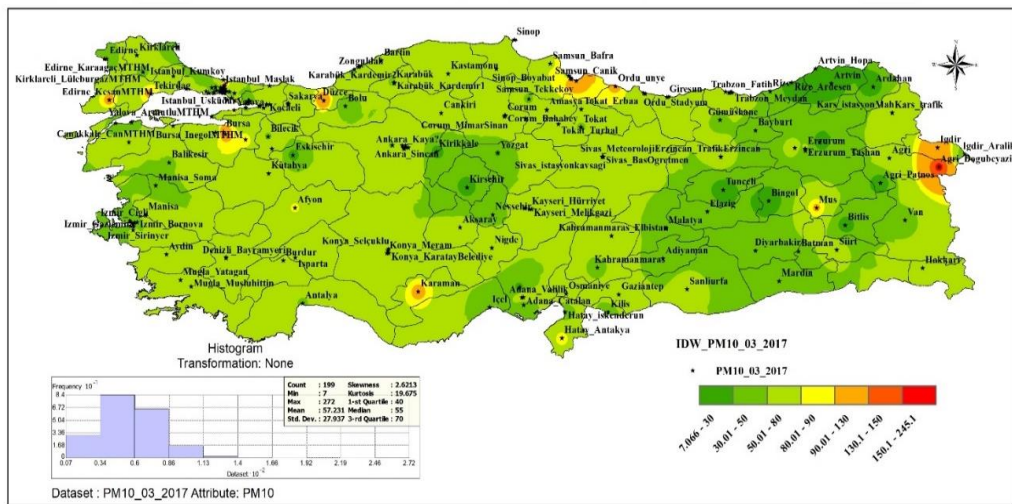


Figure 4. 16: Spatial analysis of PM₁₀ in March 2017 by applying IDW model

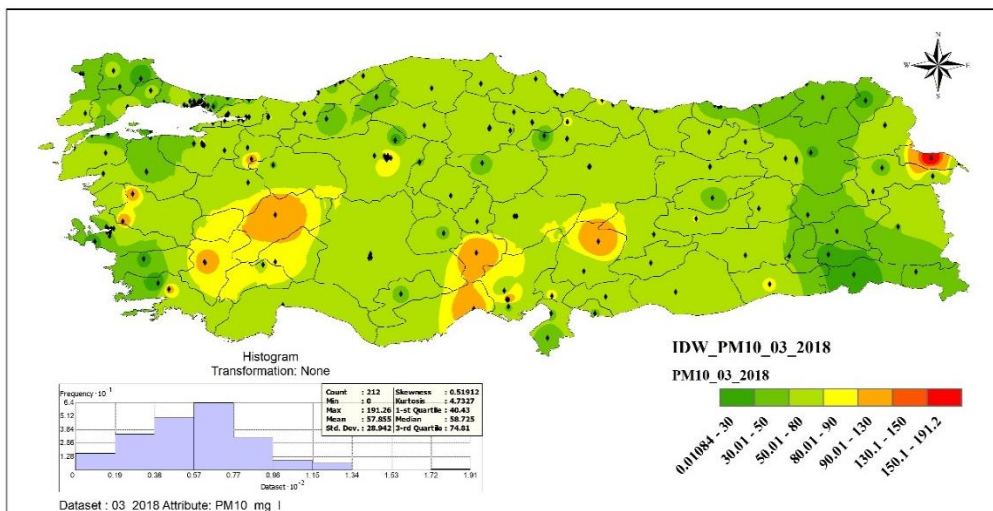


Figure 4. 17: Spatial analysis of PM₁₀ in March 2018 by applying IDW model

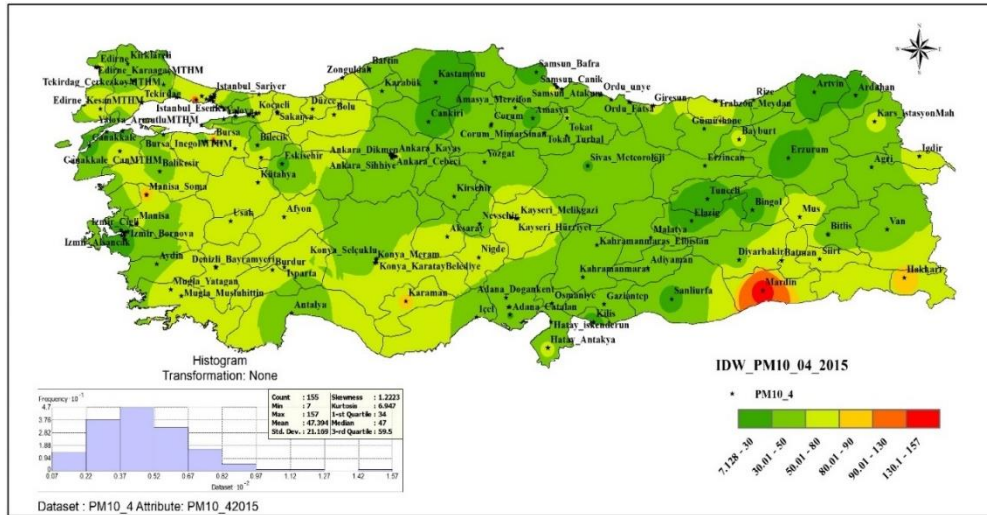


Figure 4. 18: Spatial analysis of PM₁₀ in April 2015 by applying IDW model

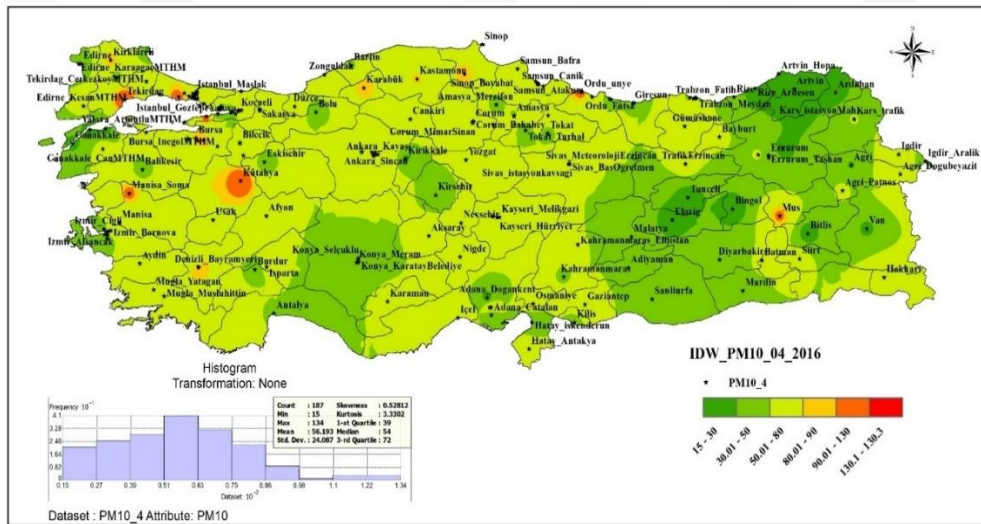


Figure 4. 19: Spatial analysis of PM₁₀ in April 2016 by applying IDW model

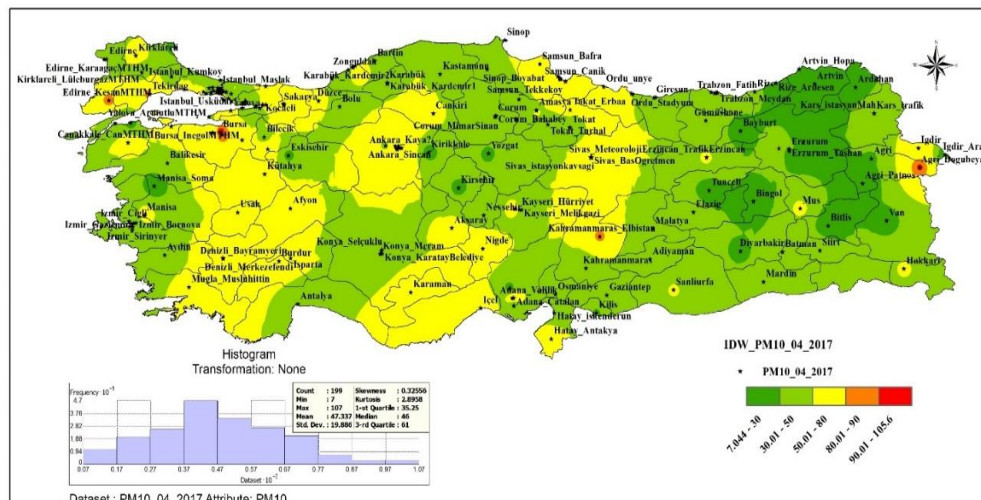


Figure 4. 20: Spatial analysis of PM₁₀ in April 2017 by applying IDW model

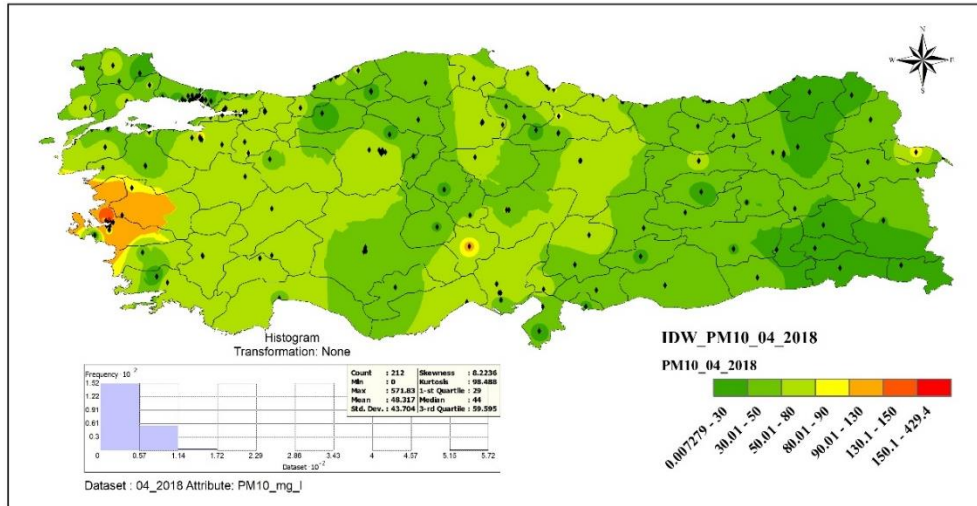


Figure 4. 21: Spatial analysis of PM₁₀ in April 2018 by applying IDW model

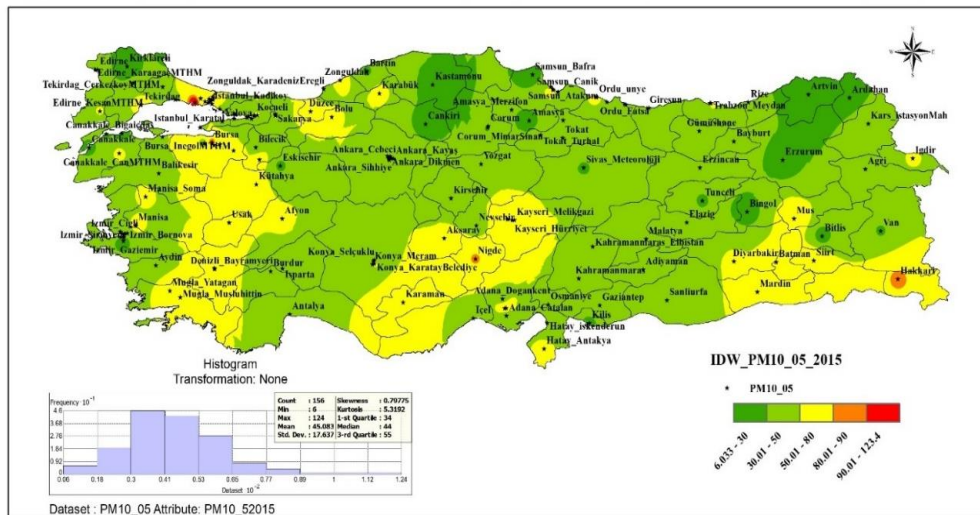


Figure 4. 22: Spatial analysis of PM₁₀ in May 2015 by applying IDW model

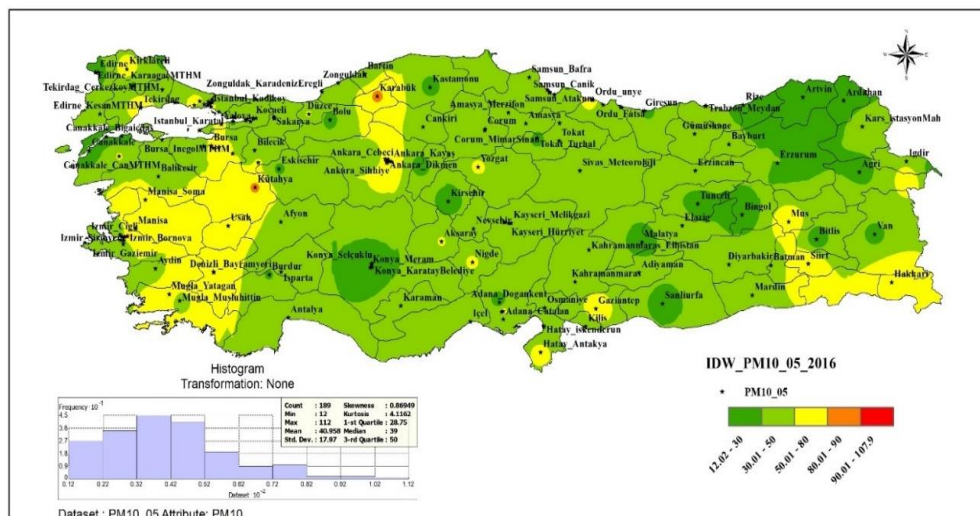


Figure 4. 23: Spatial analysis of PM₁₀ in May 2016 by applying IDW model

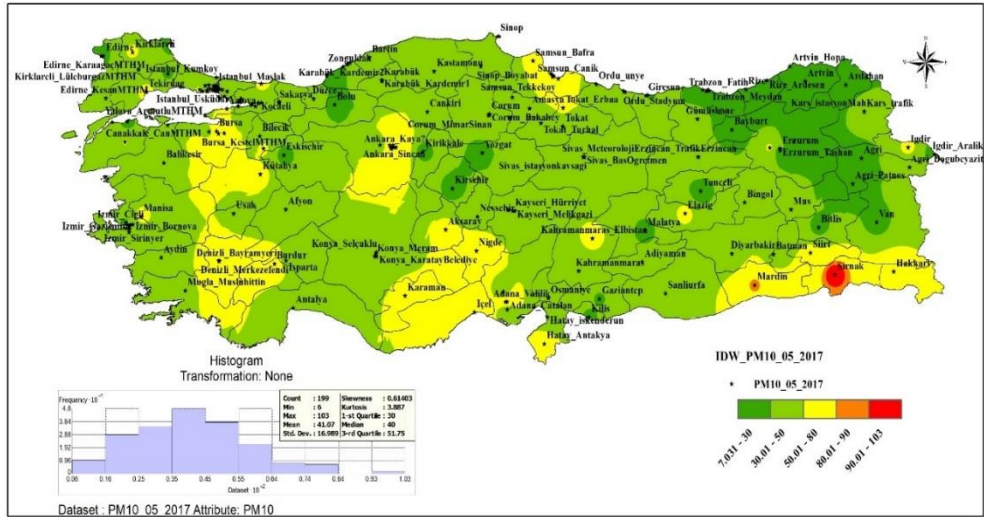


Figure 4. 24: Spatial analysis of PM₁₀ in May 2017 by applying IDW model

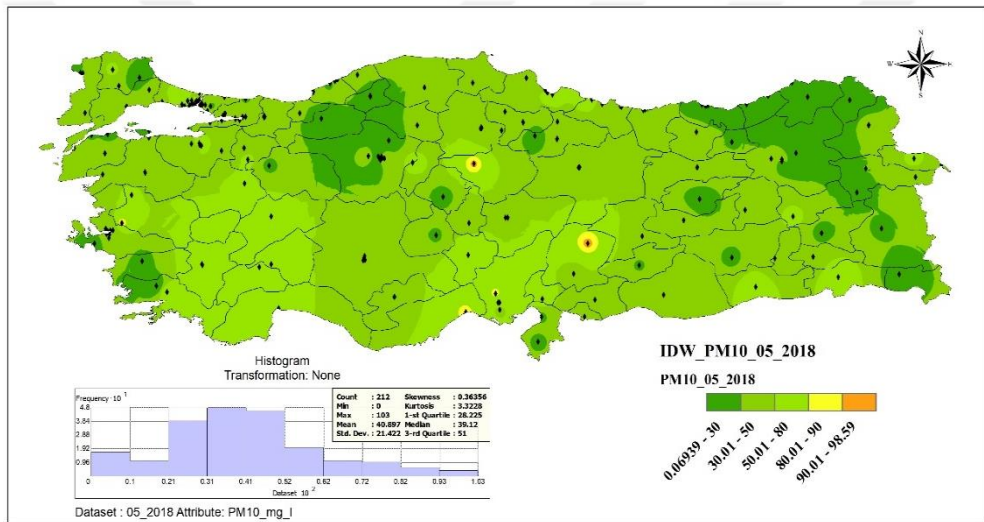


Figure 4. 25: Spatial analysis of PM₁₀ in May 2018 by applying IDW model

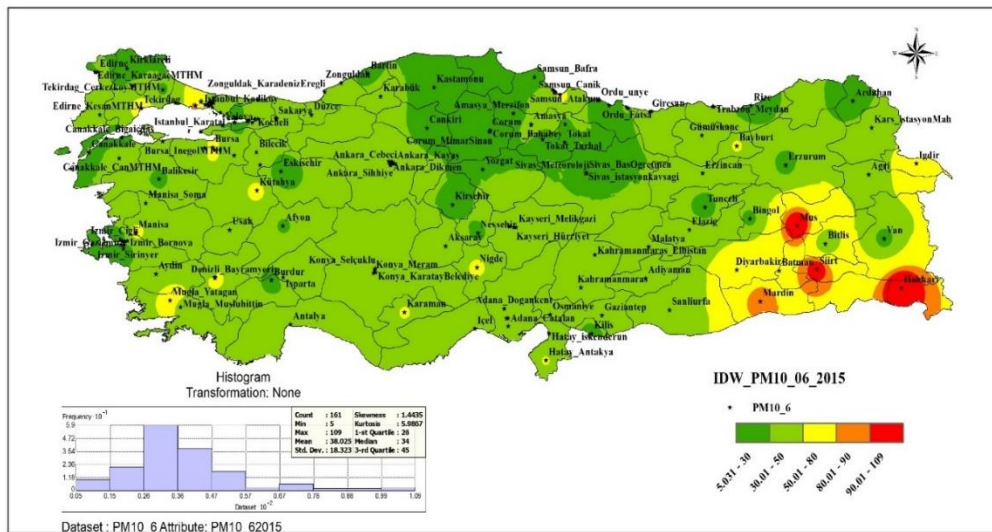


Figure 4. 26: Spatial analysis of PM₁₀ in June 2015 by applying IDW model

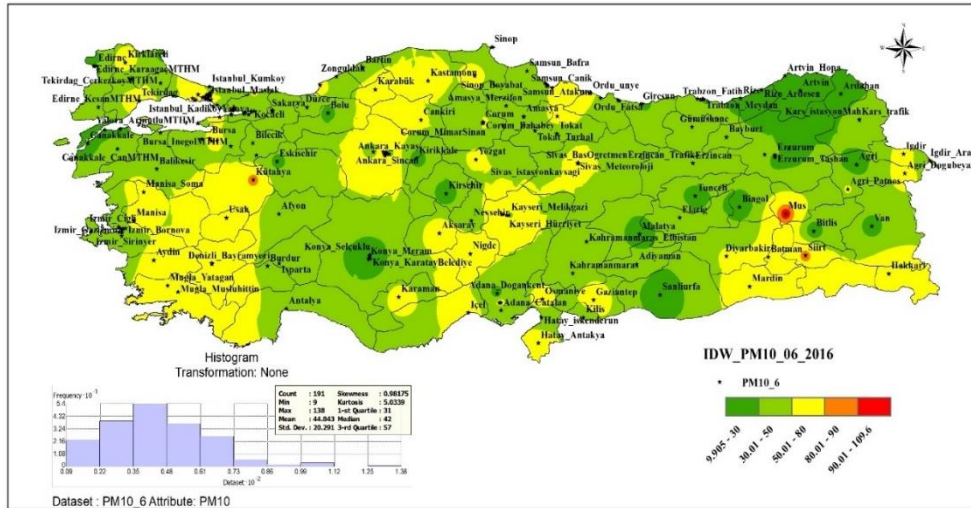


Figure 4. 27: Spatial analysis of PM₁₀ in June 2016 by applying IDW model

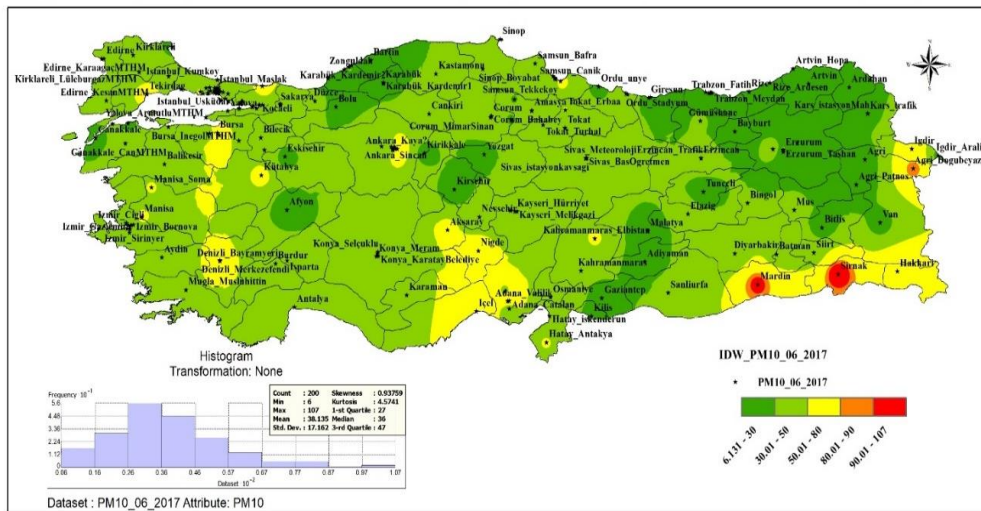


Figure 4. 28: Spatial analysis of PM₁₀ in June 2017 by applying IDW model

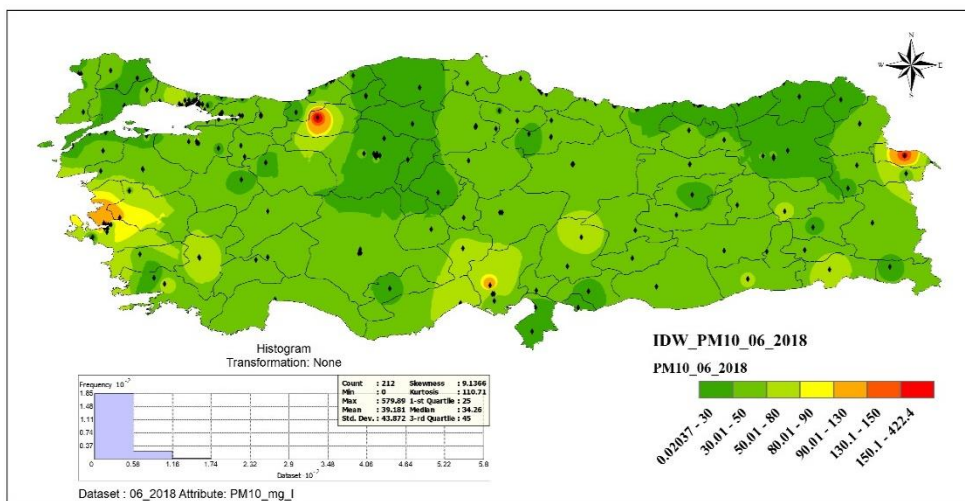


Figure 4. 29: Spatial analysis of PM₁₀ in June 2018 by applying IDW model

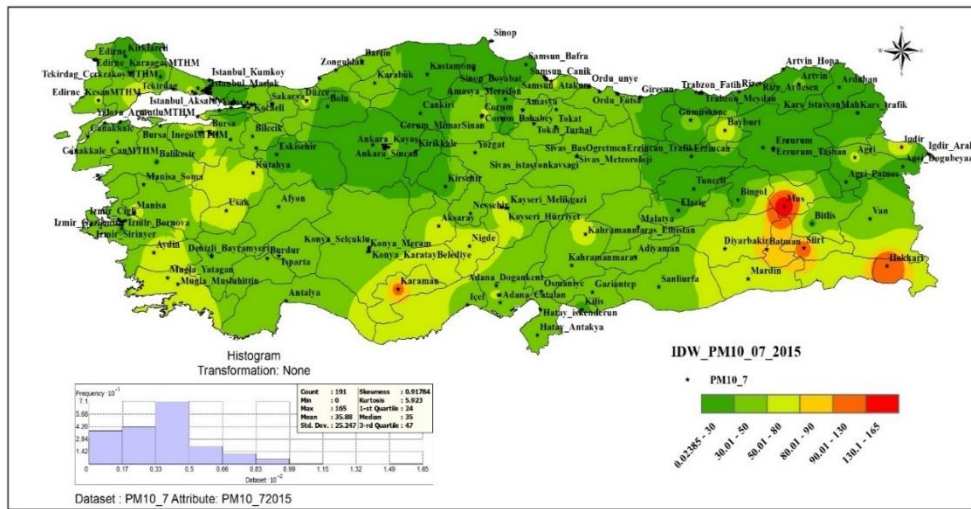


Figure 4.30: Spatial analysis of PM₁₀ in July 2015 by applying IDW model

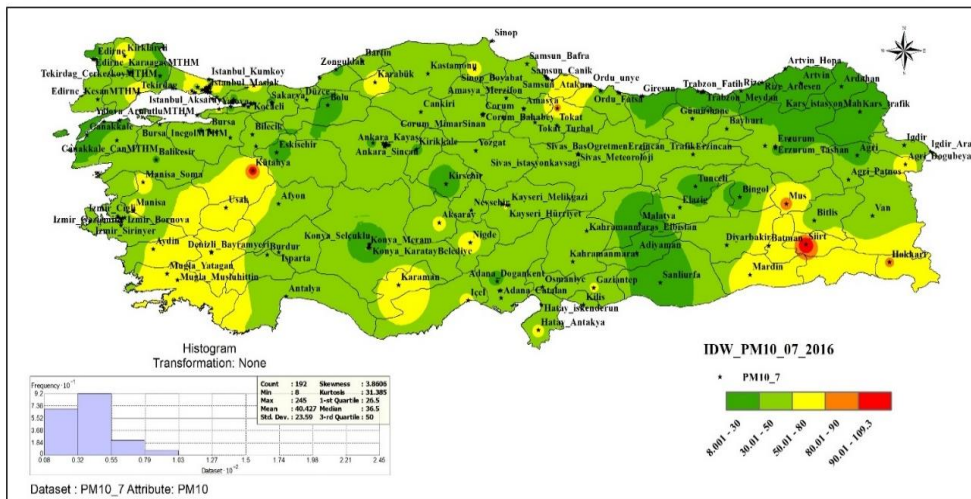


Figure 4.31: Spatial analysis of PM₁₀ in July 2016 by applying IDW model

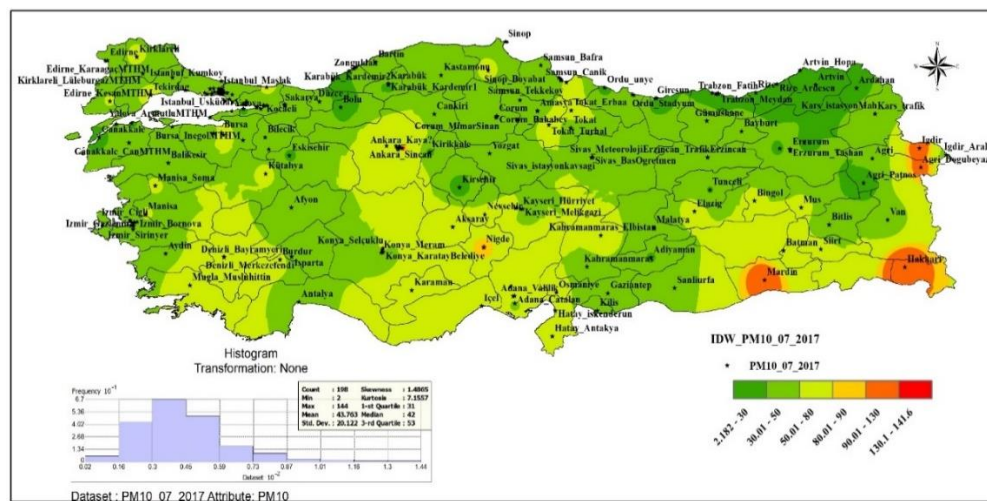


Figure 4.32: Spatial analysis of PM₁₀ in July 2017 by applying IDW model

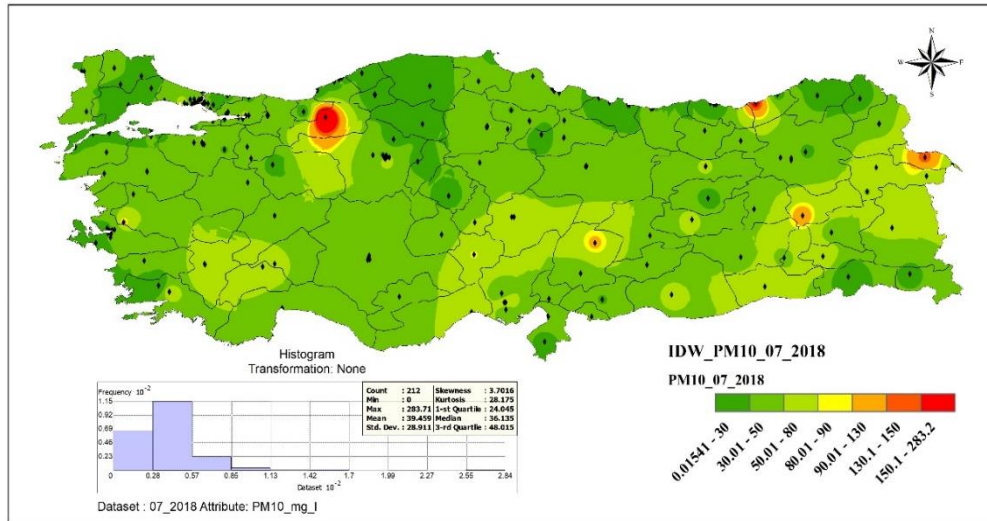


Figure 4. 33: Spatial analysis of PM₁₀ in July 2018 by applying IDW model

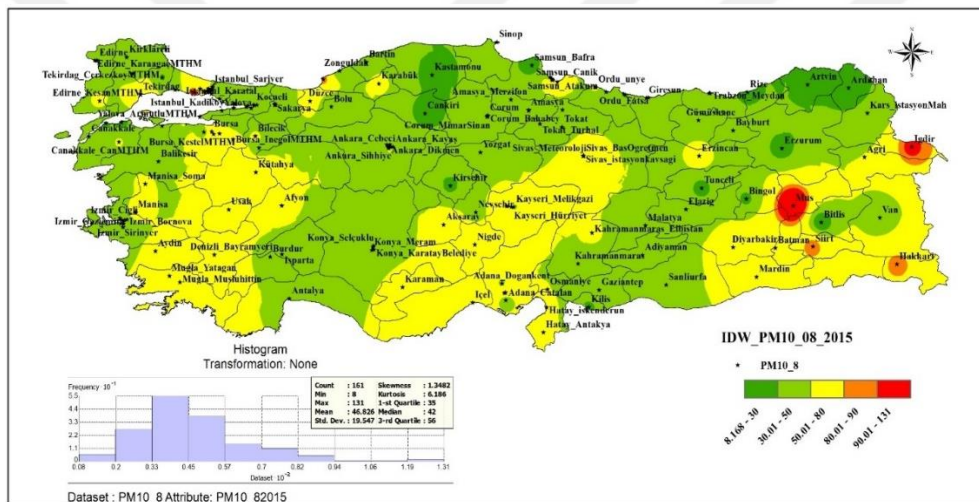


Figure 4. 34: Spatial analysis of PM₁₀ in August 2015 by applying IDW model

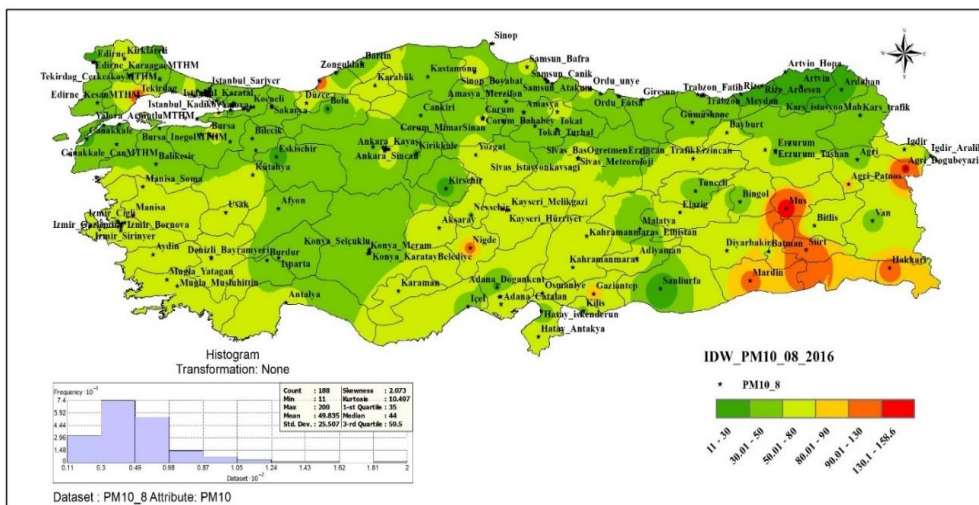


Figure 4. 35: Spatial analysis of PM₁₀ in August 2016 by applying IDW model

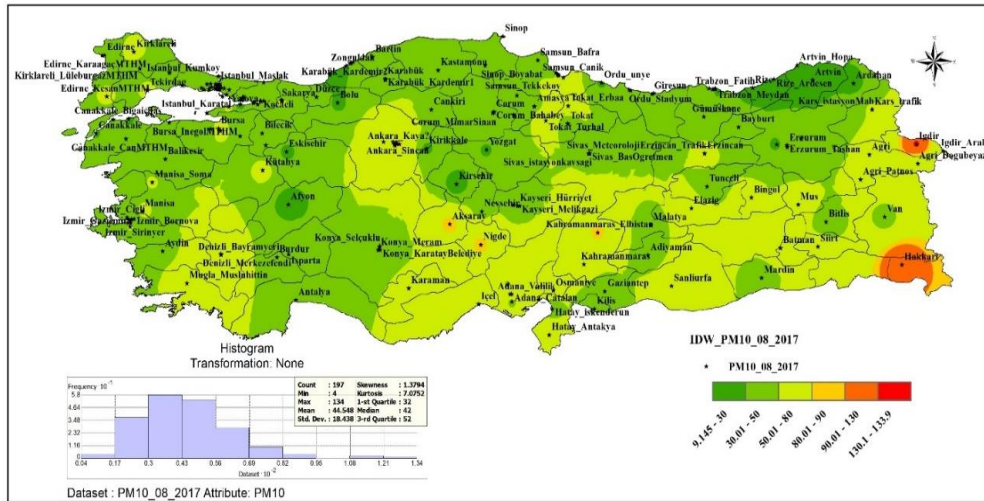


Figure 4. 36: Spatial analysis of PM₁₀ in August 2017 by applying IDW model

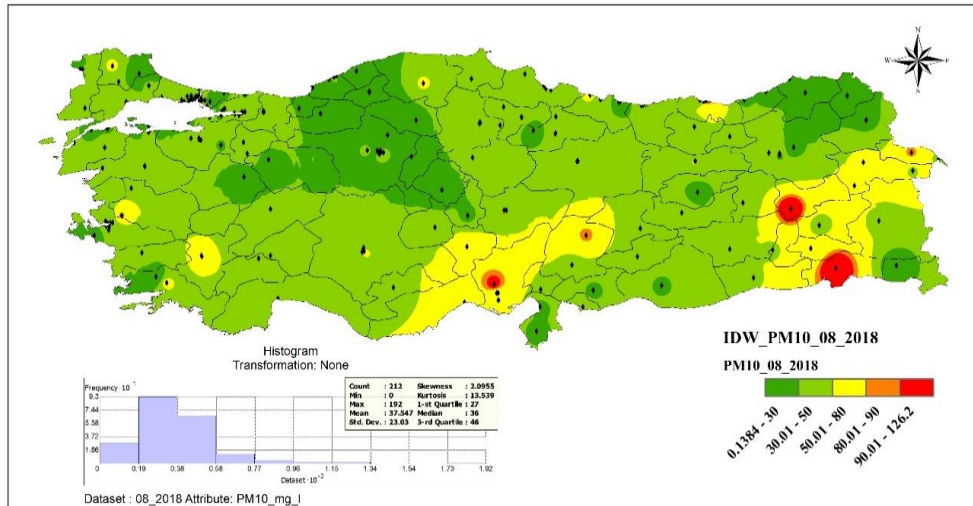


Figure 4. 37: Spatial analysis of PM₁₀ in August 2018 by applying IDW model

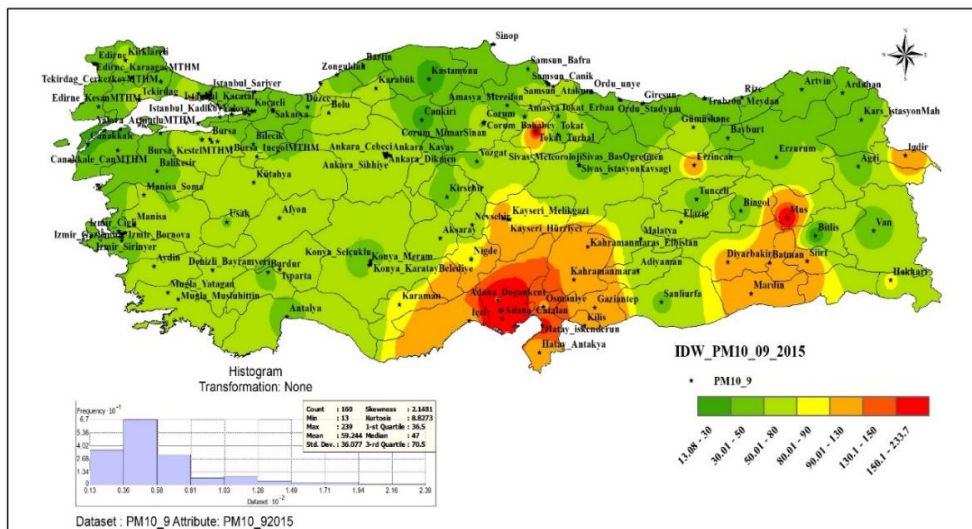


Figure 4. 38: Spatial analysis of PM₁₀ in September 2015 by applying IDW model

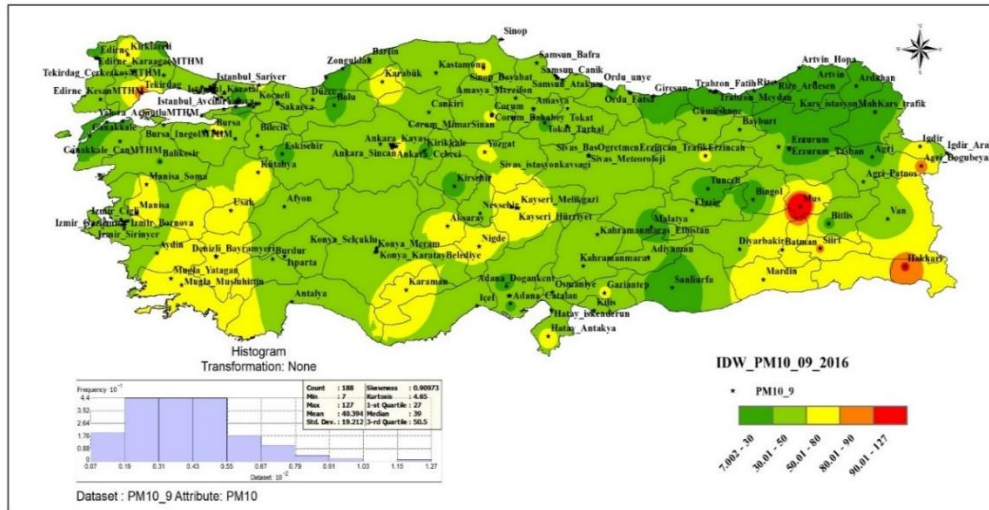


Figure 4. 39: Spatial analysis of PM₁₀ in September 2016 by applying IDW model

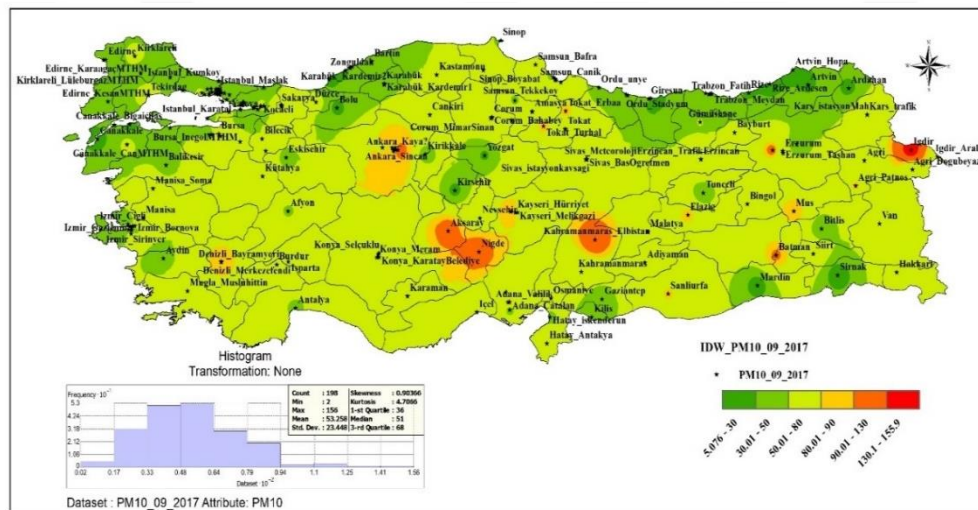


Figure 4. 40: Spatial analysis of PM₁₀ in September 2017 by applying IDW model

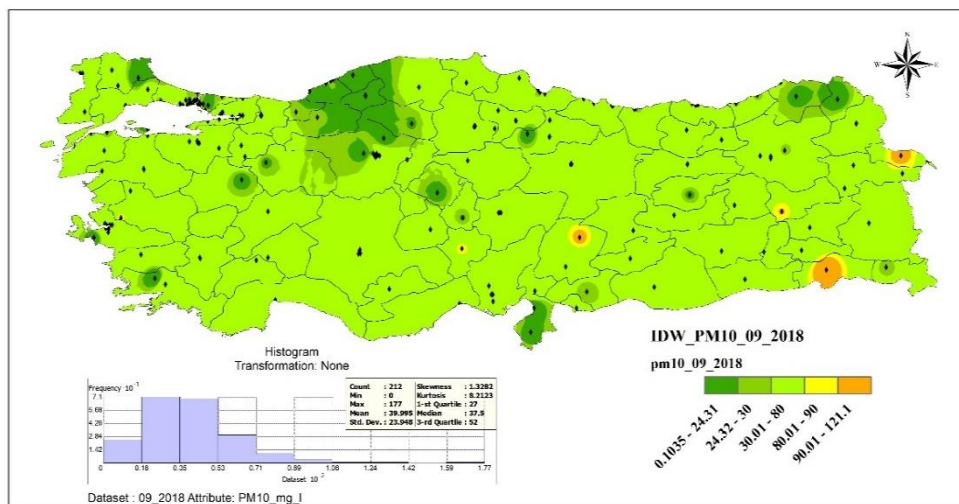


Figure 4. 41: Spatial analysis of PM₁₀ in September 2018 by applying IDW model

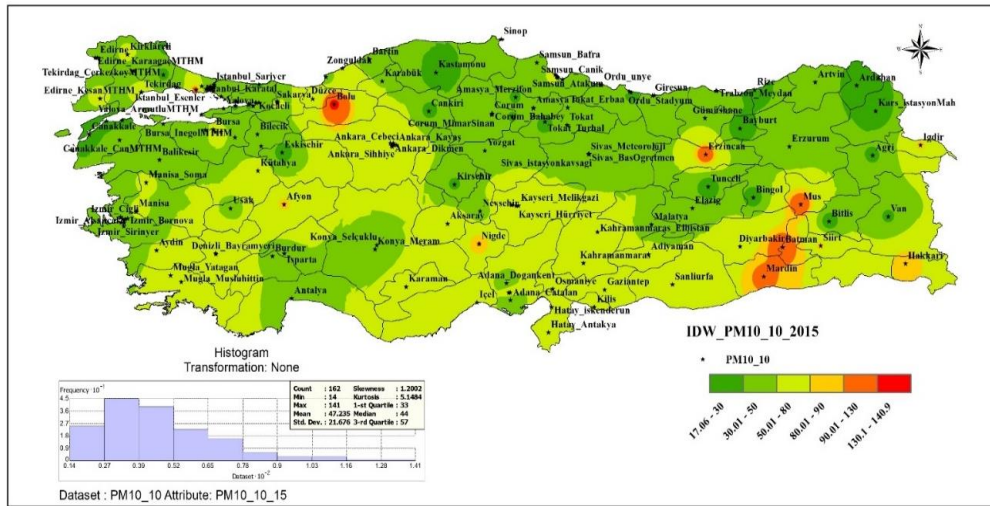


Figure 4. 42: Spatial analysis of PM₁₀ in October 2015 by applying IDW model

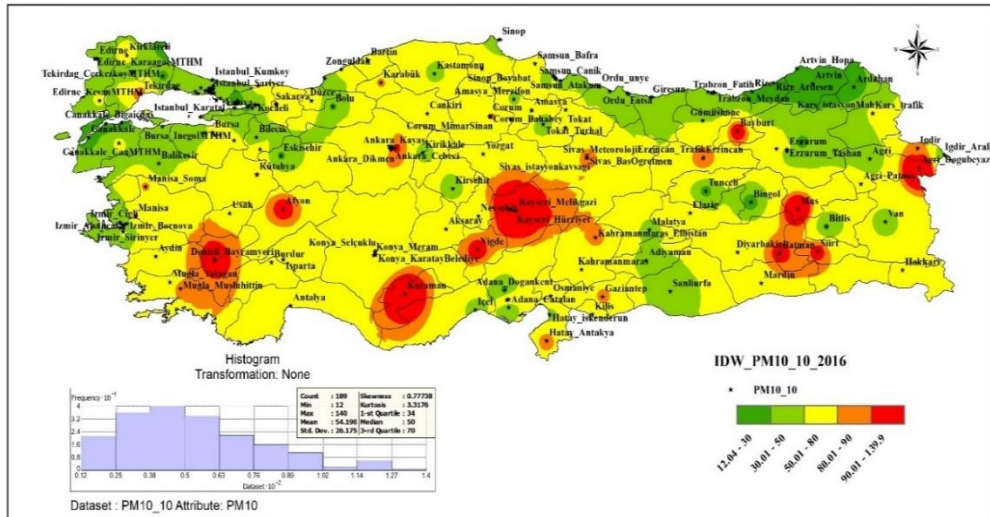


Figure 4. 43: Spatial analysis of PM₁₀ in October 2016 by applying IDW model

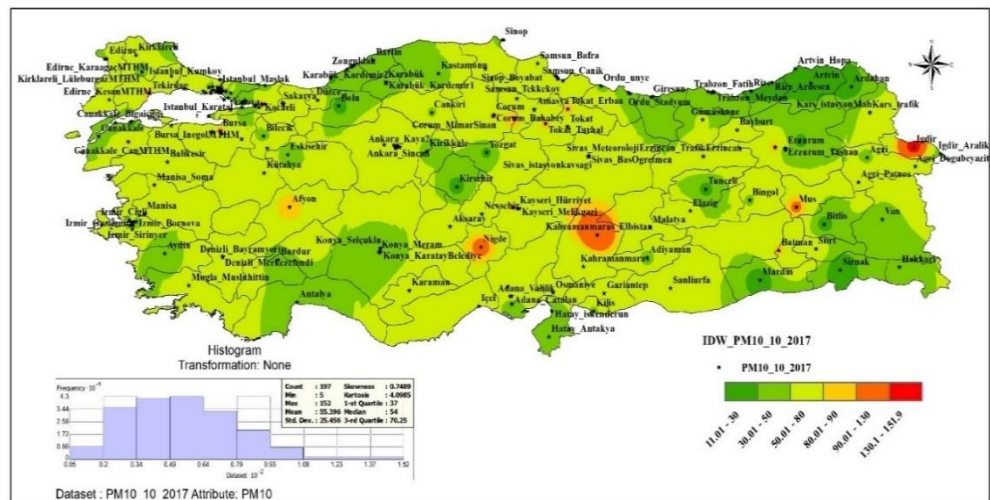


Figure 4. 44: Spatial analysis of PM₁₀ in October 2017 by applying IDW model

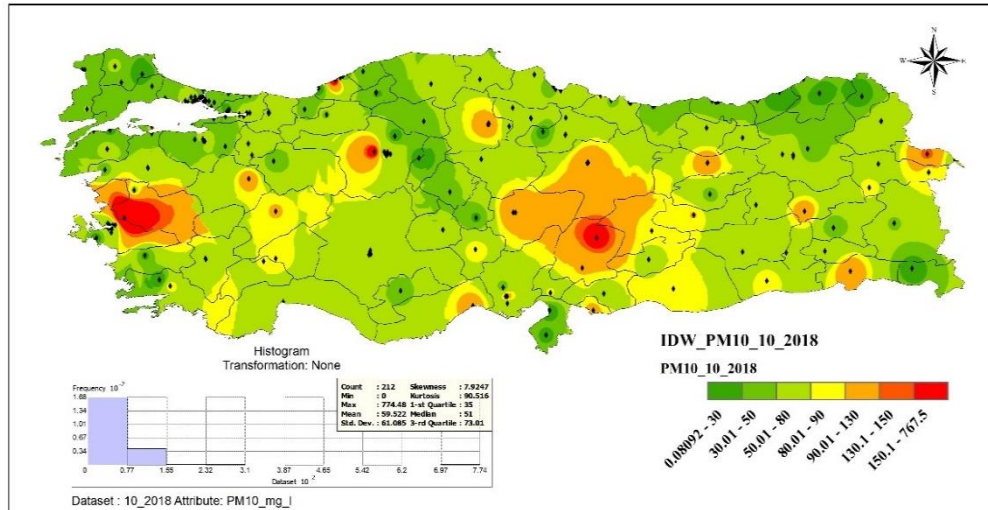


Figure 4. 45: Spatial analysis of PM₁₀ in November 2018 by applying IDW model

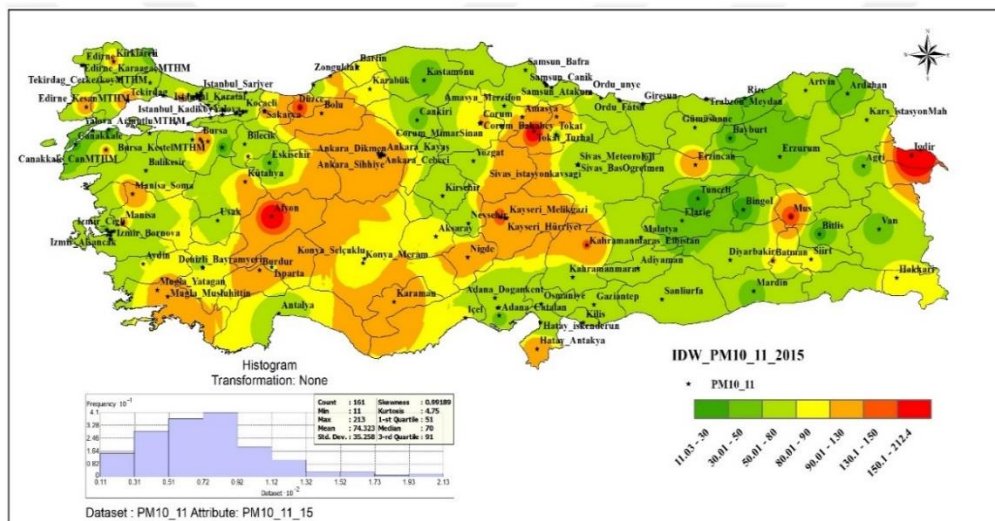


Figure 4. 46: Spatial analysis of PM₁₀ in November 2015 by applying IDW model

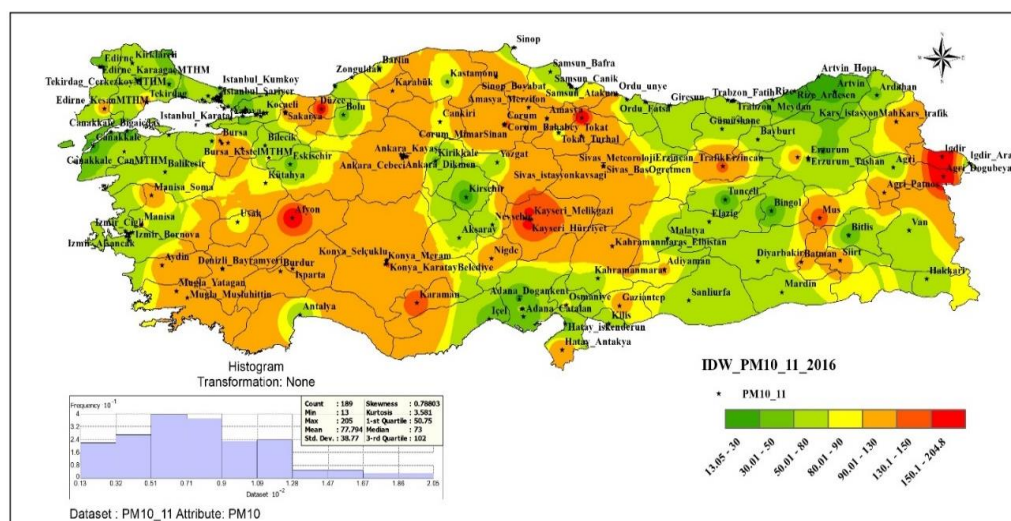


Figure 4. 47: Spatial analysis of PM₁₀ in November 2016 by applying IDW model

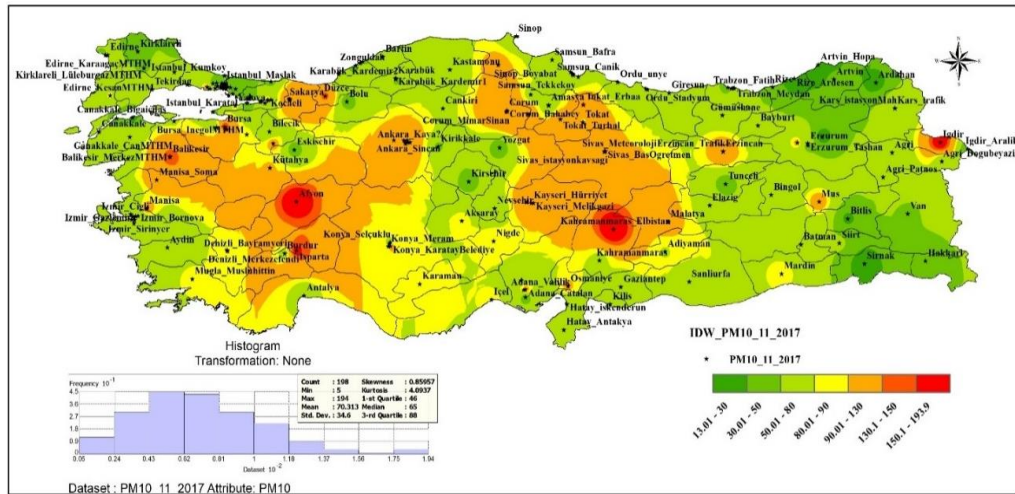


Figure 4. 48: Spatial analysis of PM₁₀ in November 2017 by applying IDW model

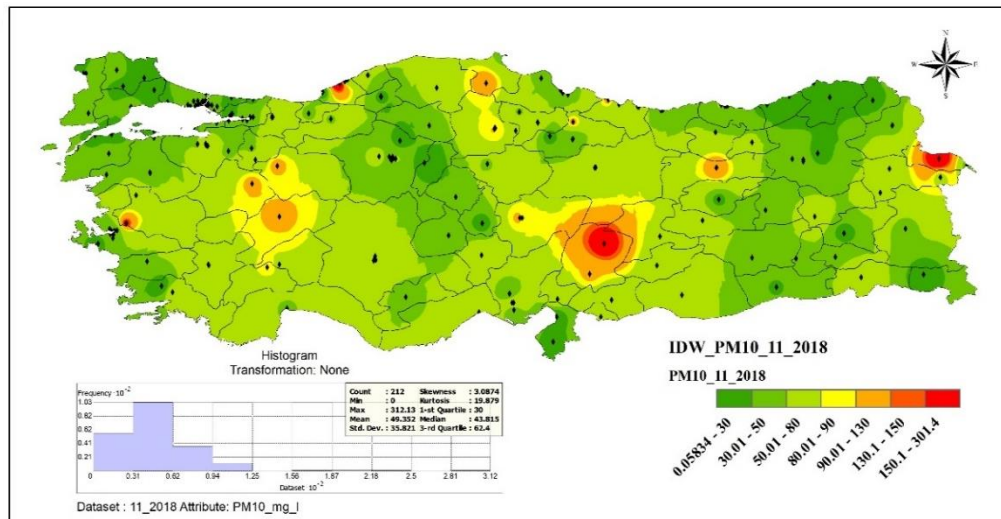


Figure 4. 49: Spatial analysis of PM₁₀ in November 2018 by applying IDW model

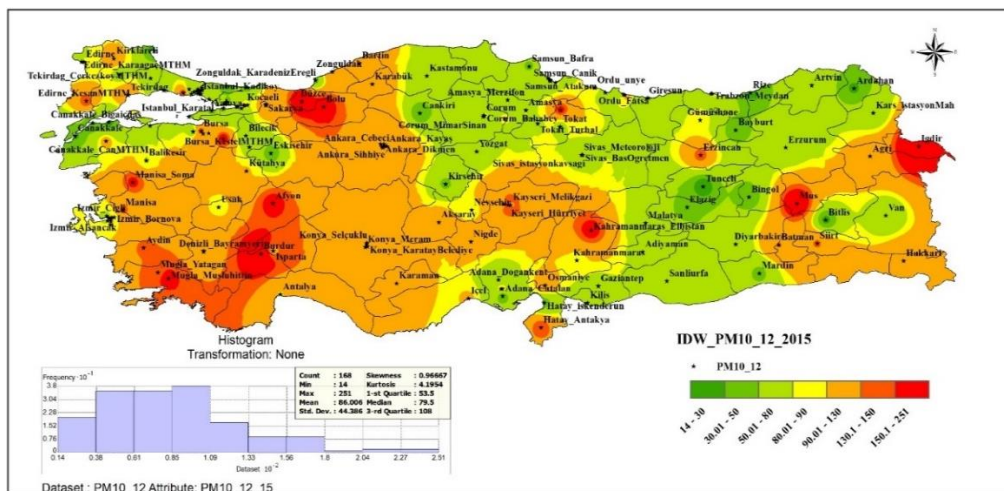


Figure 4. 50: Spatial analysis of PM₁₀ in December 2015 by applying IDW model

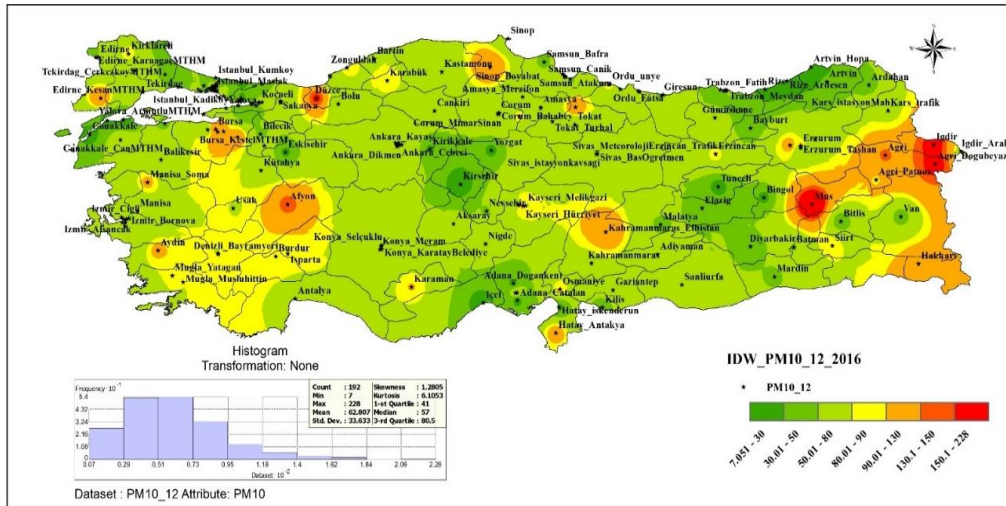


Figure 4. 51: Spatial analysis of PM₁₀ in December 2016 by applying IDW model

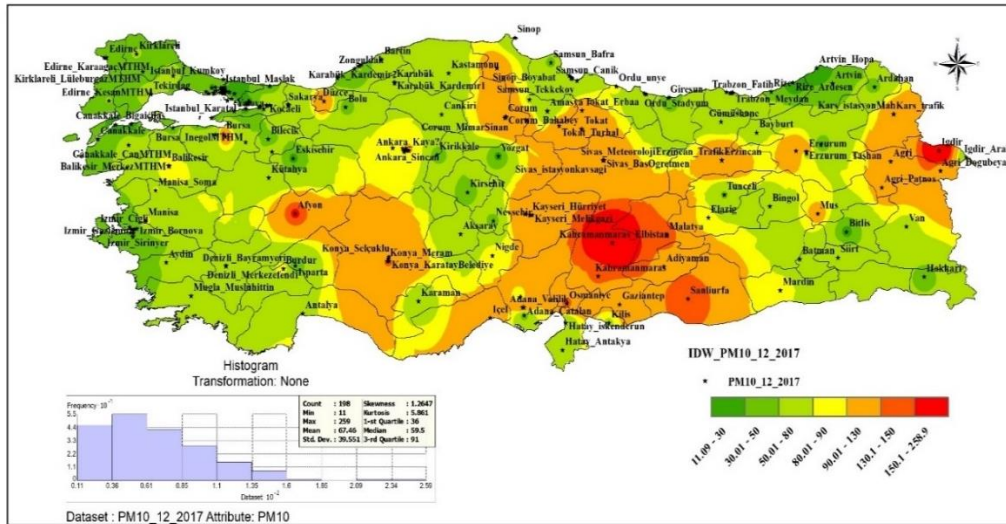


Figure 4. 52: Spatial analysis of PM₁₀ in December 2017 by applying IDW model

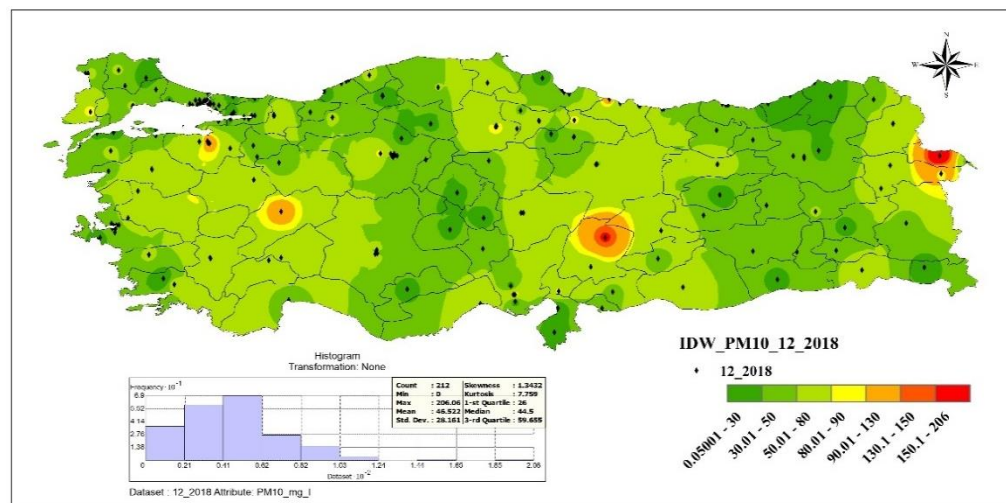


Figure 4. 53: Spatial analysis of PM₁₀ in December 2018 applying IDW model

4.3 The Spatial analysis of SO₂ during 2015-2018 by using IDW interpolation method

The atmospheric concentrations of SO₂ are generally very high in cities where coal use is common for home heating. There has been a tendency to decrease concentrations in time due to the use of different energy sources, which have developed technology and less pollution over time. Outdoor concentrations of SO₂ are generally high in central areas of the city and around industrial areas. When SO₂ is combined with particles present in exhaust gases, the inverse impacts on health are growing. By the usage of natural gas, the amount of SO₂ in the flue gas will be greatly reduced by air pollution. Natural gas produces very low particulate matter emissions. The biggest problem during the conversion to natural gas is the initial investment cost. However, natural gas is 20% cheaper than imported coal. Natural gas is known as an ideal fuel in the world because of its high efficiency and it is used in many different areas. For this reason, up to 80% of the existing public and private buildings must be immediately transformed into natural gas ([Ibrahimova 2013](#), [Ağbulut 2019](#), [Basoglu and Uzar 2019](#), [Baykara, Im et al. 2019](#), [Coady, Parry et al. 2019](#), [Erdin and Ozkaya 2019](#), [Feng, Wang et al. 2019](#), [Hosseini 2019](#), [Lanzi and Dellink 2019](#), [Oberschelp, Pfister et al. 2019](#), [Serebrisky and Wiznia 2019](#)).

The results were showing commonly, the concentrations of SO₂ increasing in winter months in most provinces of Turkey and approximately at the same stations especially in January, February, March, October, November and December because of consuming the fossil fuels in domestic heating in winter months, and decreasing in the summer months as shown in the figures 4.54 - 4.101, it is seen that the maximum value of SO₂ emissions reached to the range of 2015-2018 season in January 2015, 2016 and 2017 (501.9, 932.4 and 397 µg/m³, respectively), whereas in February 2015, 2016 and 2018 reached to (483.2, 627.9 and 449.2 µg/m³, respectively), while in March 2015, 2016 and 2018 reached to (450.2, 571 and 316.5 µg/m³, respectively) and in November 2015, 2017 and in December 2016 and 2018 reached to (560, 396.3, 344.4 and 326.5 µg/m³, respectively) all of these values of SO₂ found in Edirne-Keşan station except one of these in Şirnak station in January 2015. Also [Emre Özşahin \(2016\)](#) observed the SO₂ rate 2746 µg/m³ in Edirne-Keşan city was much higher than the guideline standard value, and the major contaminant of air is gas originating from the heating systems in which bad quality

fuel is consumed. In addition, it has been determined that the city has climatic and particularly topographic conditions driving to air pollution. In the region where there are mostly workshop type industrial facilities, there are industrial establishments, flour factory and automobile repairers. These facilities, which have a small increase in air pollution, are becoming more effective due to the city's topographic and climatic conditions. Therefore, it is thought that the industrial facilities established in the city center should be taken out of the city considering the prevailing wind direction and topographic conditions. Additionally, morphoclimatic conditions must be taken into consideration especially in the chosen of new industrial plants and filters should be installed in the chimneys of all existing and new industrial facilities in the city and necessary inspections should be made.

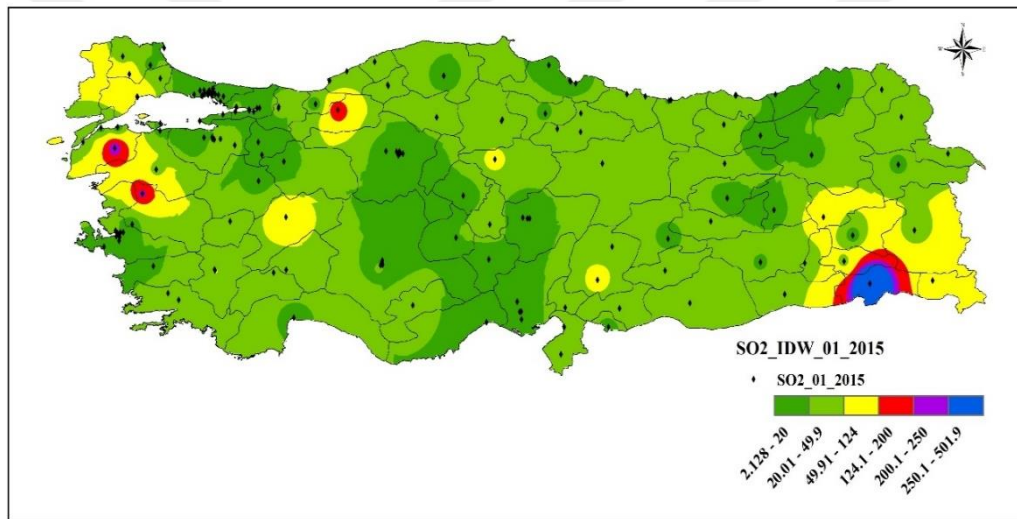


Figure 4. 54: Spatial analysis of SO₂ in January 2015 by applying IDW model

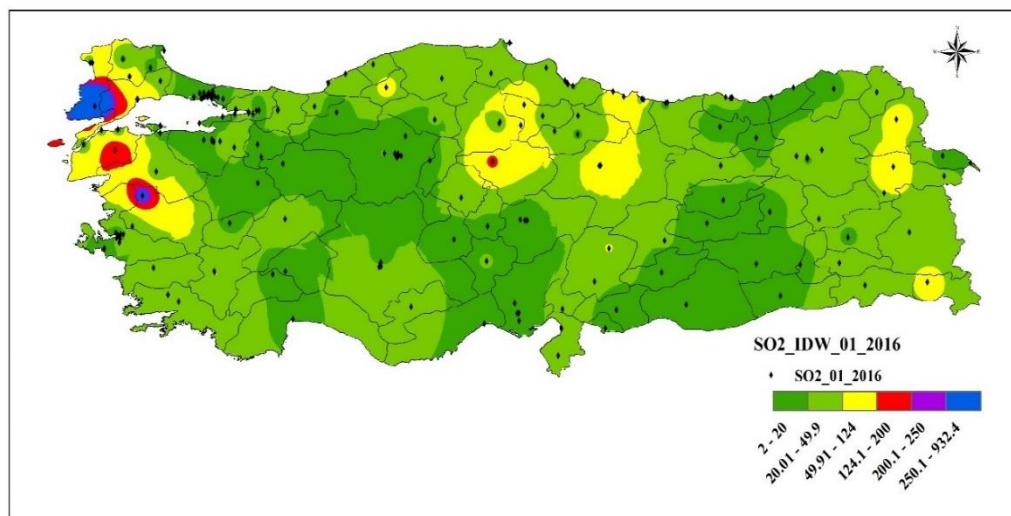


Figure 4. 55: Spatial analysis of SO₂ in January 2016 by applying IDW model

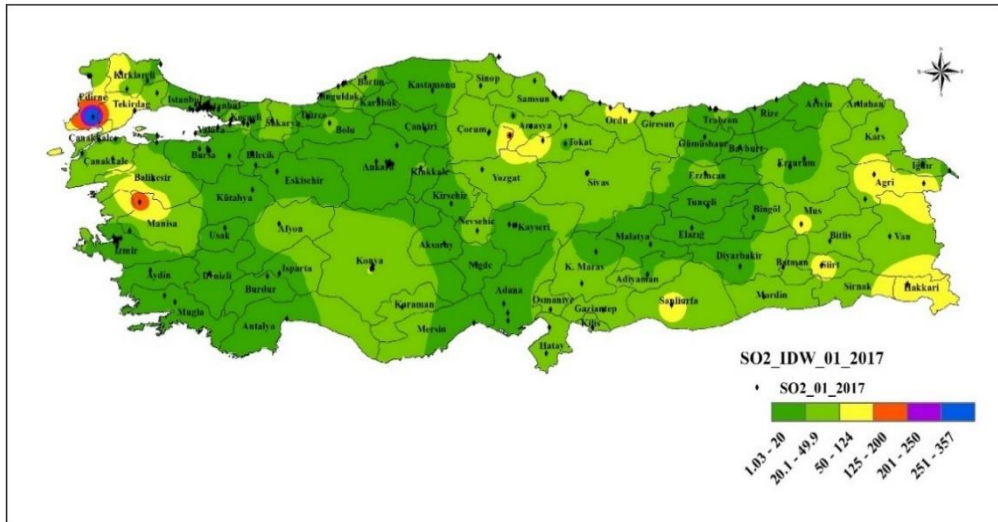


Figure 4. 56: Spatial analysis of SO₂ in January 2017 by applying IDW model

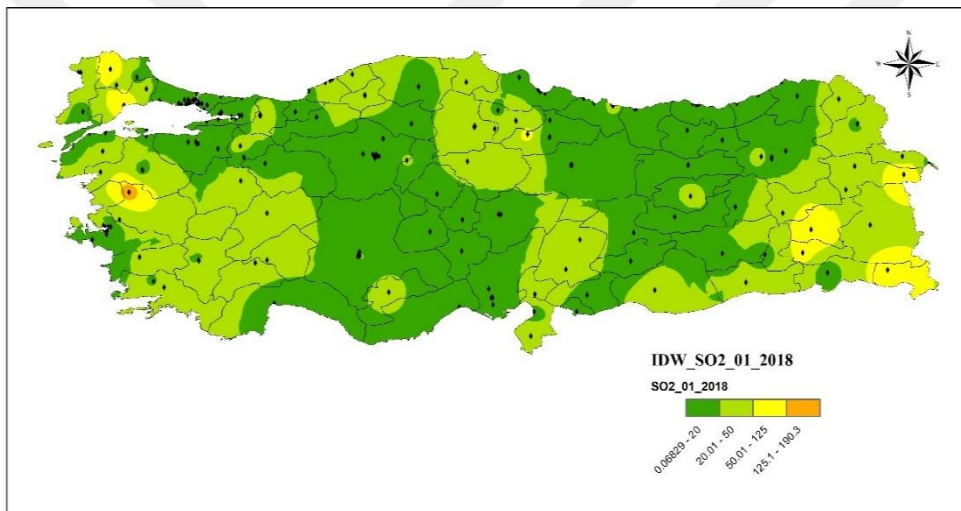


Figure 4. 57: Spatial analysis of SO₂ in January 2018 by applying IDW model

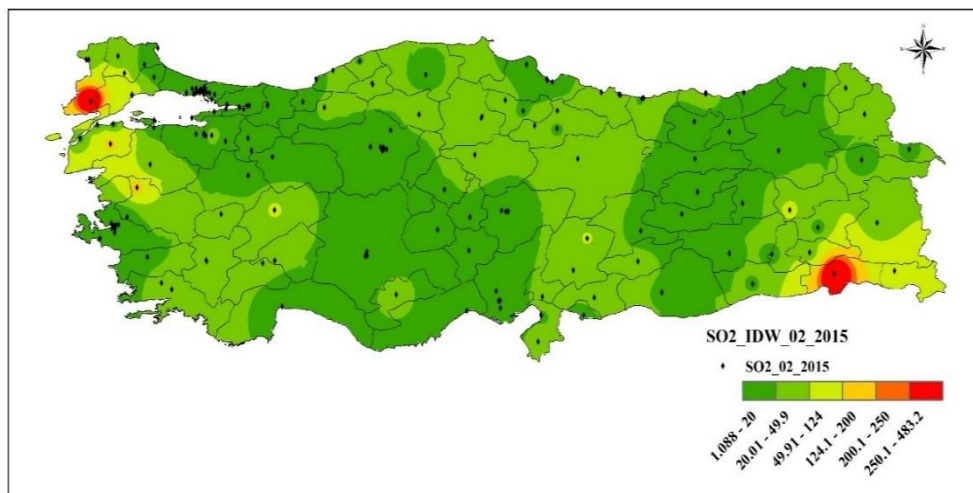


Figure 4. 58: Spatial analysis of SO₂ in February 2015 by applying IDW model

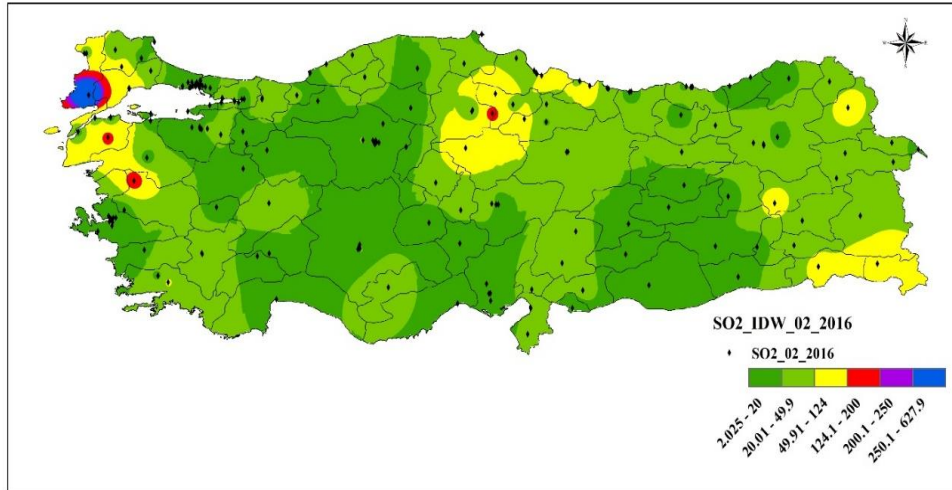


Figure 4. 59: Spatial analysis of SO₂ in February 2016 by applying IDW model

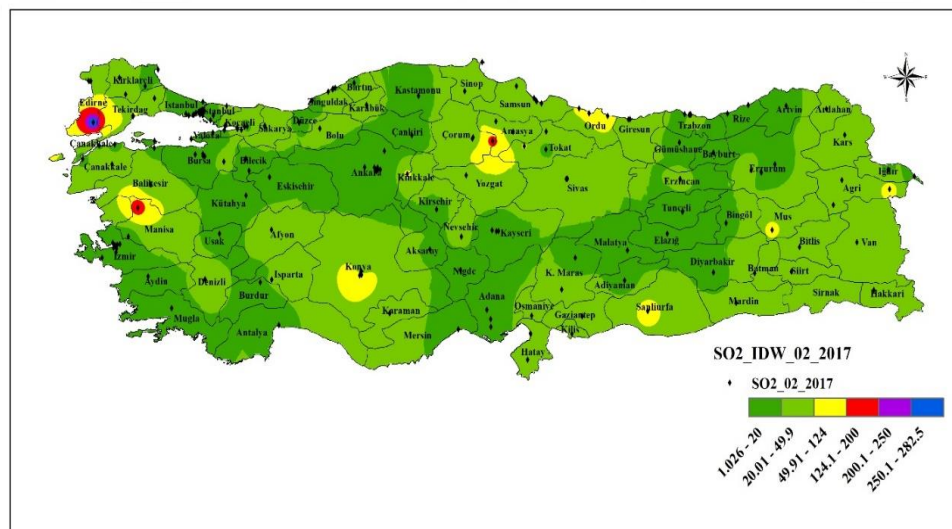


Figure 4. 60: Spatial analysis of SO₂ in February 2017 by applying IDW model

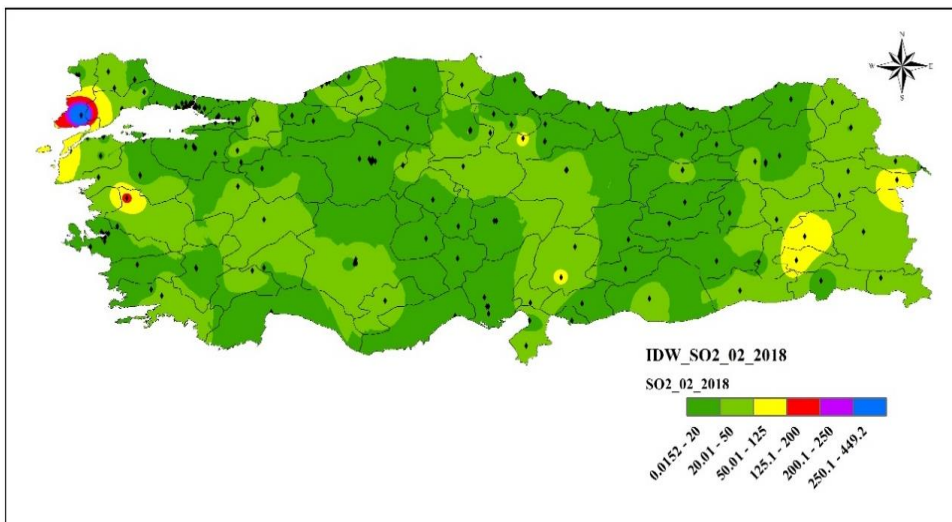


Figure 4. 61: Spatial analysis of SO₂ in February 2018 by applying IDW model

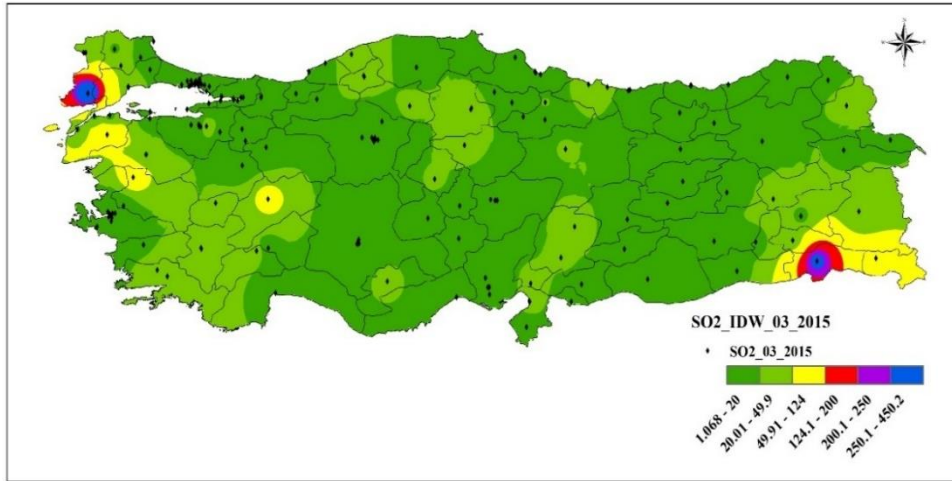


Figure 4. 62: Spatial analysis of SO₂ in March 2015 by applying IDW model

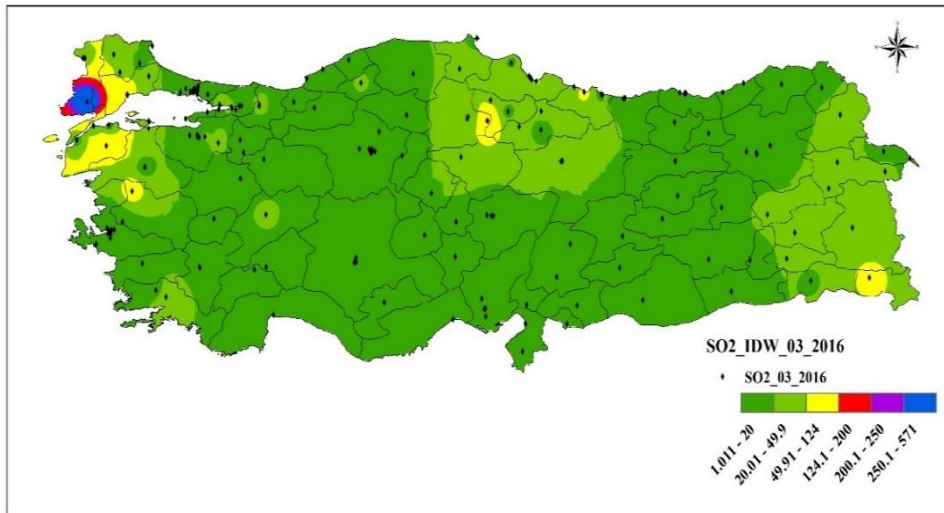


Figure 4. 63: Spatial analysis of SO₂ in March 2016 by applying IDW model

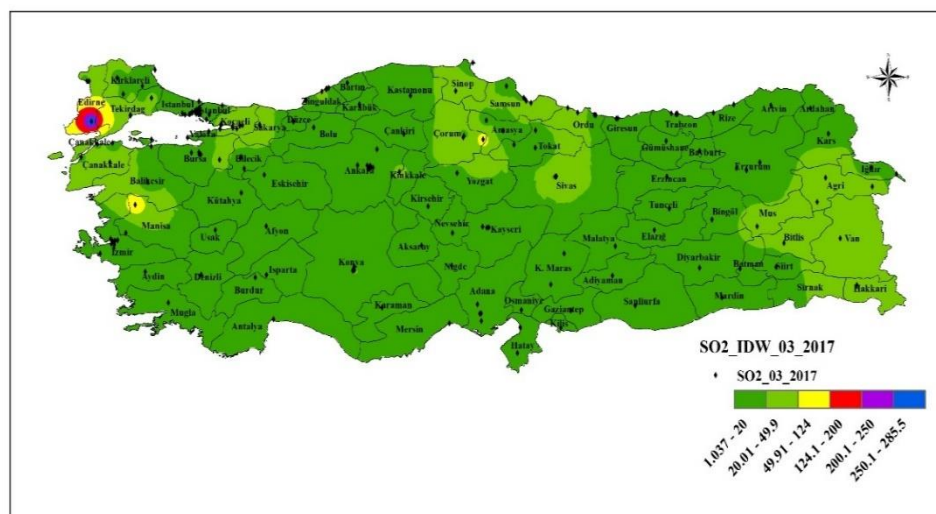


Figure 4. 64: Spatial analysis of SO₂ in March 2017 by applying IDW model

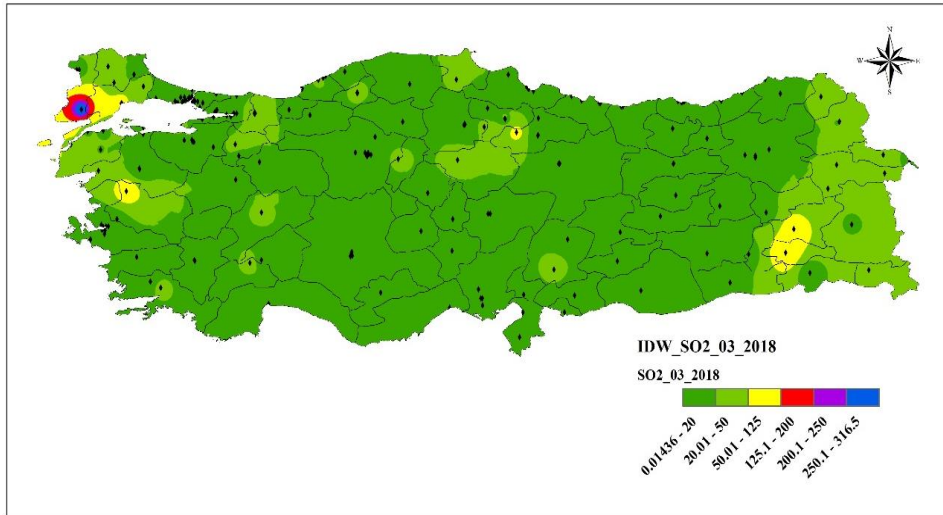


Figure 4. 65: Spatial analysis of SO₂ in March 2018 by applying IDW model

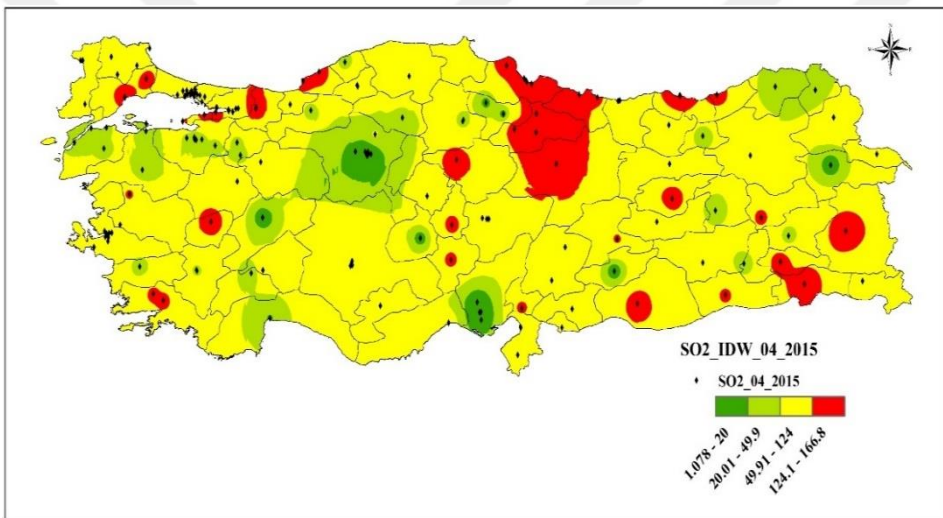


Figure 4. 66: Spatial analysis of SO₂ in April 2015 by applying IDW model

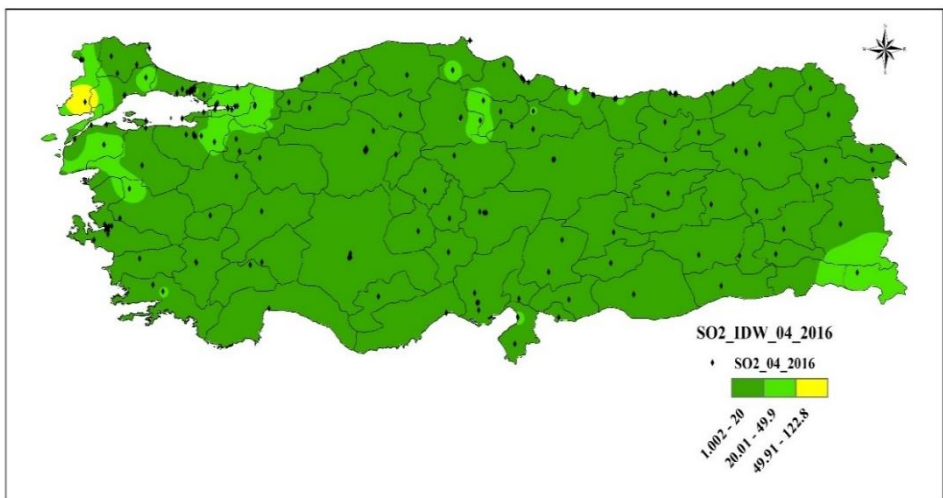


Figure 4. 67: Spatial analysis of SO₂ in April 2016 by applying IDW model

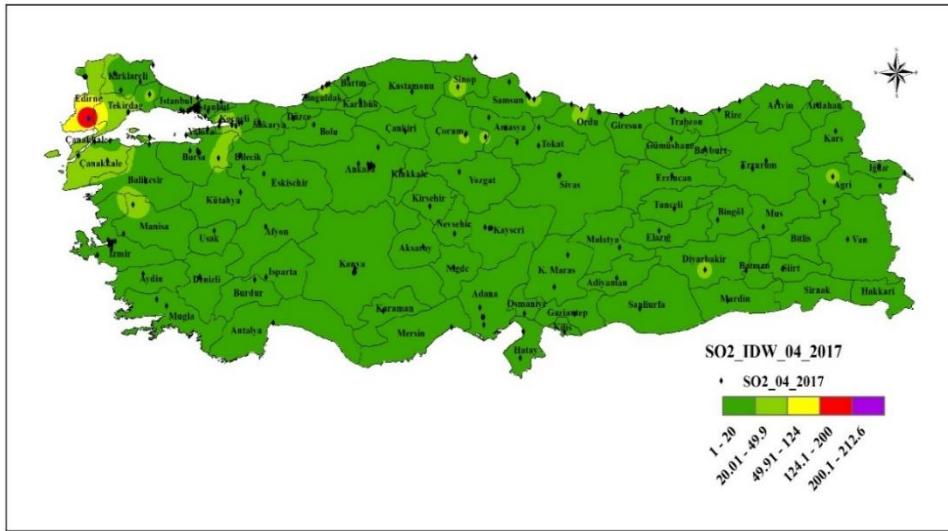


Figure 4. 68: Spatial analysis of SO₂ in April 2017 by applying IDW model

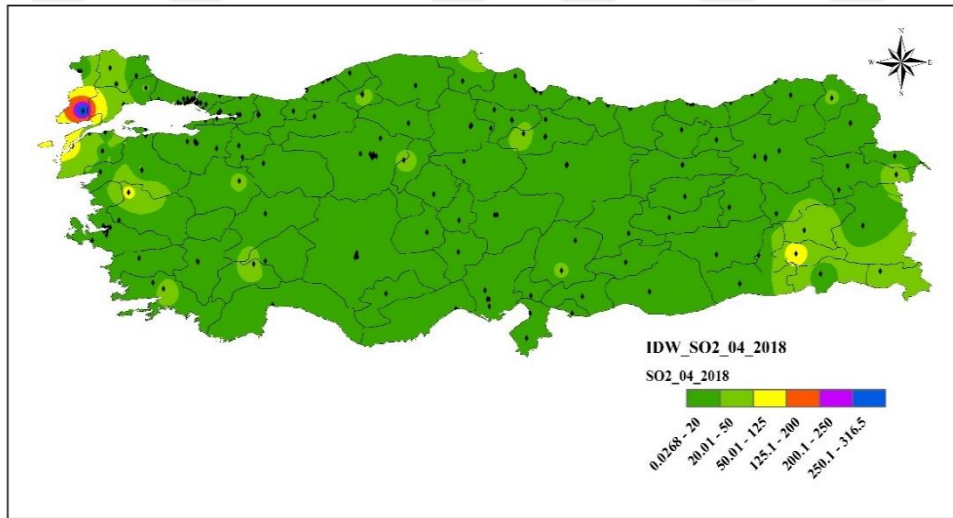


Figure 4. 69: Spatial analysis of SO₂ in April 2018 by applying IDW model

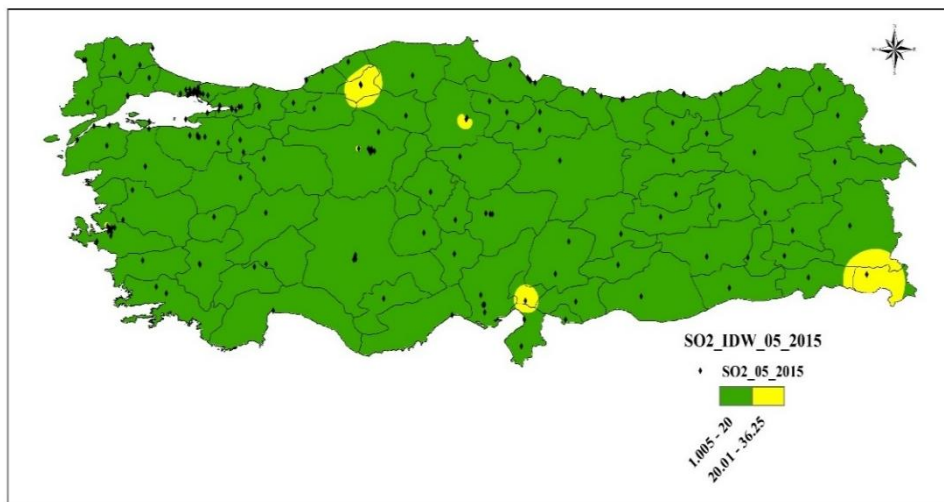


Figure 4. 70: Spatial analysis of SO₂ in May 2015 by applying IDW model

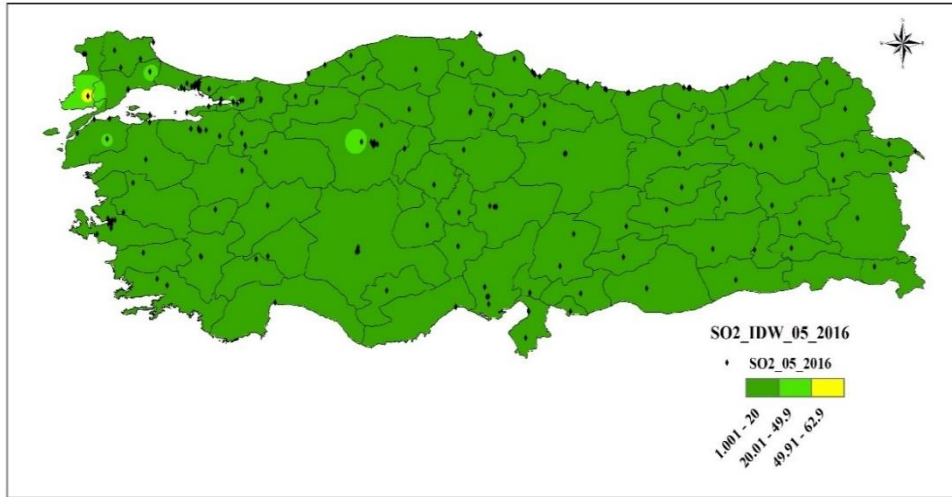


Figure 4. 71: Spatial analysis of SO₂ in May 2016 by applying IDW model

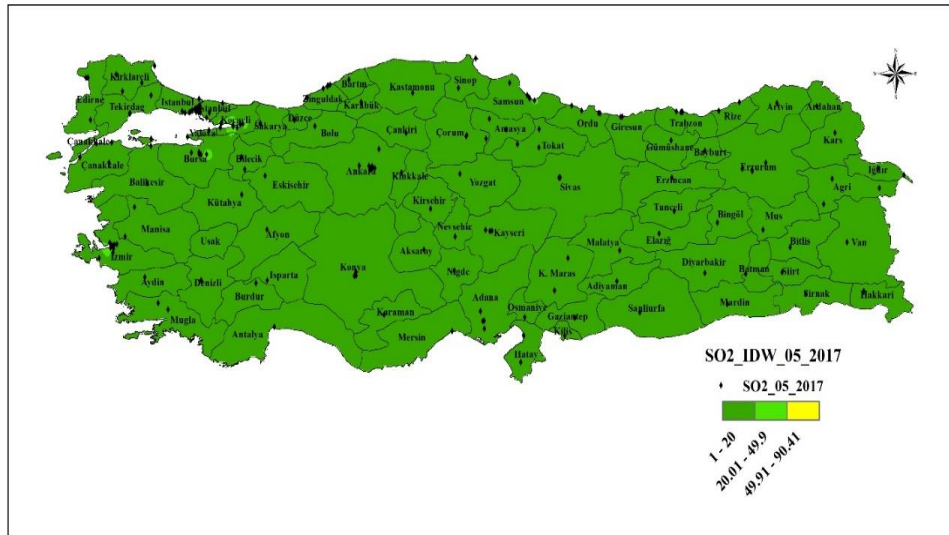


Figure 4. 72: Spatial analysis of SO₂ in May 2017 by applying IDW model

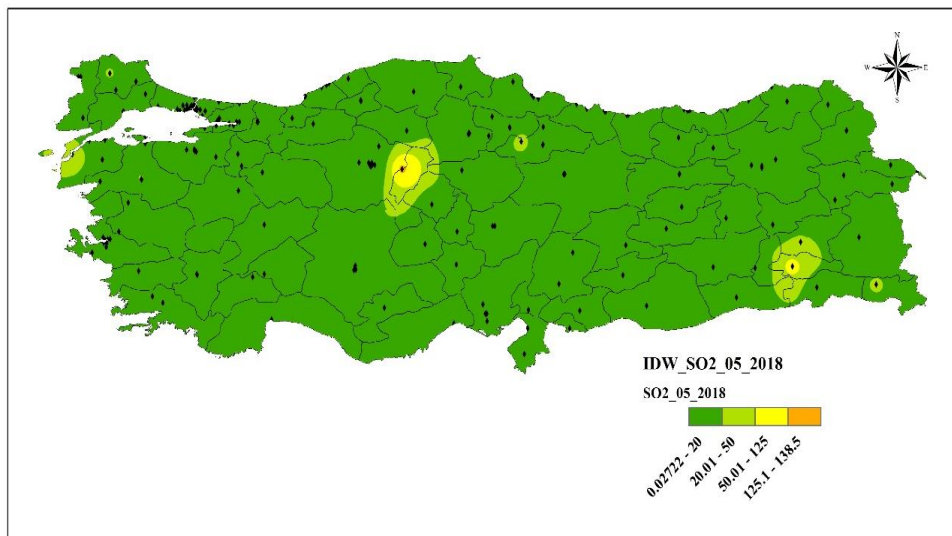


Figure 4. 73: Spatial analysis of SO₂ in May 2018 by applying IDW model

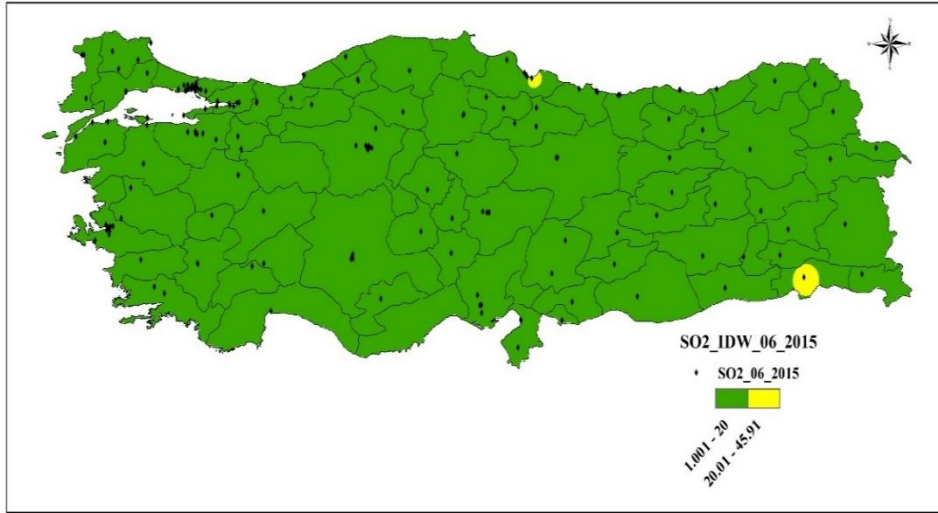


Figure 4. 74: Spatial analysis of SO₂ in June 2015 by applying IDW model

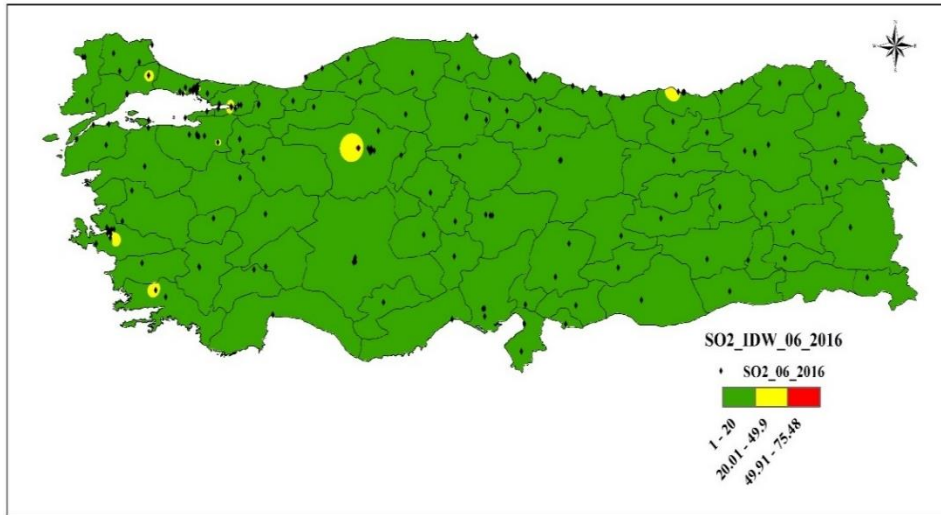


Figure 4. 75: Spatial analysis of SO₂ in June 2016 by applying IDW model

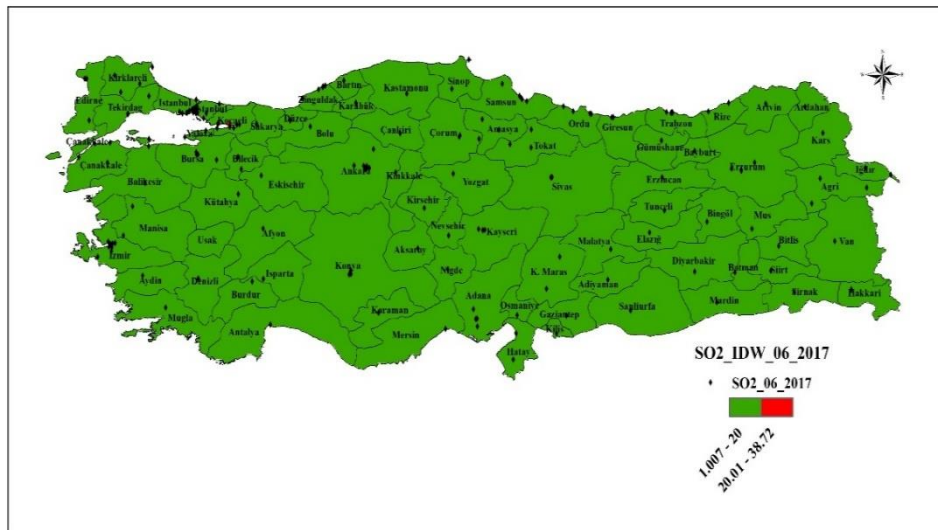


Figure 4. 76: Spatial analysis of SO₂ in June 2017 by applying IDW model

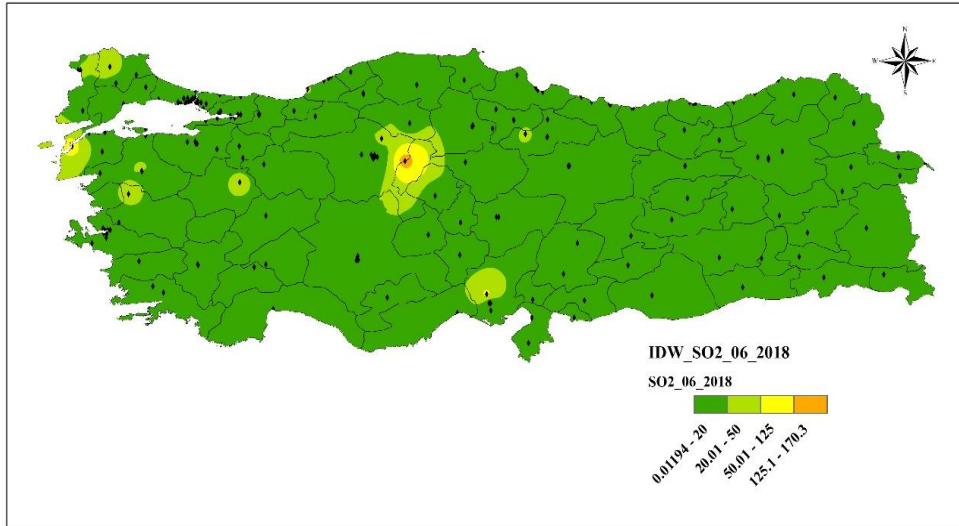


Figure 4. 77: Spatial analysis of SO₂ in June 2018 by applying IDW model

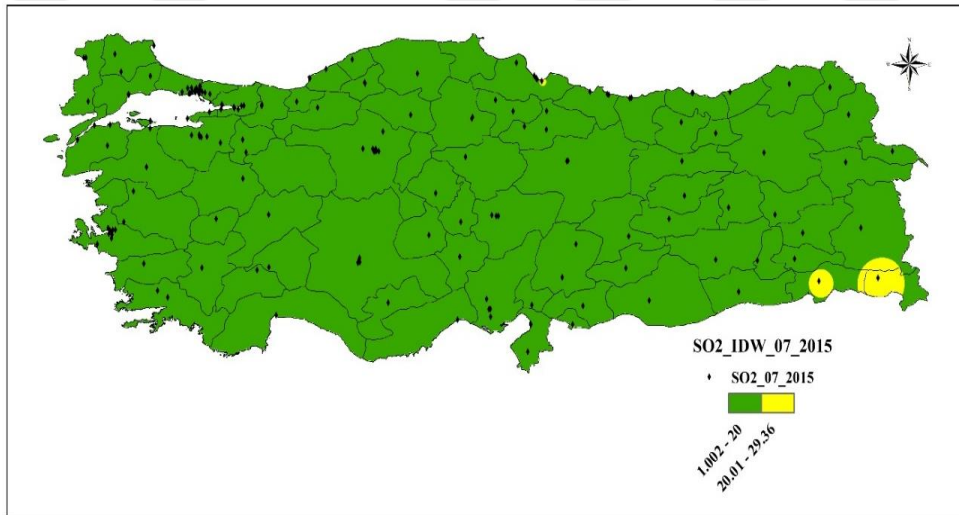


Figure 4. 78: Spatial analysis of PM₁₀ in July 2015 by applying IDW model

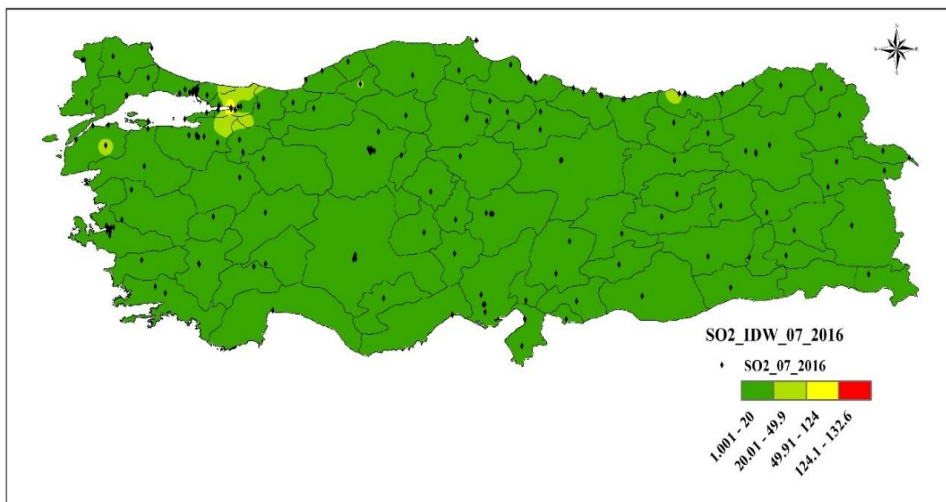


Figure 4. 79: Spatial analysis of SO₂ in July 2016 by applying IDW model

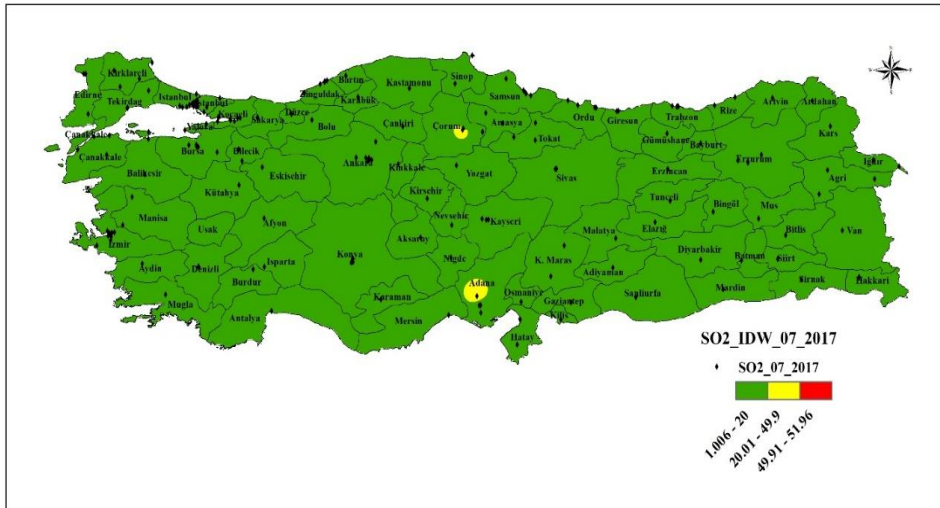


Figure 4. 80: Spatial analysis of SO₂ in July 2017 by applying IDW model

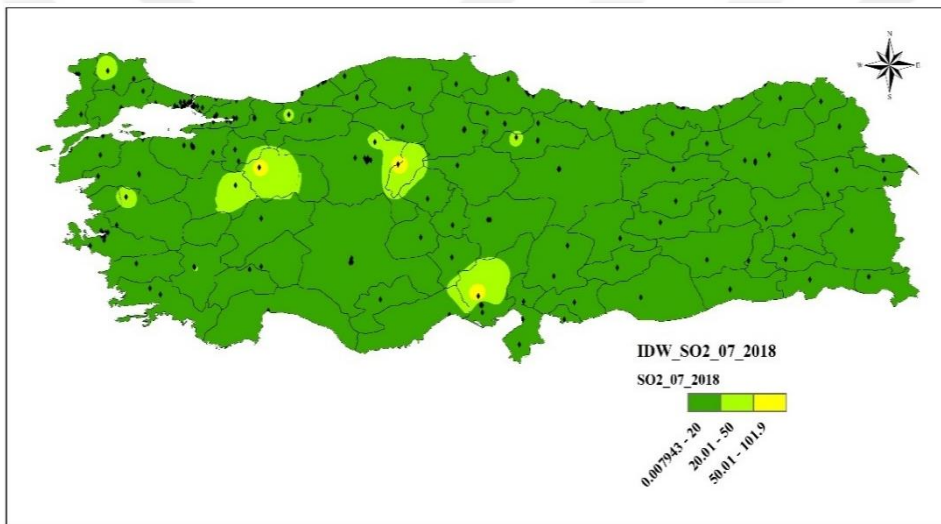


Figure 4. 81: Spatial analysis of SO₂ in July 2018 by applying IDW model

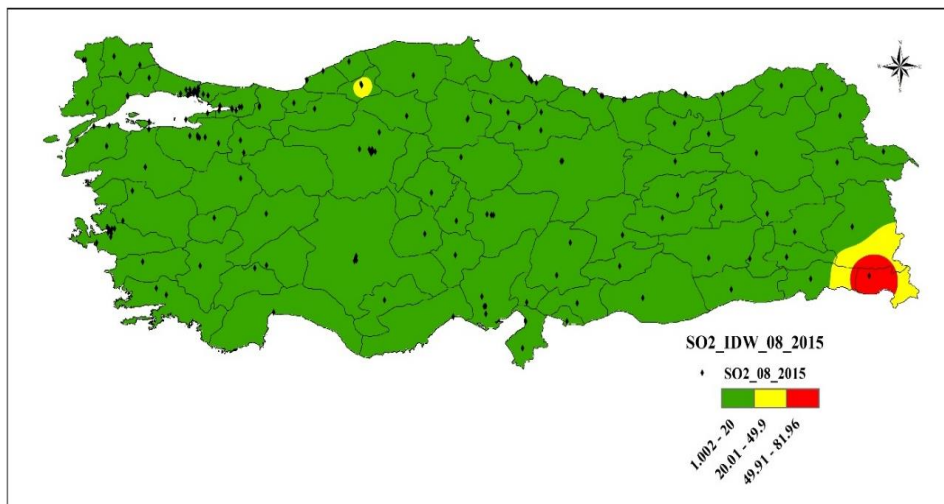


Figure 4. 82: Spatial analysis of SO₂ in August 2015 by applying IDW model

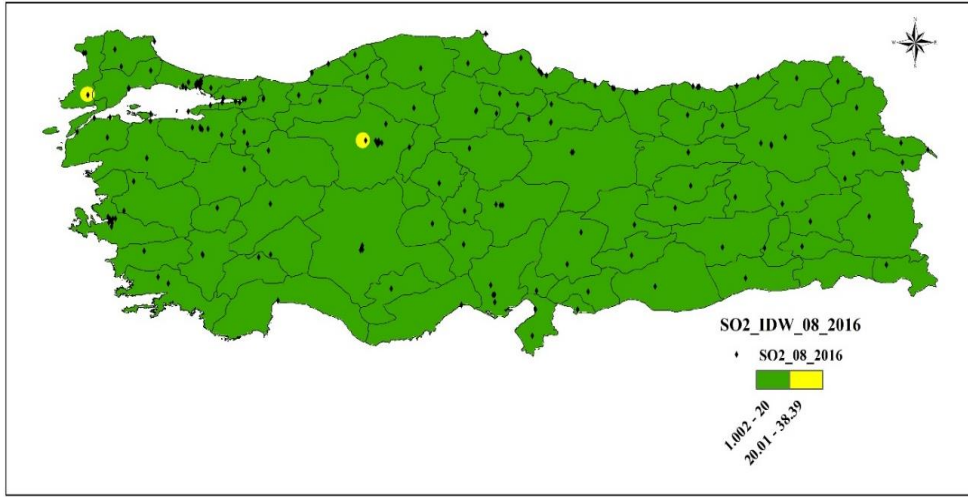


Figure 4. 83: Spatial analysis of SO₂ in Augusts 2016 by applying IDW model



Figure 4. 84: Spatial analysis of SO₂ in Augusts 2017 by applying IDW model

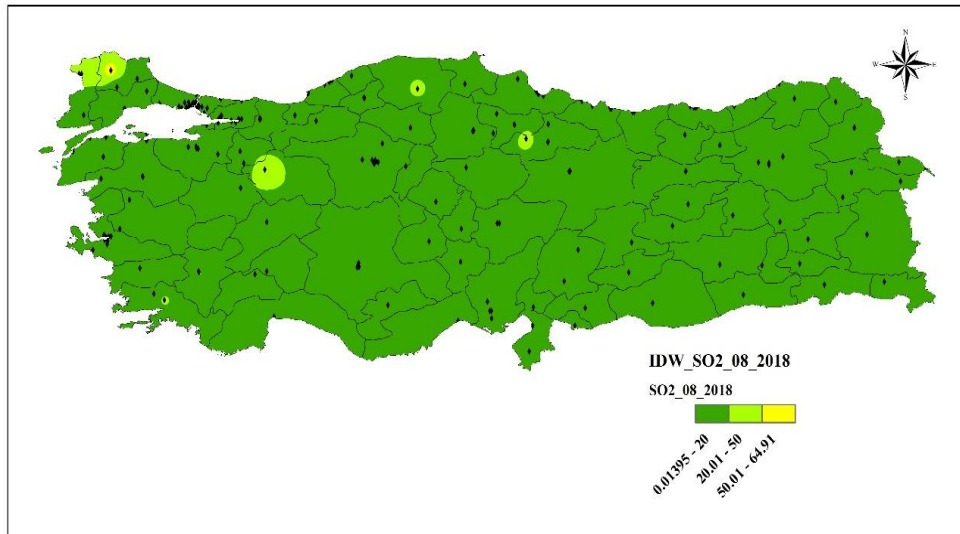


Figure 4. 85: Spatial analysis of SO₂ in Augusts 2018 by applying IDW model

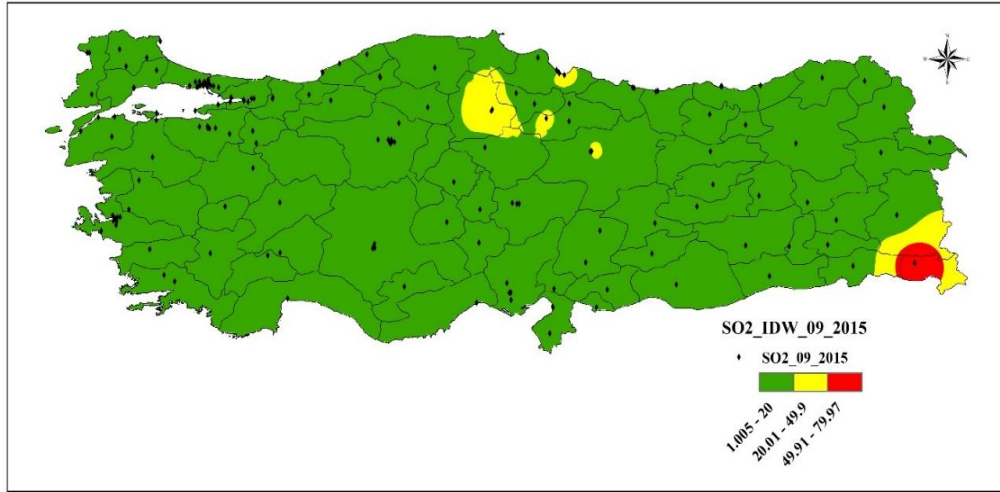


Figure 4. 86: Spatial analysis of SO₂ in September 2015 by applying IDW model

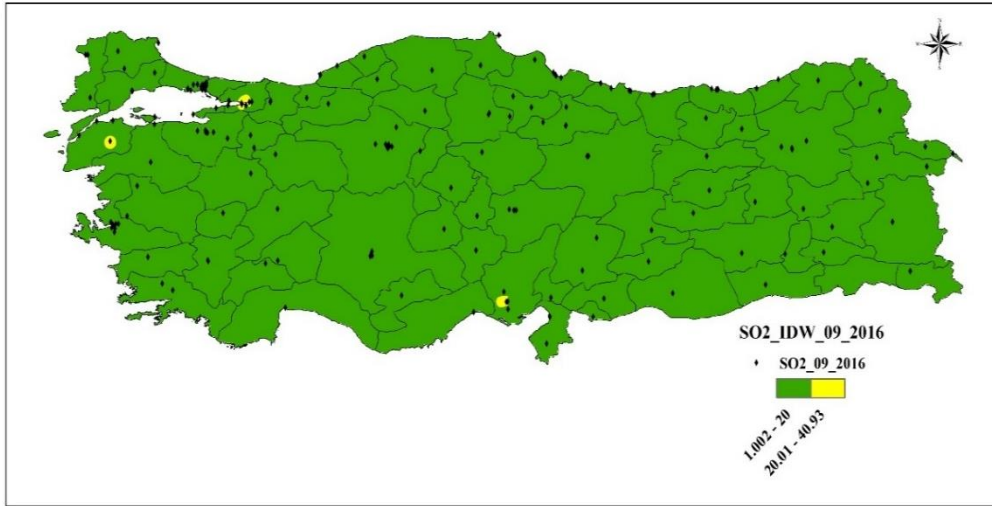


Figure 4. 87: Spatial analysis of SO₂ in September 2016 by applying IDW model



Figure 4. 88: Spatial analysis of SO₂ in September 2017 by applying IDW model

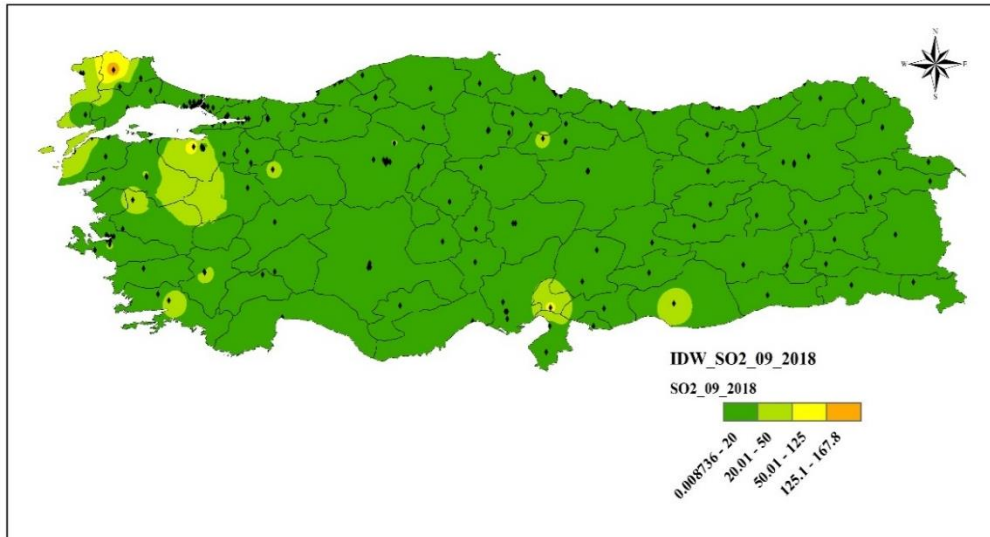


Figure 4. 89: Spatial analysis of SO₂ in September 2018 by applying IDW model

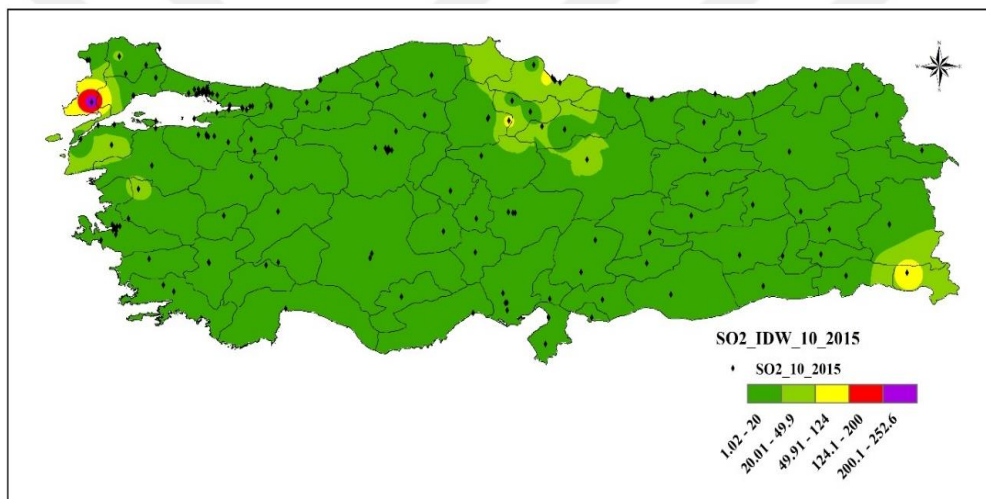


Figure 4. 90: Spatial analysis of SO₂ in October 2015 by applying IDW model

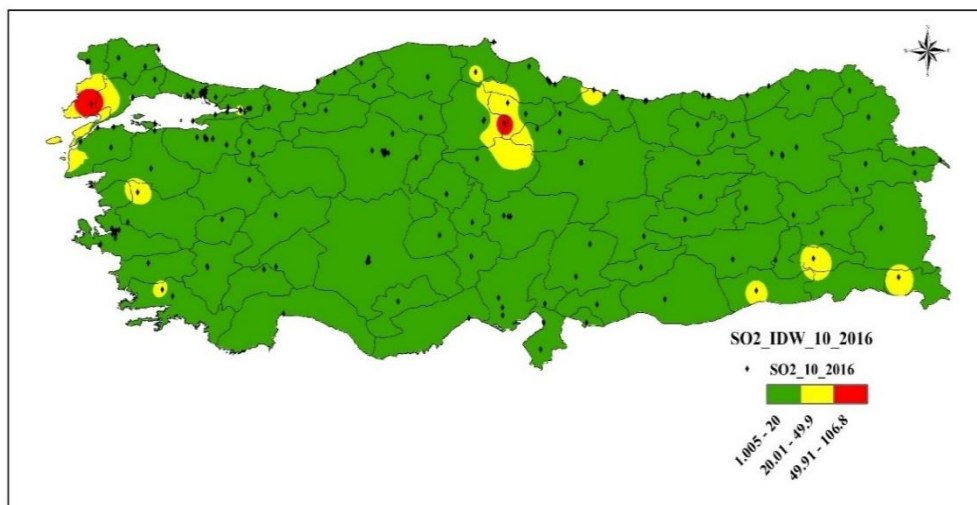


Figure 4. 91: Spatial analysis of SO₂ in October 2016 by applying IDW model

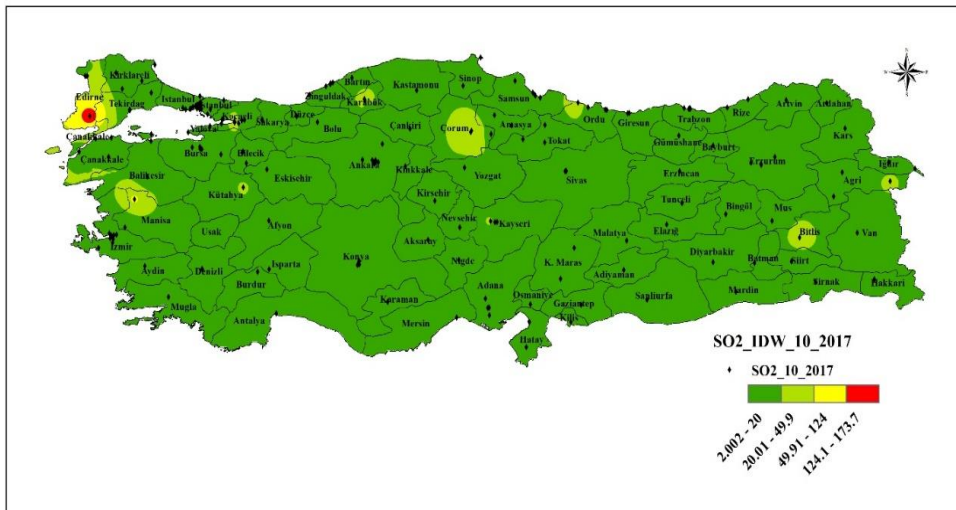


Figure 4. 92: Spatial analysis of SO₂ in October 2017 by applying IDW model

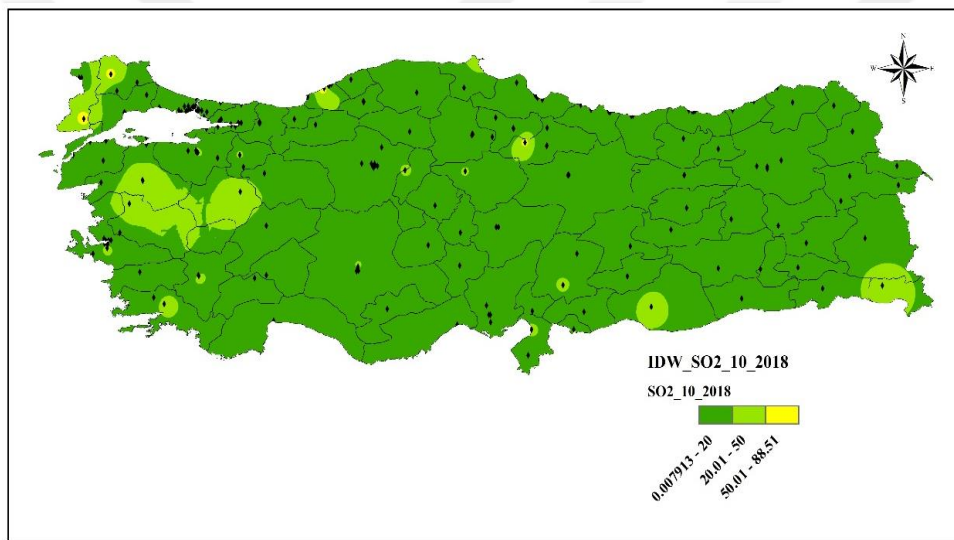


Figure 4. 93: Spatial analysis of SO₂ in October 2018 by applying IDW model

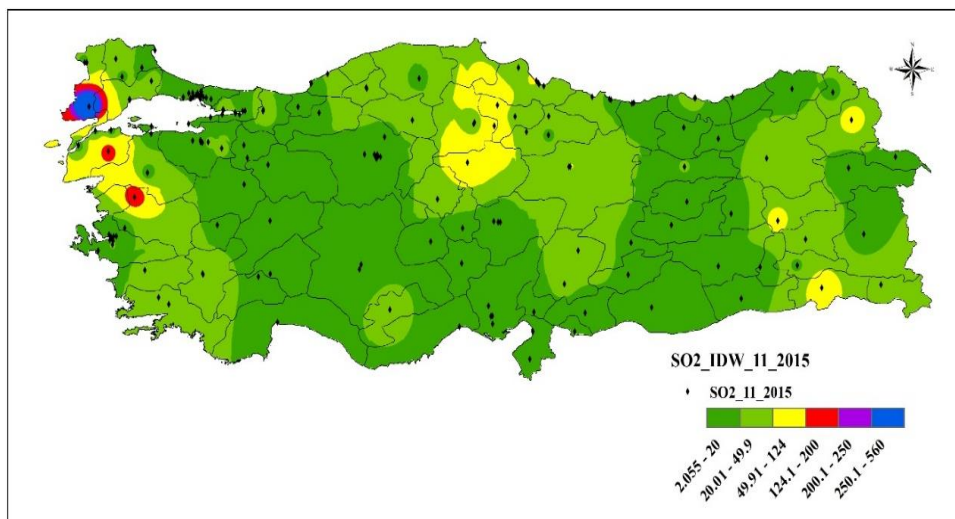


Figure 4. 94: Spatial analysis of SO₂ in November 2015 by applying IDW model

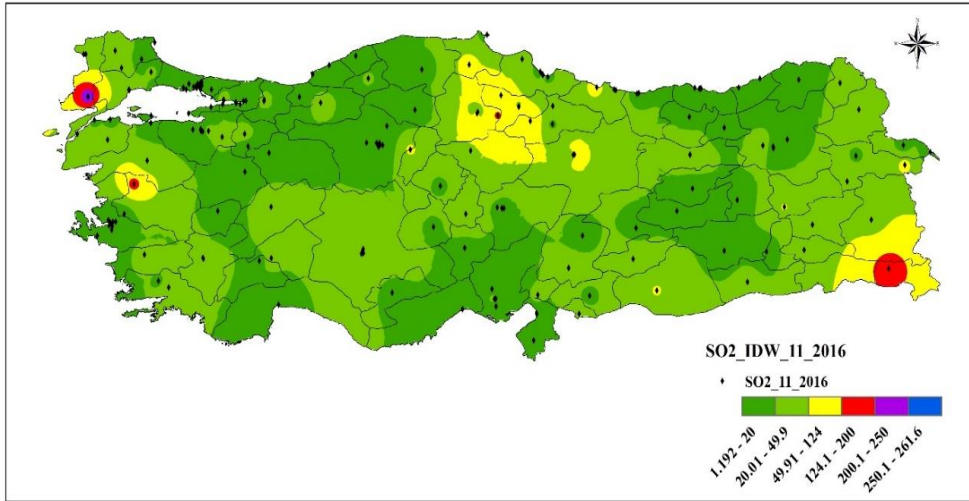


Figure 4. 95: Spatial analysis of SO₂ in November 2016 by applying IDW model

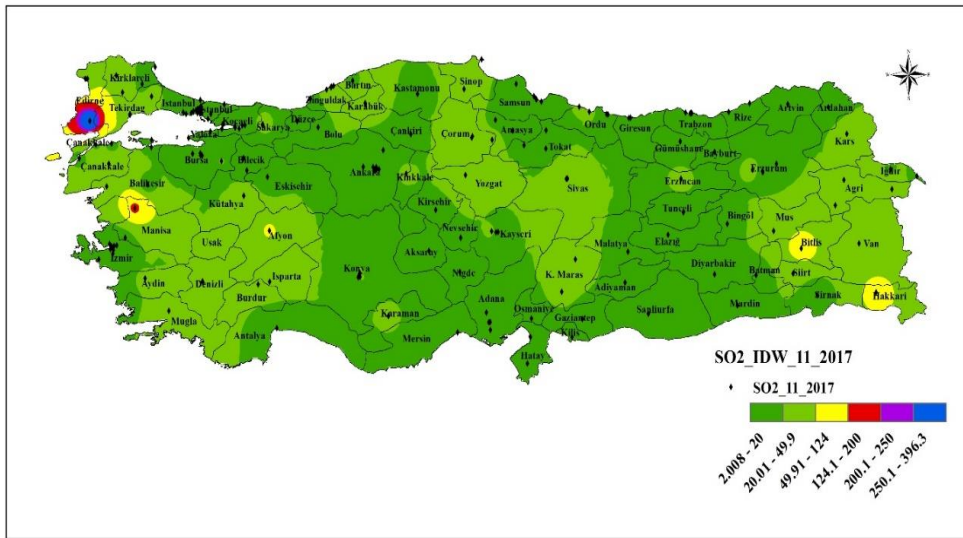


Figure 4. 96: Spatial analysis of SO₂ in November 2017 by applying IDW model

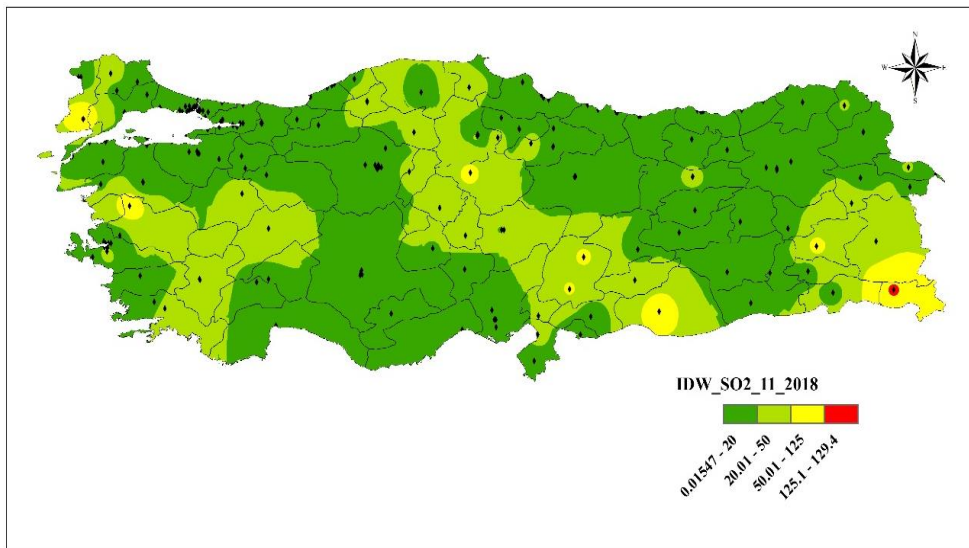


Figure 4. 97: Spatial analysis of SO₂ in November 2017 by applying IDW model

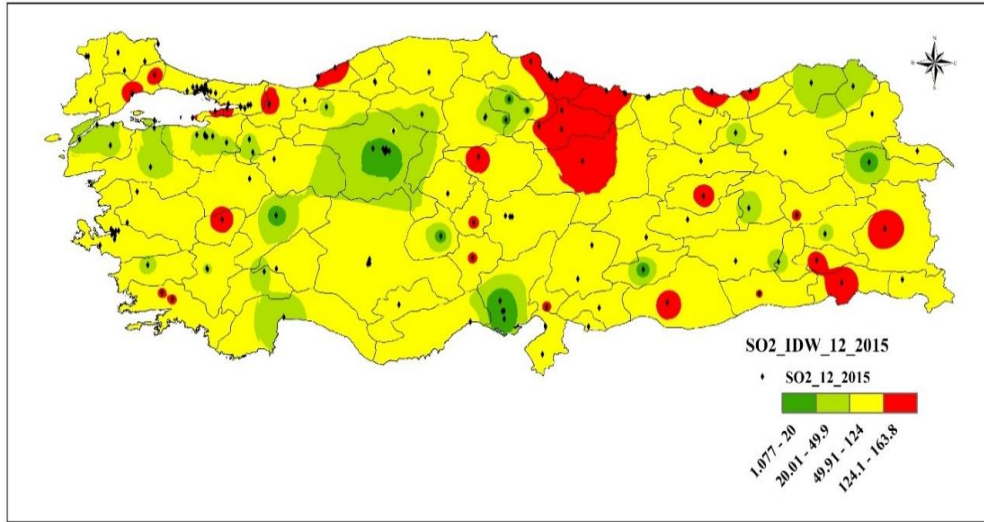


Figure 4. 98: Spatial analysis of SO₂ in December 2015 by applying IDW model

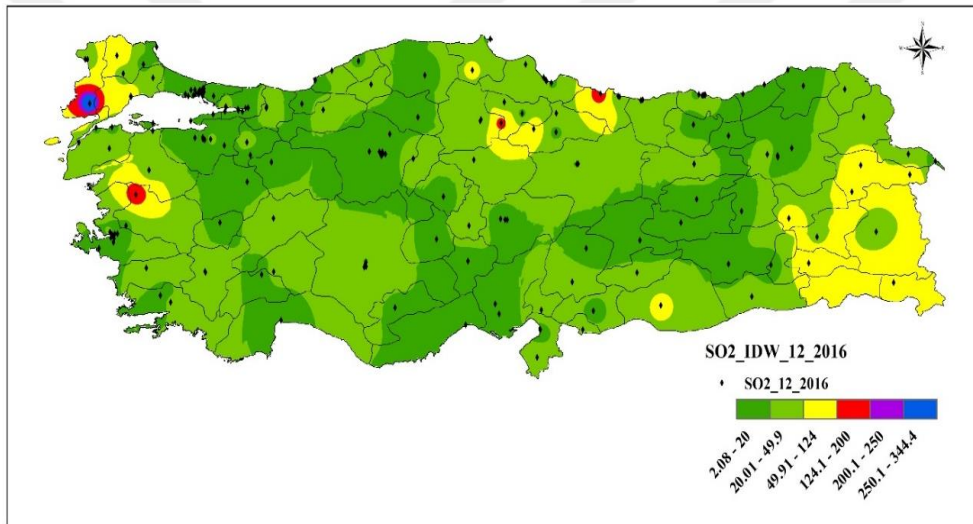


Figure 4. 99: Spatial analysis of SO₂ in December 2016 by applying IDW model

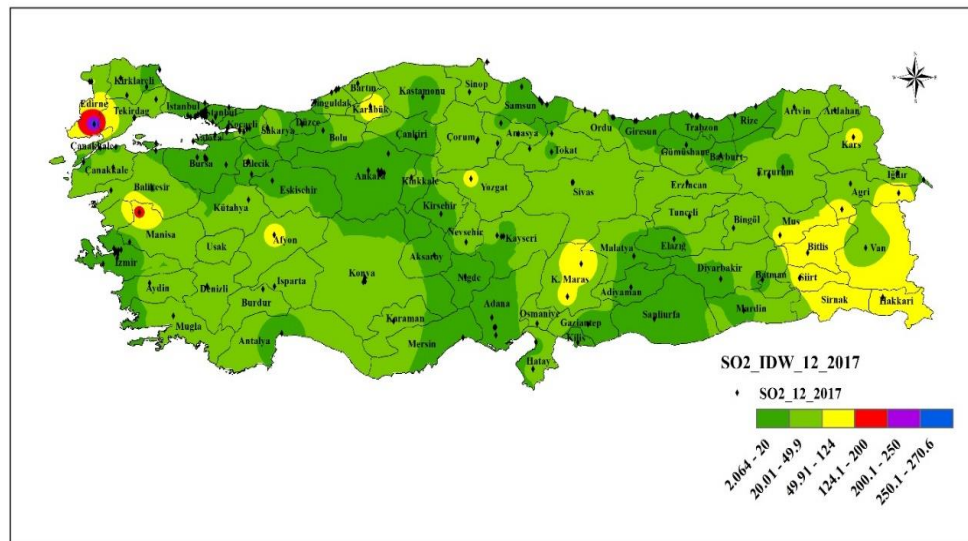


Figure 4. 100: Spatial analysis of SO₂ in December 2017 by applying IDW model

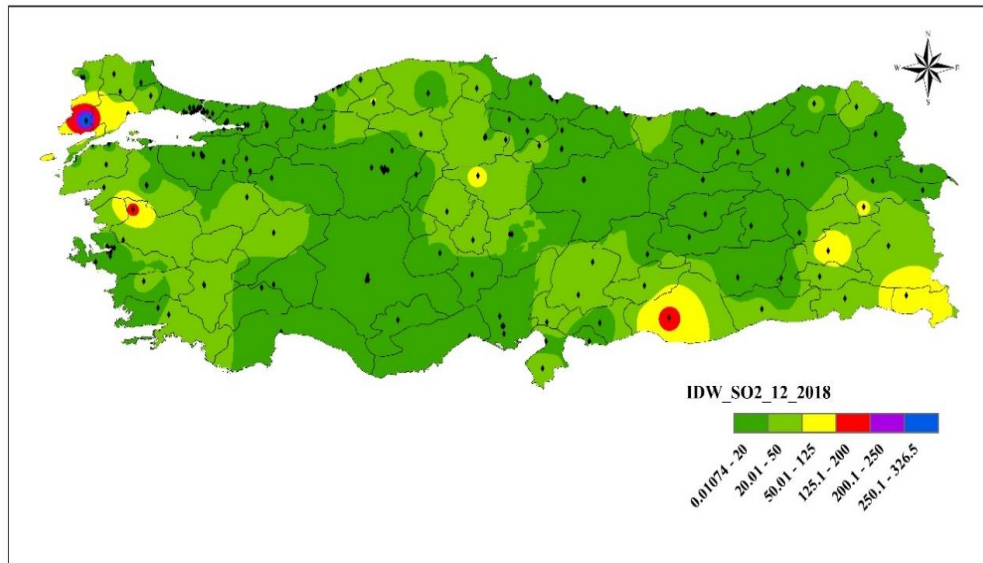


Figure 4. 101: Spatial analysis of SO₂ in December 2018 by applying IDW model

Figure 4.102 shows the average monthly SO₂ concentrations in $\mu\text{g}/\text{m}^3$ during winter season from March 2013- April 2019 in Edirne_Kesan MTHM station that recorded the highest values of SO₂ through these periods. The concentration distribution of the annual averages is significant in determining the parts of the region that will be exposed to long-term effects. From this point of view, it is seen that the highest SO₂ concentration is in Edirne_Kesan MTHM station, figure 4.103 shows the average annual SO₂ values during 2013-2018, according to Turkish (annual/ Winter period) allowable limit value of SO₂ (20 $\mu\text{g}/\text{m}^3$) these values are very high in this station. As in many cities of Turkey, the major causes of air pollution in the Edirne-Keşan station; natural properties as well as the poor quality of the fuel used for heating purposes, the use of illegal coal and incineration systems are not suitable ([Yıldırım and Korkmaz \(1998\)](#), [Menteşe and Tağıl \(2014\)](#), [Özşahin \(2016\)](#)). In the evaluation of air quality in Edirne province, it is stated that the biggest source of air pollution is the emissions resulting from heating for 70%, emissions from traffic of 20%, and emissions of 10% industrial. Air pollution is mainly noticed in winter months. This is because fossil fuels are widely used in heating [Demirarslan and Akıncı \(2018\)](#). In the Keşan district, the dominant wind direction is closed by the hilly areas surrounding the city from the north and the northeast was investigated by [Özşahin \(2016\)](#). This mean to be a negative development in terms of the effects on the air quality.

Whereas Figure 4.104 shows the average annual SO₂ Concentrations during 2010-2019 in some cities of Turkey that had been chosen as maximum values of SO₂

concentrations during this period. ([Kunt \(2014\)](#), [Dursun, Kunt et al. \(2015\)](#)) determined daily SO₂ concentrations in Konya city applying Infrared SO₂ Analyzer equipment and climatological station was utilized for measurement of atmospheric pressure, temperature, wind speed, relative humidity and rainfall parameters on a daily basis. A new technique, Artificial Neural Networks and Fuzzy Logic models greatly successful results showed utilizing SO₂ measurements and climatological information, modeling and organization of predicting programs were targeted. While [Ozturk \(2016\)](#) modelled SO₂ pollution in Seydişehir city using Artificial Neural Networks (ANN) that usages features of biological neurons and efficient of resolving greatly complex problems creating parallel calculations. Meteorological elements and earlier day's SO₂ concentrations were combined to model as input parameters and next day's SO₂ concentration was tested to be forecast. Two seasons were chosen for model development, Prediction shows of improve models are 67% for winter season and 81% for summer season. Only the burning periods of SO₂ concentrations which were thought to arise due to heating-related. The decrease in sulfur dioxide ratios over the years is more evident in the burning periods. In the early 1990s, it decreased to minimum levels by increasing the fuel quality and increasing the natural gas usage [Garipağaoğlu and Duman \(2017\)](#).

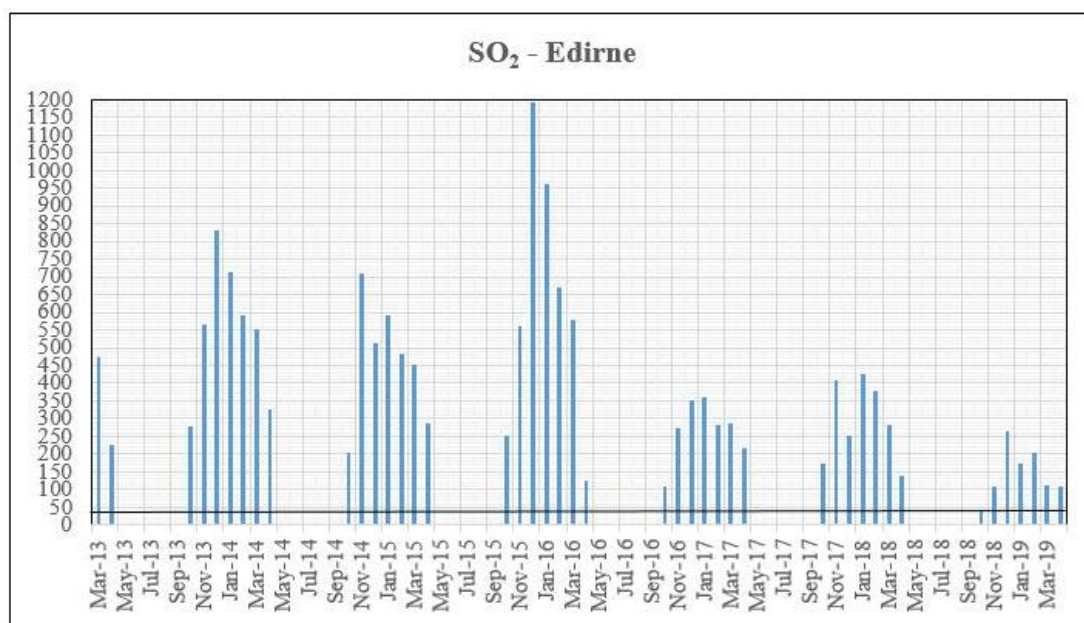


Figure 4. 102: Average monthly SO₂ Concentrations during winter season March 2013-April 2019 in Edirne City.

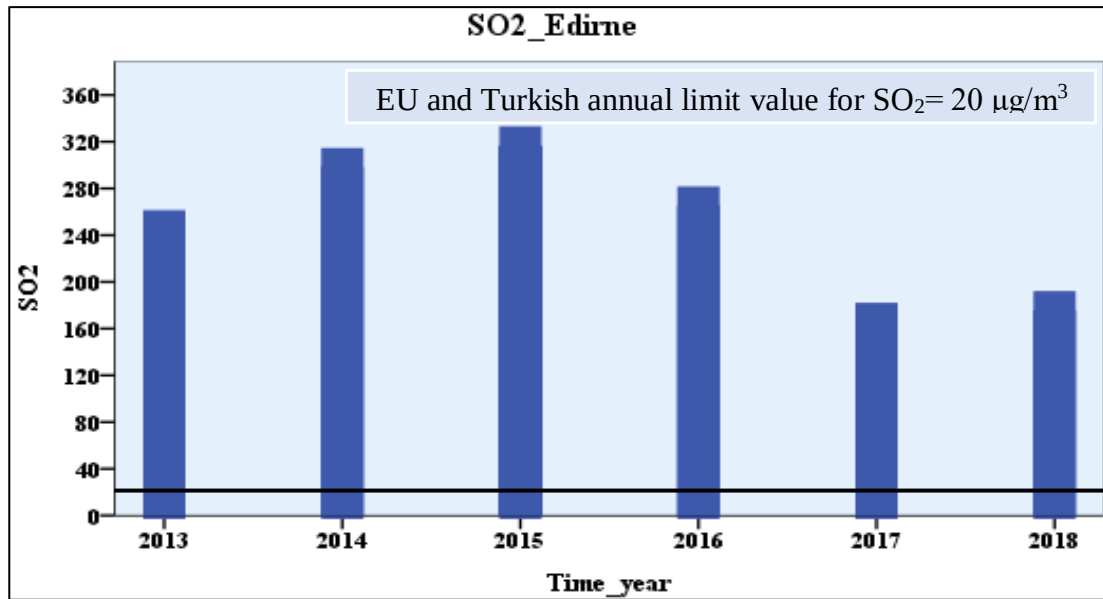


Figure 4. 103: Average annual SO₂ Concentrations during 2013-2018 in Edirne City.

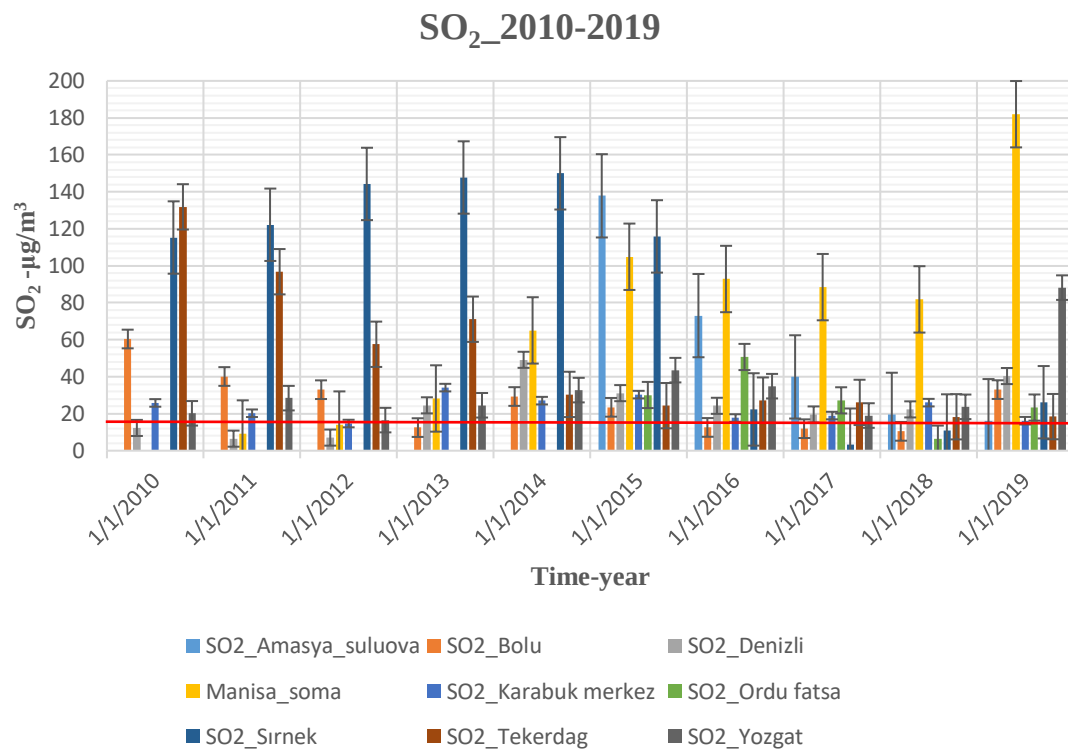


Figure 4. 104: Average annual SO₂ Concentrations during January 2010-April 2019 in some cities of Turkey as maximum values chosen.

4.4 The Spatial analysis of NO_x during 2015-2018 by using IDW interpolation method

Nitrogen oxides (NO_x) are the most significant pollutant gases in the atmosphere. NO_x is yielded from the reaction of nitrogen with oxygen gases in the atmosphere through burning, particularly at high temperatures. In areas of high motor vehicle traffic, for instance in big cities, the quantity of nitrogen oxides released into the atmosphere as air contamination can be considerable. NO_x gases are produced when combustion occurs in the existence of nitrogen, such as in car motors; they are also generated naturally by lightning. Apart from their contribution to acid rainfall, they are also considered as the main factors in the formation of photochemical mist, in addition, NO₂ is a gas that is directly toxic to human health and vegetation ([Svachula, Ferlazzo et al. 1993](#), [Kunt 2014](#), [Alfoldy, Mahfouz et al. 2019](#), [Ercan, Dinçer et al. 2019](#), [Güçlü, Dabanlı et al. 2019](#), [Wang, Lv et al. 2019](#)).

The critical level of NO_x for the protection of vegetation is 30 µg/m³ measured as an annual mean. In ArcGIS 10.5 GIS software, a point layer was created using the coordinates of measurement stations and the annual average concentration values were added to this point layer as the attribute data. In the ArcGIS software, the NO_x distribution maps of the Turkey were produced applying the inverse Distance Weighted Interpolation Method (IDW). The results indicated that most NO_x concentrations, about 77.4%, 79% and 65.5% during 2016, 2017 and 2018 respectively, exceeding (30 µg/m³) the allowable limit value especially in the central parts of Turkey as shown in the figures 4.105, 4.106 and 4.107, where the maximum values of NO_x found in the Konya city in Konya_Selçuklu_Belediye (811.1675 µg/m³) and Konya_Karatay_Belediye (562.4825 µg/m³) stations during 2018, the high levels of nitrogen oxides can make happen damage to the human respiratory tract and rise a person's susceptibility to, and the seriousness of, respiratory diseases and asthma.

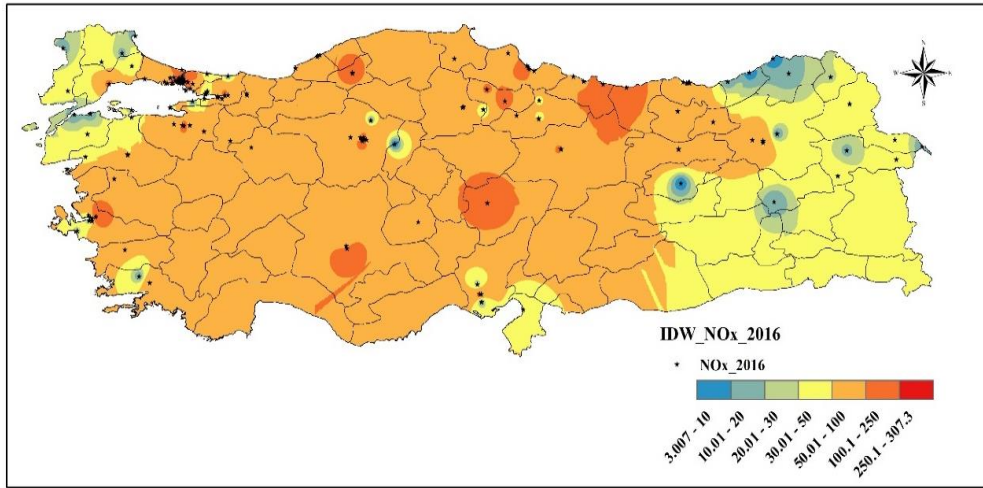


Figure 4. 105: Spatial analysis of NO_x during 2016 by applying IDW model

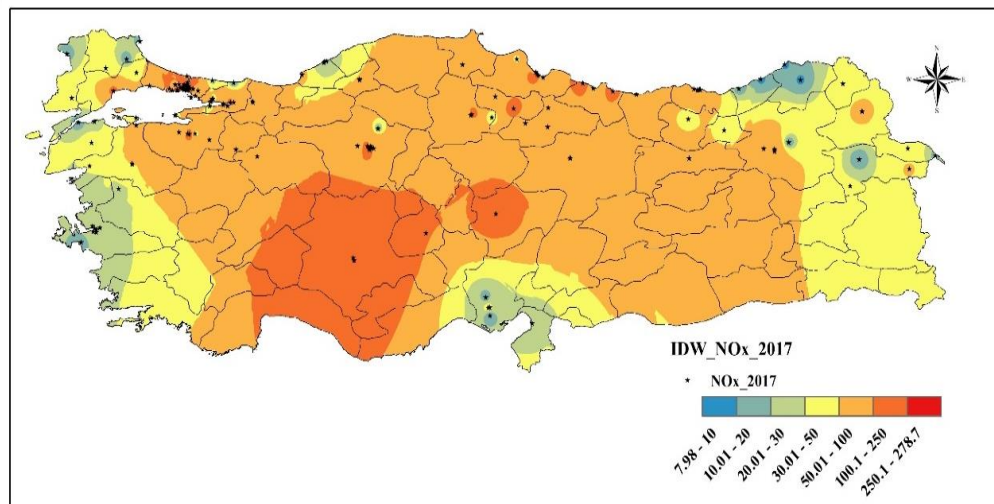


Figure 4. 106: Spatial analysis of NO_x during 2017 by applying IDW model

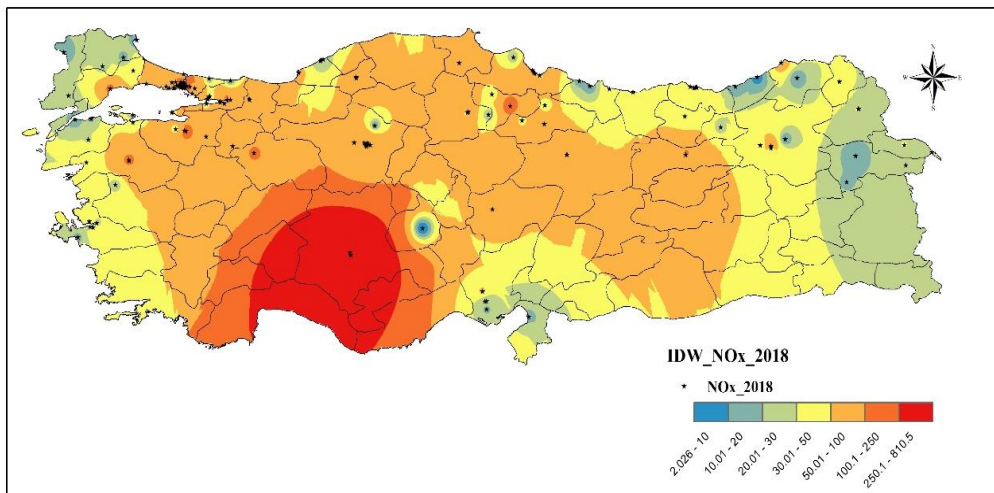


Figure 4. 107: Spatial analysis of NO_x during 2018 by applying IDW model

Figure 4.108 shows the prediction map of spatial analysis of NO_x during 2018 by using ordinary kriging prediction method that selected as better way after checking all semiveriogram methods, there are small differences when comparsion between figure 4.107 that shows IDW method and figure 4.108 that shows ordinary kriging prediction method. Figure 4.109 presents the relation between measured values of NO_x as x-axis and predicted values of NO_x as y-axis, the regression equation of the relationship is ($y=0.51*x+32.71$, $R^2=0.97$) R^2 values indicated to the strong correlation between measured and predicted values of NO_x this mean fitting model.

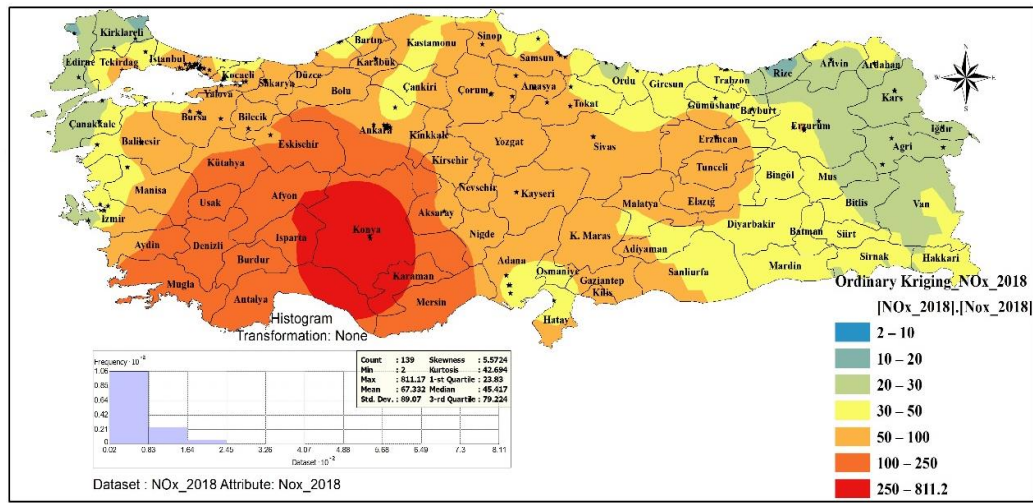


Figure 4. 108: Spatial analysis of NO_x during 2018 by using Ordinary Kriging prediction method.

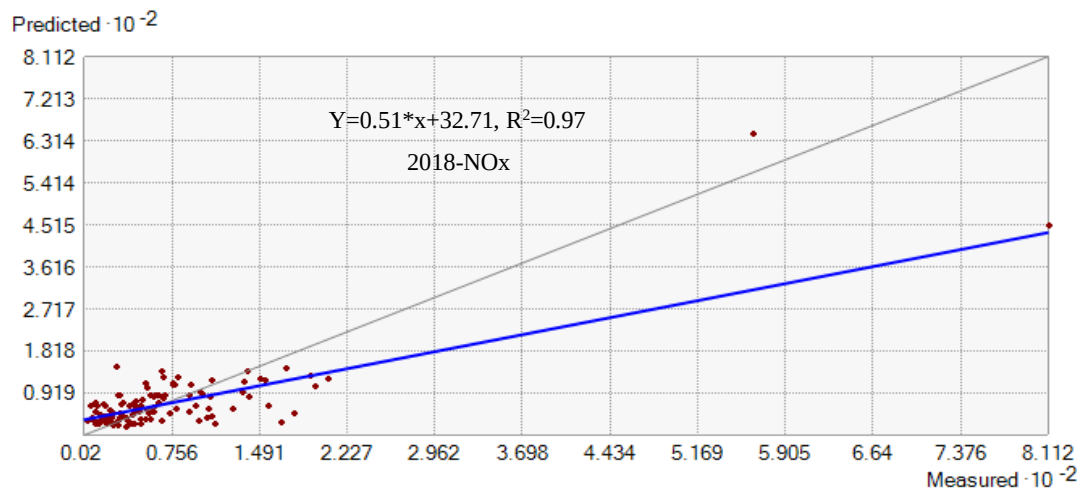


Figure 4. 109: The relation between measured and prediction values of NO_x, OK method.

4.5 The Statistical Analysis by SPSS program

Pollution parameter PM_{10} was selected as dependent variable, while temperature ($^{\circ}C$), wind direction (Degree), wind speed (m/s), relative humidity (%) and air pressure (mbar), were expressed as independent variables. Evaluation equations were advanced by IBM SPSS Statistics 24.0 for winter and summer seasons during October 2014-April 2019 in Iğdir station are produced.

Table 4.2 shows regression coefficients between PM_{10} and meteorological measurements by applying multiply liner regression method during winter 2014-2015 in Iğdir station, R^2 value obtained according to this method is 0.17. In multiple regression analysis, it was found that temperature, wind direction, wind speed and relative humidity had an effect on PM_{10} , while the effect of air pressure was not detected. While table 4.3 appears regression coefficients between PM_{10} and meteorological measurements by applying multiply liner regression method during summer 2015, R^2 value obtained according to this method is 0.042, indicating to poor relation between the parameters. In multiple regression analysis, it was found that only wind direction and wind speed had an effect on PM_{10} , the coefficient for wind direction (-2.607) and wind speed (-36.426) were statistically significant because its p-value of 0.000 is less than 0.05. While the effect of other meteorological parameters was not detected.

Table 4. 2: Investigation of regression coefficients between PM_{10} and meteorological measurements according to multiply regression analysis during winter 2014-2015 in Iğdir station

Model_ PM_{10} _winter 2014-2015	B	Std. Error	Beta	t	P-value or Sig.
(Constant) $R^2 = 0.17$	597.84	44.798		13.345	0.000
temperature	2.405	0.547	0.067	4.395	0.000
wind direction	-2.607	0.143	-0.275	-18.200	0.000
wind speed	-36.426	1.838	-0.290	-19.816	0.000
relative humidity	-0.075	0.019	-0.054	-3.923	0.000
air pressure	0.062	0.042	0.020	1.466	0.143
$PM_{10} = 597.84 + 2.405T - 2.607WD - 36.426WS - 0.075RH + 0.062AP$					

Table 4. 3: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2015 in Iğdir station

Model_ PM ₁₀ _summer 2015	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.042	13.164	28.186		0.467	0.640
temperature	0.215	0.224	0.017	0.957	0.339
wind direction	0.520	0.070	0.144	7.459	0.000
wind speed	-13.384	1.284	-0.195	-10.427	0.000
relative humidity	0.017	0.028	0.011	0.624	0.533
air pressure	-0.032	0.028	-0.021	-1.149	0.250
PM ₁₀ = 13.164+0.215T+0.520WD-13.384WS+0.017RH-0.032AP					

Table 4.4 shows regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2015-2016, R² value obtained according to this method is 0.29. In multiple regression analysis, the temperature, wind direction, wind speed and air pressure amounts which are stated as important in the control of the importance of the regression coefficients were found to be significant in the multiply regression method, whereas the effect of relative humidity was not detected. Table 4.5 illustrates regression coefficients between PM₁₀ and climatological parameters according to multiply regression analysis during summer 2016. R² value obtained according to this method is 0.042, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters amount had an effect on PM₁₀.

Table 4. 4: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2015-2016 in Iğdir station

Model_ PM ₁₀ _winter 2015-2016	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.29	627.496	46.615		13.461	0.000
temperature	0.602	0.097	0.081	6.187	0.000
wind direction	-3.420	0.126	-0.375	-27.098	0.000
wind speed	-34.183	1.880	-0.259	-18.181	0.000
relative humidity	-0.005	0.026	-0.003	-0.184	0.854
air pressure	0.243	0.043	0.076	5.607	0.000
PM ₁₀ = 627.496+0.602T-3.420WD-34.183WS-0.005RH+0.243AP					

Table 4. 5: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2016 in Iğdir station

Model_ PM ₁₀ _summer 2016	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.042	-146.530	25.619		-5.720	0.000
temperature	3.084	0.657	0.104	4.694	0.000
wind direction	0.788	0.069	0.197	11.453	0.000
wind speed	-3.013	0.466	-0.151	-6.468	0.000
relative humidity	0.059	0.027	0.036	2.190	0.029
air pressure	-0.054	0.015	-0.064	-3.500	0.000
PM ₁₀ = -146.530+3.084T+0.788WD-3.013WS+0.059RH-0.054AP					

Table 4.6 shows regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2016-2017, R² value obtained according to this method is 0.18, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀. While table 4.7 appears regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during summer 2017, R² value obtained according to this method is 0.13, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀.

Table 4. 6: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2016-2017 in Iğdir station

Model_ PM ₁₀ _winter 2016-2017	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.18	118.012	40.344		2.925	0.003
temperature	-1.320	0.298	-0.116	-4.424	0.000
wind direction	-1.048	0.090	-0.305	-11.693	0.000
wind speed	-20.608	1.429	-0.224	-14.423	0.000
relative humidity	0.197	0.046	0.057	4.302	0.000
air pressure	0.300	0.033	0.126	9.031	0.000
PM ₁₀ = -118.012-1.320T-1.048WD-20.608WS+0.197RH+0.300AP					

Table 4. 7: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2017 in Iğdir station

Model_ PM ₁₀ _summer 2017	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.13	-492.867	49.278		-10.002	0.000
temperature	8.183	1.200	0.161	6.818	0.000
wind direction	2.848	0.146	0.415	19.504	0.000
wind speed	-9.982	1.007	-0.234	-9.911	0.000
relative humidity	1.562	0.262	0.119	5.971	0.000
air pressure	-0.259	0.036	-0.134	-7.133	0.000
PM ₁₀ = -492.867+8.183T+2.848WD-9.982WS+1.562RH-0.259AP					

Table 4.8 illustrates regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2017-2018, R² value is 0.19. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀. While table 4.9 appears regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during summer 2018, R² value obtained according to this method is 0.12, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀.

Table 4. 8: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2017-2018 in Iğdir station

Model_ PM ₁₀ _winter 2017-2018	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.19	371.981	52.518		7.083	0.000
temperature	9.790	1.382	0.107	7.081	0.000
wind direction	-1.650	0.168	-0.150	-9.797	0.000
wind speed	-26.055	1.613	-0.275	-16.157	0.000
relative humidity	-0.794	0.308	-0.037	-2.577	0.010
air pressure	0.218	0.044	0.074	4.980	0.000
PM ₁₀ =371.981+9.790T-1.650WD-26.055WS-0.794RH+0.218AP					

Table 4. 9: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2018 in Iğdir station

Model_ PM ₁₀ _summer 2018	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.12	-82.871	21.535		-3.848	0.000
temperature	-7.418	0.574	-0.268	-12.915	0.000
wind direction	0.298	0.015	0.339	19.801	0.000
wind speed	4.174	0.585	0.152	7.140	0.000
relative humidity	1.159	0.140	0.144	8.272	0.000
air pressure	0.054	0.020	0.047	2.743	0.006
PM ₁₀ = -82.871-7.418T+0.298WD+4.174WS+1.159RH+0.054AP					

Table 4.10 illustrates regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2018-2019, R² value is 0.17. In multiple regression analysis, it was found that the temperature, wind direction, wind speed and air pressure amounts had an effect on PM₁₀, whereas the effect of relative humidity was not detected.

Table 4. 10: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2018-2019 in Iğdir station

Model_ PM ₁₀ _winter 2018-2019	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.17	548.200	110.418		4.965	0.000
temperature	15.274	0.884	0.250	17.269	0.000
wind direction	-1.267	0.263	-0.077	-4.815	0.000
wind speed	-25.205	1.012	-0.391	-24.916	0.000
relative humidity	-0.385	0.242	-0.021	-1.587	0.113
air pressure	0.101	0.041	0.038	2.488	0.013
PM ₁₀ = 548.200+15.274T-1.267WD-25.205WS-0.385RH+0.101AP					

Pollution parameter SO₂ was selected as dependent variable, while temperature (° C), wind direction (Degree), wind speed (m/s), relative humidity (%) and air pressure (mbar), were choosing as independent variables. Evaluation equations were advanced by IBM SPSS Statistics 24.0 for winter and summer seasons during October 2014-April 2019 in Edirne-Keşan station are produced.

Table 4.11 shows regression coefficients between SO₂ and meteorological parameters by applying multiply liner regression method during winter 2014-2015, R² value obtained according to this method is 0.26, indicating to poor relation between the parameters. In multiple regression analysis, it was found that temperature, wind

direction, wind speed and relative humidity had an effect on SO₂, the coefficient for temperature (-26.306) wind direction (0.120), wind speed (-185.377) and relative humidity (0.697) were statistically significant because its p-value of 0.000 is less than 0.05 while the effect of air pressure was not detected. While table 4.12 shows regression coefficients between SO₂ and meteorological measurements by applying multiply liner regression method during summer 2015, R² value obtained according to this method is 0.064, indicating to poor relation between the parameters. In multiple regression analysis, it was found that temperature, wind direction and air pressure had an effect on SO₂. While the effect of wind speed and relative humidity were not detected.

Table 4. 11: Investigation of regression coefficients between SO₂ and meteorological measurements according to multiply regression analysis during winter 2014-2015 in Edirne-Keşan

Model_ SO ₂ _winter 2014-2015	B	Std. Error	Beta	t	p-value
(Constant) R ² =0.26	189.226	290.382		0.652	0.515
temperature	-26.306	0.924	-0.425	-28.480	0.000
wind direction	0.120	0.057	0.031	2.125	0.034
wind speed	-185.377	6.669	-0.380	-27.796	0.000
relative humidity	0.697	0.288	0.033	2.419	0.016
air pressure	189.226	290.382		0.652	0.515
SO ₂ = 189.226-26.306T+ 0.129WD-185.377WS+0.697RH+189.226AP					

Table 4. 12: Investigation of regression coefficients between SO₂ and meteorological measurements according to multiply regression analysis during summer 2015 in Edirne-Keşan

Model_ SO ₂ _summer 2015	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.064	209.819	34.214		6.132	0.000
temperature	0.135	0.046	0.124	2.953	0.003
wind direction	0.006	0.001	0.102	5.003	0.000
wind speed	0.025	0.204	0.003	0.121	0.904
relative humidity	0.003	0.012	0.012	0.288	0.773
air pressure	-0.210	0.034	-0.137	-6.237	0.000
SO ₂ = 209.819+0.135T+ 0.006WD+0.025WS+0.003RH-0.210AP					

Table 4.13 illustrates regression coefficients between SO₂ and meteorological measurements by applying multiply liner regression method during winter 2015-2016, R² value is 0.42. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀, whereas the effect of relative humidity was not detected. While table 4.14 shows regression coefficients between SO₂ and

meteorological measurements by applying multiply liner regression method during summer 2016, R^2 value obtained according to this method is 0.081, indicating to poor relation between the parameters. In multiple regression analysis, it was found that temperature, wind speed and air pressure had an effect on SO_2 . While the effect of wind direction and relative humidity were not detected.

Table 4. 13: Investigation of regression coefficients between SO_2 and meteorological measurements according to multiply regression analysis during winter 2015-2016 in Edirne-Keşan

Model_ SO_2 _winter 2015-2016	B	Std. Error	Beta	t	Sig.
(Constant) $R^2 = 0.42$	-4240.94	863.065		-4.914	0.000
temperature	-51.570	1.260	-0.599	-40.913	0.000
wind direction	0.767	0.088	0.116	8.666	0.000
wind speed	-229.911	11.527	-0.249	-19.946	0.000
relative humidity	-0.908	0.471	-0.026	-1.927	0.054
air pressure	5.563	0.838	0.092	6.637	0.000
$SO_2 = -4240.94 - 51.570T + 0.767WD - 229.911WS - 0.908RH + 5.563AP$					

Table 4. 14: Investigation of regression coefficients between SO_2 and meteorological measurements according to multiply regression analysis during summer 2016 in Edirne-Keşan

Model_ SO_2 _summer 2016	B	Std. Error	Beta	t	Sig.
(Constant) $R^2 = 0.081$	2269.508	411.045		5.521	0.000
temperature	-4.045	0.438	-0.284	-9.241	0.000
wind direction	0.035	0.022	0.030	1.600	0.110
wind speed	12.221	3.097	0.078	3.946	0.000
relative humidity	0.031	0.146	0.007	0.211	0.833
air pressure	-2.177	0.403	-0.107	-5.396	0.000
$SO_2 = 2269.51 - 4.045T + 0.035WD + 12.221WS + 0.031RH - 2.177AP$					

Table 4.15 shows regression coefficients between SO_2 and meteorological parameters by applying multiply liner regression method during winter 2016-2017, R^2 value obtained according to this method is 0.25, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on SO_2 . While table 4.16 shows regression coefficients between SO_2 and meteorological measurements by applying multiply liner regression method during summer 2017, R^2 value obtained according to this method is 0.17, indicating to poor relation between the parameters. In multiple regression analysis, it was found that

temperature, wind direction, relative humidity and air pressure had an effect on SO₂, while the effect of wind speed was not detected.

Table 4. 15: Investigation of regression coefficients between SO₂ and meteorological measurements according to multiply regression analysis during winter 2016-2017 in Edirne-Keşan

Model_ SO ₂ _winter 2016-2017	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.25	-1115.84	452.501		-2.466	0.014
temperature	-13.432	0.525	-0.523	-25.575	0.000
wind direction	0.329	0.043	0.122	7.620	0.000
wind speed	-73.687	4.319	-0.240	-17.060	0.000
relative humidity	-1.268	0.195	-0.115	-6.514	0.000
air pressure	1.579	0.441	0.061	3.583	0.000
SO ₂ = -1115.84-13.432T+ 0.329WD-73.687WS-1.268RH+1.579AP					

Table 4. 16: Investigation of regression coefficients between SO₂ and meteorological measurements according to multiply regression analysis during summer 2017 in Edirne-Keşan

Model_ SO ₂ _summer 2017	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.17	439.782	21.926		20.058	0.000
temperature	-0.160	0.023	-0.223	-7.077	0.000
wind direction	0.010	0.001	0.158	8.339	0.000
wind speed	-0.081	0.153	-0.010	-0.527	0.598
relative humidity	-0.017	0.007	-0.074	-2.412	0.016
air pressure	-0.431	0.022	-0.381	-19.911	0.000
SO ₂ = 439.78-0.160T+ 0.010WD-0.081WS-0.017RH-0.431AP					

Table 4.17 shows regression coefficients between SO₂ and meteorological parameters by applying multiply liner regression method during winter 2017-2018, R² value obtained according to this method is 0.41. In multiple regression analysis, it was found that all meteorological parameters had an effect on SO₂. While table 4.18 shows regression coefficients between SO₂ and meteorological measurements by applying multiply liner regression method during summer 2018, R² value obtained according to this method is 0.076, indicating to poor relation between the parameters. In multiple regression analysis, it was found that temperature, wind direction, wind speed and relative humidity had an effect on SO₂, while the effect of air pressure was not detected.

Table 4. 17: Investigation of regression coefficients between SO₂ and meteorological measurements according to multiply regression analysis during winter 2017-2018 in Edirne-Keşan

Model_ SO ₂ _winter 2017-2018	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.41	2154.387	478.465		4.503	0.000
temperature	-23.792	0.721	-0.580	-32.989	0.000
wind direction	0.175	0.055	0.044	3.153	0.002
wind speed	-155.985	6.264	-0.320	-24.901	0.000
relative humidity	-0.825	0.250	-0.055	-3.299	0.001
air pressure	-1.424	0.465	-0.042	-3.062	0.002
SO ₂ = 2154.39-23.792T+ 0.175WD-155.985WS-0.825RH-1.424AP					

Table 4. 18: Investigation of regression coefficients between SO₂ and meteorological measurements according to multiply regression analysis during summer 2018 in Edirne-Keşan

Model_ SO ₂ _summer 2018	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.076	33.574	15.132		2.219	0.027
temperature	-0.161	0.018	-0.293	-8.903	0
wind direction	0.011	0.001	0.231	11.165	0
wind speed	0.497	0.126	0.08	3.939	0
relative humidity	-0.028	0.005	-0.172	-5.34	0
air pressure	-0.027	0.015	-0.041	-1.833	0.067
SO ₂ = 33.574-0.161T+ 0.011WD+0.497WS-0.028RH-0.027AP					

Table 4.19 illustrates regression coefficients between SO₂ and meteorological parameters by applying multiply liner regression method during winter 2018-2019, R² value obtained according to this method is 0.27, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on SO₂.

Table 4. 19: Investigation of regression coefficients between SO₂ and meteorological measurements according to multiply regression analysis during winter 2018-2019 in Edirne-Keşan

Model_ SO ₂ _winter 2018-2019	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.27	1811.714	340.541		5.32	0
temperature	-12.824	0.448	-0.45	-28.649	0
wind direction	0.344	0.037	0.141	9.239	0
wind speed	-102.894	3.786	-0.36	-27.177	0
relative humidity	-1.346	0.156	-0.13	-8.641	0
air pressure	-1.39	0.335	-0.058	-4.152	0
SO ₂ = 1811.714-12.824T+ 0.344WD-102.894WS-1.346RH-1.39AP					

Table 4.20 shows regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2014-2015 in İstanbul - Esenyurt-MTHM station, R² value is 0.11, indicating to poor relation between the parameters. In multiple regression analysis, it was found that wind direction, wind speed and relative humidity had an effect on PM₁₀, were statistically significant because its p-value of 0.000 is less than 0.05, while the effect of temperature and air pressure were not detected. While table 4.21 appears regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during summer 2015, R² value obtained according to this method is 0.068, indicating to poor relation between the parameters. In multiple regression analysis, it was found that temperature, wind speed, relative humidity and air pressure had an effect on PM₁₀ value, while the effect of wind direction was not detected.

Table 4. 20: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2014-2015 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _winter 2014-2015	B	Std. Error	Beta	t	Sig. or p-value
(Constant)	-367.868	369.641		-0.995	0.320
temperature	0.585	0.555	0.027	1.055	0.292
wind direction	0.063	0.017	0.069	3.671	0.000
wind speed	-25.619	1.804	-0.266	-14.198	0.000
relative humidity	-1.324	0.153	-0.188	-8.666	0.000
air pressure	0.608	0.357	0.037	1.705	0.088
PM ₁₀ = -367.868+0.585T+ 0.063WD-25.619WS-1.324RH+0.608AP R ² =0.11					
PM ₁₀ =145.04+1.152T-26.03WS R ² =0.089					

Table 4. 21: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2015 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _summer 2015	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.068	88.779	19.745		4.496	0.000
temperature	-0.895	0.317	-0.063	-2.822	0.005
wind direction	0.008	0.008	0.018	0.965	0.335
wind speed	-3.949	1.173	-0.065	-3.367	0.001
relative humidity	-1.197	0.085	-0.321	-14.117	0.000
air pressure	0.132	0.023	0.113	5.759	0.000
PM ₁₀ = 88.779-0.895T+ 0.008WD-3.949WS-1.197RH+0.132AP R ² =0.068					
PM ₁₀ = 75.82+1.527T-0.96WS R ² =0.011					

Table 4.22 appears regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2015-2016 in İstanbul - Esenyurt-MTHM station, R² value is 0.16, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀. While table 4.23 appears regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during summer 2016, R² value obtained according to this method is 0.018, indicating to poor relation between the parameters. In multiple regression analysis, it was found that relative humidity and air pressure had an effect on PM₁₀ value, while the effect of temperature, wind direction and wind speed were not detected.

Table 4. 22: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2015-2016 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _winter 2015-2016	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.16	-1870.20	228.691		-8.178	0.000
temperature	2.107	0.404	0.092	5.217	0.000
wind direction	0.171	0.018	0.140	9.725	0.000
wind speed	-37.209	1.670	-0.316	-22.287	0.000
relative humidity	-0.619	0.123	-0.081	-5.047	0.000
air pressure	2.025	0.221	0.143	9.182	0.000
PM ₁₀ = -1870.20+2.107T+ 0.171WD-37.209WS-0.619RH+2.025AP R ² =0.16 PM ₁₀ =196.35+1.093T-42.48WS R ² =0.13					

Table 4. 23: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2016 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _summer 2016	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.018	972.039	163.222		5.955	0.000
temperature	0.147	0.174	0.018	0.847	0.397
wind direction	0.011	0.009	0.025	1.287	0.198
wind speed	-0.254	0.721	-0.007	-0.353	0.724
relative humidity	-0.203	0.048	-0.084	-4.186	0.000
air pressure	-0.901	0.160	-0.100	-5.630	0.000
PM ₁₀ = 972.039_0.147T+ 0.011WD-0.254WS-0.203RH-0.901AP R ² =0.018 PM ₁₀ = 44.993+0.717T-2.834WS R ² =0.008					

Table 4.24 shows regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2016-2017 in İstanbul - Esenyurt-MTHM station, R² value is 0.15, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀. While table 4.25 appears regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during summer 2017, R² value obtained according to this method is 0.063, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀ value.

Table 4. 24: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2016-2017 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _winter 2016-2017	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.15	656.077	148.554		4.416	0.000
temperature	-1.296	0.196	-0.118	-6.623	0.000
wind direction	0.121	0.012	0.146	10.443	0.000
wind speed	-19.052	0.794	-0.325	-23.993	0.000
relative humidity	-0.944	0.063	-0.237	-15.062	0.000
air pressure	-0.475	0.144	-0.051	-3.303	0.001
PM ₁₀ = 656.077-1.296T+ 0.121WD-19.052WS-0.944RH-0.475AP R ² =0.15 PM ₁₀ = 125.58-0.408T-21.262WS R ² =0.124					

Table 4. 25: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2017 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _summer 2017	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.063	1882.289	189.143		9.952	0.000
temperature	-0.609	0.190	-0.078	-3.202	0.001
wind direction	0.043	0.009	0.095	4.932	0.000
wind speed	-3.203	0.712	-0.082	-4.498	0.000
relative humidity	-0.408	0.052	-0.179	-7.806	0.000
air pressure	-1.762	0.185	-0.180	-9.537	0.000
PM ₁₀ = 1882.289-0.609T+ 0.043WD-3.203WS-0.408RH-1.762AP R ² =0.063 PM ₁₀ = 67.79+0.699T-8.52WS R ² =0.041					

Table 4.26 shows regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2017-2018 in İstanbul - Esenyurt-MTHM station, R² value is 0.22, indicating to poor relation between

the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀ value. While table 4.27 appears regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during summer 2018, R² value obtained according to this method is 0.013, indicating to poor relation between the parameters. In multiple regression analysis, it was found that temperature, wind speed and relative humidity had an effect on PM₁₀ value, while the effect of wind direction and air pressure were not detected.

Table 4. 26: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2017-2018 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _winter 2017-2018	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.22	-482.317	134.951		-3.574	0.000
temperature	1.675	0.227	0.125	7.387	0.000
wind direction	0.158	0.012	0.177	13.092	0.000
wind speed	-24.491	0.840	-0.392	-29.145	0.000
relative humidity	-0.251	0.070	-0.060	-3.572	0.000
air pressure	0.572	0.131	0.061	4.381	0.000
PM ₁₀ = -482.317+1.675T+ 0.158WD-24.491WS-0.251RH+0.572AP R ² =0.22 PM ₁₀ = 114.831+1.709T-26.322WS R ² =0.20					

Table 4. 27: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during summer 2018 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _summer-2018	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.013	14.592	118.547		0.123	0.902
temperature	-0.532	0.158	-0.088	-3.370	0.001
wind direction	0.002	0.007	0.005	0.223	0.823
wind speed	-1.861	0.576	-0.067	-3.229	0.001
relative humidity	-0.247	0.042	-0.150	-5.824	0.000
air pressure	0.076	0.116	0.013	0.654	0.513
PM ₁₀ = 14.592-0.895T+ 0.008WD-3.949WS-1.197RH+0.132AP R ² =0.013 PM ₁₀ = 68.102-0.171T-2.873WS R ² =0.012					

Table 4.28 shows regression coefficients between PM₁₀ and meteorological measurements by applying multiply liner regression method during winter 2018-2019 in İstanbul - Esenyurt-MTHM station, R² value is 0.15, indicating to poor relation between the parameters. In multiple regression analysis, it was found that all meteorological parameters had an effect on PM₁₀ value except temperature was not noticed.

Table 4. 28: Investigation of regression coefficients between PM₁₀ and meteorological measurements according to multiply regression analysis during winter 2018-2019 in İstanbul - Esenyurt-MTHM station

Model_ PM ₁₀ _ winter 2018-2019	B	Std. Error	Beta	t	Sig.
(Constant) R ² =0.15	-362.997	115.564		-3.141	0.002
temperature	-0.248	0.155	-0.024	-1.603	0.109
wind direction	0.085	0.010	0.123	8.425	0.000
wind speed	-17.291	0.684	-0.359	-25.269	0.000
relative humidity	-0.443	0.050	-0.137	-8.894	0.000
air pressure	0.477	0.114	0.059	4.197	0.000
PM ₁₀ = -362.997-0.248T+ 0.085WD-17.291WS-0.443RH+0.477AP R ² =0.15					
PM ₁₀ = 101.31+0.028T-17.467WS R ² =0.131					

The results appeared that there is an important relationship between meteorological parameters and concentration of pollutant. Summarize of Statistical analysis of multiple linear regression of PM₁₀ and SO₂ in Iğdir and Edirne_ Keşan stations were given in tables 4.29 and 4.30, respectively. Whereas table 4.31 shows summarize of statistical analysis of multiple linear regression of PM₁₀ in İstanbul - Esenyurt-MTHM station.

Table 4. 29: Summarize of statistical analysis of multiple linear regression of PM₁₀ in Iğdir station

Time	Regression Equations in Iğdir station	Values of R ²
Winter 2014-2015	PM ₁₀ =597.84+2.405T-2.607WD-36.426WS-0.075RH+0.062AP	0.17
Summer2015	PM ₁₀ =13.164+0.215T+0.520WD-13.384WS+0.017RH-0.032AP	0.042
Winter 2015-2016	PM ₁₀ = 627.496+0.602T-3.420WD-34.183WS-0.005RH+0.243AP	0.29
Summer 2016	PM ₁₀ = -146.530+3.084T+0.788WD-3.013WS+0.059RH-0.054AP	0.042
Winter 2016-2017	PM ₁₀ = -118.012-1.320T-1.048WD-20.608WS+0.197RH+0.300AP	0.18
Summer 2017	PM ₁₀ = -492.867+8.183T+2.848WD-9.982WS+1.562RH-0.259AP	0.13
Winter 2017-2018	PM ₁₀ =371.981+9.790T-1.650WD-26.055WS-0.794RH+0.218AP	0.19
Summer 2018	PM ₁₀ = -82.871-7.418T+0.298WD+4.174WS+1.159RH+0.054AP	0.12
Winter 2018-2019	PM ₁₀ = 548.200+15.274T-1.267WD-25.205WS-0.385RH+0.101AP	0.17

Table 4. 30: Summarize of statistical analysis of multiple linear regression results of SO₂ in Edirne_ Keşan station

Time	Regression Equations in Edirne_ Keşan station	Values of R ²
Winter 2014-2015	SO ₂ = 189.23-26.306T+ 0.129WD-185.38WS+0.697RH+189.23AP	0.26
Summer2015	SO ₂ = 209.819+0.135T+ 0.006WD+0.025WS+0.003RH-0.210AP	0.064
Winter 2015-2016	SO ₂ = -4240.94-51.570T+ 0.767WD-229.911WS-0.908RH+5.563AP	0.42
Summer 2016	SO ₂ = 2269.51-4.045T+ 0.035WD+12.221WS+0.031RH-2.177AP	0.081
Winter 2016-2017	SO ₂ = -1115.84-13.432T+ 0.329WD-73.687WS-1.268RH+1.579AP	0.25

Summer 2017	$SO_2 = 439.78 - 0.160T + 0.010WD - 0.081WS - 0.017RH - 0.431AP$	0.17
Winter 2017-2018	$SO_2 = 2154.39 - 23.792T + 0.175WD - 155.985WS - 0.825RH - 1.424AP$	0.42
Summer 2018	$SO_2 = 33.574 - 0.161T + 0.011WD + 0.497WS - 0.028RH - 0.027AP$	0.076
Winter 2018-2019	$SO_2 = 1811.714 - 12.824T + 0.344WD - 102.894WS - 1.346RH - 1.39AP$	0.27

Table 4. 31: Summarize of statistical analysis of multiple linear regression of PM_{10} in İstanbul - Esenyurt-MTHM station

Time	Regression Equations in İğdır station	Values of R^2
Winter 2014-2015	$PM_{10} = -367.87 + 0.585T + 0.063WD - 25.619WS - 1.324RH + 0.608AP$ $PM_{10} = 145.04 + 1.152T - 26.03WS$	0.11 0.089
Summer 2015	$PM_{10} = 88.779 - 0.895T + 0.008WD - 3.949WS - 1.197RH + 0.132AP$ $PM_{10} = 75.82 + 1.527T - 0.96WS$	0.068 0.011
Winter 2015-2016	$PM_{10} = -1870.20 + 2.107T + 0.171WD - 37.209WS - 0.619RH + 2.025AP$ $PM_{10} = 196.35 + 1.093T - 42.48WS$	0.16 0.13
Summer 2016	$PM_{10} = 972.039 - 0.147T + 0.011WD - 0.254WS - 0.203RH - 0.901AP$ $PM_{10} = 44.993 + 0.717T - 2.834WS$	0.018 0.008
Winter 2016-2017	$PM_{10} = 656.077 - 1.296T + 0.121WD - 19.052WS - 0.944RH - 0.475AP$ $PM_{10} = 125.58 - 0.408T - 21.262WS$	0.15 0.124
Summer 2017	$PM_{10} = 1882.289 - 0.609T + 0.043WD - 3.203WS - 0.408RH - 1.762AP$ $PM_{10} = 67.79 + 0.699T - 8.52WS$	0.063 0.041
Winter 2017-2018	$PM_{10} = -482.317 + 1.675T + 0.158WD - 24.491WS - 0.251RH + 0.572AP$ $PM_{10} = 114.831 + 1.709T - 26.322WS$	0.22 0.20
Summer 2018	$PM_{10} = 14.592 - 0.895T + 0.008WD - 3.949WS - 1.197RH + 0.132AP$ $PM_{10} = 68.102 - 0.171T - 2.873WS$	0.013 0.012
Winter 2018-2019	$PM_{10} = -362.997 - 0.248T + 0.085WD - 17.291WS - 0.443RH + 0.477AP$ $PM_{10} = 101.31 + 0.028T - 17.467WS$	0.15 0.131

4.6 The Spatial analysis of air quality Index (AQI) for PM_{10} during winter and summer season 2015-2018 by using IDW interpolation method

Air quality monitoring studies in Turkey dates back to the 1982 Constitution and the 1983 Environment Law. A number of legislative amendments, regulations and circulars on air quality regulation have recently been published. From 1982 to 2004, SO_2 and PM_{10} pollutant parameters were measured by semi-automatic stations. In 2004, 8 automatic air quality measurement stations, which can be viewed online first, were put into service in Ankara. Then, between 2005 and 2007, air quality measurement stations have been established in 81 provinces (URL-3 2018). Next granted access to the UHKİA web site (www.havaizleme.gov.tr) established in 2005. Table 2.2 shows the AQI category that is divided into six groups, good (0-50), moderate (51-100), unhealthy for sensitive groups (101-150), unhealthy (151-200), very unhealthy (201-300), and Hazardous (301-500). Where in moderate group, unusually sensitive people must

consider decreasing prolonged or heavy exertion, values of Air quality index (AQI) are calculated from the formula below:

$$AQI_{\text{pollutant}} = \frac{\text{Pollutant data reading}}{\text{Standard}} * 100$$

In unhealthy for sensitive groups, increasing probability of respiratory symptoms and aggravation of lung illness, like asthma. Persons with respiratory illness, for instance asthma, must ended outdoor exertion.

Unhealthy group, increased respiratory symptoms and aggravation of lung illness, for instance asthma; probable respiratory influences in common population. Persons with respiratory or heart illness, the elderly and children must take avoiding action prolonged hard work; everyone else must limit prolonged exertion. Sensitive group persons with respiratory illness are the group most at danger.

Very unhealthy group, important increase in respiratory symptoms and aggravation of lung illness, like asthma; increasing possibility of respiratory impacts in common population. Persons with respiratory illness, like asthma, must avoid any outdoor activity; everybody else, particularly the elderly and children, must limit outdoor exertion.

Hazardous, serious risk of respiratory symptoms and aggravation of lung illness, like asthma; respiratory impacts likely in common population. Everybody must avoid any outdoor exertion; people with respiratory disease, such as asthma, should remain indoors.

In order to understand the air quality of a region, it is significant to examine the change over the years. Therefore, in this study, winter season averages were formed based on PM₁₀ and SO₂ values per day between 2015 and 2018. Figure 4.110 shows the spatial distribution of AQI for PM₁₀ by using IDW method from January to April 2015, It is understood that the most important part of the air pollution seen in Igdir, Mus, Bursa, Duzce, Siirt, Kayseri_hurriyet, Karabuk, Edirne_Kesan, Istanbul_Kadikoy, Istanbul_Sariyer, Konya_KaratayBelediye, Zonguldak, Kocali_Dilovasi, Mardin, Bolu, Manisa_Soma, Batman, Muğla, Hakkari, Trabzon_Meydan, Tekirdag_Merkez, Samsun_ilkadamhastane, Afyon, Çanakkale_Can, Manisa, Bursa, Denizli, Hatay, and Karaman stations, is the very poor air quality on the basis of PM₁₀ parameter that had

been classified as very unhealthy and hazardous air quality, is caused by the fuel consumed for heating purposes, as well as industrial and traffic activities, about 2.83% found within good classification, 16.38% within moderate classification, 41.24% within unhealthy for sensitive groups, 21.47% within unhealthy classification, 16.38% within very unhealthy and 1.7% within hazardous classification. We see from the results that most parts of the southeastern and west parts of country occurs within unhealthy – hazardous classification, therefore must find solutions for the emission sources of PM₁₀ in these parts, The World Health Organization (WHO) recommends reducing energy production based on coal as a means of reducing air pollution ([Odası 2007](#)). Southeastern area of Turkey is more contaminated and most area of Black Sea side is the less contaminated depending on PM₁₀ concentrations. However, in some emerging frugalities for instance China, India and South Africa, and in some advanced countries for instance Australia, Canada and the United States, coal extraction and utilization are predictable to increase in the future years ([Hope 2014](#)). In 1990, 5.5 million tons of coal imports for coal power plants in Turkey has reached 69 million tons in 2017 ([Şişman 2019](#)).

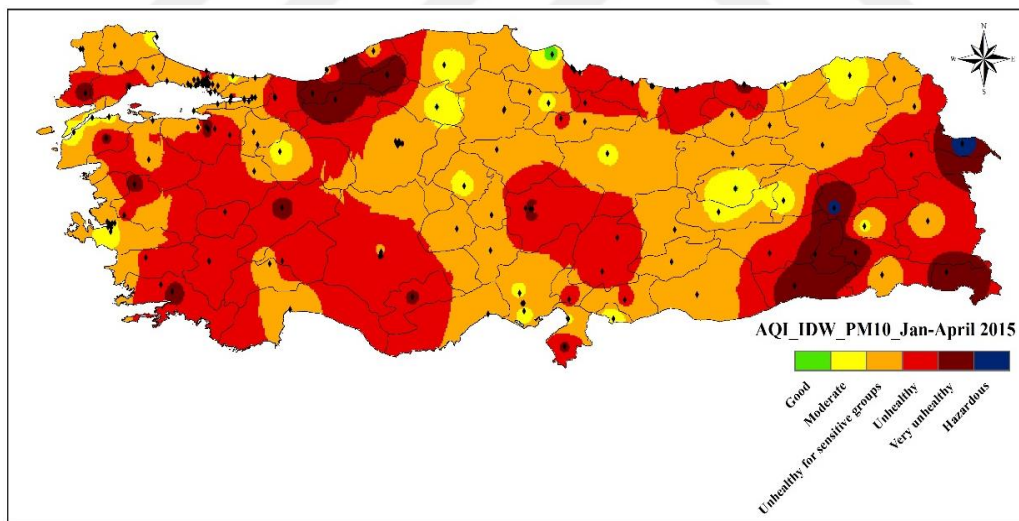


Figure 4. 110: Spatial analysis of AQI for PM₁₀, winter 2015 by applying IDW model

While figure 4.111 illustrates the spatial distribution of AQI for PM₁₀ by using IDW method during summer 2015, It is observed that the most significant part of the air contamination seen in Muş station is the very bad air quality on the basis of PM₁₀ parameter that had been classified as Hazardous air quality, Whereas in the stations, Istanbul_EsenyurtMTHM, Adana_Valilik, Siirt, Hakkari, Batman, Iğdir,

Adana_Meteoroloji and Mardin had been classed as very unhealthy within air quality index classification. When comparison between the winter and summer seasons we see the difference in the pollution where it's the highest pollution can be noticed in the winter season than summer season because of using coal fuel in domestic heating, as well as we can see the high values of PM₁₀ in the summer season in some stations that may be because traffic, industrial or from desert dust specially in the south eastern parts and in some southern parts of the country. Maximum PM₁₀ concentrations in summer happen in southeastern regions of Turkey that is credited to the local dust storms.

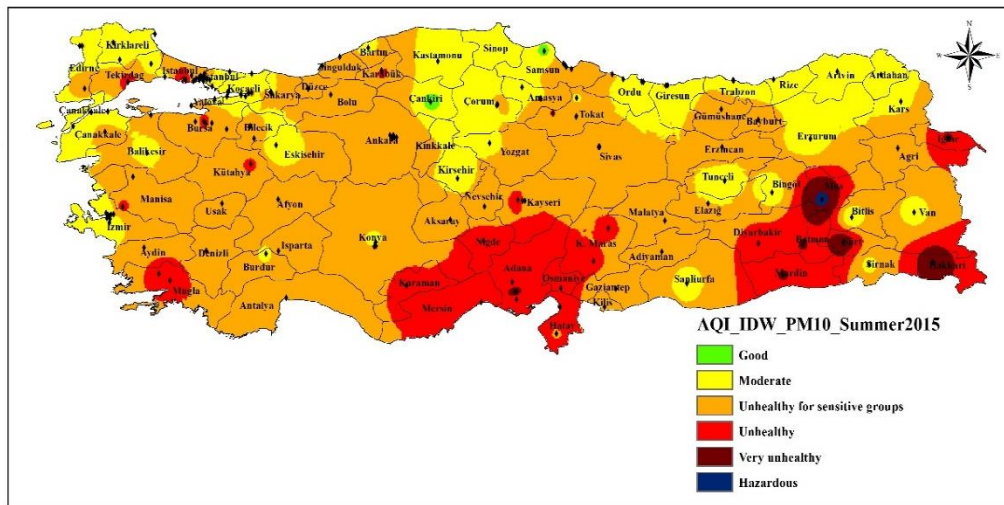


Figure 4. 111: Spatial analysis of AQI for PM₁₀, summer 2015 by applying IDW model

Figure 4.112 shows spatial analysis of AQI for PM₁₀ from Oct. 2015 to April 2016 by using IDW method, the most parts of the country mainly covered the poor polluted area. About 18.53% classed as good and moderate group, 29.76% classed as unhealthy for sensitive group, 29.76 as unhealthy group, 20% very unhealthy group and 1.95% as hazardous, the most important part of the air pollution seen in Iğdir, Mus, Bursa, Düzce, Siirt, Kayseri_hurriyet, Edirne_Kesan, Istanbul_Kumkoy, Istanbul_Aksaray, Istanbul_selimiye, Istanbul_Sariyer, Konya_KaratayBelediye, Zonguldak, Kocali_Dilovasi, Bolu, Manisa_Soma, Batman, Mugla, Hakkari, Trabzon, , Afyon, Çanakkale_Can, Manisa, Bursa, Denizli, Hatay, Karaman, Kars_trafik, Erzurum, Ankara, Erzincan, Kahramanmaras, Amasya, Sivas, Burdur, Ordu, Kutahya, Corum, Trabzon, Agri, Tokat, Malatya and Tokat stations, which had been classified as very unhealthy and hazardous air quality, which serious risk of respiratory symptoms and aggravation of lung illness, such as asthma; respiratory impacts likely in common

population. Everybody must avoid any outdoor exertion; persons with respiratory illness, for instance asthma, must stay indoors.

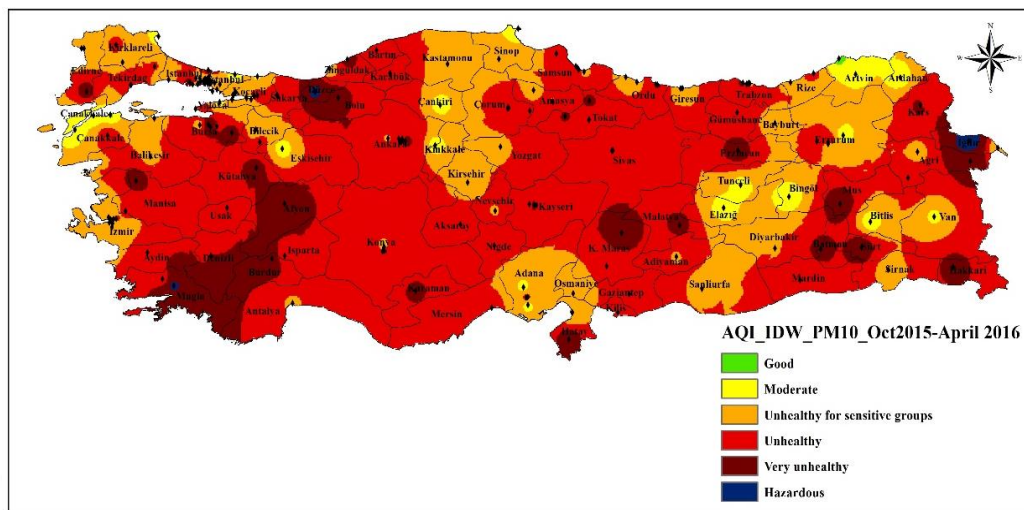


Figure 4. 112: Spatial analysis of AQI for PM₁₀, winter 2015-2016 by applying IDW model

While figure 4.113 shows the spatial distribution of AQI for PM₁₀ during summer 2016, the most important areas of the air pollution had been noticed in Istanbul_Kagithane and Istanbul_Maslak stations that had been classified as Hazardous air quality, Whereas in the stations Mus, Siirt, Izmir_Alsancak, Tekirdag_MerkezMTHM, Hakkari and Agri_Dogubeyazit had been classified as very unhealthy air quality.

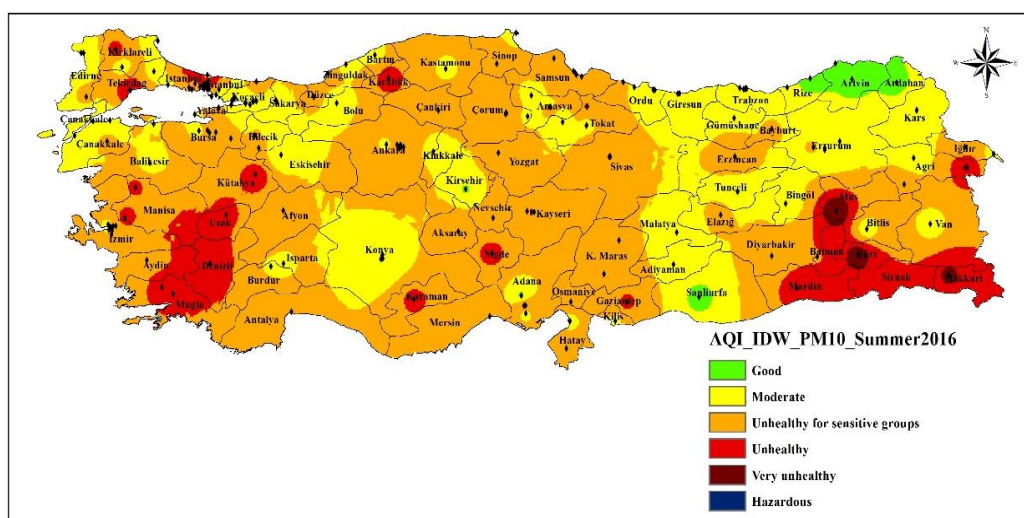


Figure 4. 113: Spatial analysis of AQI for PM₁₀, summer 2016 by applying IDW model

Figure 4.114 shows spatial analysis of AQI for PM₁₀ from Oct. 2016 to April 2017, about 2.41% found within good classification, 18.75% within moderate classification, 33.17% within unhealthy for sensitive groups, 26.44% within unhealthy classification, 17.79% within very unhealthy and 1.44% within Hazardous classification, the highest values of the air pollution noticed in Istanbul_Kumkoy, Igdir, Düzce, Mugla_Musluhittin, Bursa, Istanbul_EsenyurtMTHM, Afyon, Kars_trafik, Konya_KaratayBelediye, Mus, Kayseri_Hürriyet, Erzurum_Tashan, Denizli_Bayramyeri, Manisa_Soma, Ankara, Hatay_Antakya, Siirt, Erzincan, Kahramanmaras_Elbistan, Istanbul_Aksaray, Bursa_InegolMTHM, Edirne_KesanMTHM, Amasya_Sehzade, Sivas_istasyonkavsagi, Burdur, Ordu_Karsiyaka, Kütahya, Istanbul_Selimiye, Corum_Bahabey, Trabzon_Akçaabat, Agri_Dogubeyazit, Tokat_Erbaa, Batman, Malatya, Zonguldak, Trabzon_Besirli, Bursa_BeyazitCadMTHM, Bolu, Hakkari, Tokat_Turhal, Karaman, Kocaeli and Erzincan_Trafik stations that had been classed as very unhealthy and hazardous air quality index.

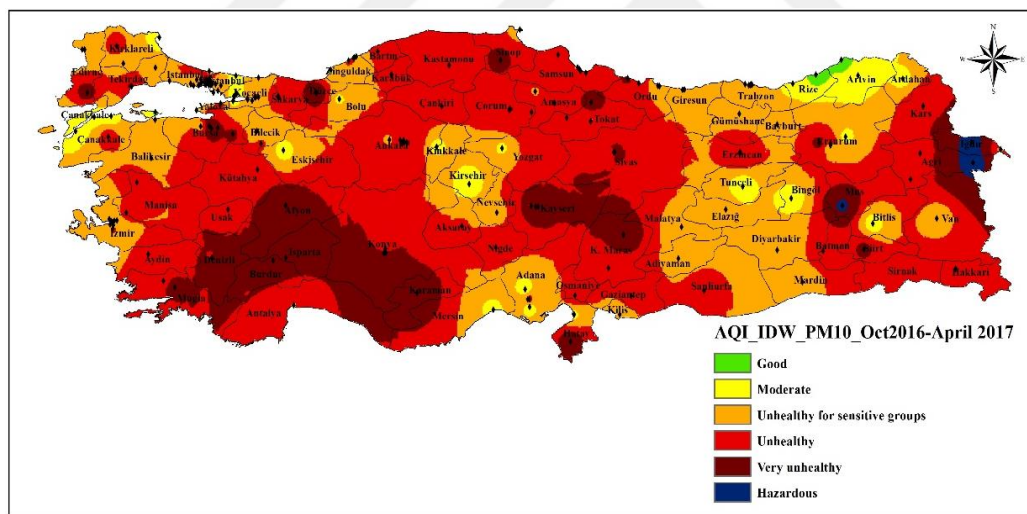


Figure 4. 114: The spatial distribution of AQI for PM₁₀, winter 2016-2017 by applying IDW model

Whereas figure 4.115 appears the spatial distribution of AQI for PM₁₀ during summer 2017, the most significant regions of the air pollution had been observed in Ankara_Kayaş, Igdir, Hakkari, Nigde, Adana_Meteoroloji, Ankara_Sihhiye and Bursa stations that had been classified as very unhealthy air quality.

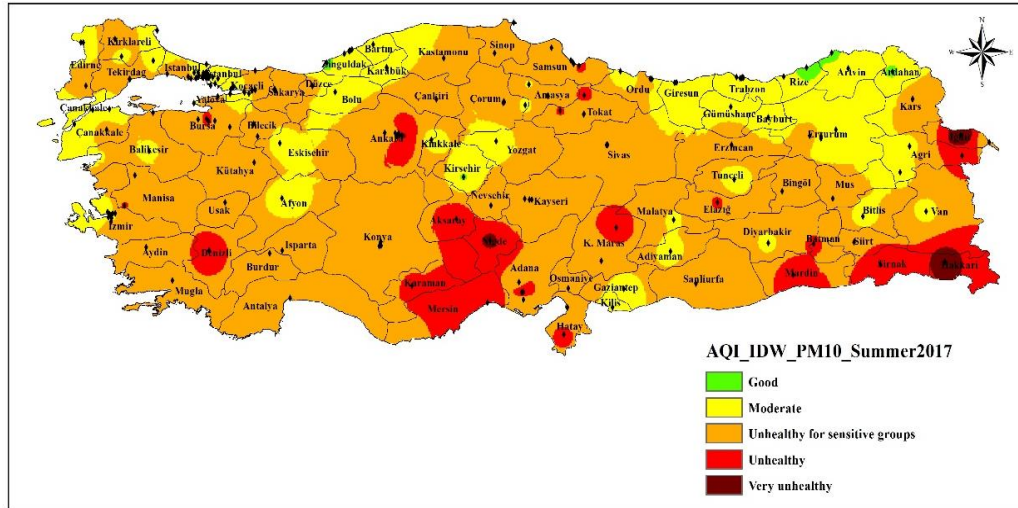


Figure 4. 115: Spatial analysis of AQI for PM₁₀, summer 2017 by applying IDW model

Whereas figure 4.116 shows spatial analysis of AQI for PM₁₀ from Oct. 2017 to April 2018, about 1.42% found within good classification, 21.8% within moderate classification, 31.76% within unhealthy for sensitive groups, 27.01% within unhealthy classification, 16.59% within very unhealthy and 1.42% within Hazardous classification, the highest values of the air pollution observed in Iğdir, Kahramanmaraş_Elbistan, İzmir_Sirinyer, Bursa, Bursa_BeyazıtCadMTHM, Afyon, Ordu_Fatsa, Adana_Meteoroloji, Erzincan, Kocaeli_Dilovası, Manisa, Kayseri_Hürriyet, Çorum_Bahabey, Ankara_Sihhiye, Sakarya_MerkezMTHM, Osmaniye, Kayseri_OSB, Tokat_Erbaa, Manisa_Soma, Konya_KaratayBelediye, Tokat_Meydan, Niğde, Erzurum_Taşhan, Düzcce, Sanliurfa, İçel, Kocaeli_izmitMTHM, Denizli_Bayramyeri, Malatya, Amasya_Sehzade, Ankara_Keçioren, Tekirdağ_MerkezMTHM, Çorum_MimarSinan, Muğla_Yatağan, Erzurum_Aziziye, Ankara_Sincan, Mus and Samsun_Yüzüncüyıl stations that had been categorized as very unhealthy and hazardous air quality index. Generally, air pollution occurs in the same stations with small differences (especially in 2018) during period 2015-2018, this means the air pollution emission from the same sources in each station. In these stations where pollution rate is high, priority should be given to studies to improve air quality by evaluating this situation which may adversely affect public health. The determination of the PM contribution caused by long distance transport is very important for evaluating the excesses due to natural resources, With the NASA satellite images, Barcelona Dust Forecast Center BSC models were used to determine the long-distance dust transport periods visually ([EC Commission Staff \(2011\)](#), [Tosun \(2017\)](#)).

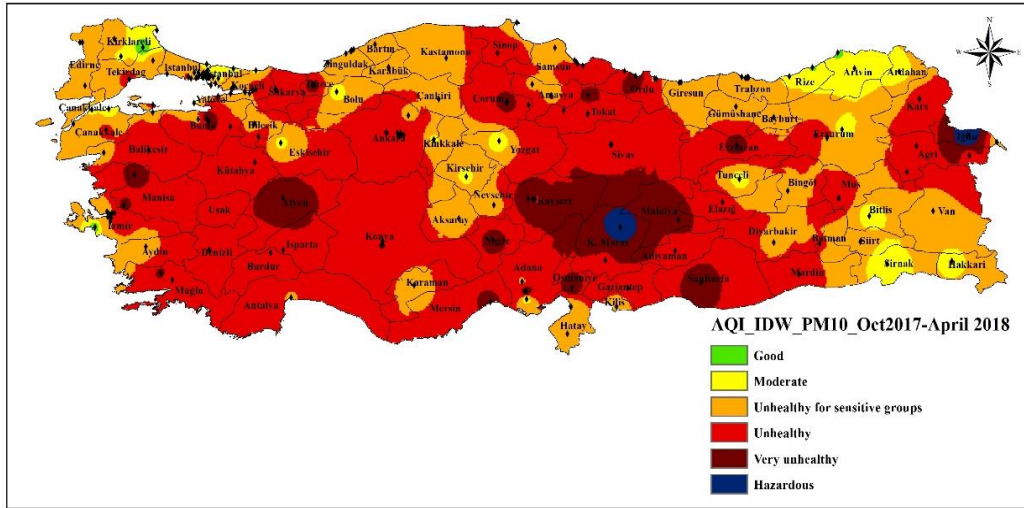


Figure 4. 116: Spatial Analysis of AQI for PM₁₀, winter 2017-2018 by applying IDW model

While figure 4.117 illustrates the spatial distribution of AQI for PM₁₀ during summer 2018, the highest value of air pollution had been noticed in Izmir_Karsiyaka station that had been classified as hazardous air quality, whereas in the stations Igdir, Sirnak, Manisa, Kahramanmaras_Elbistan, Trabzon_Meydan, Mus, and Ankara_Sihhiye had been classified as very unhealthy air quality.

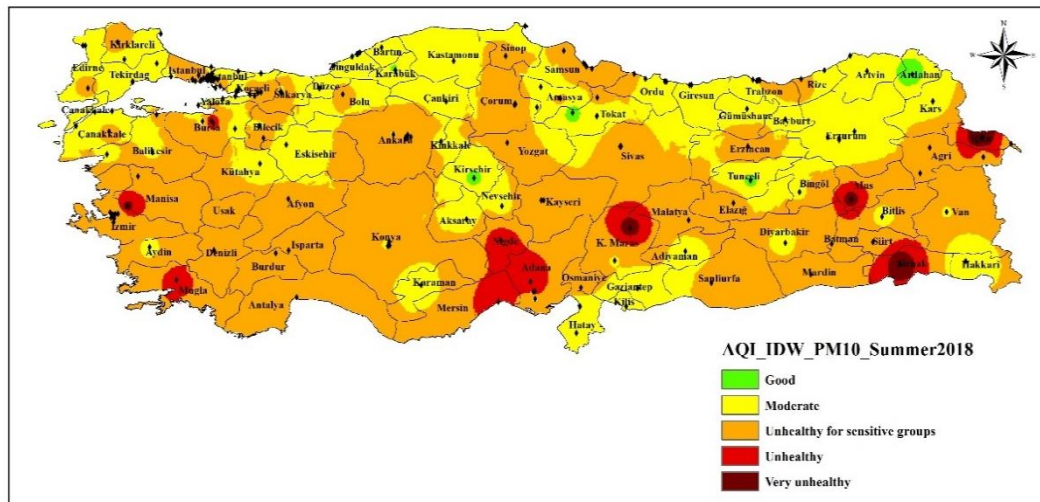


Figure 4. 117: Spatial analysis of AQI for PM₁₀, summer 2018 by applying IDW model

4.7 The Spatial analysis of air quality Index (AQI) for SO₂ during winter and summer season 2015-2018 by using IDW interpolation method

Emissions that cause air pollution occur because of natural phenomena and the activities necessary for us to live, and they affect the environment and human health

negatively when released at high values. Generally sulfur dioxide (SO₂), carbon monoxide (CO), nitrous oxide (N₂O, NO), such as many gases that release to the atmosphere through these means (Şişman 2019). According to the targets of the gradual reduction within the scope of the Air Quality Estimation Regulation and Administration, for the SO₂ parameter, which must below the limit values within the scope of compliance with the EU limit values, it is essential to maintain the level of air quality at the clean air center while audits and clean fuel should be used in the regions which are above the limits especially for the winter period.

Figure 4.118 shows spatial analysis of AQI for SO₂ from Jan. to April 2015, about 40.11% found within good classification, 29.94% within moderate classification, 15.25% within unhealthy for sensitive groups, 7.92% within unhealthy classification, 3.39% within very unhealthy and 3.39% within Hazardous classification that causes severe respiratory symptoms. The maximum values of the air pollution observed in Edirne_Keşan_MTHM, Şırnak, Çanakkale_CanMTHM, Manisa_Soma, Tekirdag_MerkezMTHM and Afyon stations that had been classed as hazardous within air quality index classification, which causes severe respiratory symptoms, everyone else should avoid outdoor exertion. While the stations Hakkari, Bolu, Kırklareli_LüleburgazMTHM, Muş, Karabük_Kardemir2 and Bursa_KestelMTHM had been classed as very unhealthy within air quality index classification that causes important increase in respiratory symptoms.

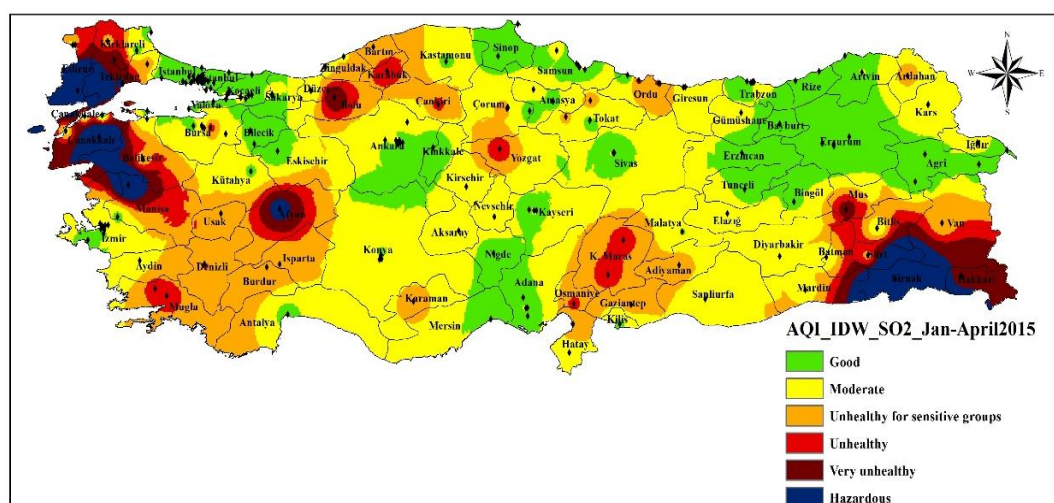


Figure 4. 118: Spatial Analysis of AQI for SO₂, winter 2015 by applying IDW model

While figure 4.119 shows the spatial distribution of AQI for SO₂ during summer 2015, the highest value of air pollution had been noticed in Hakkari station that had been classified as very unhealthy air quality, whereas in the stations Karabük_Kardemir2, Corum_Mimar Sinan, and Samsun_Tekkekoy had been classified as unhealthy air quality classification.

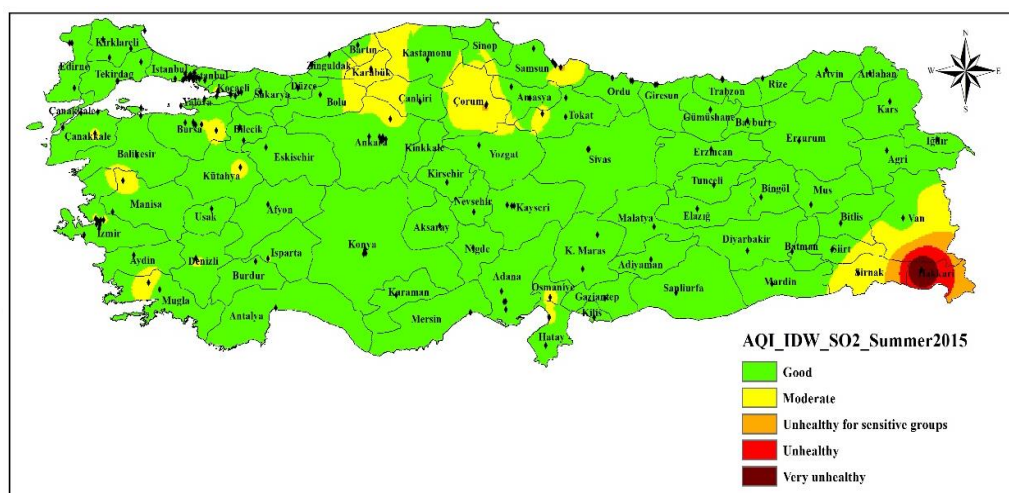


Figure 4. 119: Spatial analysis of AQI for SO₂, summer 2015 by applying IDW model

Figure 4.120 shows spatial analysis of AQI for SO₂ from Oct. 2015 to April 2016, about 29.41% found within good classification, 34.22% within moderate classification, 17.65% within unhealthy for sensitive groups, 7.49% within unhealthy classification, 5.88% within very unhealthy and 5.35% within Hazardous classification, the maximum values of the air pollution observed in Edirne_KesanMTHM, Manisa_Soma, Amasya_Suluova, Çanakkale_CanMTHM, Amasya_Şehzade, Yozgat, Ordu_Fatsa, Amasya_Merzifon, Karabük_Kardemir1 and Karabük_Kardemir2 stations that had been classed as hazardous air quality index. Whereas the stations such as Tekirdag_MerkezMTHM, Hakkari, Tekirdag_CerkezkoyMTHM, Sivas_BasOgretmen, Samsun_Atakum, Sirnak, Denizli_Bayramyeri, Kars_istasyonMah, Tekirdag, Karabük and Samsun_Tekkekoy had been classed as very unhealthy air quality index.

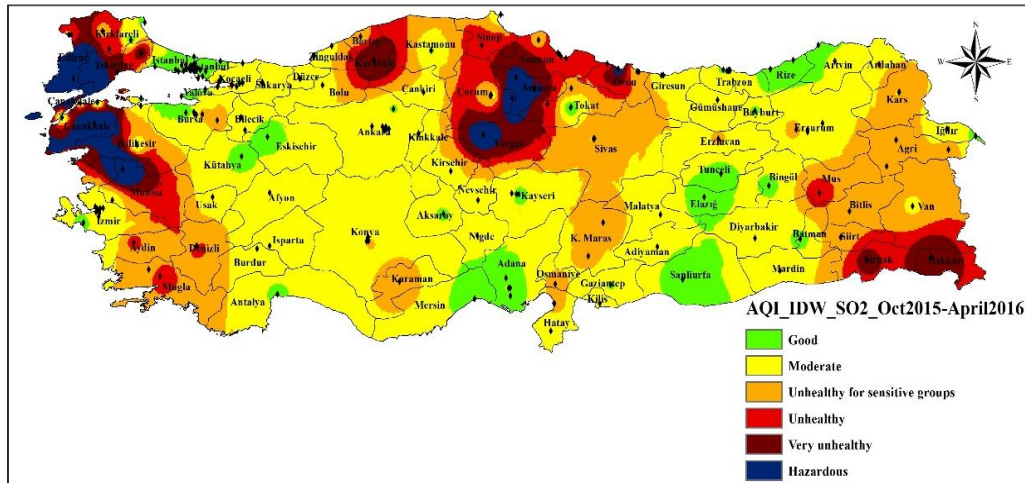


Figure 4. 120: Spatial Analysis of AQI for SO₂, winter 2015-2016 by applying IDW model

Whereas figure 4.121 shows the spatial distribution of air quality index (AQI) for SO₂ during summer 2016, the maximum value of air pollution had been observed in Kocaeli_KorfezMTHM station that had been classified as very unhealthy air quality, whereas in the stations Ankara Sincan, Istanbul Kandilli MTHM, Kocaeli Golcük MTHM, Istanbul_Catladikapi, Trabzon_Akçaabat and Samsun_Yüzüncüyıl had been classified as unhealthy air quality classification, sensitive classifies must avoid prolonged or heavy exertion; general public must decrease prolonged or heavy exertion.

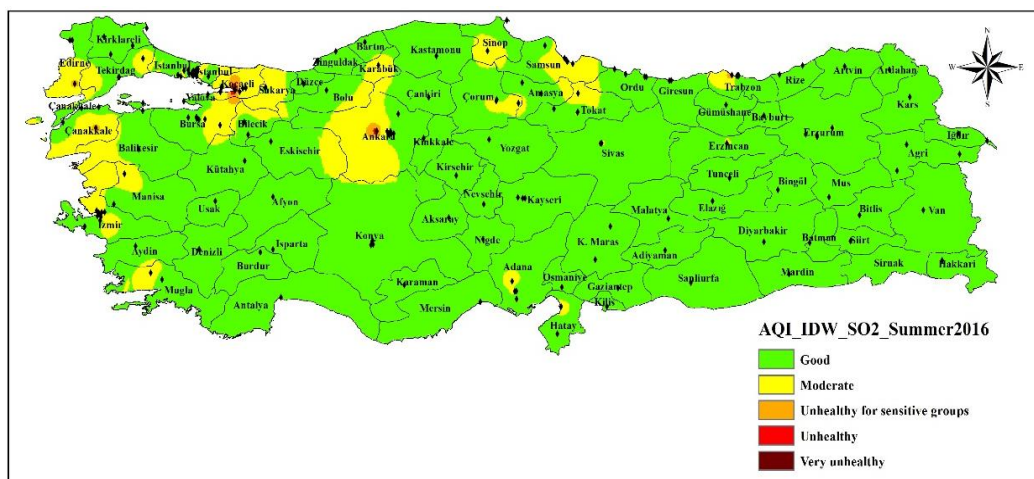


Figure 4. 121: Spatial analysis of AQI for SO₂, summer 2016 by applying IDW model

Figure 4.122 shows spatial analysis of AQI for SO₂ from Oct. 2016 to April 2017, about 35.21% found within good classification, 33.67% within moderate classification, 14.29% within unhealthy for sensitive groups, 8.67% within unhealthy classification,

5.10% within very unhealthy and 3.06% within Hazardous classification, the maximum values of the air pollution observed in Edirne_KesanMTHM, Amasya_Suluova, Manisa_Soma, Amasya_Sehzade, Hakkari, Ordu_Fatsa stations that had been classed as hazardous air quality index. Whereas the stations such as Tekirdag_MerkezMTHM, Tokat_Turhal, Sivas_BasOgretmen, Agri_Patnos, Ordu_Karsiyaka, Agri_Dogubeyazit, Corum_MimarSinan, Siirt, Sinop_Boyabat, Mus had been classed as very unhealthy air quality index.

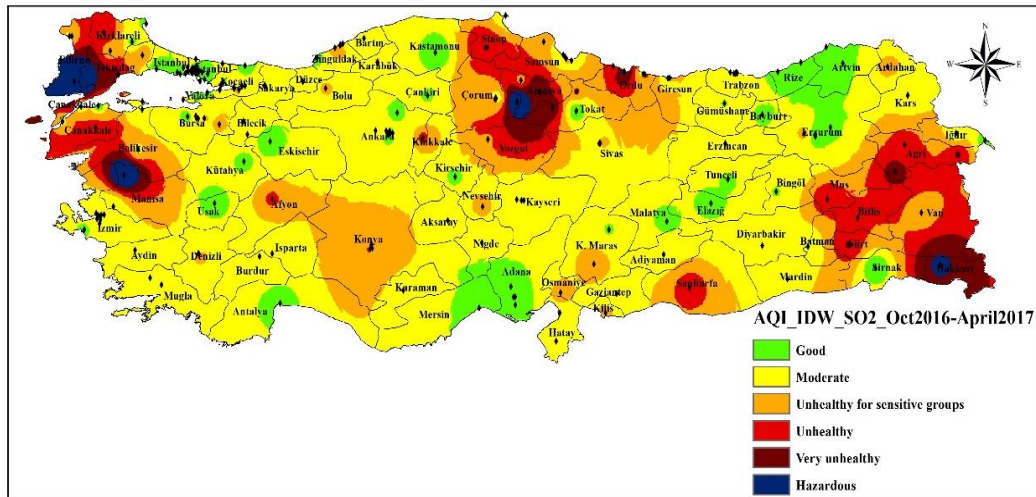


Figure 4. 122: Spatial Analysis of AQI for SO₂, winter 2016-2017 by applying IDW model

Whereas figure 4.123 appears the spatial distribution of AQI for SO₂ during summer 2017, the maximum value of air pollution had been observed in Istanbul_SirinevlerMTHM and Kocaeli_KorfezMTHM had been classed as unhealthy air quality index.

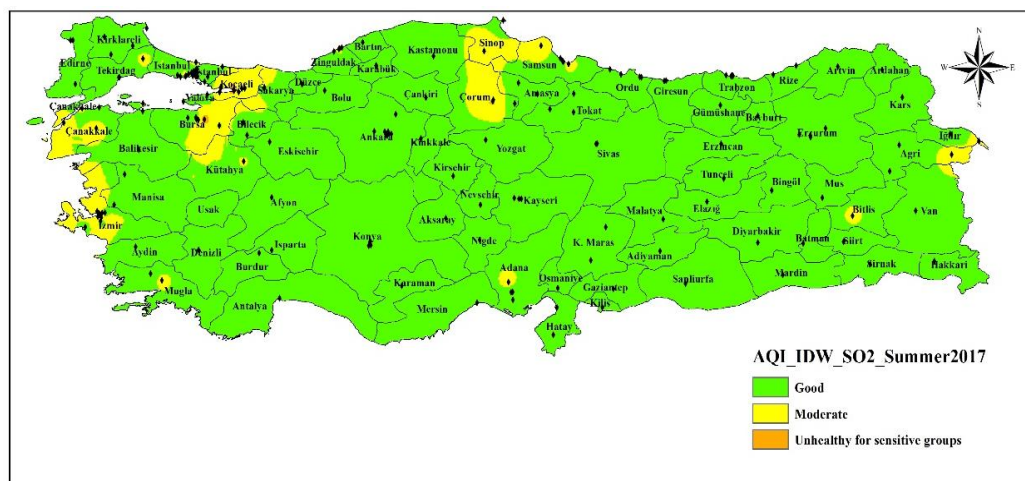


Figure 4. 123: Spatial analysis of AQI for SO₂, summer 2017 by applying IDW model

Whereas Figure 4.124 shows spatial analysis of AQI for SO₂ from Oct. 2017 to April 2018, about 35.31% found within good classification, 34.83% within moderate classification, 14.43% within unhealthy for sensitive groups, 10.45% within unhealthy classification, 3.48% within very unhealthy and 1.49% within Hazardous classification, the maximum values of the air pollution observed in Edirne_KesanMTHM, Manisa_Soma and Bitlis stations that had been classed as hazardous air quality index. Whereas the stations such as Agri_Dogubeyazit, Hakkari, Siirt, Amasya_Sehzade, Tekirdag_MerkezMTHM, Tokat_Turhal and Karabük_Kardemir1 had been classed as very unhealthy air quality index.

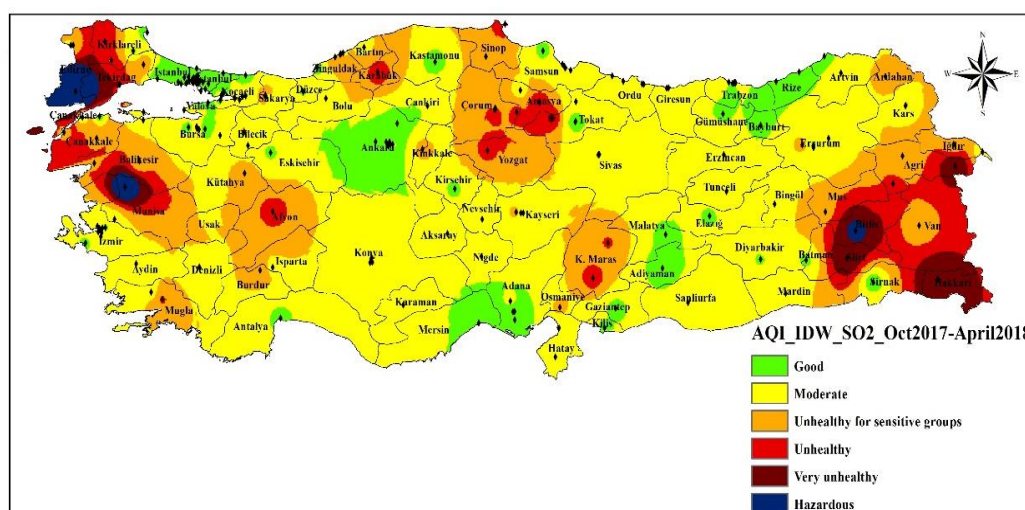


Figure 4. 124: Spatial Analysis of AQI for SO₂, winter 2017-2018 applying IDW model

Whereas figure 4.125 illustrates the spatial distribution of AQI for SO₂ during summer 2018, the maximum value of air pollution had been observed in Kirikkale and Kırklareli that had been classed as hazardous air quality index, Whereas in Adana_Dogankent station had been classed as very unhealthy air quality, and in the stations like Canakkale, Tokat_Turhal and Balıkesir_MerkezMTHM had been classified as unhealthy air quality.

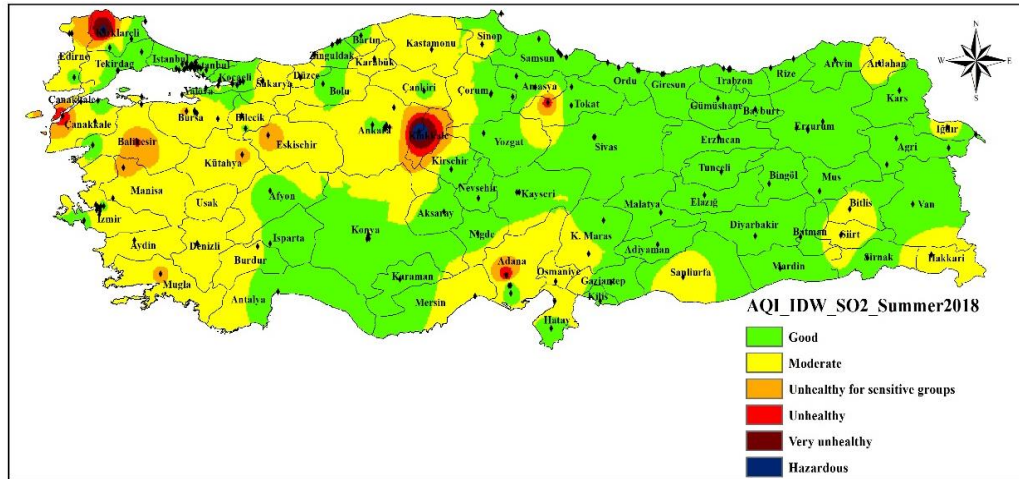


Figure 4. 125: Spatial analysis of AQI for SO₂, summer 2018 by applying IDW model

It is clear that the PM₁₀ and the SO₂ levels increase in parallel in the provinces that continued use of fossil fuel, such as coal solid fuels. Generally, the concentrations of PM₁₀ and SO₂ in the winter seasons higher than in the summer seasons.

4.8 The Cokriging modelling

The Kriging method is a geostatistical technique employed for spatial estimation. It is possible to estimate the difference between the positions of the measured points and the data obtained by using the correlations with the smallest variance. Simple Kriging, Ordinary Kriging, Universal Kriging, Cokriging, etc. were used. The estimator of CoKriging is an improved kriging process that has secondary variables, cokriging can be utilized to forecast the mean values of a multi-variate process at a wide scale, Its application becomes excessive when too many information are available, but the screening influence approximation may permit one to decrease the number of initial and/or secondary information without much loss of accuracy in the prediction. ([Pebesma 2004](#), [Forrester, Sóbester et al. 2007](#), [Calcagno, Chilès et al. 2008](#), [Castrignanò, Quarto et al. 2019](#), [Madani and Emery 2019](#), [Momejian, Najm et al. 2019](#)).

Figure 4.126 appears the spatial distribution of air quality index (PM₁₀) using kriging method through winter 2017-2018 and figure 4.127 presents the semivariogram modeling of PM₁₀ Kriging method where the exponential semivariogram modeling had been selected as the better model after checking all the semivariogram methods.

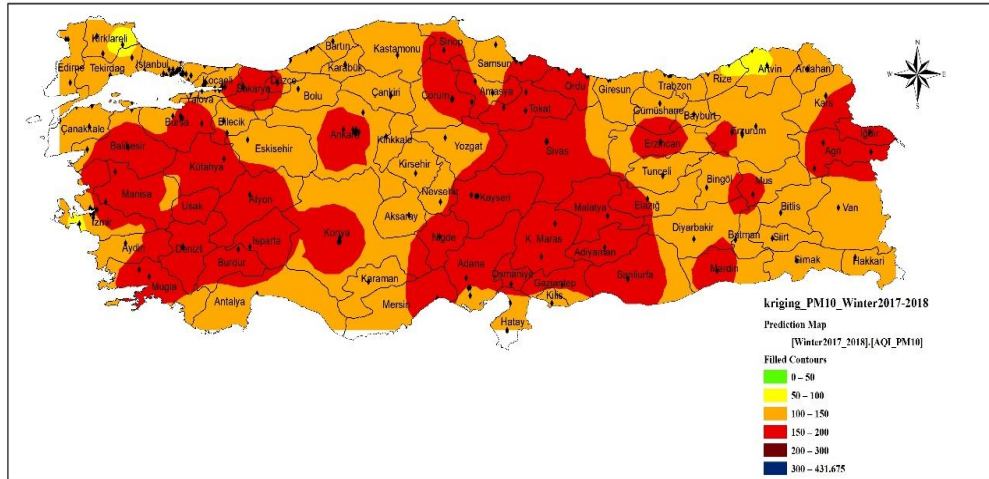


Figure 4. 126: Spatial analysis of PM₁₀, simple Kriging method during winter 2017-2018

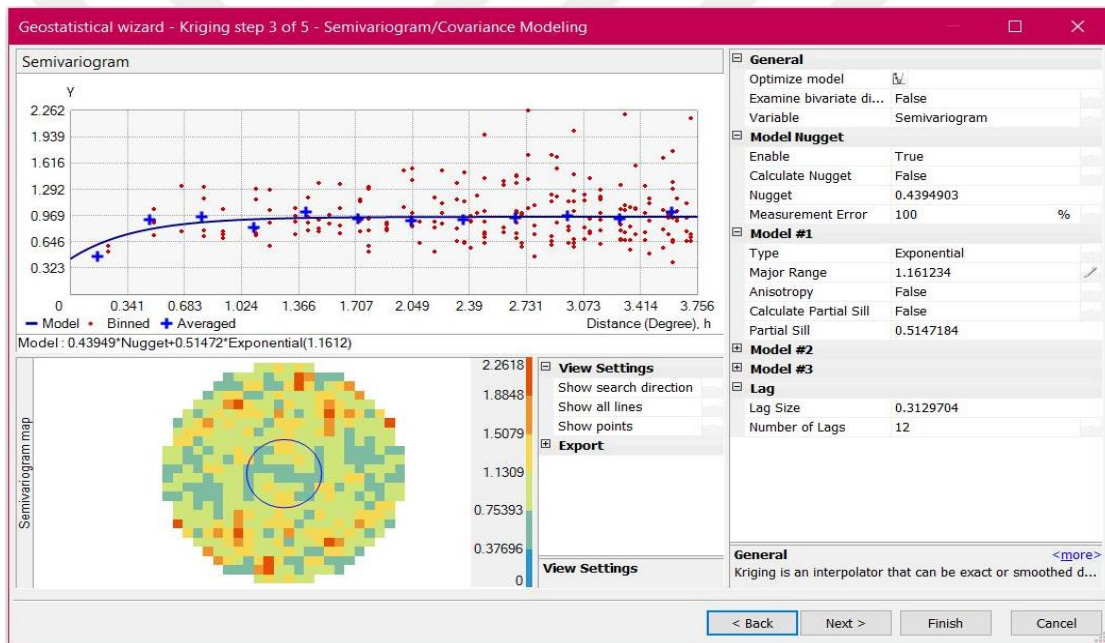


Figure 4. 127: Semivariogram modeling of PM₁₀ simple Kriging method

Whereas figure 4.128 shows the spatial distribution of PM₁₀-SO₂ using CoKriging method during winter 2017-2018, while figure 4.129 presents the semivariogram modeling of PM₁₀-SO₂, CoKriging method during winter 2017-2018, where the Exponential semivariogram modeling had been selected as the better model for PM₁₀ after testing all the semivariogram methods and J-Bessel semivariogram modeling had been chosen as the best model for SO₂ after testing all the semivariogram methods. When comparison the kriging (figure 4.126) and cokriging (figure 4.128)

methods we can see the pollution increasing in cokriging method where the SO_2 values enter to the semivariogram model beside PM_{10} values.

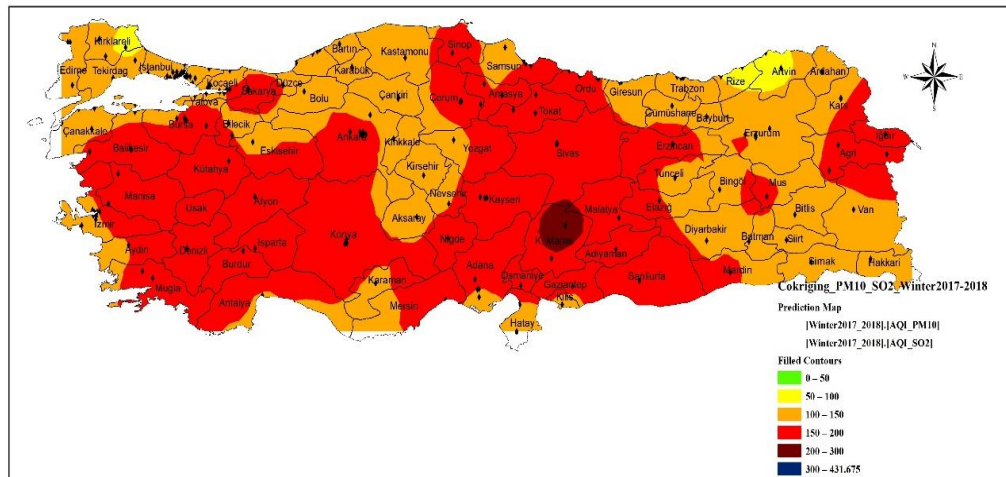


Figure 4. 128: Spatial analysis of PM_{10} - SO_2 , CoKriging method during winter 2017-2018

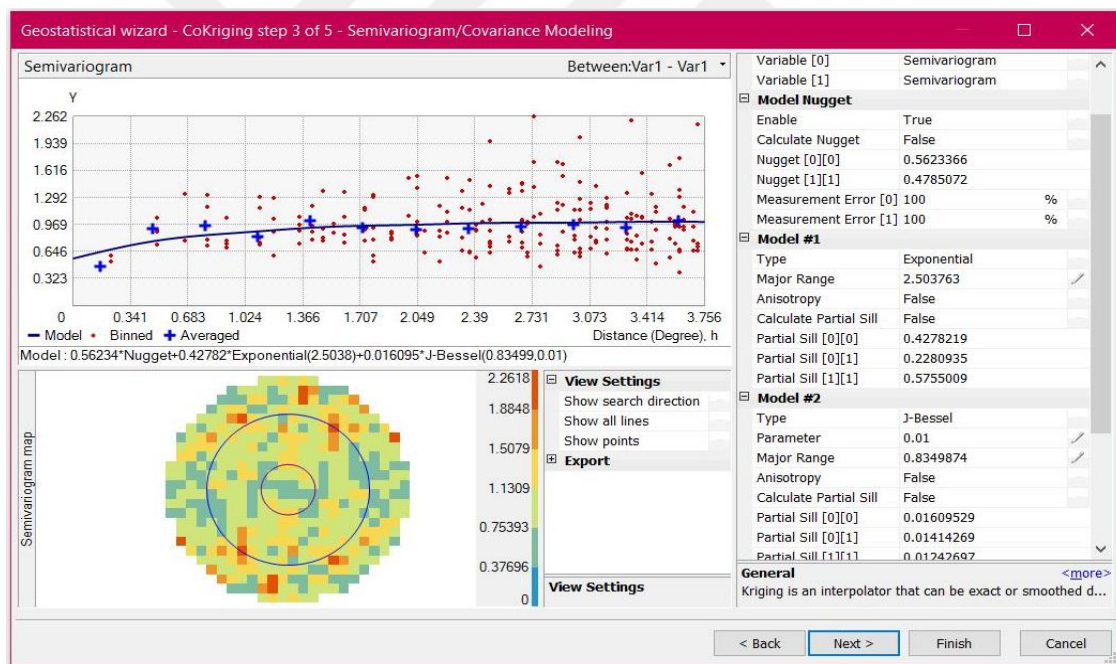


Figure 4. 129: Semivariogram modeling of PM_{10} - SO_2 , simple CoKriging method

Figure 4.130 shows Cross-validation comparison between CoKriging (PM_{10} - SO_2) and Kriging (PM_{10}) that had been selected as the best methods during winter 2017-2018, we can see from this figure that the cokriging method give best prediction than from kriging method based on the prediction errors.

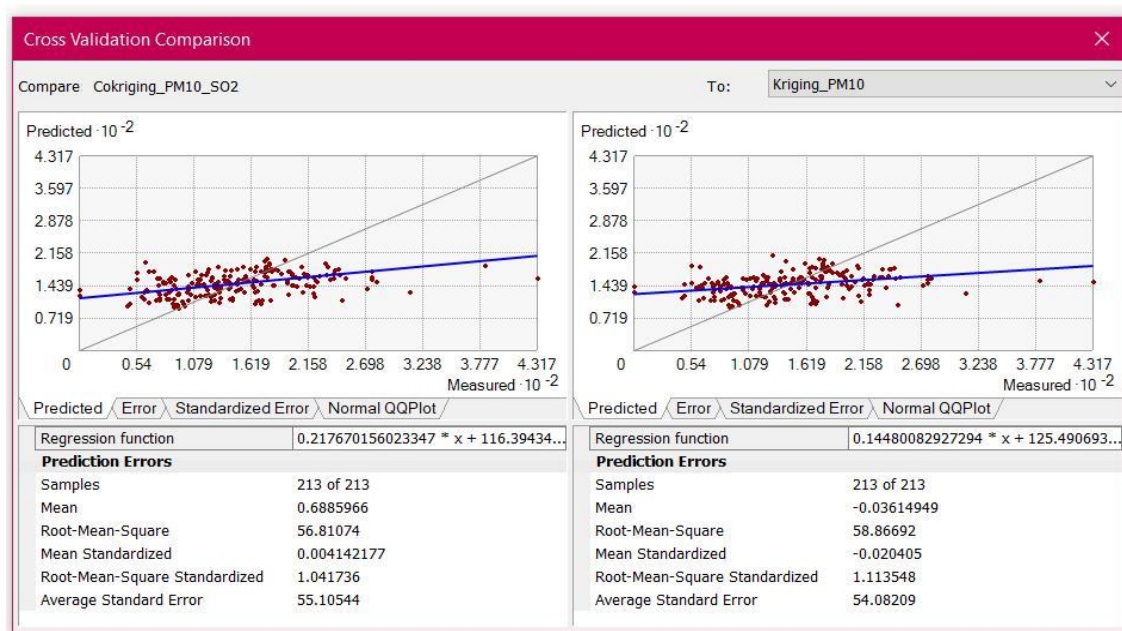


Figure 4. 130: Cross-validation comparison between CoKriging (PM₁₀-SO₂) and Kriging (PM₁₀) that had been selected as the best methods during winter 2017-2018

Whereas figure 4.131 shows the spatial distribution of PM₁₀ (Exponential semivariogram modeling) as dependable variable and effect of NO_x (Gaussian semivariogram modeling) as undependable variable by using simple CoKriging method during winter 2017-2018, based on this method the distribution of pollution spread more than PM₁₀ kriging method.

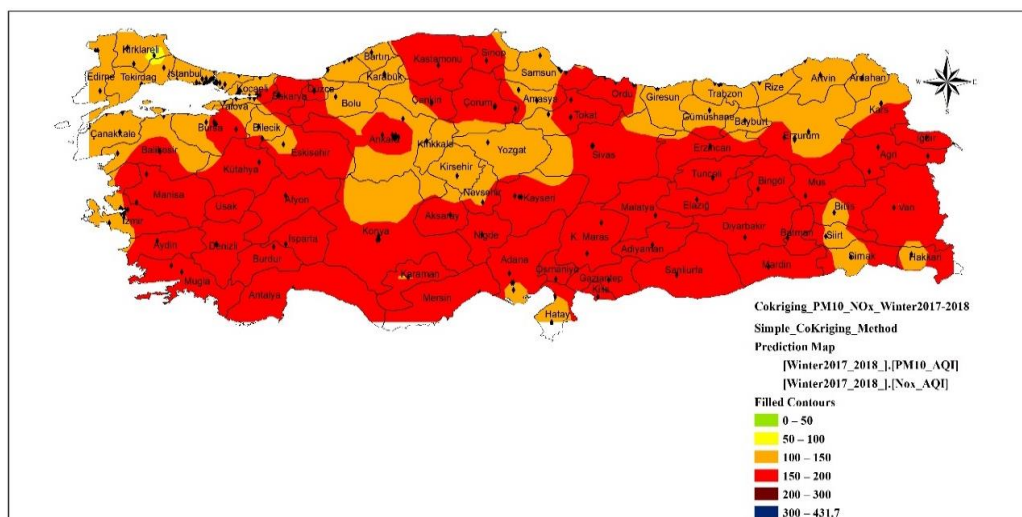


Figure 4. 131: Spatial analysis of PM₁₀-NO_x, CoKriging method during winter 2017-2018

Figure 4.132 shows semivariogram modeling of PM_{10} - NO_x by utilizing simple CoKriging method that had been chosen as best method after testing all method.

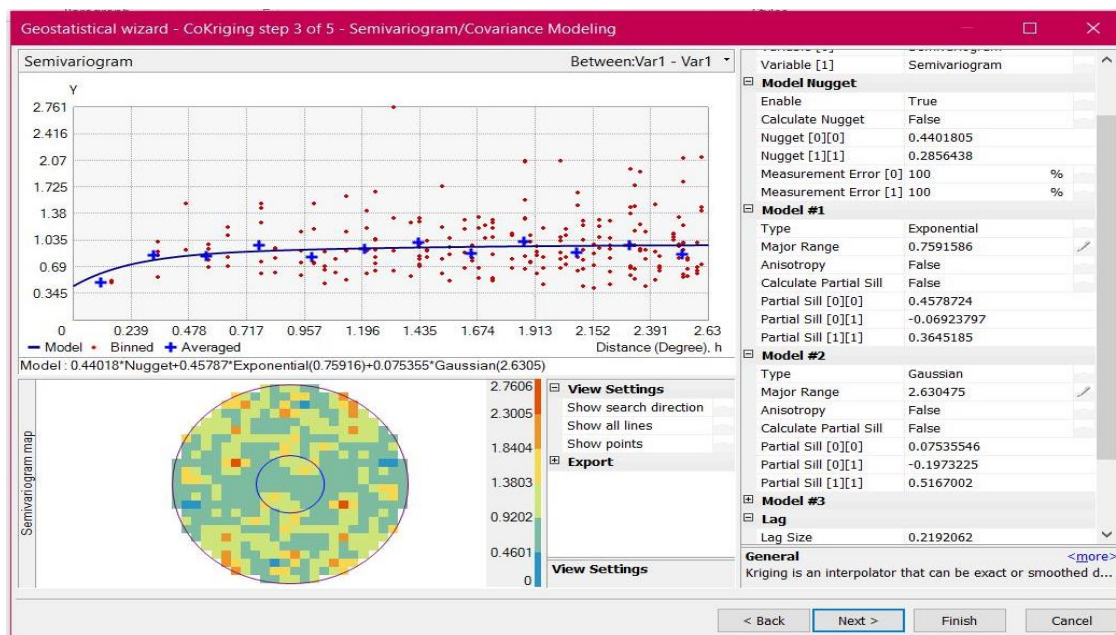


Figure 4. 132: Semivariogram modeling of PM_{10} - NO_x , simple CoKriging method

Figure 4.133 shows the spatial distribution of PM_{10} (Exponential semivariogram modeling) as dependable variable and effect of SO_2 (J-Bessel semivariogram modeling) and NO_x (Gaussian semivariogram modeling) as undependable variable by using simple CoKriging method during winter 2017-2018, based on this method the distribution of pollution spread more than other above methods.

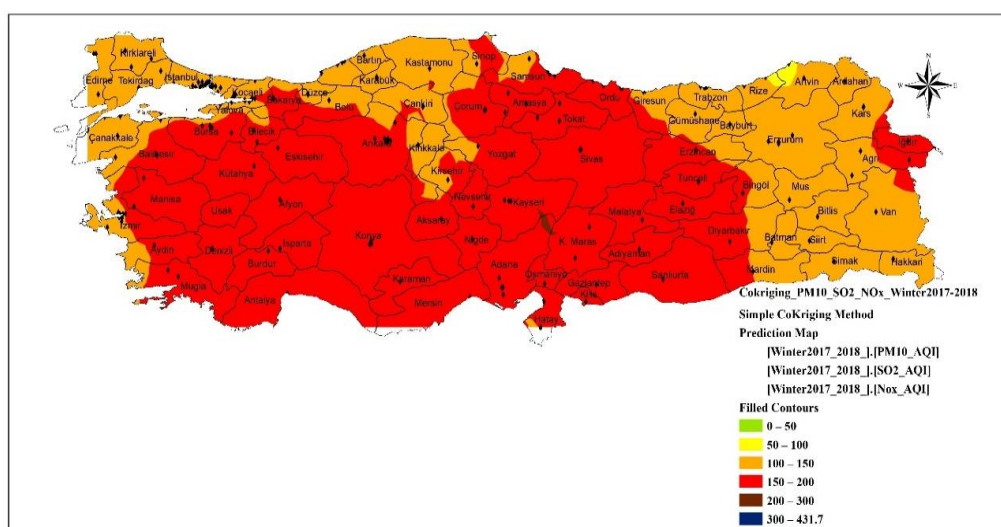


Figure 4. 133: Spatial analysis of PM_{10} - SO_2 - NO_x , CoKriging method during winter 2017-2018

Figure 4.134 appears semivariogram modeling of PM₁₀-SO₂-NO_x by applying simple CoKriging method after choosing Exponential (PM₁₀), J-Bessel (SO₂) and Gaussian (NO_x) semivariogram modeling as the best semivariogram models to give the best prediction map of PM₁₀ and that shows the effects of SO₂ and NO_x values on this model.

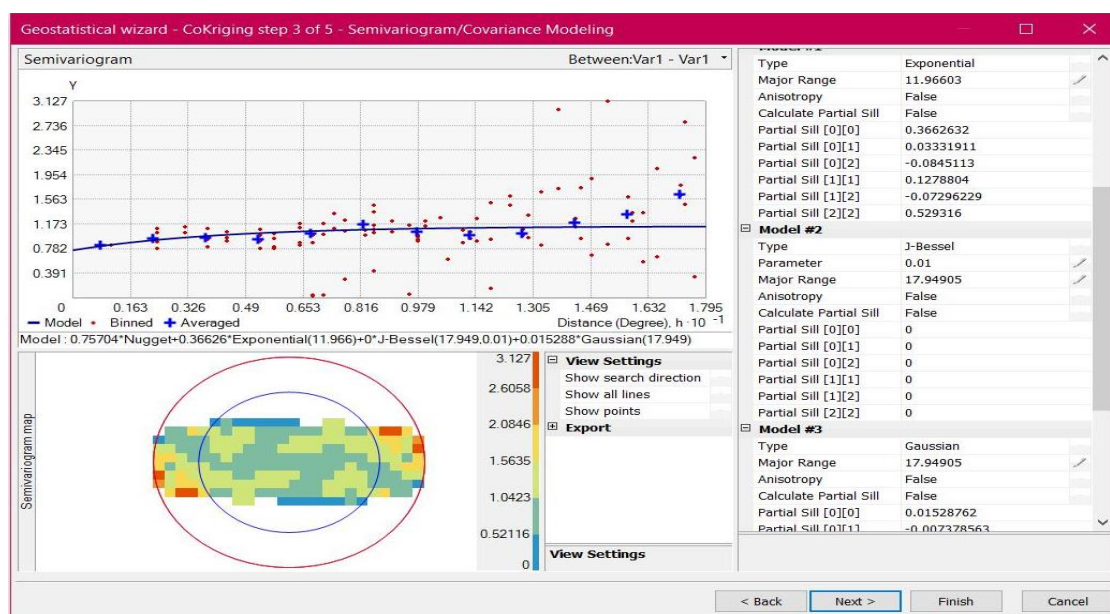


Figure 4. 134: Semivariogram modeling of PM₁₀-SO₂-NO_x, simple CoKriging method

Tables 4.33 and 4.34 show semivariogram modelling properties and fitted factors of the theoretical semivariogram model for PM₁₀ depending on prediction errors that are Mean (M), Root-Mean-Square (RMS), Mean-Standardized (MS), Root-Mean-Square-Standardized (RMSS) and Average-Standard-Error (ASE), during winter 2017-2018 for Turkey country that had been selected as best models after experimenting of all semivariogram models

Table 4. 32: Semivariogram modelling for PM₁₀ during winter 2017-2018

Geostatistical Method	Method Type	Model Type	Nugget	Partial Sill	Major Range
PM₁₀_Kriging	Simple Kriging	Exponential	0.439	0.515	1.161
PM₁₀-SO₂_CoKriging	Simple Kriging	Exponential_J-Bessel	0.562	0.428	2.504
PM₁₀-NO_x_CoKriging	Simple Kriging	Exponential_Gaussian	0.440	0.458	0.759
PM₁₀-SO₂-NO_x_CoKriging	Simple Kriging	Exponential_J-Bessel_Gaussian	0.757	0.366	11.966

Table 4. 33: The best fitted factors of the theoretical semivariogram model for PM₁₀ depending on prediction errors during winter 2017-2018

Geostatistical Method	M	RMS	MS	RMSS	ASE	Regression function
PM ₁₀ _Kriging	-0.036	58.867	-0.020	1.114	54.082	0.145 * x + 125.49
PM ₁₀ -SO ₂ _CoKriging	0.689	56.81	0.004	1.04	55.105	0.218 * x + 116.394
PM ₁₀ -NO _x _CoKriging	5.046	60.64	0.055	1.12	55.639	0.116 * x + 138.076
PM ₁₀ -SO ₂ -NO _x _CoKriging	2.092	58.210	0.032	0.998	58.68	0.179 * x + 123.435

Table 4.35 shows some statistical factors, such as minimum, maximum, mean and standard deviation for values of PM₁₀, SO₂ and NO_x, in addition to the multiply liner regression equation of PM₁₀ in provinces of Turkey during winter 2017-2018. Equation below was obtained from the results, and each coefficient has a positive value, this means PM₁₀ increases with increasing of SO₂ and NO_x, $R^2 = 0.086$, indicating to weak correlation between the parameters.

Table 4. 34: Descriptive Statistics of pollutants and regression equation of PM₁₀

Pollutants	Minimum	Maximum	Mean	Std. Deviation
PM ₁₀ _AQI	44.857	431.675	144.528	60.026
SO ₂ _AQI	11.429	500	82.074	68.539
NO _x _AQI	6.667	500	223.678	145.310
PM ₁₀ =108.52+0.198 SO ₂ +0.088 NO _x $R^2 = 0.086$				
PM ₁₀ =136+0.14 SO ₂ $R^2 = 0.026$				
PM ₁₀ =127+0.08NO _x $R^2=0.036$				

Figures 4.135 and 4.136 show the scatter relation between PM₁₀ and SO₂, PM₁₀ and NO_x during winter 2017-2018, respectively, R^2 in both figure under 50% indicates to poor relationship between the variables.

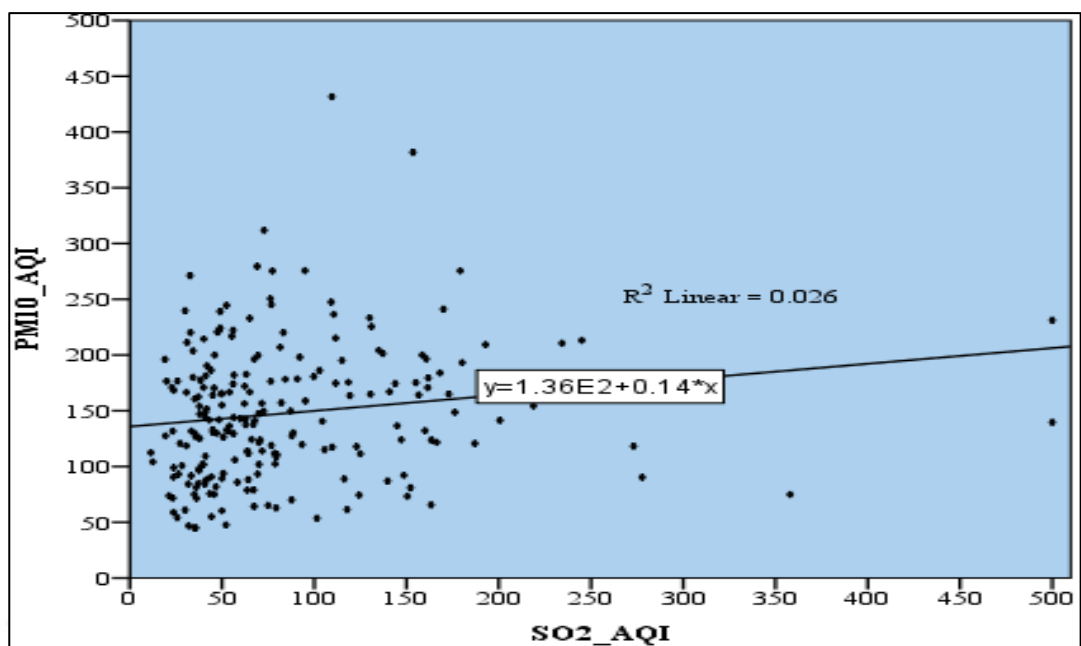


Figure 4. 135: Relation between PM₁₀ and SO₂

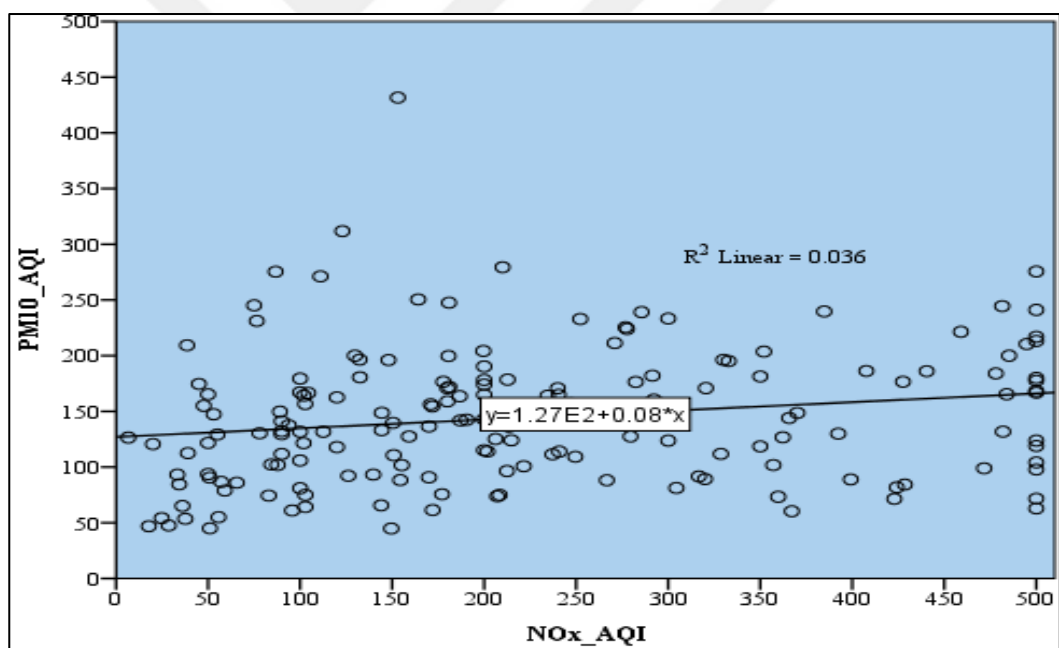


Figure 4. 136: Relation between PM₁₀ and NO_x

V. CONCLUSION AND RECOMMENDATION

5.1 Conclusions

There is an air pollution problem in Turkey. This problem, which has a tendency to increase day by day, may cause big problems in the future if the necessary precautions are not taken in time. Turkey, which has achieved great progress in the field of tourism in recent years, is growing rapidly and its population is increasing every year. Considering migration, population growth has reached significant rates. This means more housing and more flue gas. In addition, the number of vehicles is increasing every year. As a result, air pollution tends to increase continuously.

A. The most values of PM₁₀ were exceed the value of Turkish limit of 50 µg/m³.

When we compare the average monthly with the maximum limit values of PM₁₀ pollution, we see that there is a pollution in the most stations above the limit value. As it is understood from this point, there is a serious air pollution in the most parts of Turkey where the most important source that negatively affects the air quality is domestic heating and the fuels used for it. The results were showing generally, the concentrations of PM₁₀ increasing in winter months in most provinces of Turkey and approximately at the same stations especially in January, February, November and December because of using the fossil fuels in domestic heating in winter months, and decreasing in the summer months during periods from 2015-2018, except in southeastern part of some Turkey cities where the concentrations of PM₁₀ was increasing during the months July (7) to October (10), may be due to occurring of desert dust.

B. The results were showing commonly, the concentrations of SO₂ increasing in winter months in most provinces of Turkey and approximately at the same stations especially in January, February, March, October, November and December because of consuming the fossil fuels in domestic heating in winter months, and decreasing in the summer months. The maximum value of SO₂ emissions reached to 932.4 µg/m³ in Edirne-Keşan station, the maximum value of SO₂ emissions reached to the range of 2015-2018 season in January 2015, 2016 and 2017 (501.9, 932.4 and 397 µg/m³, respectively), whereas in February 2015, 2016 and 2018 reached to (483.2, 627.9 and 449.2 µg/m³, respectively), while in March 2015, 2016 and 2018 reached to (450.2, 571 and 316.5 µg/m³,

respectively) and in November 2015, 2017 and in December 2016 and 2018 reached to (560, 396.3, 344.4 and 326.5 $\mu\text{g}/\text{m}^3$, respectively) all of these values of SO_2 found in Edirne-Keşan station except one of these in Şirnek station in January 2015, the main causes of air pollution in the Edirne-Keşan station; natural properties as well as the poor quality of the fuel used for heating purposes, the use of illegal coal and incineration systems are not suitable.

- C. The most NO_x concentrations exceeding (30 $\mu\text{g}/\text{m}^3$) the allowable limit value, about 77.4%, 79% and 65.5% during 2016, 2017 and 2018 respectively, especially in the central parts of Turkey. The high levels of nitrogen oxides can make happen harm to the human respiratory tract and rise a person's susceptibility to, and the seriousness of, respiratory diseases and asthma.
- D. According to AQI for PM_{10} , the results shown the most parts of the southeastern, central and west parts of country occurs within unhealthy, very unhealthy and hazardous classification during 2015-2018 especially in winter seasons, therefore must find solutions for the emission sources of PM_{10} in these parts.
- E. According to AQI for SO_2 , the results shown the most parts of the southeastern, and some central and west parts of country occurs within unhealthy, very unhealthy and hazardous classification during 2015-2018 especially in winter seasons, therefore must find solutions for the emission sources of SO_2 in these parts.
- F. It is clear that the PM_{10} and the SO_2 levels increase in parallel in the provinces that continued use of fossil fuel, such as coal solid fuels. Generally, the concentrations of PM_{10} and SO_2 in the winter seasons higher than in the summer seasons.
- G. By using simple CoKriging method during winter 2017-2018, the best semivariogram modeling for PM_{10} was Exponential semivariogram modeling that applied as dependable variable, for SO_2 was J-Bessel semivariogram modeling and for NO_x (Gaussian semivariogram modeling) that applied as undependable variable, based on this method the distribution of pollution spread more than other Kriging methods.

5.2 Recommendations

The recommendations that can be proposed to reduce air pollution in urban living environments are listed below. No matter how much the population and the number of vehicles increase, no problems arise if necessary measures are taken. Suggestions and solutions for monitoring, eliminating or minimizing air pollution can be listed as follows:

- A. The most important factor that creates pollution in Turkey is domestic heating and the fuels used for it, to reduce pollution, the first thing must to do is to improve fuel quality. Lignite coal should not be used for heating purposes if possible.
- B. Central heating and natural gas should be expanded. This will make it easier to install filters.
- C. Fuels must be burned according to the combustion technique and full combustion must be ensured. Therefore, education services should be provided to raise public awareness on combustion technology.
- D. Starting from large buildings and institutions with high fuel consumption, the application of chimney filter should be ensured, the controls of buildings that emit more pollutant smoke from the chimneys should be carried out by the relevant institutions and sanctions should be applied and the chimney heights should be ensured.
- E. On the other hand, the green areas should be increased. Particularly in areas exposed to air pollution, they should be surrounded by trees that do not ever leave their leaves during the winter season to reduce the spreading of the pollutants.
- F. The usability of renewable energy sources needs to be investigated. Solar energy is one of the cleanest energies. The use of solar energy systems needs to be expanded and encouraged, wind energy, wave energy, biomass energy and hydraulic energy that do not cause environmental pollution should be provided.
- G. Various meetings, seminars and symposiums should inform the public about the seriousness of air pollution and what they can do to prevent pollution.
- H. Spatial analysis with GIS and thematic maps to be created on different topics will help decision makers to better understand environmental problems and take precautions. As a result, all the studies related to the protection and spatial distribution of air quality require joint studies, control strategies or new legal arrangements. In addition, in order to support public health research, it may be

possible to investigate the epidemiological effects of air pollution, especially in risky areas and to integrate the databases to be established for this purpose with GIS. It is very important for local governments to carry out such works in their areas of responsibility in terms of protecting the environment and human health.



REFERENCES

- Abass, M., A. T. Ziboon and Z. Bahaa (2016). "Assessment of Air pollution in AL-Nahrawan Suburban-Baghdad city by Geographic Information System (GIS)." Engineering and Technology Journal **34**(11 Part (A) Engineering): 1959-1969.
- Abdul-Wahab, S. A., S. C. F. En, A. Elkamel, L. Ahmadi and K. Yetilmezsoy (2015). "A review of standards and guidelines set by international bodies for the parameters of indoor air quality." Atmospheric Pollution Research **6**(5): 751-767.
- Abdul Wahab, A. S., I. A.-H. Shukri, A. A. Adnan and T. A.-S. Hamid (2013). "Ambient Air Quality in the Industrial Area of." Journal of Petroleum Research & Studies مجلة البحوث والدراسات النفطية **114** (8th): 1-11.
- Adam-Poupart, A., A. Brand, M. Fournier, M. Jerrett and A. Smargiassi (2014). "Spatiotemporal modeling of ozone levels in Quebec (Canada): a comparison of kriging, land-use regression (LUR), and combined Bayesian maximum entropy–LUR approaches." Environmental health perspectives **122**(9): 970.
- Adams, M. D. and P. S. Kanaroglou (2016). "Mapping real-time air pollution health risk for environmental management: combining mobile and stationary air pollution monitoring with neural network models." Journal of environmental management **168**: 133-141.
- Adedeji, O. H., O. Oluwafunmilayo and T.-A. O. Oluwaseun (2016). "Mapping of traffic-related air pollution using GIS techniques in Ijebu-Ode, Nigeria." Indonesian Journal of Geography **48**(1): 73-83.
- Ağbulut, Ü. (2019). "Turkey's electricity generation problem and nuclear energy policy." Energy Sources, Part A: Recovery, Utilization, and Environmental Effects **41**(18): 2281-2298.
- Ahmad, S. S. and N. Aziz (2013). "Spatial and temporal analysis of ground level ozone and nitrogen dioxide concentration across the twin cities of Pakistan." Environmental monitoring and assessment **185**(4): 3133-3147.
- Ahmed, E., K.-H. Kim, Z.-H. Shon and S.-K. Song (2015). "Long-term trend of airborne particulate matter in Seoul, Korea from 2004 to 2013." Atmospheric Environment **101**: 125-133.
- Ahn, J. Y. (2015). "Spatial Analysis of Air Pollution Data Based on Linked Micromap Plots in Korea."
- Akçay, K. (2000). "Trabzon İçin İstatistiksel Bir Hava Kirliliği Modelinin Geliştirilmesi." Yüksek Lisans Tezi, K.T.Ü., Fen Bilimleri Enstitüsü, Trabzon.
- Akman, Y. and O. Ketenoğlu (1986). "The climate and vegetation of Turkey." Proceedings of the Royal Society of Edinburgh, Section B: Biological Sciences **89**: 123-134.

Akyürek, Ö., O. Arslan and A. Karademir (2013). "SO₂ ve PM₁₀ hava kirliliği parametrelerinin CBS ile konumsal analizi: Kocaeli örneği." TMMOB Coğrafi Bilgi Sistemleri Kongresi: 11-13.

Al-Saadi, J., J. Szykman, R. B. Pierce, C. Kittaka, D. Neil, D. A. Chu, L. Remer, L. Gumley, E. Prins and L. Weinstock (2005). "Improving national air quality forecasts with satellite aerosol observations." Bulletin of the American Meteorological Society **86**(9): 1249-1262.

Alfoldy, B., M. Mahfouz, O. Yigiterhan, M. Safi, A. Elnaiem and S. Giamberini (2019). "BTEX, nitrogen oxides, ammonia and ozone concentrations at traffic influenced and background urban sites in an arid environment." Atmospheric Pollution Research **10**(2): 445-454.

Ali, M. H., A.-R. A. Mustafa and A. A. El-Sheikh (2016). "Geochemistry and spatial distribution of selected heavy metals in surface soil of Sohag, Egypt: a multivariate statistical and GIS approach." Environmental Earth Sciences **75**(18): 1257.

Analyst, A. G. (2001). "Statistical Tools for Data Exploration, Modeling, and Advanced Surface Generation. ." An ESRI White Paper. the United States of America.

Anderson, J. O., J. G. Thundiyil and A. Stolbach (2012). "Clearing the air: a review of the effects of particulate matter air pollution on human health." Journal of Medical Toxicology **8**(2): 166-175.

Andrews, D. F. (1974). "A robust method for multiple linear regression." Technometrics **16**(4): 523-531.

Arabameri, A., B. Pradhan, K. Rezaei and C. Conoscenti (2019). "Gully erosion susceptibility mapping using GIS-based multi-criteria decision analysis techniques." Catena **180**: 282-297.

Arı, E. S., H. Özköse and C. Gencer (2016). "Ranking Turkish Cities and Regions for Air Quality Using a Multi-Criteria Decision-Making Method." Polish Journal of Environmental Studies **25**(5): 1823-1830.

Astivia, O. L. O. and B. D. Zumbo (2019). "Heteroskedasticity in Multiple Regression Analysis: What it is, How to Detect it and How to Solve it with Applications in R and SPSS." Practical Assessment, Research & Evaluation **24**(1): 2.

Atalay, I. (1994). "Türkiye vejetasyon coğrafyası." Izmir: Ege Üniversitesi Basımevi.

Aydin Coskun, A., O. Türker and N. Velioglu (2011). "Air pollution regulations in Turkey and harmonization with the EU legislation." iForest-Biogeosciences and Forestry **4**(4): 181.

Aydın, M. E., S. S. Durduran, S. Özcan and F. Bedük (2007). "Konya'da hava kalitesi değişiminin coğrafi bilgi sistemi (CBS) ile değerlendirilmesi. 7." Ulusal Çevre Mühendisliği Kongresi: 22-27.

Babak, O. and C. V. Deutsch (2009). "Statistical approach to inverse distance interpolation." Stochastic Environmental Research and Risk Assessment **23**(5): 543-553.

Baldasano, J., E. Valera and P. Jimenez (2003). "Air quality data from large cities." Science of the Total Environment **307**(1): 141-165.

Banja, M., E. Como, B. Murtagj and A. Zotaj (2010). Mapping air pollution in urban tirana area using GIS. International Conference SDI.

Bank, E. and H. Taştan (1994). "Coğrafi Bilgi Sistemlerinde Analiz Türleri, Kullanım Amaçları ve Uygulama Alanları.+ DULWD'HUJLVL." Sayı **112**: 1.

Başbozkurt, H. (2015). Mekansal regresyon metotları kullanımı ile toprağın bazı fiziksel ve kimyasal özelliklerinin analizi, Selçuk Üniversitesi Fen Bilimleri Enstitüsü, konya, Turkey.

Basoglu, A. and U. Uzar (2019). "An empirical evaluation about the effects of environmental expenditures on environmental quality in coordinated market economies." Environmental Science and Pollution Research: 1-11.

Baykara, M., U. Im and A. Unal (2019). "Evaluation of impact of residential heating on air quality of megacity Istanbul by CMAQ." Science of the Total Environment **651**: 1688-1697.

Bayraktar, H. and F. S. Turalioglu (2005). "A Kriging-based approach for locating a sampling site—in the assessment of air quality." Stochastic Environmental Research and Risk Assessment **19**(4): 301-305.

Bayram, H., Z. Dörtbudak, F. E. Fişekçi, M. Kargın and B. Bülbül (2006). "Hava Kirliliğinin İnsan Sağlığına Etkileri, Dünyada, Ülkemizde ve Bölgemizde Hava Kirliliği Sorunu" Paneli Ardından." Tıp Dergisi **33**: 105-112.

Beelen, R., G. Hoek, E. Pebesma, D. Vienneau, K. de Hoogh and D. J. Briggs (2009). "Mapping of background air pollution at a fine spatial scale across the European Union." Science of the Total Environment **407**(6): 1852-1867.

Behr, F. J. (1995). Assessing Benefits of Geographical Information Systems Implementation. Proc. Joint European Conference and Exhibition on Geographical Information, Den Haag.

Bertazzon, S., M. Johnson, K. Eccles and G. G. Kaplan (2015). "Accounting for spatial effects in land use regression for urban air pollution modeling." Spatial and spatio-temporal epidemiology **14**: 9-21.

Bertrams, N. (2017). "Türkiye’de Hava Kirliliği: Kara Rapor." http://www.greenpeace.org/turkey/Global/turkey/report/2016/hava_kirliligi_rapor_baski.pdf.

Bishoi, B., A. Prakash and V. Jain (2009). "A comparative study of air quality index based on factor analysis and US-EPA methods for an urban environment." Aerosol and Air Quality Research **9**(1): 1-17.

Biswas, A. and B. C. Si (2013). "Model averaging for semivariogram model parameters." Advances in Agrophysical Research **4**: 81-96.

Bıyık, İ. (2010). Hava kirliliğinin yapay zeka teknikleri ile belirlenmesi Yüksek Lisans Tezi, Bahçeşehir Üniversitesi Fen Bilimleri Enstitüsü, İstanbul, Turkey.

Bohling, G. (2005). "Introduction to geostatistics and variogram analysis." Kansas geological survey: 1-20.

Bon, A. F., S. D. Aoudou, A. M. Ndam, E. A. Bineli and E. D. Fita (2019). Groundwater Pollution Index Evaluation Test Using Electrical Conductivity in a Semi-arid Quaternary Aquifer (Kousseri-Cameroon, Lake Chad Basin): Multivariate Statistical Analysis Approach. Advances in Sustainable and Environmental Hydrology, Hydrogeology, Hydrochemistry and Water Resources, Springer: 295-297.

Bossomaier, T. and B. A. Hope (2015). Online GIS and spatial metadata. Boca Raton, CRC Press.

Box, G. E. and D. R. Cox (1964). "An analysis of transformations." Journal of the Royal Statistical Society: Series B (Methodological) **26**(2): 211-243.

Boyda, D. C., S. B. Holzman, A. Berman, M. K. Grabowski and L. W. Chang (2019). "Geographic Information Systems, spatial analysis, and HIV in Africa: A scoping review." PloS one **14**(5): e0216388.

Brauer, M., G. Hoek, P. van Vliet, K. Meliefste, P. Fischer, U. Gehring, J. Heinrich, J. Cyrys, T. Bellander and M. Lewne (2003). "Estimating long-term average particulate air pollution concentrations: application of traffic indicators and geographic information systems." Epidemiology **Vol. 14**(No. 2): 228-239.

Briggs, D. (2005). "The role of GIS: coping with space (and time) in air pollution exposure assessment." Journal of Toxicology and Environmental Health, Part A **68**(13-14): 1243-1261.

Briggs, D. J., S. Collins, P. Elliott, P. Fischer, S. Kingham, E. Lebre, K. Pryl, H. Van Reeuwijk, K. Smallbone and A. Van Der Veen (1997). "Mapping urban air pollution using GIS: a regression-based approach." International Journal of Geographical Information Science **11**(7): 699-718.

Brook, R. D., S. Rajagopalan, C. A. Pope III, J. R. Brook, A. Bhatnagar, A. V. Diez-Roux, F. Holguin, Y. Hong, R. V. Luepker and M. A. Mittleman (2010). "Particulate matter air pollution and cardiovascular disease: an update to the scientific statement from the American Heart Association." Circulation **121**(21): 2331-2378.

Bruno, F., M. Cameletti, M. Franco-Villoria, F. Greco, R. Ignaccolo, L. Ippoliti, P. Valentini and M. Ventrucci (2016). "A survey on ecological regression for health hazard associated with air pollution." Spatial Statistics **18**: 276-299.

Brunt, H., J. Barnes, J. Longhurst, G. Scally and E. Hayes (2016). "Local Air Quality Management policy and practice in the UK: The case for greater Public Health integration and engagement." Environmental Science & Policy **58**: 52-60.

Büke, T. and A. Ç. Köne (2016). "Assessing Air Quality in Turkey: A Proposed, Air Quality Index." Sustainability **8**(1): 73.

Burns, J., H. Boogaard, S. Polus, L. M. Pfadenhauer, A. C. Rohwer, A. M. van Erp, R. Turley and E. Rehfuess (2019). "Interventions to reduce ambient particulate matter air pollution and their effect on health." Cochrane Database of Systematic Reviews(5).

Büyüköztürk, Ş. (2003). "Sosyal bilimler için veri analizi el kitabı: istatistik, araştırma deseni SPSS uygulamaları ve yorum." Baskı. Ankara: Pegem A Yayıncılık.

Calcagno, P., J.-P. Chilès, G. Courrioux and A. Guillen (2008). "Geological modelling from field data and geological knowledge: Part I. Modelling method coupling 3D potential-field interpolation and geological rules." Physics of the Earth and Planetary Interiors **171**(1-4): 147-157.

Campbell, H. E. and K. E. Wikstrom (2019). Studying Water Policy and Environmental Justice: Using Geographic Information Systems and Spatial Econometrics. California, SAGE Publications Ltd.

Çapraz, Ö. (2014). İstanbul Da 2007-2012 Yılları Arasında Hava Kirliliğinin Ölüm Üzerindeki Etkisinin Modellenmesi, Fen Bilimleri Enstitüsü.

Castrignanò, A., R. Quarto, A. Venezia and G. Buttafuoco (2019). "A comparison between mixed support kriging and block cokriging for modelling and combining spatial data with different support." Precision Agriculture: 1-21.

Cetin, M., A. K. Onac, H. Sevik and B. Sen (2019). "Temporal and regional change of some air pollution parameters in Bursa." Air Quality, Atmosphere & Health **12**(3): 311-316.

Chang, K.-t. (2006). Introduction to geographic information systems, McGraw-Hill Higher Education Boston.

Change, I. P. O. C. (2006). 2006 IPCC guidelines for national greenhouse gas inventories, 2013-04-28]. <http://www.ipcc-nggip.iges.or.jp/public/2006gl/index.html>.

Cheewinsiriwat, P. (2016). "Estimation of nitrogen dioxide concentrations in Inner Bangkok using Land Use Regression modeling and GIS." Applied Geomatics **8**(2): 107-116.

Chen, L., Z. Bai, S. Kong, B. Han, Y. You, X. Ding, S. Du and A. Liu (2010). "A land use regression for predicting NO₂ and PM₁₀ concentrations in different seasons in Tianjin region, China." Journal of Environmental Sciences **22**(9): 1364-1373.

Chen, R., P. Yin, X. Meng, L. Wang, C. Liu, Y. Niu, Y. Liu, J. Liu, J. Qi and J. You (2019). "Associations between coarse particulate matter air pollution and cause-specific mortality: a nationwide analysis in 272 Chinese cities." Environmental health perspectives **127**(01): 017008.

Çilingir, B. M. (2016). "Hava Kirliliği ve Akciğer." Çağdaş Tıp Dergisi **6**: 131-137.

Coady, D., I. Parry, N.-P. Le and B. Shang (2019). Global Fossil Fuel Subsidies Remain Large: An Update Based on Country-Level Estimates. Washington D.C., USA, International Monetary Fund.

Çolak, H. (2010). "Coğrafi Bilgi Sistemleri ile Doğu Karadeniz Bölgesindeki Kansere Vakalarının Konumsal Analizleri." Harita Mühendisliği Ana Bilim Dalı, Trabzon, Karadeniz Teknik Üniversitesi. Doktora, Trabzon, Turkey.

Coşkun, A. (2008). "Şehir atmosferinde taşıt emisyonlarından kaynaklanan hava kirliliğinin belirlenmesi. Marmara Üniversitesi." Fen Bilimleri Enstitüsü, Yüksek Lisans Tezi, İstanbul.

Cowen, D. J. (1988). "GIS versus CAD versus DBMS: What are the differences?" Photogramm. Eng. Remote Sens. **54**(11): 1551-1555.

Cressie, N. and G. Johannesson (2008). "Fixed rank kriging for very large spatial data sets." Journal of the Royal Statistical Society: Series B (Statistical Methodology) **70**(1): 209-226.

Cromie, M., B. Saef, M. Montgomery, C. Rios, S.-H. Cho, J. Everman, V. Medina, S. Oh, C. Eng and J. Rodriguez-Santana (2019). Organic Components of Air Pollution Particulate Matter 2.5 (PM_{2.5}) Elicit Changes in the Airway Epithelial Transcriptome of Asthmatic Children. A61. Epithelial Biology, American Thoracic Society: A2142-A2142.

CSB (2017). "Çevre ve Şehircilik Bakanlığı tarafından Hava Kalitesi İzleme Ağı, <http://www.havaizleme.gov.tr/Default.ltr.aspx>."

havaizleme.gov.tr /Default.ltr.aspx."

ÇŞB (2016). "Hava Kalitesi Bülteni,."

Çubukçu, K. M. (2015). Planlamada ve coğrafyada temel istatistik ve mekansal istatistik. Ankara, Turkey, Nobel.

Dalyan, E. G. and S. Incecik (2002). "İstanbul'da Coğrafi Bilgi Sistemleri ile Hava Kalitesinin incelenmesi." İTÜ Dergisi **1**: 51-62.

de Albuquerque, J. P., F. E. A. Horita, L. C. Degrossi, R. dos Santos Rocha, S. C. de Andrade, C. Restrepo-Estrada and W. Leyh (2019). Leveraging volunteered geographic information to improve disaster resilience: lessons learned from AGORA and future research directions. Environmental Information Systems: Concepts, Methodologies, Tools, and Applications, IGI Global: 1636-1662.

DeFries, J. C. and D. W. Fulker (1985). "Multiple regression analysis of twin data." Behavior genetics **15**(5): 467-473.

Demirarslan, K. O. and H. Akıncı (2018). "Cbs ve hava kalitesi verileri kullanılarak marmara bölgesinin kış sezonunda hava kalitesinin değerlendirilmesi." Doğal Afetler ve Çevre Dergisi **4**(1): 11-27.

Dias, D., O. Tchepel and A. P. Antunes (2016). "Integrated modelling approach for the evaluation of low emission zones." Journal of environmental management **177**: 253-263.

Dimitriou, K., A. Paschalidou and P. Kassomenos (2013). "Assessing air quality with regards to its effect on human health in the European Union through air quality indices." Ecological indicators **27**: 108-115.

Dirks, K., J. Hay, C. Stow and D. Harris (1998). "High-resolution studies of rainfall on Norfolk Island: Part II: Interpolation of rainfall data." Journal of Hydrology **208**(3-4): 187-193.

Dobie, N. (1992). Procedures for emission-inventory preparation. Volume 4: Mobile sources, Environmental Protection Agency, Ann Arbor, MI (United States). Office of Mobile Sources.

Dominici, F., R. D. Peng, C. D. Barr and M. L. Bell (2010). "Protecting human health from air pollution: shifting from a single-pollutant to a multi-pollutant approach." Epidemiology (Cambridge, Mass.) **21**(2): 187.

Du, X. and A. S. Varde (2016). Mining PM2.5 and traffic conditions for air quality. 2016 7th International Conference on Information and Communication Systems (ICICS), Irbid, Jordan, IEEE.

Dubois, J.-J. B., K. J. Novak, T. L. Greaver, R. L. Dennis, J. D. Herrick, T. J. Sullivan, G. B. Lawrence, A. T. Herlihy, C. L. Goodale and M. C. Barber (2012). "Ecological effects of nitrogen and sulfur air pollution in the US: what do we know?".

Dursun, S., F. Kunt and O. Taylan (2015). "Modelling sulphur dioxide levels of Konya city using artificial intelligent related to ozone, nitrogen dioxide and meteorological factors." International journal of environmental science and technology **12**(12): 3915-3928.

EC (1996). "Air Quality Framework Directive, Council Directive 96/62/EC on ambient air quality assessment and management. ." Official Journal of the European Union, OJ L **296**: 55-63.

EC (1999). "First Daughter Directive, Council Directive 30/EC relating to limit values for sulphur dioxide, nitrogen dioxide and oxides of nitrogen, particulate matter, and lead in ambient. OJ L 163." http://eurlex.europa.eu/LexUriServ/site/en/oj/1999/l_163/l_16319990629en00410060.pdf.: 41-60.

EC_Commission_Staff (2011). " establishing guidelines for demonsturation and subtraction of exceedances attributable to natural sources under the Directive 2008/50/EC on ambient air quality and cleaner air for Europe, SEC(2011) 208 final, Brussels.".

EEA, T. E. E. A. (2019). "Air quality standards under the Air Quality Directive, and WHO air quality guidelines."

Elbir, T. (2004). "A GIS based decision support system for estimation, visualization and analysis of air pollution for large Turkish cities." Atmospheric Environment **38**(27): 4509-4517.

Elbir, T., N. Mangir, M. Kara, S. Simsir, T. Eren and S. Ozdemir (2010). "Development of a GIS-based decision support system for urban air quality management in the city of Istanbul." Atmospheric Environment **44**(4): 441-454.

Elshahat, A. I., A. A. Soliman and M. Elshahat (2019). "Studying the Effect of the Fuel used on the Pollutants Emission from the Power Plants west Cairo." Life Science Journal **16**(4): 16-25.

Emre Özşahin, İ. E., Halid Pektezel (2016). "Air Pollution in Keşan (Edirne)." Selçuk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi **36**(1302-1796).

Ercan, Ö., F. Dinçer and Ö. Ceylan (2019). "Spatial and seasonal variations of atmospheric BTEX, sulfur dioxide, nitrogen dioxide, and ozone concentrations in Istanbul, and health risk assessment of BTEX." Environmental Forensics **20**(2): 149-161.

Erdin, C. and G. Ozkaya (2019). "Turkey's 2023 Energy Strategies and Investment Opportunities for Renewable Energy Sources: Site Selection Based on ELECTRE." Sustainability **11**(7): 2136.

Evci, M. (2009). "Determination of ozone, nitrogen dioxide and sulfur dioxide pollution around aliğa by passive sampling. İzmir: Dokuz Eylül Üniversitesi." Fen Bilimleri Enstitüsü, Yüksek Lisans Tezi, İzmir, Turkey.

Falaize, A., E. Liberge and A. Hamdouni (2019). "POD-based reduced order model for flows induced by rigid bodies in forced rotation." Journal of Fluids and Structures.

Farias, P. R., J. C. Barbosa, A. C. Busoli, W. L. Overal, V. S. Miranda and S. M. Ribeiro (2008). "Spatial analysis of the distribution of *Spodoptera frugiperda* (JE Smith)(Lepidoptera: Noctuidae) and losses in maize crop productivity using geostatistics." Neotropical Entomology **37**(3): 321-327.

Feng, R., Q. Wang, C.-c. Huang, J. Liang, K. Luo, J.-r. Fan and K.-f. Cen (2019). "Investigation on air pollution control strategy in Hangzhou for post-G20/pre-Asian-games period (2018–2020)." Atmospheric Pollution Research **10**(1): 197-208.

Forrester, A. I., A. Sóbester and A. J. Keane (2007). "Multi-fidelity optimization via surrogate modelling." Proceedings of the royal society a: mathematical, physical and engineering sciences **463**(2088): 3251-3269.

Fu, W., P. Jiang, G. Zhou and K. Zhao (2014). "Using Moran's I and GIS to study the spatial pattern of forest litter carbon density in a subtropical region of southeastern China." Biogeosciences **11**(8): 2401-2409.

Furrer, R. and M. G. Genton (2011). "Aggregation-cokriging for highly multivariate spatial data." Biometrika **98**(3): 615-631.

Garipağaoğlu, N. and C. Duman (2017). "Bursa Kenti Hava Kalitesinin Zaman İçerisindeki Değişimi." Marmara Coğrafya Dergisi(1303-2429): 57-70.

Ge, Y. and H. Wu (2019). "Prediction of corn price fluctuation based on multiple linear regression analysis model under big data." Neural Computing and Applications: 1-13.

Genereux, A. J. J. (2019). Exhausted with Emissions: Exploring the Link Between Anthropogenic Emissions and Urban Pollution on Public Health Master thesis, Carleton University.

Ghorbanzadeh, N., A. Salehi, H. Pourbabaei, A. A. S. Tolarod and S. J. Alavi (2019). "Spatial variability of soil microbial indices in common alder COMMON ALDER (*Alnus glutinosa*) stands using a geostatistical approach in northern Iran." Journal of forestry research **30**(2): 679-688.

Godish, T., W. T. Davis and J. S. Fu (2014). Air quality. Boca Raton, CRC Press.

Gökgöz, F. (2009). "Korelasyon ve tekli regresyon analizi - en küçük kareler yöntemi." Açık Ders Notları, Ankara Üniversitesi, Ankara.

Goodchild, M. F., P. Longley and M. SMITH (2013). Geospatial analysis, University College London, UC Santa Barbara.

Goovaerts, P. (1997). Geostatistics for natural resources evaluation, Oxford University Press on Demand.

Goovaerts, P. (1999). "Using elevation to aid the geostatistical mapping of rainfall erosivity." Catena **34**(3-4): 227-242.

Goovaerts, P. (2008). "Kriging and semivariogram deconvolution in the presence of irregular geographical units." Mathematical Geosciences **40**(1): 101-128.

Gopalaswami, P. (2016). "A study on effects of weather, vehicular traffic and other sources of particulate air pollution on the city of Delhi for the year 2015." Journal of Environment Pollution and Human Health **4**(2): 24-41.

Grsic, Z., D. M. Dramlić, P. Milutinovic, S. Pavlovic, D. Arbutina, S. D. Dramlić, J. Kaljevic, D. Joksimovic and N. Miljevic (2014). "Representativity of air quality control in limited number of grid points." Journal of Environmental Protection and Ecology **15**(1): 1-6.

Güçlü, Y., İ. Dabanlı, E. Şişman and Z. Şen (2019). "Air quality (AQ) identification by innovative trend diagram and AQ index combinations in Istanbul megacity." Atmospheric Pollution Research **10**(1): 88-96.

Gülersoy, A. E. (2014). "Seferihisar’da arazi kullanımının zamansal değişimi (1984-2010) ve ideal arazi kullanımı için öneriler." Süleyman Demirel Üniversitesi Fen-Edebiyat Fakültesi Sosyal Bilimler Dergisi **2014**(31): 155-180.

Gulliver, J. and D. Briggs (2011). "STEMS-Air: A simple GIS-based air pollution dispersion model for city-wide exposure assessment." Science of the total environment **409**(12): 2419-2429.

Gulliver, J. and D. J. Briggs (2005). "Time–space modeling of journey-time exposure to traffic-related air pollution using GIS." Environmental research **97**(1): 10-25.

Gulliver, J., K. de Hoogh, D. Fecht, D. Vienneau and D. Briggs (2011). "Comparative assessment of GIS-based methods and metrics for estimating long-term exposures to air pollution." Atmospheric environment **45**(39): 7072-7080.

Günlü, A., İ. Ercanli, M. Şenyurt and S. Keleş (2019). "Estimation of some stand parameters from textural features from WorldView-2 satellite image using the artificial neural network and multiple regression methods: a case study from Turkey." Geocarto International(just-accepted): 1-16.

Guo, Y., F. Liu, Y. Lu, Z. Mao, H. Lu, Y. Wu, Y. Chu, L. Yu, Y. Liu and M. Ren (2016). "Factors Affecting Parent's Perception on Air Quality—From the Individual to the Community Level." International journal of environmental research and public health **13**(5): 493.

Gurjar, B. R., L. T. Molina and C. S. P. Ojha (2010). Air pollution: health and environmental impacts. Boca Raton, CRC press.

Gurjar, B. R. and C. Ojha (2016). "Special Issue on Hazardous and Toxic Pollutants in the Air." Journal of Hazardous, Toxic, and Radioactive Waste **20**(4): A2016001.

Gustafson, P. (2009). Exposure to some carcinogenic compounds in air, with special reference to wood smoke.

Hakan Erdun, Ali Öztürk, Özkan Çapraz , Hüseyin Toros, Sükrü Dursun and A. Deniz (2015). "Spatial Variation of PM10 in Turkey." VII. Atmospheric Science Symposium.

Hamzelo, M., A. Gharagozlou, S. Sadeghian, S. Baikpour and A. Rajabi (2015). "Modelling of Carbon Monoxide Air Pollution in Large Cities by Evaluation of Spectral LANDSAT8 Images." The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences **40**(1): 281.

Han, J., Y. Hayashi, X. Cao and H. Imura (2009). "Application of an integrated system dynamics and cellular automata model for urban growth assessment: A case study of Shanghai, China." Landscape and Urban Planning **91**(3): 133-141.

Harrison, R. M. (2001). Pollution: causes, effects and control, Royal Society of Chemistry.

Hatiboğlu, Z. (1994). "Temel istatistik." İstanbul: Beta Basım Yayın Dağıtım.

Heinsohn, R. J. and R. L. Kabel (1999). Sources and control of air pollution, Prentice Hall.

Hennig, F., D. Sugiri, L. Tzivian, K. Fuks, S. Moebus, K.-H. Jöckel, D. Vienneau, T. A. Kuhlbusch, K. de Hoogh and M. Memmesheimer (2016). "Comparison of Land-Use Regression Modeling with Dispersion and Chemistry Transport Modeling to Assign Air Pollution Concentrations within the Ruhr Area." Atmosphere **7**(3): 48.

Hochadel, M., J. Heinrich, U. Gehring, V. Morgenstern, T. Kuhlbusch, E. Link, H.-E. Wichmann and U. Krämer (2006). "Predicting long-term average concentrations of traffic-related air pollutants using GIS-based information." Atmospheric Environment **40**(3): 542-553.

Hoek, G., R. Beelen, K. De Hoogh, D. Vienneau, J. Gulliver, P. Fischer and D. Briggs (2008). "A review of land-use regression models to assess spatial variation of outdoor air pollution." Atmospheric environment **42**(33): 7561-7578.

Holst, J., H. Mayer and T. Holst (2008). "Effect of meteorological exchange conditions on PM10 concentration." Meteorologische Zeitschrift **17**(3): 273-282.

Hope, M. (2014). "The future of coal in China, India, Australia, the US, EU and UK." The Carbon Brief.

Hosseini, S. E. (2019). "Development of solar energy towards solar city Utopia." Energy Sources, Part A: Recovery, Utilization, and Environmental Effects: 1-14.

Hou, Q., X. An, Y. Tao and Z. Sun (2016). "Assessment of resident's exposure level and health economic costs of PM 10 in Beijing from 2008 to 2012." Science of The Total Environment **563**: 557-565.

Houyoux, M. R., J. M. Vukovich, C. J. Coats, N. J. Wheeler and P. S. Kasibhatla (2000). "Emission inventory development and processing for the Seasonal Model for Regional Air Quality (SMRAQ) project." Journal of Geophysical Research: Atmospheres **105**(D7): 9079-9090.

Huisman, O. and R. De By (2009). "Principles of geographic information systems." ITC Educational Textbook Series **1**.

Hystad, P., E. Setton, A. Cervantes, K. Poplawski, S. Deschenes, M. Brauer, A. van Donkelaar, L. Lamsal, R. Martin and M. Jerrett (2015). Creating national air pollution models for population exposure assessment in Canada, University of British Columbia.

Ibrahimova, I. (2013). "Investigation of SO₂ Roles on Air Pollution of Baku and Relation with Meteorological Factors." M. Sc. THESIS.

Incecik, S. (1994). "Hava Kirliligi." Istanbul Teknik Universite Matbaasi, Gumussuyu, Istanbul.

Indicators, O. K. E. (2004). "OECD Environment Directorate." Paris, France.

Ispat, T. (2006). "GENERAL INFORMATION ABOUT TURKEY'S INVESTMENT ENVIRONMENT."

Jeong, D., A. St-Hilaire, Y. Gratton, C. Bélanger and C. Saad (2017). "A guideline to select an estimation model of daily global solar radiation between geostatistical interpolation and stochastic simulation approaches." Renewable Energy **103**: 70-80.

Jerrett, M., R. T. Burnet, R. Ma, C. A. Pope III, D. Krewski, B. Newbold, G. Thurston, Y. Shi, N. Finkelstein and E. E. Calle (2006). "Spatial analysis of air pollution and mortality in Los Angeles." Epidemiology **17**(6): S69.

Jerrett, M., R. T. Burnett, R. Ma, C. A. Pope III, D. Krewski, K. B. Newbold, G. Thurston, Y. Shi, N. Finkelstein and E. E. Calle (2005). "Spatial analysis of air pollution and mortality in Los Angeles." Epidemiology **16**(6): 727-736.

Johnson, L. E. (2016). Geographic information systems in water resources engineering, CRC Press.

Johnston, K. (2004). ArcGIS 9: using ArcGIS geostatistical analyst, Esri Press.

Johnston, K., J. M. Ver Hoef, K. Krivoruchko and N. Lucas (2001). Using ArcGIS geostatistical analyst, Esri Redlands.

Jørgensen, J. T., M. S. Johansen, L. Ravnskjaer, K. K. Andersen, E. V. Bräuner, S. Loft, M. Ketzel, T. Becker, J. Brandt and O. Hertel (2016). "Long-term exposure to ambient air pollution and incidence of brain tumours: The Danish nurse cohort." Neurotoxicology.

Kabatas, B., A. Unal, R. Pierce, T. Kindap and L. Pozzoli (2014). "The contribution of Saharan dust in PM 10 concentration levels in Anatolian Peninsula of Turkey." Science of the Total Environment **488**: 413-421.

Kadioğlu, M. (2000). "Regional variability of seasonal precipitation over Turkey." International Journal of Climatology: A Journal of the Royal Meteorological Society **20**(14): 1743-1760.

Kampa, M. and E. Castanas (2008). "Human health effects of air pollution." Environmental pollution **151**(2): 362-367.

Kara, M. B. and B. K. Tezel (2017). "Türkiye'deki SO₂ Yer Ölçümlerinin Değerlendirilmesi ve SO₂ Kirliliğinin Zamansal ve Mekansal Değişiminin İncelenmesi." VII. Ulusal Hava Kirliliği ve Kontrolü Sempozyumu, Hava Kirlenmesi Araştırmaları ve Denetimi Türk Milli Komitesi Akdeniz Üniversitesi Mühendislik Fakültesi Çevre Mühendisliği Bölümü, 1-3 Kasım 2017-Antalya.

Karabulut, M. (2006). "NOAA AVHRR verilerini kullanarak Türkiye'de bitki örtüsünün izlenmesi ve incelenmesi." Coğrafi Bilimler Dergisi **4**(1): 29-42.

Karaca, F. (2012). "Determination of air quality zones in Turkey." Journal of the Air & Waste Management Association **62**(4): 408-419.

Karaca, M. and R. J. Nicholls (2008). "Potential implications of accelerated sea-level rise for Turkey." Journal of Coastal Research **24**(2): 288-298.

Karagulian, F., C. A. Belis, C. F. C. Dora, A. M. Prüss-Ustün, S. Bonjour, H. Adair-Rohani and M. Amann (2015). "Contributions to cities' ambient particulate matter (PM): A systematic review of local source contributions at global level." Atmospheric environment **120**: 475-483.

Kardeşoğlu, E., M. Yalçın and Z. Işılak (2011). "Hava kirliliği ve kardiyovasküler sistem." TAF Preventive Medicine Bulletin **10**(1): 97-106.

Karimi, H., A. Soffianian, N. Mirghaffari and S. Soltani (2016). "Determining Air Pollution Potential Using Geographic Information Systems and Multi-criteria Evaluation: A Case Study in Isfahan Province in Iran." Environmental Processes **3**(1): 229-246.

Katsoulis, B. and P. Kassomenos (2004). "Assessment of the air-quality over urban areas by means of biometeorological indices. The case of Athens, Greece." Environmental technology **25**(11): 1293-1304.

Kayabasi, A., D. Turer, N. Yesiloglu-Gultekin and C. Gokceoglu (2016). "Spatial distribution of coal quality parameters with respect to production requirements: an adaptive neuro-fuzzy application for the Can coal field (Turkey)." Geocarto International **31**(2): 193-209.

Kaygusuz, K. and H. K. A. KAYGUSUZ (1996). "Role of the clean energy potential for energy savings and air pollution control in Turkey." Energy sources **18**(8): 885-901.

Keser, N. (2002). "Kütahya'da hava kirliliğine etki eden topografik ve iklimik faktörler."

Khafaie, M. A., A. Ojha, S. S. Salvi and C. S. Yajnik (2016). "Methodological approach in air pollution health effects studies." Journal of Air Pollution and Health **1**(3): 219-226.

Khan, S. U. and N. Ali (2013). "Ambient air quality of Aligarh city (UP, India) at Diwali." International Journal of Current Engineering and Technology **3**(5): 1730-1732.

Kho, W. F., J. Sentian, M. Radojevic, C. Tan, P. Law and S. Halipah (2007). "Computer simulated versus observed NO₂ and SO₂ emitted from elevated point source complex." International Journal of Environmental Science & Technology **4**(2): 215-222.

Kılıç, A., S. Kum, A. Ünal and T. Kındap (2016). "Marmara Bölgesi'ndeki Hava Kirliliğinin Modellenmesi, Kirlilik Azaltımı ve Maruziyet Analizi." Balıkesir Üniversitesi Fen Bilimleri Enstitüsü Dergisi **16**(1): 27-46.

Kiš, I. M. (2016). "Comparison of Ordinary and Universal Kriging interpolation techniques on a depth variable (a case of linear spatial trend), case study of the Šandrovac Field." Rudarsko-geološko-naftni zbornik **31**(2): 41-58.

Köne, A. Ç. and T. Büke (2012). "A comparison for Turkish provinces' performance of urban air pollution." Renewable and Sustainable Energy Reviews **16**(2): 1300-1310.

Koren, H. (2016). Illustrated dictionary and resource directory of environmental and occupational health. Boca Raton, CRC press.

KoşanI, Z., D. Kavuncuoğlu, S. Yılmaz, A. S. Bilici and A. Aras (2019). "An evaluation of the relation between air quality and hospital presentations due to respiratory tract diseases: A cross-sectional study." International Research Journal of Public and Environmental Health **6**(1): 1-6.

Krasnov, H., I. Kloog, M. Friger and I. Kutra (2016). "The Spatio-Temporal Distribution of Particulate Matter during Natural Dust Episodes at an Urban Scale." PloS one **11**(8): e0160800.

Krivoruchko, K. and C. Gotay (2003). Using spatial statistics in GIS. International congress on modelling and simulation, Citeseer.

Krzyzanowski, M. and A. Cohen (2008). "Update of WHO air quality guidelines." Air Quality, Atmosphere & Health **1**(1): 7-13.

Kumar, A., I. Gupta, J. Brandt, R. Kumar, A. K. Dikshit and R. S. Patil (2016). "Air quality mapping using GIS and economic evaluation of health impact for Mumbai city, India." Journal of the Air & Waste Management Association **66**(5): 470-481.

Kumar, A., R. S. Patil, A. K. Dikshit and R. Kumar (2016). "Comparison of predicted vehicular pollution concentration with air quality standards for different time periods." Clean Technologies and Environmental Policy: 1-11.

Kunt, F. (2014). "Modelling of Konya City Centre Air Pollution Using Artificial Neural Networks and Fuzzy Logic Methods." Ph.D. thesis, Selcuk university, Konya, Turkey.

Kurland, K. (2016). Geographic Information Systems in Health. Public Health Intelligence. College and School of Architecture , Carnegie Mellon University , USA, Springer: 111-127.

Lanzi, E. and R. Dellink (2019). "Economic interactions between climate change and outdoor air pollution." OECD Environment Working Papers **7**(148).

Larkin, A., A. van Donkelaar, J. A. Geddes, R. V. Martin and P. Hystad (2016). "Relationships between changes in urban characteristics and air quality in East Asia from 2000 to 2010." Environmental science & technology **50**(17): 9142-9149.

Lee, S.-J., J. W. Kim, Y. woo Hwang, J. Kim, Y. Kim and S. Chen (2019). "Butadiene substance flow analysis and management in South Korea." Journal of Cleaner Production **220**: 331-339.

Lee, Y., C. Jung and S. Kim (2019). "Spatial distribution of soil moisture estimates using a multiple linear regression model and Korean geostationary satellite (COMS) data." Agricultural Water Management **213**: 580-593.

Li, H., H. Fan and F. Mao (2016). "A Visualization Approach to Air Pollution Data Exploration—A Case Study of Air Quality Index (PM_{2.5}) in Beijing, China." Atmosphere **7**(3): 35.

Li, X., W. Liu, Z. Chen, G. Zeng, C. Hu, T. León, J. Liang, G. Huang, Z. Gao and Z. Li (2015). "The application of semicircular-buffer-based land use regression models incorporating wind direction in predicting quarterly NO₂ and PM₁₀ concentrations." Atmospheric Environment **103**: 18-24.

Lichtenstern, A. (2013). "Kriging methods in spatial statistics." Bachelor's Thesis, Garching, Almany.

Lin, W., X. Xu, X. Yu, X. Zhang and J. Huang (2013). "Observed levels and trends of gaseous SO₂ and HNO₃ at Mt. Waliguan, China: Results from 1997 to 2009." Journal of Environmental Sciences **25**(4): 726-734.

Little, R. J. and D. B. Rubin (2019). Statistical analysis with missing data. Hoboken, USA, John Wiley & Sons.

- Longley, P. A., M. F. Goodchild, D. J. Maguire and D. W. Rhind (2005). Geographic information systems and science. British John Wiley & Sons.
- Loomis, D., W. Huang and G. Chen (2014). "The International Agency for Research on Cancer (IARC) evaluation of the carcinogenicity of outdoor air pollution: focus on China." Chin J Cancer **33**(4): 189-196.
- Lu, G. Y. and D. W. Wong (2008). "An adaptive inverse-distance weighting spatial interpolation technique." Computers & Geosciences **34**(9): 1044-1055.
- Ma, X., I. Longley, J. Gao, A. Kachhara and J. Salmond (2019). "A site-optimised multi-scale GIS based land use regression model for simulating local scale patterns in air pollution." The Science of the total environment **685**: 134-149.
- Madani, N. and X. Emery (2019). "A comparison of search strategies to design the cokriging neighborhood for predicting coregionalized variables." Stochastic Environmental Research and Risk Assessment **33**(1): 183-199.
- Malik, M. R. S., E. R. Mohideen, L. Ali and S. Raziuddin (2016). "Weighted distance grey wolf optimizer to control air pollution of delhi thermal power plant." Journal of Industrial Pollution Control **32**(1): 361-367.
- Marko Sarstedt and E. Mooi (2019). Concise Guide to Market Research: The Process, Data, and Methods Using IBM Spss Statistics. Berlin, Germany, Springer.
- Mason, C. H. and W. D. Perreault Jr (1991). "Collinearity, power, and interpretation of multiple regression analysis." Journal of marketing research **28**(3): 268-280.
- Matejicek, L. (2005). "Spatial modelling of air pollution in urban areas with GIS: a case study on integrated database development." Advances in geosciences **4**: 63-68.
- McCullagh, P. (2019). Generalized linear models. New York, Routledge.
- Mehta, Y., M. M. Pai, S. Mallisery and S. Singh (2016). Cloud enabled air quality detection, analysis and prediction-a smart city application for smart health. 2016 3rd MEC International Conference on Big Data and Smart City (ICBDSC), Muscat, Oman, IEEE.
- Memarianfard, M., M. M. Aghdam and H. Memarianfard (2016). "Health risks zonation in megacities vis-à-vis PM using GIS-based model." Journal of Fundamental and Applied Sciences **8**(3): 193-202.
- Mendez, M., P. Lebègue, N. Visez, V. Fèvre-Nollet, V. Crenn, V. Riffault and D. Petitprez (2016). "Modeling of the chemical composition of fine particulate matter: Development and performance assessment of EASYWRF-Chem." Atmospheric Research **170**: 41-51.
- Menteşe, S. and Ş. Tağıl (2014). "Topografyanın Hava Kirliliği Üzerindeki Etkisi: Zonguldak Örneği." Türkiye Coğrafyası Araştırma ve Uygulama Merkezi VII. Coğrafya Sempozyumu, Ankara Üniversitesi, Ankara: 18-19.

- Miller, C. A., G. Hidy, J. Hales, C. E. Kolb, A. S. Werner, B. Haneke, D. Parrish, H. C. Frey, L. Rojas-Bracho and M. Deslauriers (2006). "Air emission inventories in North America: A critical assessment." Journal of the Air & Waste Management Association **56**(8): 1115-1129.
- Mohammady, S. and M. R. Delavar (2016). "Urban sprawl assessment and modeling using landsat images and GIS." Modeling Earth Systems and Environment **2**(3): 155.
- Momejian, N., M. A. Najm, I. Alameddine and M. El-Fadel (2019). "Groundwater Vulnerability Modeling to Assess Seawater Intrusion: a Methodological Comparison with Geospatial Interpolation." Water Resources Management **33**(3): 1039-1052.
- Montero, J.-M. and J. Mateu (2015). Spatial and spatio-temporal geostatistical modeling and kriging. United Kingdom, John Wiley & Sons.
- Mussatti, D. C., R. Srivastava, P. M. Hemmer and R. Strait (2002). "EPA air pollution control cost manual." Air Quality Strategies and Standards Division of the Office of Air Quality Planning and Standards, US Environmental Protection Agency, Research Triangle Park, NC, Washington, USA **27711**.
- Nadoushan, N., N. Mansouri and F. Nezhadkurki (2016). "Assessment of Aermod Model's Sensitivity to Terrain Features for Identifying Air Pollutants Receptor Points in Steel Industry." Journal of Fundamental and Applied Sciences **8**: 1399-1413.
- Nalder, I. A. and R. W. Wein (1998). "Spatial interpolation of climatic normals: test of a new method in the Canadian boreal forest." Agricultural and forest meteorology **92**(4): 211-225.
- Nerini, D., P. Monestiez and C. Manté (2010). "Cokriging for spatial functional data." Journal of Multivariate Analysis **101**(2): 409-418.
- Nevruz, E. and Ş. K. Yıldırak (2019). "Spatiotemporal interpolation through an extension of differential evolution algorithm for agricultural insurance claims." Journal of Computational and Applied Mathematics **352**: 278-292.
- Nicolás, J., M. Chiari, J. Crespo, N. Galindo, F. Lucarelli, S. Nava and E. Yubero (2011). "Assessment of potential source regions of PM_{2.5} components at a southwestern Mediterranean site." Tellus B: Chemical and Physical Meteorology **63**(1): 96-106.
- Oberschelp, C., S. Pfister, C. Raptis and S. Hellweg (2019). "Global emission hotspots of coal power generation." Nature Sustainability **2**(2): 113.
- Obroślak, R. and O. Dorozhynskyy (2017). "Selection of a semivariogram model in the study of spatial distribution of soil moisture." Journal of water and land development **35**(1): 161-166.
- Ocak, S. and N. Demircioğlu (2002). "Erzurum ili Kasım 1995-Nisan 1996 hava kalitesi profili." 1. ulusal çevre sempozyumu, Atatürk Üniversitesi, Erzurum **1**.
- Ocak, S. and F. S. Turalioglu (2008). "Effect of meteorology on the atmospheric concentrations of traffic-related pollutants in Erzurum, Turkey." J. Int. Environmental Application & Science **3**(5): 325-335.

Odası, T. Ç. M. (2007). "TMMOB Çevre Mühendisleri Odasının Noyan Özkan'a yazdığı e-mail: 6 Temmuz 2007."

Odası, T. Ç. M. (2018). Hava kirliliği raporu,(2017).

Olgun, S. (2017). " Ülkemizde Hava Kalitesi İzleme Çalışmaları, <http://ekolojikanaliz.com/guncel-haberler/ulkeizde-hava-kalitesi-izleme-calismalari>." Accessed on August, 2017.

Onay, T. T., N. K. Coptı, H. B. Gökçe, D. Aydın-Sarıkurt, M. Mumcu and E. Arioğlu (2019). "Air quality impact assessment for the Eurasia Tunnel in Istanbul, Turkey." Environmental monitoring and assessment **191**(3): 195.

Önder, D., M. Aydın, S. BERBEROĞLU, S. Önder and T. Yano (2009). "The use of aridity index to assess implications of climatic change for land cover in Turkey." Turkish Journal of Agriculture and Forestry **33**(3): 305-314.

Organization, W. H. (1992). United Nations Environment Programme. 1992. Urban air pollution in megacities of the world, Blackwell Publishers, Oxford: 7-13.

Organization, W. H. (2006). Air quality guidelines: global update 2005: particulate matter, ozone, nitrogen dioxide, and sulfur dioxide, World Health Organization.

Organization, W. H. (2013). "Review of evidence on health aspects of air pollution—REVIHAAP project: final technical report, Bonn: WHO European Centre for Environment and Health, European Union." 302.

Orhan, G. (2012). "Hava kirliliği ve asit yağmurları: Uzun menzilli sınırlar ötesi hava kirliliği sözleşmesi ve protokolleri karşısında Türkiye'nin konumu." Marmara Avrupa Araştırmaları Dergisi **20**(1): 123-150.

Özaslan, Ü. (2008). " Kocaeli kentinde hava kirliliğine neden olan inorganik gaz kirleticilerin düzeylerinin, dağılımlarının ve kaynaklarının belirlenmesi." Yüksek Lisans Tezi, Kocaeli Üniversitesi, Kocaeli, Turkey.

Özcan, N. (2016). "Kentsel hava kirliliğini etkileyen ve şehir planlama ile kontrol edilebilen fiziksel faktörlerin mekânsal istatistik yöntemleri ile incelenmesi." Fen Bilimleri Enstitüsü, Doktora Tezi, İzmir, Türkiye.

Ozcan, N. S. and K. M. Cubukcu (2016). "Examination of the Relationship between Urban Air Pollution and Urban Planning Decisions in Cigli Case, Izmir (Turkey)." Environment-Behaviour Proceedings Journal **1**(2): 178-187.

Özcan, N. S. and T. M. Çubukçu (2013). "Explaining the level of air pollution in Turkey at the county level using employment distribution." Journal of Selcuk University Natural and Applied Science **2**(1): 882-892.

Özden, Ö., T. Döğeroğlu and S. Kara (2008). "Assessment of ambient air quality in Eskişehir, Turkey." Environment International **34**(5): 678-687.

- Özdilek, H. G. (2006). "An analogy on assessment of urban air pollution in Turkey over the turn of the millennium (1992–2001)." Environmental monitoring and assessment **122**(1): 203-219.
- Özer, F. (2013). "Reduce the Impact of Air Pollution on the Use of Natural Gas in Karabuk." M. Sc. Thesis.
- Özşahin, E., Eroğlu, İlker, Pektezel, Halid (2016). "Keşan’da (Edirne) Hava Kirliliği." Selçuk Üniversitesi Sosyal Bilimler Enstitüsü Dergisi(36): 83-100.
- Ozturk, Z. C. (2016). "Modelling of atmospheric SO₂ pollution in Seydişehir town by artificial neural networks." Journal of International Environmental Application and Science **11**(1): 1-7.
- Park, C., R. T. Haftka and N. H. Kim (2017). "Remarks on multi-fidelity surrogates." Structural and Multidisciplinary Optimization **55**(3): 1029-1050.
- Parker, H. D. (1988). "The unique qualities of a geographic information system: a commentary." Photogrammetric Engineering and Remote Sensing **54**(11): 1547-1549.
- Partigöç, N. S. (2019). "CBS Tabanlı Yerleşilebilirlik Analizi: Çiğli İlçesi Örneği." Bilişim Teknolojileri Dergisi **11**(1): 9-21.
- Partigöç, N. S. and K. M. Çubukçu (2017). "Hava Kirliliği ve Kent İlişisine Ampirik Bakış: Ekolojik Sürdürülebilirlik Ekseninde Bir Değerlendirme." Akademia Disiplinlerarası Bilimsel Araştırmalar Dergisi **3**(2): 28-45.
- Pebesma, E. J. (2004). "Multivariable geostatistics in S: the gstat package." Computers & Geosciences **30**(7): 683-691.
- Po, J. Y., J. M. FitzGerald and C. Carlsten (2011). "Respiratory disease associated with solid biomass fuel exposure in rural women and children: systematic review and meta-analysis." Thorax **66**(3): 232-239.
- Pope III, C. A., R. T. Burnett, M. J. Thun, E. E. Calle, D. Krewski, K. Ito and G. D. Thurston (2002). "Lung cancer, cardiopulmonary mortality, and long-term exposure to fine particulate air pollution." Jama **287**(9): 1132-1141.
- Poulsen, A. H., M. Sørensen, Z. J. Andersen, M. Ketzel and O. Raaschou-Nielsen (2016). "Air pollution from traffic and risk for brain tumors: a nationwide study in Denmark." Cancer Causes & Control **27**(4): 473-480.
- Preacher, K. J., P. J. Curran and D. J. Bauer (2006). "Computational tools for probing interactions in multiple linear regression, multilevel modeling, and latent curve analysis." Journal of educational and behavioral statistics **31**(4): 437-448.
- Prieto, A. J., A. Silva, J. de Brito, J. M. Macías-Bernal and F. J. Alejandre (2017). "Multiple linear regression and fuzzy logic models applied to the functional service life prediction of cultural heritage." Journal of Cultural Heritage **27**: 20-35.
- Qian, W., L. Qingliang, G. Jinbo, L. Qiaoying, X. Qiufang, P. M. GROFFMAN and Y. Shen (2017). "Non-Algorithmically Integrating Land Use Type with Spatial

Interpolation of Surface Soil Nutrients in an Urbanizing Watershed." Pedosphere **27**(1): 147-154.

Ramos, C. A., H. T. Wolterbeek and S. M. Almeida (2016). "Air pollutant exposure and inhaled dose during urban commuting: a comparison between cycling and motorized modes." Air Quality, Atmosphere & Health **9**(8): 867-879.

Ribeiro Jr, P. J. and P. J. Diggle (2001). "geoR: a package for geostatistical analysis." R news **1**(2): 14-18.

Ribeiro, M. C., P. Pinho, C. Branquinho, E. Llop and M. J. Pereira (2016). "Geostatistical uncertainty of assessing air quality using high-spatial-resolution lichen data: A health study in the urban area of Sines, Portugal." Science of the Total Environment **562**: 740-750.

Rossi, J.-P., P. Lavelle and J. E. Tondoh (1995). "Statistical tool for soil biology: X. Geostatistical analysis." European Journal of Soil Biology **31**(4): 173-181.

Saad, S., Shakaff, A., Saad, A., Yusof, A., Andrew, A., Zakaria, A., & Adom, A. (2017). Development of indoor environmental index: Air quality index and thermal comfort index. Paper presented at the AIP Conference Proceedings.

Sá, E., H. Martins, J. Ferreira, M. Marta-Almeida, A. Rocha, A. Carvalho, S. Freitas and C. Borrego (2016). "Climate change and pollutant emissions impacts on air quality in 2050 over Portugal." Atmospheric Environment **131**: 209-224.

Sadoti, G., M. G. Pollock, K. T. Vierling, T. P. Albright and E. K. Strand (2014). "Variogram models reveal habitat gradients predicting patterns of territory occupancy and nest survival among vesper sparrows." Wildlife biology **20**(2): 97-108.

Salah, A., Z. Bahaa and G. Hasan (2014). "Mapping Dispersion of Urban Air Particulate Matter Over Kirkuk City Using Geographic Information System." Journal of Environment and Earth Science **4**(8): 80-87.

Salvi, S. S. and P. J. Barnes (2009). "Chronic obstructive pulmonary disease in non-smokers." The lancet **374**(9691): 733-743.

Sarangi, A., C. Cox and C. Madramootoo (2005). "Geostatistical methods for prediction of spatial variability of rainfall in a mountainous region." Transactions of the ASAE **48**(3): 943-954.

Sari, M. F., Y. Tasdemir and F. Esen (2019). "Major air pollutants in Bursa, Turkey: their levels, temporal changes, interactions, and sources." Environmental Forensics **20**(2): 182-195.

Say, N. P. (2006). "Lignite-fired thermal power plants and SO₂ pollution in Turkey." Energy policy **34**(17): 2690-2701.

Selmi, W., C. Weber, E. Rivière, N. Blond, L. Mehdi and D. Nowak (2016). "Air pollution removal by trees in public green spaces in Strasbourg city, France." Urban Forestry & Urban Greening **17**: 192-201.

Sensoy, S. (2004). The mountains influence on Turkey climate. Balwois Conference on Water Observation and Information System for Decision Support, Ohrid, FY Republic of Macedonia, 25-29 May 2004, Ankara, Turkey.

Sensoy, S., M. Demircan, Y. Ulupinar and İ. Balta (2008). "Climate of Turkey." Turkish state meteorological service **401**.

Serebrisky, D. and A. Wiznia (2019). "Pediatric asthma: a global epidemic." Annals of global Health **85**(1): 1-6.

Shahbazi, H., M. Reyhanian, V. Hosseini and H. Afshin (2016). "The Relative Contributions of Mobile Sources to Air Pollutant Emissions in Tehran, Iran: an Emission Inventory Approach." Emission Control Science and Technology **2**(1): 44-56.

Shareef, M. M., T. Husain and B. Alharbi (2016). "Optimal Air Quality Monitoring Network for Green Cities." International Journal of Environment and Sustainability **5**(2): 72-88.

Shareef, M. M., T. Husain and B. Alharbi (2016). "Optimization of air quality monitoring network using GIS based interpolation techniques." Journal of Environmental Protection **7**(06): 895-911.

Sillaparassamee, R., K. Tantrakarnapa and S. Chinwetkitvanich (2016). "Development Model of Oxide of Nitrogen Concentration and Land Use Characteristics in Bangkok Area." EnvironmentAsia **9**(2): 111-117.

Sim, L. H. (2016). Statistical methods for air quality model calibration and validation in urban areas, University of Glasgow.

Şişman, E. (2019). "Türkiye’de Seçilen Hava Kalitesi İzleme İstasyonları için Eğilim (Trend) Değerlendirmeleri." Doğal Afetler ve Çevre Dergisi **5**(1): 134-152.

Slovic, A. D., M. A. de Oliveira, J. Biehl and H. Ribeiro (2016). "How Can Urban Policies Improve Air Quality and Help Mitigate Global Climate Change: a Systematic Mapping Review." Journal of Urban Health **93**(1): 73-95.

Smith, T. B., N. Smith and R. G. Weleber (2017). "Comparison of nonparametric methods for static visual field interpolation." Medical & biological engineering & computing **55**(1): 117-126.

Sousa, S., F. G. Martins, M. Alvim-Ferraz and M. C. Pereira (2007). "Multiple linear regression and artificial neural networks based on principal components to predict ozone concentrations." Environmental Modelling & Software **22**(1): 97-103.

Stein, A. and L. Corsten (1991). "Universal kriging and cokriging as a regression procedure." Biometrics **47**(2): 575-587.

Svachula, J., N. Ferlazzo, P. Forzatti, E. Tronconi and F. Bregani (1993). "Selective reduction of nitrogen oxides (NO_x) by ammonia over honeycomb selective catalytic reduction catalysts." Industrial & engineering chemistry research **32**(6): 1053-1060.

Tang, U. and Z. Wang (2007). "Influences of urban forms on traffic-induced noise and air pollution: Results from a modelling system." Environmental Modelling & Software **22**(12): 1750-1764.

Tashayo, B. and A. Alimohammadi (2016). "Modeling urban air pollution with optimized hierarchical fuzzy inference system." Environmental Science and Pollution Research **23**(19): 19417-19431.

Taşpınar, F. (2015). "Time Series Models for Air Pollution Modelling Considering the Shift to Natural Gas in a Turkish City." CLEAN–Soil, Air, Water **43**(7): 980-988.

Tayanç, M., U. İm, M. Doğruel and M. Karaca (2009). "Climate change in Turkey for the last half century." Climatic Change **94**(3-4): 483-502.

Tecer, L. H., N. Tomac, F. Karaca, A. Kaplan, T. Tuncer and H. Aydin (2009). "The evaluation of the effect of air pollution on the health status of children in Zonguldak City, Turkey." International Journal of Environment and Pollution **39**(3-4): 352-364.

Tecim, V. (2008). "Coğrafi bilgi sistemleri harita tabanlı bilgi yönetimi." Renk Form Ofset Matbaacılık Ltd. Şti., Ankara, ISBN: 978-605.

Thad, G. (1997). Air quality, Florida: Chemical Rubber Company (CRC) Press. New York, USA, CRC Press.

Theunis, J., J. Peters and B. Elen (2017). Participatory Air Quality Monitoring in Urban Environments: Reconciling Technological Challenges and Participation. Participatory Sensing, Opinions and Collective Awareness, Springer: 255-271.

Thill, J.-C. (2019). Spatial multicriteria decision making and analysis: A geographic information sciences approach, Routledge.

Tokgöz, D. D. G., İ. Balcılar, A. İ. İlhan, T. Balta and G. Tuncel (2017). "Bati Karadeniz Aerosolunun Zamansal Değişiminin Değerlendirilmesi." VII. Ulusal Hava Kirliliği ve Kontrolü Sempozyumu, Hava Kirlenmesi Araştırmaları ve Denetimi Türk Milli Komitesi, Akdeniz Üniversitesi Mühendislik Fakültesi Çevre Mühendisliği Bölümü, 1-3 Kasım 2017-Antalya.

Torabi-Kaveh, M., R. Babazadeh, S. Mohammadi and M. Zaresefat (2016). "Landfill site selection using combination of GIS and fuzzy AHP, a case study: Iranshahr, Iran." Waste Management & Research: 0734242X16633777.

Toros, H., H. Erdun, Ö. Çapraz, B. Özer, E. B. Daylan and A. İ. Öztürk (2013). "Air Pollution and Quality Levels in Metropolitans of Turkey for Sustainable life." Avrupa Bilim ve Teknoloji Dergisi, European Journal of Science and Technology **1**(1): 12-18.

Tosun, E. (2017). Türkiye'nin 2009-2016 Yillari Arasindaki Hava Kalitesi Verilerinin Değerlendirilmesi, Fen Bilimleri Enstitüsü, Yüksek Lisans Tezi, Ankara, Turkey.

Trivedy, R. and P. Goel (2010). An introduction to air pollution, ABD Publishers.

Tsiflikiotou, M., E. Kostenidou, D. Papanastasiou, D. Patoulas, P. Zampas, D. Paraskevopoulou, E. Diapouli, C. Kaltsonoudis, K. Florou and A. Bougiatioti (2019).

"Summertime particulate matter and its composition in Greece." Atmospheric Environment **213**: 597-607.

Tuik (2010). "Address Based Population Registration System, ." Turkish Statistical Institute, <http://www.tuik.gov.tr> (accessed December 2010).

Tuik (2012). "Address Based Population Registration System, ." Turkish Statistical Institute, <http://www.tuik.gov.tr> (accessed 26 December 2012).

Tuna, F. and M. Buluç (2015). "Analysis of PM10 pollutant in Istanbul by using Kriging and IDW methods: between 2003 and 2012." Analysis **4**(01): ü.

Tuncel, G., Müezzinoğlu, A., Tuncel, S., Bayram., Odabaşı, M., Sofuoğlu, S.C. ve diğer (2008). "İzmir Aliğa endüstri bölgesinde hava kirliliğine neden olan organik ve inorganik kirleticilerin düzeylerinin, kaynaklarının ve sağlık etkilerinin belirlenmesi," TÜBİTAK 104Y276 Nolu Proje Raporu, İzmir.

Tuncel, S. G., A. H. Baykal, G. Tuncel and U. Özer (1994). "Measurement of NO_x, SO₂, SPM, and O₃ at a High Altitude Station in Northwestern Turkey." Israel Journal of Chemistry **34**(3-4): 403-409.

Türkeş, M. (1996). "Spatial and temporal analysis of annual rainfall variations in Turkey." International journal of Climatology **16**(9): 1057-1076.

Turner, M. C., D. Krewski, C. A. Pope III, Y. Chen, S. M. Gapstur and M. J. Thun (2011). "Long-term ambient fine particulate matter air pollution and lung cancer in a large cohort of never-smokers." American journal of respiratory and critical care medicine **184**(12): 1374-1381.

Turoğlu, H. (2000). Coğrafi Bilgi Sistemlerinin Temel Esaslar. Istanbul, Çantay Kitapevi, Istanbul.

Ujang, U., F. Anton, A. Ariffin, D. Mioc and S. Azri (2015). "An amalgamation of 3D city models in urban air quality modelling for improving visual impact analysis." Air Pollution XXIII **198**: 51.

Unal, Y. S., H. Toros, A. Deniz and S. Incecik (2011). "Influence of meteorological factors and emission sources on spatial and temporal variations of PM10 concentrations in Istanbul metropolitan area." Atmospheric Environment **45**(31): 5504-5513.

Uraloğlu, A. (2019). ""Trafik Hacim Haritaları." <http://www.kgm.gov.tr/Sayfalar/KGM/SiteTr/Trafik/TrafikHacimHaritalari2017.aspx>.

Uznir, U., A. Francois and R. Alias Abdul (2013). "Unified data model of urban air pollution dispersion and 3D spatial city model: groundwork assessment towards sustainable urban development for Malaysia." Journal of Environmental Protection **2013**.

Valdor, P. F., A. G. Gómez, V. Velarde and A. Puente (2016). "Can a GIS toolbox assess the environmental risk of oil spills? Implementation for oil facilities in harbors." Journal of environmental management **170**: 105-115.

van Ginkel, J. R. (2019). "Significance Tests and Estimates for R^2 for Multiple Regression in Multiply Imputed Datasets: A Cautionary Note on Earlier Findings, and Alternative Solutions." Multivariate behavioral research: 1-16.

Vienneau, D., K. De Hoogh and D. Briggs (2009). "A GIS-based method for modelling air pollution exposures across Europe." Science of the Total Environment **408**(2): 255-266.

Vlachokostas, C., S. Nastis, C. Achillas, K. Kalogeropoulos, I. Karmiris, N. Moussiopoulos, E. Chourdakis, G. Baniyas and N. Limperi (2010). "Economic damages of ozone air pollution to crops using combined air quality and GIS modelling." Atmospheric Environment **44**(28): 3352-3361.

Wang, R., S. B. Henderson, H. Sbihi, R. W. Allen and M. Brauer (2013). "Temporal stability of land use regression models for traffic-related air pollution." Atmospheric Environment **64**: 312-319.

Wang, X. and K. M. Kockelman (2009). "Forecasting network data: Spatial interpolation of traffic counts from texas data." Transportation Research Record **2105**(1): 100-108.

Wang, Z., J. Lv, Y. Tan, M. Guo, Y. Gu, S. Xu and Y. Zhou (2019). "Temporospatial variations and Spearman correlation analysis of ozone concentrations to nitrogen dioxide, sulfur dioxide, particulate matters and carbon monoxide in ambient air, China." Atmospheric Pollution Research **10**(4): 1203-1210.

Webster, R. and M. A. Oliver (2007). Geostatistics for environmental scientists. Great Britain, John Wiley & Sons.

Wiemann, S., J. Brauner, P. Karrasch, D. Henzen and L. Bernard (2016). "Design and prototype of an interoperable online air quality information system." Environmental Modelling & Software **79**: 354-366.

Wright, L. and L. Fulton (2005). "Climate change mitigation and transport in developing nations." Transport Reviews **25**(6): 691-717.

Yasemin, O. and V. Kırmacı (2015). "Bartın İlinde Kullanılan Isıtma Sistemlerinin Ekonomik ve Çevresel Etkilerinin İncelenmesi." Mühendislik ve Teknoloji Bilimleri Dergisi **3**(1): 4-10.

Yasobant, S., K. S. Vora and A. Upadhyay (2019). Geographic information system applications in public health: Advancing health research. Healthcare Policy and Reform: Concepts, Methodologies, Tools, and Applications. Gandhinagar, India, IGI Global: 538-561.

Yerramilli, A., V. B. R. Dodla and S. Yerramilli (2011). "Air pollution, modeling and GIS based decision support systems for air quality risk assessment." Advance air pollution, Rijeka, Croatia: 295-324.

Yerramilli, A., S. Yerramilli and V. B. R. Dodla (2011). Air pollution, modeling and GIS based decision support systems for air quality risk assessment, INTECH Open Access Publisher.

Yıldırım, U. and H. Korkmaz (1998). "Kahramanmaraş'ta coğrafi faktörlerin hava kirliliğine etkileri." Türk Coğrafya Dergisi/Turkish Geographical Review(33): 389-411.

Yılmaz, B. (2018). "Manisa'da partikül madde (PM10) kirliliğinin değerlendirilmesi." Balıkesir Üniversitesi Fen Bilimleri Enstitüsü Dergisi **20**(1): 626-633.

Yılmaz, M., E. Keşaf, H. Toros, A. Ulubey and E. Hristova (2019). Meteorological evaluation of Edirne air pollution. AIP Conference Proceedings, AIP Publishing.

Yin, Z., K. Cui, S. Chen, Y. Zhao, H.-R. Chao and G.-P. Chang-Chien (2019). "Characterization of the air quality index for Urumqi and Turfan cities, China." Aerosol Air Qual. Res **19**: 282-306.

Yu, H.-L., S.-C. Ku and A. Kolovos (2016). "A GIS tool for spatiotemporal modeling under a knowledge synthesis framework." Stochastic Environmental Research and Risk Assessment **30**(2): 665-679.



C.V

Personal Information

Name Surname : Nahida Hameed Hamza Al-Qaysi
Nationality : Iraq
Date and Place of Birth: 08.06.1977, Iraq
Telephone : 05350609694
E-mail : Nahida_mml@yahoo.com

Education Information

University: Al Mustansiriya University, Iraq, Baghdad 2000-2001
Master of Science: Al-Mustansiriya University, Iraq, Bagdad 2004/2005.
Ph.D.: Selçuk University, Turkey, Konya 2018-2019

Work Experiences

Year	Corporate	Responsibility
2006-for now	Diyala University	Asst. Lecture in the Department of Civil Engineering / University of Diyala

Field of Specialization: Environmental Engineering

Foreign Language: English, Turkish

Computer Skills – Microsoft Windows, Microsoft Office, GIS, computer fundamental, AutoCAD, SPSS, Grapher, Fortran programming.

Publications:

1. Nahida Hameed Hamza Alqaysi, (2012), Evaluation Water Quality of Diyala River for Irrigation Purposes/ Diyala Journal of Engineering Science, Vol. 5, No.
2. Al Obaidy, A. H. M. J., Kadhemi, A. J., Hamza, N. H., & Al Mashhady, A. A. (2014). Assessment of ground water quality for drinking and agricultural uses in Mouqdadiya District, Diyala, Iraq. *Engineering and Technology Journal*, 32(12 Part (A) Engineering), 2921-2936.
3. Şükrü Dursun, Nahida Hameed Hamza Alqaysi, (2016), "Estimating Air Pollution Quality in Istanbul City Centre by Geographic Information System",

International Journal of Ecosystems and Ecology Sciences (IJEES) Vol. 6 (3): 329-340

4. Abdu Rahim Jehangiri, Mojobullah Wahidy, Mohammad Nazir Malekzada, Nahida Hameed, Şükrü Dursun, (2016), "Selçuk Üniversitesi Kampüs Alanı İçerisindeki Gürültü Kirlilik Düzeyinin Ölçülmesi Ve Değerlendirilmesi", 1. Ulusal Çevre Mühendisliği Öğrencileri Sempozyumu, UÇMÖS'16, 15-19.
5. Nahida Hameed Hamza Alqaysi, Mushtaq Abdulameer Alwan Al-Muslehi, (2016), "Delineation of the Watersheds Basin in the Konya City and Modelling by Geographical Information System", J. Int. Environmental Application & Science, Vol. 11(3): 303-311.
6. Nahida Hameed Hamza Alqaysi, Şükrü Dursun, Mushtaq Abdulameer Alwan Al-Muslehi, (2017), "Estimating Drought Index Using Standardized Precipitation Index from 1901 to 2015, Turkey", J. Int. Environmental Application & Science, Vol. 12(3): 154-160.
7. Şükrü Dursun, Mushtaq Abdulameer Alwan Al-Muslehi, Nahida Hameed Hamza Alqaysi, (2017), "Modeling of Effective Temperature for Central Anadolia Region in Turkey by Utilizing ARCGIS", International Journal of Ecosystems and Ecology Sciences (IJEES), Vol. 7 (4): 873-882.
8. Nahida Hameed Hamza Alqaysi, Şükrü Dursun, (2018), "Multiple Linear Regression and Inverse Distance Weight (IDW) Interpolation for Spatial Analysis of PM10 and SO2 in Bursa City, Turkey", International Journal of Ecosystems and Ecology Science (IJEES), Vol. 8 (2): 213-220.
9. Mushtaq Abdulameer Alwan Al-Muslehi, Şükrü Dursun, Nahida Hameed Hamza Alqaysi, (2018), "Assessing of Water Quality Index Using Geographic Information System in Konya City Center", International Journal of Ecosystems and Ecology Science (IJEES), Vol. 8 (3): 679-690.
10. Mushtaq Abdulameer Alwan AlMuslehi, Şükrü Dursun, Nahida Hameed Hamza Alqaysi, (2019), "Evaluating Groundwater Quality for Irrigation Suitability in Konya City", International Symposium for Environmental Science and Engineering Research (ISESER), Konya, Turkey.
11. Nahida Hameed Hamza Alqaysi, Şükrü Dursun, Mushtaq Abdulameer Alwan AlMuslehi, (2019), "Estimation of Nitrogen Oxides Pollution Using Geographical Information System in Turkey", International Symposium for Environmental Science and Engineering Research (ISESER), Konya, Turkey.