

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**ASSESSMENT OF THE LAND AND SEA INTERACTION BY USING
DIFFERENT TYPES OF SATELLITE DATA**



Ph.D. THESIS

Aylin TUZCU KOKAL

Department of Geomatics Engineering

Geomatics Engineering Programme

JUNE 2024

ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

**ASSESSMENT OF THE LAND AND SEA INTERACTION BY USING
DIFFERENT TYPES OF SATELLITE DATA**

Ph.D. THESIS

**Aylin TUZCU KOKAL
(501192602)**

Department of Geomatics Engineering

Geomatics Engineering Programme

Thesis Advisor: Prof. Dr. Nebiye MUSAOĞLU

JUNE 2024

İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

**FARKLI ÖZELLİKTEKİ UYDU VERİLERİ İLE KARA-DENİZ
ETKİLEŞİMİNİN BELİRLENMESİ**

DOKTORA TEZİ

**Aylin TUZCU KOKAL
(501192602)**

Geomatik Mühendisliği Anabilim Dalı

Geomatik Mühendisliği Programı

Tez Danışmanı: Prof. Dr. Nebiye MUSAOĞLU

HAZİRAN 2024

Aylin TUZCU KOKAL, a Ph.D. student of İTÜ Graduate School student ID 501192602, successfully defended the dissertation entitled “ASSESSMENT OF THE LAND AND SEA INTERACTION BY USING DIFFERENT TYPES OF SATELLITE DATA”, which she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor : **Prof. Dr. Nebiye MUSAOĞLU**
Istanbul Technical University

Jury Members : **Prof. Dr. Ayşe Gül TANIK**
Istanbul Technical University

Prof. Dr. Cem GAZİOĞLU
Istanbul University

Asst. Prof. Nazlı OLGUN KIYAK
Istanbul Technical University

Asst. Prof. Meltem KAÇIKOÇ
Süleyman Demirel University

Date of Submission : 2 May 2024
Date of Defense : 3 June 2024





To my family,



FOREWORD

As I embark on the journey of presenting this dissertation, I am filled with a profound sense of gratitude and excitement. Completing this study has been a journey of discovery, and academic growth, and I am immensely thankful to all those who have supported and guided me along the way.

First, I extend my deepest appreciation to my advisor, Prof. Dr. Nebiye MUSAOĞLU, whose expertise, guidance, and support have been invaluable throughout this study. Your mentorship has not only shaped this dissertation but has also profoundly influenced my academic development. I am truly grateful for your encouragement. I would also like to express my heartfelt gratitude to the members of the jury, Prof. Dr. Ayşe Gül TANIK, Prof. Dr. Cem GAZİOĞLU, Asst. Prof. Nazlı OLGUN KIYAK, and Asst. Prof. Meltem KAÇIKOÇ for their invaluable feedback. Your collective expertise has enriched this dissertation.

I extend my gratitude to Assistant Professor Cédric G. FICHOT from Boston University, who has provided valuable perspectives and insights while I was working as a visiting scholar at the Boston University. Your willingness to share your knowledge and offer guidance has been immensely appreciated. I also want to express my appreciation to the team of Fichot's Lab for their collective support and contributions.

I am also deeply grateful to my family for their love, and support throughout this journey. Their belief in me has been a constant source of strength and motivation, and I am profoundly thankful for their encouragement. I would like to thank my dear friend İrem İSMAİLOĞLU for supporting me.

Finally, I would like to acknowledge the financial support of Istanbul Technical University Scientific Research Projects Office (BAP) under project number MDK-2021-43054 and of the Scientific and Technological Research Council of Türkiye (TUBITAK) under project number 1059B142200399 (TUBITAK-2214/A Grant Program) and under project number 121G142.

Also, I would like to acknowledge to Istanbul Technical University (ITU) Center for Satellite Communication and Remote Sensing (CSCRS) and Maxar for providing Worldview-3 satellite image. Besides, I would like to acknowledge to the Turkish State Meteorological Service for providing the in-situ meteorological data. This study was carried out using PRISMA Products, © of the Italian Space Agency (ASI), delivered under an ASI License to use. Bathymetric data was provided by the General Bathymetric Chart of the Oceans (GEBCO).

June 2024

Aylin TUZCU KOKAL
(Geomatics Engineer)



TABLE OF CONTENTS

	<u>Page</u>
FOREWORD	ix
TABLE OF CONTENTS	xi
ABBREVIATIONS	xiii
SYMBOLS	xv
LIST OF TABLES	xvii
LIST OF FIGURES	xix
SUMMARY	xxi
ÖZET	xxv
1. INTRODUCTION	1
1.1 Background and Context	1
1.2 Literature Summary	3
1.3 Problem Statement	10
1.4 Purpose and Scope of the Thesis	11
2. STUDY AREA AND DATA USED	13
2.1 Study Area	13
2.2 Data Used	15
2.2.1 Satellite Data	15
2.2.2 Ancillary Data	18
3. METHODOLOGY	19
3.1 Methodology of Detection of Mucilage Phenomenon by Satellite Images	19
3.2 Methodology of Sea Surface Temperature Detection Using Satellite Images	26
3.3 Methodology of LU/LC Assessment of the Coastal Cities of the Sea of Marmara	28
4. RESULTS	31
4.1 The Mucilage Detection Results	31
4.2 The SST Results	35
4.3 The LU/LC Results of CORINE	39
5. DISCUSSION	53
6. CONCLUSION	57
REFERENCES	61
CURRICULUM VITAE	76



ABBREVIATIONS

AMEI	: Automated Mucilage Extraction Index
ANOVA	: Analysis of variance
BT	: Brightness Temperature
CDR	: Climate Data Records
CLC	: CORINE Land Cover
CORINE	: Coordination of Information on the Environment
DN	: Digital Number
FAO	: The Food and Agriculture Organization
GEE	: Google Earth Engine
GIS	: Geographic Information System
GLCM	: Gray-Level Cooccurrence Matrix
LU/LC	: Land use / land cover
LUCAS	: Land Use / Cover Area Frame Survey
MMU	: Minimum Mapping Unit
MODIS	: The Moderate Resolution Imaging Spectroradiometer
NDTI	: Normalized Difference Turbidity Index
NLCD	: National Land Cover Database
NOAA	: National Oceanic and Atmospheric Administration
OBIA	: Object-based Image Analysis
OISST V2	: Optimum Interpolation 1/4° Daily SST Version 2
RF	: Random Forest
RMSE	: Root Mean Square Error
SLSTR	: Sentinel-3 Sea and Land Surface Temperature Radiometer
SST	: Sea Surface Temperature
SSTA	: Sea surface temperature anomalies
STL	: Seasonal-Trend decomposition using LOESS
SVM	: Support Vector Machine
TOA	: Top of Atmosphere
TSMS	: Turkish State Meteorological Service
TSS	: Total Suspended Solids

TURKSTAT : Turkish Statistical Institute

TÜDAV: : Türk Deniz Araştırmaları Vakfı

WWTP : Wastewater Treatment Plant



SYMBOLS

$E_{\lambda_{band}}$	: Averaged solar exoatmopsheric irradiance
$L_{pixel,band}$	: Sensor radiance
d_{ES}	: Earth Sun distance
θ_s	: Solar zenith angle
AL	: Band-specific additive rescaling factor provided in metadata file
ML	: Band-specific multiplicative rescaling factor
n	: Number of the samples
Q_{cal}	: Quantized and calibrated standard product pixel values for Band 10
R_v	: Remainder component
S_v	: Seasonal component
T_s	: Surface temperature
T_v	: Trend component
X_{obs}	: In-situ data
X_{sens}	: Acquired data
ϵ	: Emissivity value of sea
λ	: Wavelength of emitted radiance
ρ	: Top of atmosphere reflectance



LIST OF TABLES

	<u>Page</u>
Table 2.1 : The technical specifications of satellite data used (Reynolds et al., 2008; SUHET, 2015; Kuester, 2016; Url-3; Url-4; Url-5; Url-6; Url-7; Url-8; Url-9; Url-10; Url-11, Url-23, Url-24, Url-25).....	16
Table 4.1 : ANOVA test results of the Worldview-3 and Sentinel-2 images.	31
Table 4.2 : Areal extents of the mucilage classes in İzmit Bay based on satellite data in May 2021. The corresponding study sites are shown in Figure 3.2. ...	35
Table 4.3 : Anomaly detected days.	38
Table 4.4 : LU/LC changes in the coastal cities along the Sea of Marmara between 1990 and 2021.	49



LIST OF FIGURES

	<u>Page</u>
Figure 2.1 : The Sea of Marmara Basin (Musaoğlu et al., 2022).....	13
Figure 2.2 : The bathymetry map of the Sea of Marmara was produced by bathymetric data provided by the GEBCO.	14
Figure 2.3 : The geographical location of the study area and the meteorological stations.	18
Figure 3.1 : Flow chart of the methodology.....	19
Figure 3.2 : Study area. a) The map of Türkiye with the dark blue box that showing the Sea of Marmara, b) the map of İzmit Bay with the red box represents the sub-region, c) natural color composition of Sentinel-2 satellite image from May 24, 2021, d) Worldview-3 satellite image from May 24, 2021, and May 25, 2021, respectively.	20
Figure 3.3 : Flow chart of the mucilage phenomenon detection.....	21
Figure 3.4 : Examples of different mucilage shown with representative photographs; (a) yellow mucilage (Url-17), and (b) white mucilage (Url-18); the Sentinel-2 satellite image of (d) yellow in open water on 24.05.2021, and (e) white mucilage in open water on 25.05.2021; c) Spectral reflectance curves of the yellow mucilage, the white mucilage and water that were retrieved from the Sentinel-2 satellite data.	23
Figure 3.5 : Examples of different mucilage shown with representative photographs; (a) brown (Url-16), (b) yellow (Url-17), and (c) white mucilage (Url-18); the Worldview-3 satellite image of (e) brown in Kocaeli coast on 25.05.2021, (f) yellow in Kocaeli coast on 25.05.2021, and (g) white mucilage in open water on 25.05.2021; d) Spectral reflectance curves of the brown mucilage, the yellow mucilage, the white mucilage and water that were retrieved from the Worldview-3 satellite data.	23
Figure 3.6 : Examples of mucilage appearances shown with the field photographs from different sites in İzmit Bay including a) the eastern side of the coast of Darıca (in Kocaeli), taken on May 7, 2021 (Url-19), b) the coast of Körfez (in Kocaeli), taken on May 7, 2021 (Url-19), c) the western side of the coast of Darıca (in Kocaeli), taken on May 7, 2021 (Url-17), d) nearby Topçular Ferry Pier taken on May 26, 2021, e) Osmangazi Bridge, on May 26, 2021.	25
Figure 3.7 : Projection of the data into a higher dimension, adapted from Mather and Tso, (2009).....	26
Figure 3.8 : Flow chart of the methodology used.	27
Figure 3.9 : The flow diagram of the methodology used (Sentinel logo was retrieved from the website of ESA (ESA, n.d.) and the CORINE image was retrieved from the CORINE website (Copernicus, n.d.-a)	29

Figure 4.1 : Results of mucilage texture analyses performed on two pilot locations (a, e) in the İzmit Bay by using the Gray-Level Co-occurrence Matrix (GLCM) method (Haralick et al., 1973). The two study areas are shown orange boxes in a) Worldview-3 satellite image from May 25, 2021 and e) Sentinel-2 satellite image from May 24, 2021. The mucilage textures are characterized by using (b,f) Contrast, (c,g) Dissimilarity and (d,h) Angular Second Moment method described in GLCM method.	32
Figure 4.2 : The thematic map of the different mucilage types that was produced by applying SVM classification method to Sentinel-2 satellite image. The zoomed images to monitor spatial variations of different mucilage types in locations a), b), c).	33
Figure 4.3 : The thematic map of the different mucilage types that was produced by applying SVM classification method to Worldview-3 satellite image. The zoomed images to monitor spatial variations of different mucilage types in locations a), b), c), d).	34
Figure 4.4 : SST maps retrieved from Landsat-8 satellite images.	35
Figure 4.5 : SST maps retrieved from Sentinel-3 satellite images.	36
Figure 4.6 : SST maps retrieved from NOAA OISST V2 satellite images.	36
Figure 4.7 : a) Original series, b) trend component, c) seasonal component, d) residual component, e) threshold values are shown with gray color on the residual values, f) anomaly detected days are represented by the red dots on the time-series data.	37
Figure 4.8 : a) The residual component that was obtained from STL method, b) anomaly band result of the NOAA OISST V2 data.	39
Figure 4.9 : Generated LU/LC map of coastal cities along the Sea of Marmara for 2021.	40
Figure 4.10 : LU/LC maps of 2021 and areal distribution of a) İstanbul, b) Yalova, c) Kocaeli, d) Balıkesir, e) Bursa, f) Çanakkale, and g) Tekirdağ.	41
Figure 4.11 : a) Length of city coastlines along the Sea of Marmara with the location of ports and main industries. İstanbul Metropolitan Agglomeration is shown as dark grey area, Bursa Agglomeration is shown in green area, b) Night time view of city lights around the Sea of Marmara (NASA Worldview Snapshots, 2017).	43
Figure 4.12 : The map of roads and railways retrieved from OSM (Url-12).	44
Figure 4.13 : Overall LU/LC change of the coastal cities between 1990-2021.	45
Figure 4.14 : LU/LC change per class during 1990 - 2021 in a) İstanbul, b) Çanakkale and c) Balıkesir.	45
Figure 4.15 : Assessing land-sea interaction through discharge, WWTPs, currents, and drainage network data, adapted from the studies of Meriç et al. (2018) and Musaoğlu et al. (2022).	51
Figure 4.16 : The diagram illustrating the land and sea interaction.	51

ASSESSMENT OF THE LAND AND SEA INTERACTION BY USING DIFFERENT TYPES OF SATELLITE DATA

SUMMARY

Seas are crucial for regulating climate conditions and supporting biodiversity, thereby sustaining environment, which is essential for life. Earth observation satellite images provide rich data sources, enabling long-term monitoring in a cost-effective and time-efficient manner. The Sea of Marmara (Türkiye), a semi-enclosed basin, stands out with its unique hydrodynamic and biogeochemical characteristics, having a significant role in the marine ecosystem. As the Sea of Marmara in Türkiye is surrounded by the densely populated provinces, the sea's water quality has increasingly become significant for both scientific and public communities over the years.

In the Sea of Marmara, marine mucilage, a viscous organic substance, has been observed in 2021. The presence of thick, different colored mucilage blankets raised public concern due to their potential toxicity and the pathogens, which can accumulate with prolonged mucilage presence. The outbreak of marine mucilage significantly impacted the marine ecosystem. Consequently, the presence of marine mucilage is a one of the indicators of water quality.

While remote sensing data was used to identify mucilage-covered areas in the Sea of Marmara in other case studies previously, there is lack of study about determining the areal extents and spectral characteristics of the different colored mucilage types while examining the probable reasons by using remote sensing data and technologies.

This study focuses on the mucilage phenomenon and its possible causes, such as increases in Sea Surface Temperature (SST) and changes in Land Use / Land Cover (LU/LC) in coastal cities along the sea. It aims to achieve three main objectives: (1) identifying different types of mucilage, (2) detecting SST trend and anomalies, and (3) observing changes in LU/LC by using different types of satellite data.

Mucilage, which varies in type and form, includes three different types detected in İzmit Bay (the Sea of Marmara) using Sentinel-2 and Worldview-3 satellite images. These mucilage types are white mucilage, yellow mucilage, and brown mucilage. White mucilage, characterized by smaller aggregates and a high reflectance spectrum, especially between 600-900 nm, represents dispersed patterns. Yellow mucilage results from aged aggregates, influenced by wind and currents, representing accumulated mucilage. Brown mucilage, distinguished by a high organic matter concentration, represents densely accumulated ageing mucilage. The study leveraged the high spatial resolution of these satellites to analyze the areal extents and characteristics of these mucilage types, with Sentinel-2 providing an overview and Worldview-3 offering detailed information. Spectral analysis using GLCM method and the SVM classification method differentiated these types, revealing that yellow mucilage often surrounds white mucilage, showing dispersed patterns, while brown

mucilage, mostly found along coastlines, is more accurately detected with Worldview-3 due to its higher spatial resolution. The ANOVA analysis revealed significant differences (P-value <0.05) among these three mucilage types. The accuracy assessment analysis of the classifications showed the detailed detection capabilities of the high-resolution Worldview-3 (Overall accuracy = 0.93) compared to Sentinel-2 (Overall accuracy = 0.86) for distinguishing mucilage distributions.

Continuously monitoring SST and detecting anomalies play a critical role in assessing the water quality of the sea. One probable cause of the mucilage phenomenon is related to the increase in SST. Therefore, investigation of temporal and spatial variations in SST and detection of SST anomalies were conducted. The spatial variations of the Sea of Marmara's SST were examined in detail using Sentinel-3 and Landsat-8 satellite imagery. Sentinel-3's ability to capture the entire area in a single frame provides a significant advantage for recent year monitoring. Validation with Landsat-8 images provided consistent results, highlighting the detection of cold water influx from the Black Sea through the Istanbul Strait. However, the National Oceanic and Atmospheric Administration (NOAA) OISST V2 satellite's coarser resolution limited its effectiveness in distinguishing these spatial SST variations. To assess accuracy, SSTs derived from satellite data were compared against in-situ measurements, which were that were derived from Turkish State Meteorological Service, with RMSE and bias calculated for each dataset, confirming the suitability of all three satellite sources for SST monitoring in the Sea of Marmara. Additionally, a time-series analysis from 1990 to 2021, utilizing the NOAA CDR OISST v02r01 dataset on the GEE platform and applying the STL method, detected SST trend and anomalies, including an increase in SSTs, particularly in 2020, and approximately 2°C variations over 32 years. Anomalies, especially in recent years, were compared with the NOAA OISST V2 anomaly band, highlighting the critical role of STL method in eliminating trend effect from the residual component.

Due to the dynamism of the highly urbanized coastal cities along the Sea of Marmara, especially the LU/LC changes between 2018 and 2021 are of great significance. This study evaluates the extent of LU/LC changes in coastal cities along the sea in the periods of 1990-2000, 2000-2006, 2006-2012, 2012-2018, 2018-2021 by using Coordination of Information on the Environment (CORINE) data and the overall inspection period of 1990-2021 by utilizing CORINE-based methodology and Sentinel-2 images. An increase of 95.21% is observed in the artificial surfaces. Water covered areas expanded by 14%, primarily driven by the construction of new surface water collection systems. Agricultural areas and orchards were successfully conserved. There has been a prominent increase of 4% in forest areas. However, there was a decline of 25% in open spaces, and 7% decrease in pastures and complex cultivation patterns. Furthermore, the findings provide a clear evidence of a 1762 ha expansion in the aforementioned cities' area between 1990 and 2021 was due to the construction of land reclamation areas along the Sea of Marmara coast. This research study highlights a practical methodology for monitoring land resources across extensive regions over a prolonged period.

In conclusion, this dissertation provides a practical methodology for detecting, monitoring, and paying special attention to the areas that need more urgent mucilage cleaning. Furthermore, the factors that can cause the mucilage phenomenon were researched. A comprehensive SST analysis showed that there is an increasing SST

trend between 1990 – 2021. Besides, the temporal LU/LC change in the coastal cities along the sea was also examined in the scope of the land/sea interaction and the increase in artificial surfaces was seen. In this study, the capabilities of different types of satellite data were leveraged to monitor the land and sea interaction, demonstrating its indispensable role of remote sensing data in providing accurate data for environmental sustainability.





FARKLI ÖZELLİKTEKİ UYDU VERİLERİ İLE KARA-DENİZ ETKİLEŞİMİNİN BELİRLENMESİ

ÖZET

Denizler, iklim koşullarının düzenlenmesi, biyolojik çeşitliliğin desteklenmesi ve dolayısıyla yaşam için gerekli olan çevrenin sürdürülebilirliği açısından hayati öneme sahiptir. Yer gözlem uydu görüntüleri, zengin veri kaynakları sağlayarak, zaman ve maliyet etkin uzun süreli izleme olanağı sağlamaktadırlar. Yarı kapalı bir havza olan Marmara Denizi, benzersiz hidrodinamik ve biyojeokimyasal özellikleriyle öne çıkmakta ve deniz ekosisteminde önemli bir role sahip olmaktadır. Marmara Denizi'nin etrafındaki şehirlerde nüfus yoğunluğu yüksek olduğu için denizdeki su kalitesinin önemi hem bilim camiası hem de kamu için yıllar geçtikçe giderek artmaktadır.

Marmara Denizi'nde 2021 yılında viskoz bir organik madde olan deniz müsilajı gözlemlenmiştir. Müsilajın potasyel zehir etkisi ve uzun süreli müsilaj varlığı sonucu birikebilen patojenler nedeniyle kalın, farklı renkli müsilaj türlerinin varlığı kamuoyunda endişe yarattı. Deniz müsilajının ortaya çıkması deniz ekosisteminin önemli ölçüde etkilemiştir. Sonuç olarak, deniz müsilajının varlığı su kalitesinin göstergelerinden biridir.

Literatürdeki çalışmalar incelendiğinde, Marmara Denizi'ndeki müsilaj ile kaplı alanların uzaktan algılama verileri kullanılarak tespit edildiği örnek çalışmalar mevcut olmasına rağmen, Marmara Denizi'nde kara-deniz etkileşimlerini bütüncül bir yaklaşımla değerlendirmeye odaklanan çalışmaların eksikliği görülmektedir. Özellikle de Marmara Denizi'nde yakın zamanda gözlemlenen müsilaj olgusu göz önüne alındığında müsilajın spektral karakteristiğinin, müsilaj oluşumunun olası sebeplerinin ve kara-deniz etkileşimlerinin uzaktan algılama veri ve teknolojileri kullanılarak değerlendirilmesi gerektiği görülmektedir.

Müsilaj oluşumunun olası nedenlerinin belirlenmesi etkili önlemlerin alınması açısından gereklidir. Müsilaj oluşumuna olası katkıda bulunan parametreler arasında su yüzey sıcaklığındaki uzun dönemli artış ve zamansal arazi örtüsü / arazi kullanımı (AÖ / AK) değişimleri yer almaktadır. Su yüzey sıcaklığındaki artış ve zamansal AÖ / AK değişimleri bölgenin ekolojik dengesinin müsilaj oluşumunu kolaylaştıracak şekilde değiştirmektedir. Belirtilen olası sebeplerin kapsamlı bir yaklaşımla belirlenebilmesi için çeşitli uydu görüntülerinin avantajlarından faydalanmak gereklidir. Denizdeki müsilaj olgusunu incelemek için farklı renklerde bulunan müsilajın detaylı spektral analizini ve müsilajın oluşumuna sebep olan çevresel değişimlerin irdelenmesini içeren entegre bir araştırma yöntemi gereklidir. Bu çalışmanın farklı çeşitte uydu verileri kullanarak (1) farklı müsilaj türlerinin belirlenmesi, (2) deniz suyu sıcaklığındaki eğilimin ve anomalilerin belirlenmesi, (3) AÖ / AK değişimlerin belirlenmesi olmak üzere üç ana hedefi vardır.

İlk amaç kapsamında, Marmara Denizi'nin İzmit Körfezi'nde bulunan farklı renkteki müsilaj türlerinin spektral analizi ve alansal büyüklüklerinin tespiti orta mekansal

çözünürlüğe sahip Sentinel-2 ve yüksek mekansal çözünürlüğe sahip Worldview-3 uydu görüntüleri kullanılarak gerçekleştirilmiştir. İzmit Körfezi'nde tür ve şekil bakımından farklılık gösteren üç farklı tür müsilağ bulunmaktadır. Bu müsilağ türleri beyaz, sarı ve kahverengi müsilağdır. Beyaz müsilağ, küçük topluluklar halinde ve özellikle 600-900 nm arasında yüksek yansıma gösteren dağınık desenler şeklinde görülmektedir. Müsilağ topluluklarının yaşlanması sonucu oluşan sarı müsilağ ise rüzgar ve akıntılardan etkilenmektedir. Yüksek organik madde konsantrasyonu ile ayırt edilen kahverengi müsilağ, yoğun bir şekilde birikmiş yaşlanan müsilağı temsil eder. Çalışma, bu müsilağ türlerinin alansal kapsamalarını ve özelliklerini analiz etmek için bu uyduların yüksek mekansal çözünürlüğü özelliğinden yararlanmıştır. Belirtilen uydu görüntüleri kullanılarak farklı müsilağ türlerine ait spektral yansıtım eğrileri üretilmiştir. Müsilağ türlerine ait spektral yansıtımlardaki farklılığı incelemek için iki yönlü varyans analizi uygulanmıştır. Varyans analizi ile belirtilen üç müsilağ türü arasında anlamlı farklılıklar (P değeri <0.05) olduğu görülmüştür. Farklı türdeki müsilağla kaplı alanların farklı dokusal yapıya sahip olduğu görülmüştür. Bu sebeple öncelikle Sentinel-2 ve Worldview-3 uydu görüntülerine çoklu çözünürlük segmentasyonu uygulanmıştır. Segmentasyon işleminden sonra Gri Seviye Eş Oluşum Matrisi (GLCM) yöntemi uygulanarak kontrast, farklılık ve açısal ikinci moment olmak üzere üç tür dokusal öznitelikler belirlenmiştir. Farklı müsilağ türlerine ait alanların belirlenmesi amacıyla uydu görüntülerine obje tabanlı sınıflandırma uygulanmış ve girdi olarak spektral ve dokusal öznitelikler tanımlanmıştır. Kontrollü bir makine öğrenmesi yöntemi olan Destek Vektör Makineleri (SVM) sınıflandırma yöntemi ve radyal tabanlı linear olmayan çekirdek fonksiyonu kullanılarak belirtilen müsilağ türleri ayırt edilmiştir. Worldview-3 uydu görüntüsünün mekansal çözünürlüğü Sentinel-2 uydu görüntüsünün mekansal çözünürlüğünden daha yüksek olduğu için, Sentinel-2 uydu görüntüsü kullanılarak genel bir bilgi elde edilmişken Worldview-3 uydu görüntüsü kullanılarak ayrıntılı bilgi elde edilmiştir. Sentinel-2 uydu görüntüsünün mekansal çözünürlüğü beyaz ve sarı müsilağ olmak üzere sadece iki tür müsilağın tespitini yapabilirken, Worldview-3 uydu görüntüsünün çözünürlüğü beyaz, sarı ve kahverengi olmak üzere üç farklı müsilağ türünün tespitini yapabilme kapasitesine sahiptir. Analiz sonuçlarında, sarı müsilağın genellikle dağınık halde bulunan beyaz müsilağı çevrelediği ve kahverengi müsilağın ise çoğunlukla kıyı şeridinde bulunduğu görülmüştür ve kahverengi müsilağ yüksek mekansal çözünürlüğe sahip Worldview-3 uydu görüntüsü kullanılarak doğruluğu yüksek bir şekilde tespit edilmiştir. Doğruluk analizi sonuçları incelenildiğinde yüksek mekansal çözünürlüklü Worldview-3 (Genel doğruluk = 0.93) uydu görüntüsünün Sentinel-2 (Genel doğruluk = 0.86) uydu görüntüsüyle karşılaştırıldığında müsilağ türlerini ayrıntılı ayırt etme yeteneğinin daha yüksek olduğu görülmüştür.

İkinci amaç kapsamında, Marmara Denizi'nin yüzey sıcaklığı zamansal ve mekansal olarak farklı çeşitte uydu verileri kullanılarak incelenmiştir. Deniz yüzeyi sıcaklığının sürekli izlenmesi ve anomalilerin tespit edilmesi, denizin su kalitesinin değerlendirilmesinde kritik bir rol oynamaktadır. Müsilağ fenomeninin olası bir nedeni deniz yüzeyi sıcaklığında artışla ilgilidir. Bundan dolayı, çalışma kapsamında Marmara Denizi'nin deniz yüzeyi sıcaklığındaki zamansal ve mekansal değişiklikler ve deniz yüzeyi sıcaklığındaki anomaliler incelenmiştir. Bu kapsamda, Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR), Landsat-8 ve National Oceanic and Atmospheric Administration Optimum Interpolation $1/4^{\circ}$ Daily SST Version 2 (NOAA OISST V2) olmak üzere üç farklı uydu verisi kullanılmıştır. Marmara Denizi'ndeki yüzey sıcaklığının mekansal değişimi Sentinel-3 ve Landsat-8 uydu görüntüleri kullanılarak detaylı bir şekilde incelenmiştir. Bu amaç doğrultusunda 2018

– 2021 yılları arasında algılanan Sentinel-3 ve Landsat-8 uydu görüntüleri kullanılmıştır. Sentinel-3 uydu verisi sahip olduğu 1 km mekansal çözünürlük ile tüm denizi tek bir çerçeve ile görüntüleyebilmesi özelliği son yıllara ait gözlem yapılabilmesi için önemli bir avantajdır. Sentinel-3 uydu verisi 2016 yılının Mayıs ayından itibaren veri sağladığı için Sentinel-3 uydu verisiyle uzun dönemli zaman analizi yapmak mümkün olmamaktadır. Landsat-8 uydu görüntüsü termal bantlara sahip ve 100 m mekansal çözünürlüğe sahip olmakla birlikte sahip olduğu çerçeve genişliği sebebiyle Marmara Denizi'nin tamamını tek bir görüntü ile izlemek mümkün değildir. Aynı tarihlerde algılanan dokuz adet bulutsuz Sentinel-3 ve Landsat-8 uydu görüntüsü kullanılarak deniz yüzeyi sıcaklığı haritaları üretilmiş ve sonuçlar karşılaştırılarak doğrulanmıştır. Üretilen haritalarda, Karadeniz'den İstanbul Boğazı'na soğuk su girişi gözlemlenerek tutarlı sonuçlar sağlanmıştır. Ek olarak, NOAA OISST V2 verisi kullanılarak deniz yüzeyi sıcaklığı haritaları üretilmiştir fakat NOAA OISST V2 verisinin sahip olduğu düşük mekansal çözünürlük sebebiyle belirtilen mekansal değişimler ayırt edilememiştir. Üretilen haritaların doğruluk analizinin yapılması amacıyla uydu görüntülerinden elde edilen deniz yüzeyi sıcaklıkları Meteoroloji Genel Müdürlüğü'nden temin edilen yersel ölçmeler ile karşılaştırılarak karesel ortalama hatası (RMSE) ve yanlışlık (bias) metrikleri hesaplanmıştır. Doğruluk analizi sonuçları incelendiğinde NOAA OISST V2 (RMSE = 1.2°C, yanlışlık = 0.3°C), Sentinel-3 (RMSE = 1.19°C, yanlışlık = -0.25°C) ve Landsat-8 (RMSE = 1.68°C, yanlışlık = 0.89°C) setinin de Marmara Denizi'nin su yüzey sıcaklığının izlenmesi için uygun veri kaynakları olduğu görülmüştür. Ek olarak, Google Earth Engine (GEE) platformu ve NOAA CDR OISST v02r01 veri seti kullanılarak 1990 – 2021 yılları arasında su yüzey sıcaklığına ait zaman serisi oluşturulmuştur. Oluşturulan zaman serisi verisine Seasonal-Trend decomposition using LOESS (STL) yöntemi uygulanarak deniz yüzeyi sıcaklığı eğilimi ve anomalileri tespit edilmiştir. Deniz yüzeyi sıcaklığında özellikle de 2020 yılında artış görülmüştür. 32 yıllık zaman serindeki su yüzey sıcaklıkları incelendiğinde 2°C değişim gözlemlenmiştir.

Marmara Denizi'nin etrafındaki kentleşmenin yoğun olduğu kıyı şehirlerinin dinamizmi nedeniyle, özellikle 2018-2021 yılları arasındaki AÖ/AK değişimleri büyük önem taşımaktadır. Bu çalışmada, CORINE verileri ve Sentinel-2 görüntülerini kullanılarak 1990-2000, 2000-2006, 2006-2012, 2012-2018, 2018-2021 dönemlerinde ve CORINE tabanlı metodoloji ve Sentinel-2 kullanılarak 1990-2021 yılları arasındaki deniz kıyısındaki şehirlerin AÖ/AK değişiklikleri tespit edilmiştir. Yapay yüzeylerde %95.21 oranında artış gözlemlenmiştir. Suyla kaplı alanların, özellikle yeni yüzey suyu toplama sistemlerinin inşası sayesinde %14 oranında arttığı gözlemlenmiştir. Tarım alanları ve meyve bahçeleri sınıfı alanlarının korunduğu gözlemlenmiştir. Orman sınıflarında %4 oranında artış görülmüştür. Açık alanlar sınıfında ve mera ve karışık tarımsal alanlar sınıfında sırasıyla %25 ve %7 düşüş gözlemlenmiştir. Bunun yanı sıra, Marmara Denizi kıyısı boyunca dolgu alanlarının inşa edilmesinden kaynaklı olarak 1990 ve 2021 yılları arasında belirtilen kıyı şehirlerin alanında 1762 ha genişleme tespit edilmiştir. Bu çalışmada, geniş bölgelerdeki arazi kaynaklarının uzun bir süre boyunca izlenmesine yönelik bir metodoloji uygulanmıştır.

Sonuç olarak, bu tezde acil müsilaj temizliğine ihtiyaç duyan alanların tespit edilmesi, izlenmesi ve özel dikkat gösterilmesine yönelik bir metodoloji önerilmiştir. Müsilaja neden olan faktörler araştırılmıştır. Yapılan kapsamlı deniz yüzeyi sıcaklığı analizi sonucunda 1990-2021 yılları arasında sıcaklığın artış eğiliminde olduğu ortaya çıkmıştır. Ayrıca, kara/deniz etkileşiminin tespiti kapsamında kıyı şehirlerindeki zamansal AÖ/AK değişiklikleri incelenmiş ve yapay yüzeylerde artış olduğu

görülmüştür. Bu tezde, farklı özellikteki uydu verilerinin avantajlarından yararlanılarak kara/deniz etkileşimi incelenmiştir. Çalışmada uzaktan algılama verilerinin yüksek doğruluğa sahip veri sağlaması sebebiyle çevresel sürdürülebilirlik için vazgeçilmez olduğu vurgulanmaktadır.



1. INTRODUCTION

1.1 Background and Context

Water is an essential and finite natural source for all living organisms and environment. Oceans and seas have dominating roles in regulating the global and regional climatic conditions based on their larger areas covering the earth's surface. Marine ecosystems surround more than 70% of the world's surface area and host a diverse range of micro and macro-organisms. These aquatic ecosystems have great importance for various living organisms from seafloor to surface (Massana & Logares, 2013; Yentur et al., 2013; Bolhuis & Cretoiu, 2016). Changes in the marine ecosystem conditions, even at the microbial level, can harm various marine organisms, their biodiversity, marine food web and the water quality. The mucilage phenomenon, which is a viscous organic gel that is produced by the phytoplankton, threatens the marine ecosystem (Alcoverro et al., 2000; Vollenweider et al., 1998). The successive aggregation of the polysaccharide chains forms colloids and progressively forms bigger particulate assemblages that are called as mucilage.

The Sea of Marmara (Türkiye) is a semi-enclosed basin (11.350 km² area, 494-m average depth) (Okay et al., 2007) with unique hydrodynamic and biogeochemical features. It is connecting two different water bodies: the Black Sea via the Istanbul Strait in the north-east and the Aegean Sea via the Dardanelles Strait in the south-west. Besides, the sea acts as a biological corridor between these two seas and has a profound role on controlling the regional climatic conditions (TÜDAV, 2017). Marine mucilage, which is observed as viscous organic substance, has been seen in the Sea of Marmara in 2021. Since mucilage increases pathogen abundance and leads anoxic conditions in the water, it has harmful effect on the aquatic life. For that reason, marine mucilage is directly related with the water quality (Danovaro et al., 2009; Yentur et al., 2013; Özalp, 2021).

The causes of the mucilage events are still under debate whether they are initiated by eutrophication due to increased anthropogenic/natural nutrient inputs or they are

related to the temperature increases due to the climate change and its consequences on the physicochemical properties of seawater (Danovaro et al., 2009). In general, mucilage phenomenon is related to coupling effects between seawater organic matter production and the meteorological and oceanographic conditions (De Lazzari et al., 2008).

Strong correlations were found between the annual average temperatures and the mucilage events between 1870 and 2010 were previously linked to the influence of climate change on the frequency of mucilage formation (Danovaro et al., 2009). In addition, sea surface temperature (SST) is another factor for the mucilage formation. In this scope, the relation between the mucilage events and increased SSTs in Mediterranean Sea was shown in recent studies (Danovaro et al., 2009; Savun-Hekimoğlu & Gazioğlu, 2021).

Monitoring water covered areas and conserving water quality have vital importance for all living beings. Water quality parameters have different spectral characteristics in the different regions of the electromagnetic spectrum. SST is a key physical parameter to understand the prevailing water quality and the interaction among sea and atmosphere (Gholizadeh et al., 2016). SST measurement is essential to obtain noteworthy information about surface water bodies. Though conventional SST measurement techniques provide high accuracies, they have some limitations like spatial discontinuity (Zhang & Zhang, 2016; Ai et al., 2019). Earth observation satellite sensors enable to measure the surface layer temperature of the sea by the thermal infrared region of the electromagnetic spectrum (Url-1; Sarangi & Devi, 2017; Fingas, 2019).

Two important elements that significantly impact the water quality of the Sea of Marmara are the rivers carrying pollutants into the sea, along with the industrial areas surrounding İzmit Bay. The components that effect the chemistry of sea includes riverine inputs from Biga River, Gönen River, and Kocasu River and also wastewater discharges from the households and industrial wastes. İzmit Bay, located within the populated Kocaeli Province, which is a heavily industrialized area, accounting for approximately 13% of Türkiye's total industrial output (Genel & Guan, 2021). The study by Genel & Guan, (2021) detected a significant increase in urban density, the development of new ports, and the expansion of industrial plants from 2006 to 2018. Moreover, there are several case studies on heavy metal pollution in this region (Ergül

et al., 2013; Morkoç et al., 2001; Tolun et al., 2001). Therefore, the marine environment in İzmit Bay is highly susceptible to pollution.

In the scope of the land/sea interaction, the land use/land cover (LU/LC) changes in the highly urbanized coastal areas surrounded by the sea need to be understood, as they reflect the changes in the water environment. Satellite images provide valuable information since remote sensing technologies have been fastly developed (Du et al., 2012; Ge et al., 2020; Tong et al., 2020). Thus, freely accessible satellite images are the valuable data source to detect LU/LC classes in a cost and time effective way with broader spatial applicability (Mugo et al., 2020; Nguyen et al., 2020; Tadese et al., 2020; Weigand et al., 2020).

1.2 Literature Summary

The areas that are prone to pollution should be detected and controlled by assessing the water quality. Most particularly, observing coastal zones continuously has a profound impact on protecting water quality (Salem et al., 2017), particularly given the widespread occurrence of the mucilage phenomenon. The mucilage aggregate formations are a concern regarding the toxic effects of the harmful algal blooms (HABs) in the coastal regions world-wide (Genitsaris et al., 2019). For example, increased abundances of the diatom *Nitzschia delicatissima* Cleve, 1897 in the Gulf of Mexico (Malej and Harris, 1993), the dinoflagellates *Prorocentrum micans* Ehrenberg, 1834 (Monti et al., 1995) and *Karenia mikimotoi* (Miyake & Kominami ex Oda) Gert Hansen & Moestrup, 2000 in the coasts of China (Monti et al., 1995) and the heterotrophic dinoflagellate *Noctiluca scintillans* (Macartney) Kofoid & Swezy, 1921 were reported in Australia (Dela-Cruz et al., 2008) and in the Sea of Marmara (Turkoglu, 2013). Therefore, monitoring the mucilage accumulated regions are essential to detect especially the aged mucilage which is most likely be more toxic. In this context, optical remote sensing can play a critical role in mapping different types of mucilage physically due to its sensitivity to marine biodiversity. The spectral differences of these different mucilage classes are the base of marine optical measurement research.

The spectral response of mucilage can differ with the ageing of the mucilage aggregates. The spectra of the extracellular exudates of the laboratory cultured diatom species *Skeletonema costatum* (Greville) Cleve, 1873 and *Nitzschia closterium* f.

minutissima Allen & Nelson, 1910, isolated from the Adriatic mucilage aggregates showed evident similarities with the field mucilage samples collected in 1989, 1991 and 1992 (Mingazzini et al., 1995). The trend was described as a decrease in the first peak around 280 nm with a parallel increase in the second peaks at higher wavelengths between 340-500 nm. The intensity ratio calculated based on the peaks provide a tool for characterization of extracellular organic matter produced by the phytoplankton (Mingazzini et al., 1995). Similarly, Mecozzi et al., (2005) underlined that the aggregations of organic matter in mucilage causes increasing spectral response in surface mucilage. Berthon et al., (2000) evaluated the impact of bathymetry on spectral response of mucilage and showed that mucilage could not be distinguished from non-mucilage waters if the mucilage was not close to the sea surface.

Increasing frequency of mucilage phenomenon in the Mediterranean Sea in recent years has led to several research studies about the mucilage events in the Mediterranean Sea. Tassan, (1993) developed an algorithm for mucilage detection in the Adriatic Sea using AVHRR data of National Oceanic and Atmospheric Administration (NOAA). Large area coverage of NOAA satellites is beneficial for the detection of large mucilage spreads. Berthon et al., (2000) performed optical measurements of the mucilage event in the northern Adriatic Sea in 1997. Band ratio models were developed to differentiate mucilage agglomerates from the sea water. Gigliotti, (2013) has developed a Mucilage Index by using the Moderate Resolution Imaging Spectroradiometer (MODIS) data. By using the developed Mucilage Index, marine mucilage blooms in Tyrrhenian and Adriatic Seas between 2010 and 2012 are investigated. It was concluded that mucilage formation strongly affected by the sea temperature. Mucilage bloom frequency has been increased during the study time span. Genitsaris et al., (2019) investigated mucilage aggregates in Thessaloniki Bay between 2017 and 2018. A correlation between increased sea water temperature and high nitrogen and phosphorus concentrations with the mucilage producing phytoplankton abundance has been found.

Remote sensing data and technologies have an important role in assessing water quality (Chawla et al., 2020). Some of the water quality parameters such as chlorophyll-a, turbidity, total suspended solids (TSS), and SST could be detected from space by satellite images in various studies (Gholizadeh et al., 2016; Chawla et al., 2020). Chlorophyll-a parameter is a main indicator to detect biomass of the

phytoplankton, which shows the eutrophic status of the water (Moses et al., 2009). Lins et al., (2017) evaluated the performances of various NIR-Red models for the purpose of detecting chlorophyll-a parameter in the Mundaú-Manguaba Estuarine-Lagoon System (Brazil), which is a productive tropical estuarine-lagoon system. High accuracies were achieved by applying the two-band algorithm to Sentinel-2 and Sentinel-3 satellite images.

Suspended solids (SS) is one of the parameters in this category and inversely correlated with water clarity. As SS increases, it hinders the light (Gholizadeh et al., 2016). Constantin et al, (2016) examined turbidity parameter of Danube River plume with in-situ data and MODIS satellite data and high correlated relationship between the discharge and turbidity was found in the coastal zones. Tuzcu et al., (2019) applied NDTI (Normalized Difference Turbidity Index (Lacaux et al., 2007) to the Worldview-3 satellite image for the purpose of determining the turbidity situation of Akgol Wetland (Türkiye). Two turbidity levels were produced and the results were found as compatible with the ground truth data. In another case study, MODIS satellite data was used to assess two different water quality parameters, which are TSS and chlorophyll-a, in Korean West coast and it was resulted that temperature and tides effected chlorophyll-a and TSS, respectively (Kim et al., 2017).

SST is a parameter that is used not only for water quality but also global warming detection. For the purpose of determining this parameter, thermal infrared bands of the satellite data are used (Fingas, 2019). In literature, there are several researches about detecting SST by using remote sensing data and technologies. In a case study, an algorithm was generated to detect the relation between the thermal bands of the Landsat 8 satellite data and in-situ data. This algorithm was verified with forty in-situ samples (Syariz et al., 2015). Landsat-8 Earth observation mission of The National Aeronautics and Space Administration (NASA) of USA and US Geological Survey (USGS) have so far provided free-of-charge satellite images which are extensively used to make sub-mesoscale observations in aquatic ecosystems (Jang & Park, 2019; Kuroda & Toya, 2020). Thermal infrared images from the Landsat archive were preferred in various water-related researches like detecting SST (Lamaro et al., 2013; Jang & Park, 2019; Kuroda & Toya, 2020), and thermal discharge (Wang et al., 2016) for decades. On the other hand, the recently launched Sentinel-3, which is the European Copernicus mission, has the capability to conduct day-time and night-time

observations with daily global coverage by the Sea and Land Surface Temperature Radiometers (SLSTR) instrument. Zarei et al., (2021) validated SLSTR land surface temperature (LST) data with field measurements retrieved from meteorological stations and MODIS LST data, and reliable results were achieved by using Sentinel-3 SLSTR LST satellite images that were acquired in different seasons.

Qu et al. (2019) have recently compared SLSTR SST data with the shipboard infrared radiometer and reprocessed high accuracies. SST values varying in time depend on the incident solar radiation, and satellite-derived SSTs make it possible to generate time-series that provide SST variability information for a long-term. Such SST time-series are addressed as powerful data sources for the anomaly detection. Decomposition of the time-series is essential to perform anomaly detection. Seasonal-Trend decomposition procedure based on LOESS (STL) method initially described by Cleveland et al., (1990) has so far been used extensively in many researches to deconstruct a time-series into trend, seasonal and residual components (Chan et al., 2021; Mujawdiya et al., 2022). Temporal resolution is similarly an important specification of the satellite image to detect sea surface temperature anomalies (SSTA). The NOAA of USA freely provides global SST data named as NOAA Optimum Interpolation $1/4^\circ$ Daily SST (OISST) Analysis Version 2 (V2) with one-day temporal resolution from 1981 to the present (Reynolds et al., 2002). Due to its temporal resolution and coverage, it has been widely used as a feasible dataset for long-term SST observation (Fernández-Nóvoa et al., 2021; Kajtar et al., 2022) and for SSTA detection studies (Stock et al., 2015; Jing et al., 2019).

LU/LC changes are of paramount importance in ensuring a sustainable environment, especially with regards to water quality (Gani et al., 2023; Gobry et al., 2023; Wang et al., 2023). Over time, LU/LC can alter based on different human-induced activities such as expanding residential and industrial sites and strengthening transportation network (Hansen et al., 2022). Furthermore, due to rapid global population growth and urbanization, numerous megacities in different countries, such as Türkiye, Japan, and China, have already faced the need for more land. Consequently, the construction of land reclamation areas has served as a practical solution for meeting the land demand. In particular, artificial shorelines have been constructed in response to the high population densities in coastal cities, such as İstanbul (Türkiye), Jakarta (Indonesia), Shanghai (China) and Mumbai (India) (Sengupta et al., 2018; Zhang et al., 2020). Land

reclamation serves for various purposes including establishment of parks and green land, development of ports and harbors, and expanding residential areas (Sengupta et al., 2023). Monitoring all the above-mentioned man-made expansions covering the artificial surfaces on land that result in LU/LC changes over time cannot be easily maintained through ground truth inspections such as coastal cities that constitute large areas. In recent years, remote sensing data and advanced technologies provide widespread opportunities to detect the LU/LC and temporal LU/LC changes more efficiently (Bakr & Afifi, 2019; Birhanu et al., 2019; Gupta et al., 2020; Tırmanoğlu et al., 2023; Zhu et al., 2022; Kaya & Dervisoglu, 2023). Continuity and standardization are the key factors in the study of temporal LU/LC change detection. There are various standards concerning the LU/LC classification, namely ANDERSON (Anderson et al., 1976), the Food and Agriculture Organization (FAO) (Di Gregorio et al., 2016), Land Use / Cover Area Frame Survey (LUCAS) (Gallego and Bamps, 2008), National Land Cover Database (NLCD) (Lauer, 1986; Vogelmann et al., 2001) and CORINE (Copernicus, n.d.-b; Sarıyılmaz & Musaoğlu, 2016; Sarıyılmaz et al., 2017; Mutlu et al., 2020). Each of them has different standards, with Anderson being the widely embraced standard in our country. The coordination of information on the environment -CORINE Land Cover (CLC) presents a three-level hierarchical classification system (Copernicus, n.d.-d). Since CORINE CLC data, which is a part of the European Copernicus program, have extensive archive data with a standardized labelling system, they have been widely preferred for detecting LU/LC changes across a range of research studies. Notable examples include monitoring changes in the United Kingdom between 2006 and 2012 (Cole et al., 2018), detecting changes in Slovakia between 2000 and 2018 (Falt'an et al., 2020), and examining changes in İstanbul, Türkiye between 1990 and 2018 (Bozkurt et al., 2023).

In literature, the water quality of the Sea of Marmara was determined by using remote sensing data and technologies in several researches. Sunar, (1992) applied classification methods to Landsat 5 TM data and investigated pattern variations for the purpose of detect the water quality of the İzmit Bay, which is close to industrial areas. Dogan et al., (1998), investigated the impact of Black Sea on the Sea of Marmara. It was concluded that influx from the Black Sea has a profound effect on the ecological structure of the Sea of Marmara. Surface inflow from the Black Sea is affected from the rivers that drains into the Black Sea. Especially, Danube River has a share of 60%

of the water input and 20% of suspended material into the Black Sea, hence the Sea of Marmara is strongly affected from the Danube River. Örmeci et al. (1995) investigated the impact of the Danube River on the Sea of Marmara using Landsat TM images, focusing on chlorophyll-a and TSS parameters. It was concluded that, while the concentration of chlorophyll-a and TSS decreased from the origin of the Danube River to the Sea of Marmara, a significant amount still entered the sea. İkis, (2007) investigated on temporal and spatial chlorophyll-a variations in the Sea of Marmara in between 1997 and 2007 by using SeaWiFS and MODIS-Aqua satellite data. It was concluded that phytoplankton blooms were mostly seen in east part of the sea and increased in winter and spring seasons. The Golden Horn is one of the most researched regions in the Sea of Marmara. In a case study, different types of water quality parameters, which are chlorophyll-a, SDD and TSS, of the Golden Horn were detected by high spatial resolution IKONOS satellite and in-situ data. In this scope, multiple regression technique was applied and high determination coefficients were achieved. As a result, water quality thematic maps were generated and IKONOS satellite image was found as an appropriate data to assess the water quality despite having low spectral resolution (Ekercin, 2007). Örmeci et al., (2009) used in-situ data and high spatial resolution IKONOS satellite data in order to detect chlorophyll-a parameter, which is one of the important water quality parameters, of the Golden Horn. As a conclusion, it was seen that amount and locations of the in-situ samples have profound impact on modelling the relation between in-situ and satellite data. Küçükçekmece Lake is located in Istanbul and has a direct connection to the Sea of Marmara. Alparslan et al., (2009) researched effect of the temporal LU / LC changes to the quality of Küçükçekmece Lake. For this purpose, Landsat 5 data were used and multiple regression method was applied to generate water quality thematic maps. It was seen that, increment of the residential areas from 1992 to 2000 had affected the water quality adversely. Yalçın et al., (2017) compared nitrate and phosphate influx and outflux into the Sea of Marmara, and concludes that surface nutrient concentration is higher at outflux into the Aegean Sea, hence Sea of Marmara is enriched by anthropogenic effects. Also, below 25 m depth dissolved oxygen concentration decreases strongly. Orhon et al., (2021) utilized a hydrodynamic model for flow assessment in the Bosphorus strait. The model indicates that Black Sea is the major polluter of the Sea of Marmara because of the upper layer flow into the Sea of Marmara. Satellite imageries are significant data sources that provide spatial and

spectral information to discriminate mucilage- and water-covered areas instantly and efficiently. The mucilage's spatial coverage within the Sea of Marmara has been examined in various case studies. Acar et al., (2021) detected mucilage covered areas by utilizing random forest (RF) algorithm on Sentinel-2 satellite images 10th March to 6th June 2021 with high accuracy. During the period spanning from May 17th to June 6th, 2021, an increase in mucilage covered areas was observed. Kavzoglu et al., (2021) used an object-based image analysis (OBIA) approach and RF classifier on Sentinel-2 satellite imagery from May 19th to 24th, 2021, finding that object-based classification achieved an accuracy higher than 90%. Yagci et al. (2022) utilized MODIS data to delineate the mucilage, comparing the results with higher resolution Sentinel-2 data, revealing a high correlation. Moreover, Abaci et al., (2022) utilized Sentinel-2 and PRISMA (PRecursore IperSpettrale della Missione Applicativa) satellite images to detect mucilage-covered areas in the early stage of its formation in the Sea of Marmara. Hu (2022) studied on the temporal change of the mucilage distribution in the Sea of Marmara by using medium spatial resolution satellite imagery acquired in between 2000 and 2021. Besides, the spectral characteristics of the mucilage in the Sea of Marmara were detected with various satellite images by Hu et al. (2022). Because of having capability to observe offshore areas with wide range of the electromagnetic spectrum, satellite imageries are indispensable sources in order to bring the mucilage occurrence under control in a time- and cost-effective way. Colkesen et al., (2023) developed a new spectral index, Automated Mucilage Extraction Index (AMEI), aimed at distinguishing mucilage. The effectiveness of the AMEI was verified through both statistical and visual accuracy assessments.

Land use of the region around the Sea of Marmara was investigated in various studies. Göksel et al., (2001) examined water basins in İstanbul and suggested that construction of the new settlements must be prevented in water protection zones because of having high relation between the water quality and urbanization. Sarıyılmaz, (2012) observed approximately 18% decrease in forest covered area in Sarıyer district between 1987 and 2010, while artificial surfaces increased approximately 135% in the same time interval. Kaya and Kizildere, (2013) conducted an in-situ land use investigation about river basins that are water sources for İstanbul. They have observed that urbanization in the river basins threatens sustainability and quality of the essential water sources of İstanbul. Sarıyılmaz, (2017) investigated the land use in the Sazlıdere Basin.

According to the study results, forest covered areas decreased 53% between 1975 and 2012. Urban coverage increased by 167%. Özönat, (2017) investigated the water quality and land use around the Elmalı Dam Lake in Istanbul. It was seen that water quality of the lake decreases because of the highly nutrient rivers that flow into the lake. However, since the residence time of water in the lake is short, no algal bloom was observed. Besides high concentration of heavy metal pollution was detected in the Elmalı Dam Lake Basin. Sarı, (2020) investigated the land use and land coverage changes in the northern regions of Istanbul. It was reported that significant fragmentations have formed in the forest covered areas in the northern part of Istanbul. Erosion of green covered areas in the essential water source basins disrupts water quality and ecologic sustainability around Istanbul. Göksel et al., (2018) studied land cover changes between 2009 and 2016. It was seen that forest coverage is decreased significantly because of urbanization and construction of roads.

1.3 Problem Statement

In literature, there is a notable scarcity of studies focusing on evaluating the interactions between land and sea in the Sea of Marmara using a holistic approach. This gap becomes particularly relevant in the serious mucilage phenomenon that the Sea of Marmara has recently experienced. In particular, the mucilage can be observed in various colors, each with different spectral characteristics that need to be analyzed. Understanding these variations is crucial for accurately determining the mucilage phenomenon's extent and implications.

Furthermore, identifying the probable causes of mucilage formation is essential for developing effective precautions. Among the probable contributors to this environmental issue are the long-term increase in SST and changes in LU/LC. These parameters suggest that the region's ecological balance is being changed in ways that may facilitate the formation of mucilage. Assessing these causes requires a comprehensive approach that includes leveraging various satellite images. To sum up, addressing the mucilage phenomenon in the Sea of Marmara requires an integrated research strategy that combines detailed spectral analysis of the different colored mucilage types with an investigation into the environmental changes driving its formation.

1.4 Purpose and Scope of the Thesis

In this dissertation, a comprehensive assessment of land/sea interactions between the Sea of Marmara and its coastal regions was conducted, with a particular focus on evaluating the contribution of various types of satellite imagery. The main objectives of the current study are as follows: (1) the assessment of the spectral characteristics of different colored mucilage types (Tuzcu Kokal et al., 2022); (2) the investigation of changes in SST as a potential factor in mucilage formation (Tuzcu Kokal et al., 2023); and (3) the examination of temporal changes in LU/LC of the coastal cities along the Sea of Marmara (Musaoğlu et al., 2022).

The initial objective involved a detailed spectral and areal analysis of different colored mucilage types in the İzmit Bay in the Sea of Marmara by using medium-spatial resolution (Sentinel-2) and high-spatial resolution (Worldview-3) satellite images. Three different types of mucilage were characterized based on color and texture including (a) the white mucilage aggregates with dispersed patterns which are likely freshly formed, (b) the yellow mucilage accumulations in the coasts that are wind/current transported, and (c) the brown mucilage accumulations that are probably the most-aged. This analysis provides valuable information for efficient mucilage cleaning site selection.

In the second objective, the study utilized diverse satellite data, including NOAA, Sentinel-3 and Landsat-8, to detect variations in SST, a suspected driver of mucilage presence (Danovaro et al., 2009; Savun-Hekimoğlu & Gazioğlu, 2021). A time series dataset, generated using NOAA data, was analyzed using Seasonal-Trend decomposition using LOESS (STL) approach to detect temporal trends and anomalies. Additionally, this phase involved monitoring spatial variations in SST using Sentinel-3 and Landsat-8 satellite imagery. Detecting long-term variations in SST is crucial for understanding the relationship between SST and the formation of mucilage.

The final aim focused on investigating the land/sea interactions by monitoring LU/LC changes over time. Detecting terrestrial changes is important for understanding their impact on marine environment. The study utilized CORINE data from 1990, 2000, 2006, 2012, and 2018 to monitor the coastal cities along the Sea of Marmara, complemented by 2021 LU/LC data derived from Sentinel-2 imagery.



2. STUDY AREA AND DATA USED

2.1 Study Area

The focus of this dissertation is the Sea of Marmara region (Figure 2.1). The Sea of Marmara located in Türkiye which is a semi-enclosed basin connecting the Black Sea through Istanbul Strait and the Aegean Sea via Dardanelles Strait (Figure 2.1).

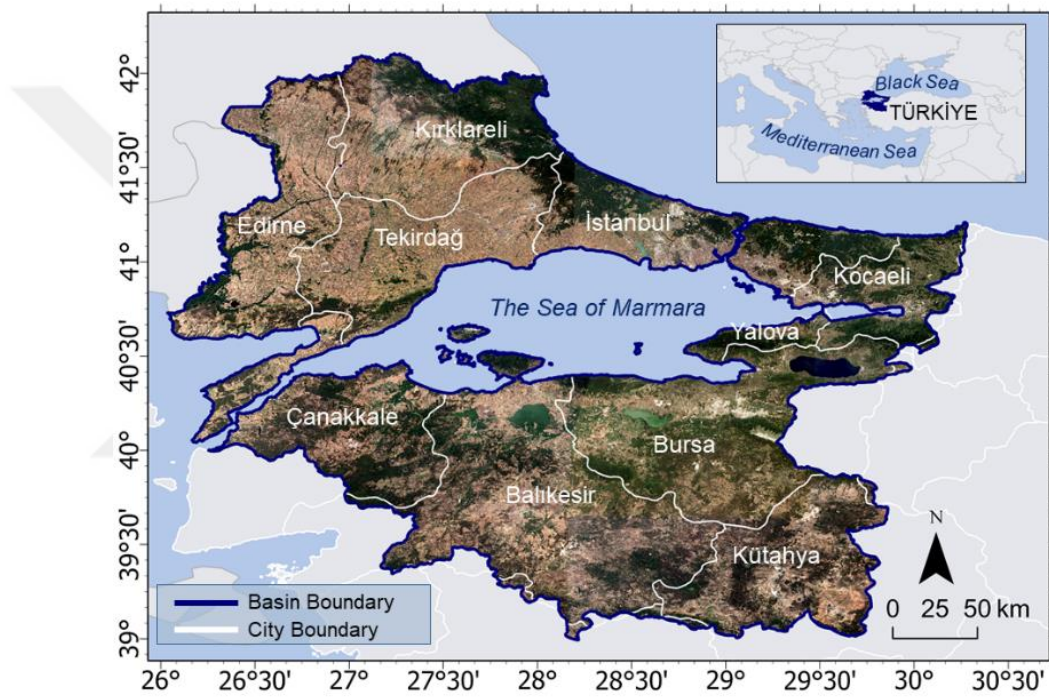


Figure 2.1 : The Sea of Marmara Basin (Musaoğlu et al., 2022).

The bathymetry map of the Sea of Marmara was produced by bathymetric data provided by the General Bathymetric Chart of the Oceans (GEBCO) (Url-2) (Figure 2.2). The shallow depths of the İstanbul and the Dardanelles Straits (– 35 m and – 65 m, respectively; Beşiktepe et al., 1994; Uysal, 2006; Okay et al., 2007) and the salinity differences between the Black Sea and Mediterranean Sea cause the formation of two stratified water in the Sea of Marmara. The brackish Black Sea waters (with 18‰ salinity) enter the Sea of Marmara (with ~ 20‰ salinity) as a strong surface current commonly named as the Bosphorus jet, while the saltier Mediterranean Sea (~ ‰39‰) waters enter the Sea of Marmara as an undercurrent (Beşiktepe et al., 1994; Chiggiato et al., 2012; Gökaşan et al., 2008; Uysal, 2006).

The stratification in the Sea of Marmara plays an important role in the exchange of the gases (e.g., oxygen) and the nutrients (e.g., nitrogen, phosphorus) between the surface and the deep waters. Because of the halocline stratification of the Sea of Marmara, the upper layer that has ~25-m depth has a eutrophic-mesotrophic characteristic, and is prone to increasing magnitude of phytoplankton blooms due to anthropogenic effects (Demir & Turkoglu, 2022; Tas & Yilmaz, 2015; Tas et al., 2020; Türkoğlu & Erdoğan, 2010; Turkoglu & Oner, 2010; Turkoglu, 2008; Turkoglu, 2010; Türkoğlu, 2010; Turkoglu, 2013; Turkoglu, 2016). Bottom layer with higher salinity that has Mediterranean Sea origin has low oxygen concentrations due to increased rates of decomposition processes and less phytoplankton activity at deeper layers (Balkis et al., 2011).

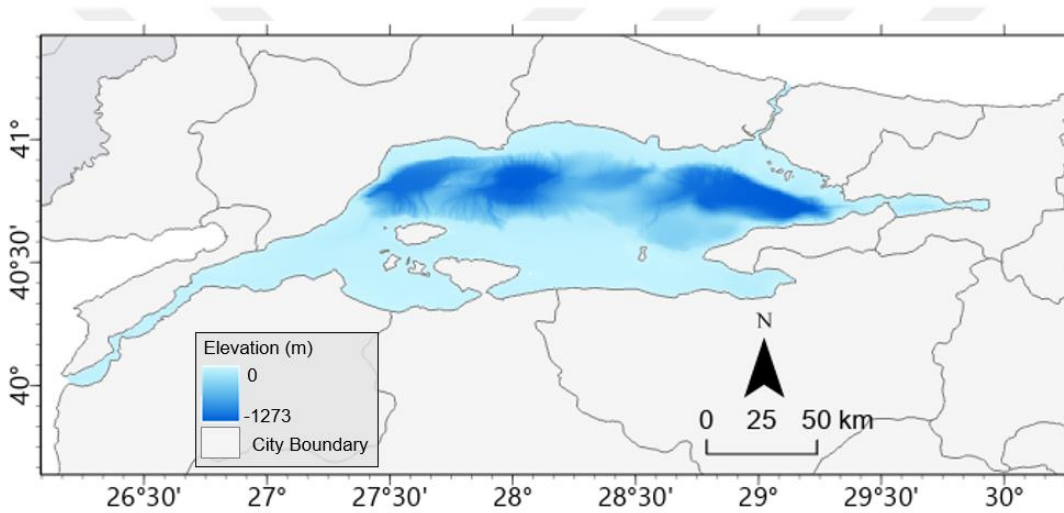


Figure 2.2 : The bathymetry map of the Sea of Marmara was produced by bathymetric data provided by the GEBCO.

This study focused on selected pilot region in the Sea of Marmara, aiming to thoroughly examine mucilage conditions. The analysis of the spectral characteristics of different colored mucilage types conducted in a selected pilot subregion in the İzmit Bay. İzmit Bay, located in the eastern section of the Sea of Marmara, is a narrow gulf that is situated within the populated Kocaeli Province. Kocaeli is a densely industrialized region which constitute of about 13% of the Türkiye's total industrial production (Genel & Guan, 2021). The common industry sectors in the İzmit Bay are the automotive and petrochemistry (petroleum and natural gas) in a higher extend together with the plastic, iron, and steel production. The significant increase in the urban density and its extension between 2006 and 2018 was shown in a recent study based on the CORINE data. New ports and the industrial plants increased especially

related to the construction of the Gebze-Orhangazi-İzmir motorway axes that opened to service in 2019 (Genel & Guan, 2021). Seawater of İzmit Bay is therefore very vulnerable to marine pollution. Previous geochemical studies on the marine sediments showed a heavy metal pollution in the İzmit Bay (Ergül et al., 2013; Morkoç et al., 2001; Tolun et al., 2001).

The SST trend and anomalies were investigated by considering the entire the Sea of Marmara. Since the importance of the interaction between land and sea, the administrative borders of 7 coastal cities along the Sea of Marmara namely, Tekirdağ, İstanbul, Kocaeli, Yalova, Bursa, Balıkesir and Çanakkale, lying within the Sea of Marmara Basin were taken into account during the investigation of land use/land cover changes. The said cities are greater metropolitan cities with the exception of Çanakkale and Yalova.

To detect the temporal LU/LC changes, the coastal cities along the Sea of Marmara were considered. The Sea of Marmara Basin (Musaoğlu et al., 2022) extends from 38° 59' 37.54" N to 42° 06' 20.10" N latitudes and 26° 02' 11.23" E to 30° 16' 52.26" E longitudes (Figure 2.1). Within the basin, certain cities encompass their entire administrative land, while others partially share their land. The 10 cities, which are Edirne, Kırklareli, Tekirdağ, İstanbul, Kocaeli, Yalova, Bursa, Kütahya, Balıkesir, Çanakkale, that had a minimum share of 5% within the basin are shown in Figure 2.1. The Sentinel-2 satellite images acquired between 02-10 August 2021 are shown in true color band combination in Figure 2.1.

2.2 Data Used

2.2.1 Satellite Data

The technical specifications of satellite data used are described in Table 2.1. In this study, both optical and thermal sensor data were used. The optical data included Sentinel-2 and Worldview-3 data, while the thermal sensor data comprised NOAA OISST V2, Sentinel-3 SLSTR, and Landsat-8 data.

Table 2.1 : The technical specifications of satellite data used (Reynolds et al., 2008; SUHET, 2015; Kuester, 2016; Url-3; Url-4; Url-5; Url-6; Url-7; Url-8; Url-9; Url-10; Url-11, Url-23, Url-24, Url-25).

Parameter	Optical Sensors			Thermal Sensors		
	Sentinel-2A	Sentinel-2B	Worldview-3	NOAA OISST V2	Sentinel-3 SLSTR	Landsat-8
Spatial Resolution (m)	10 m (B2, B3, B4, B8) 20 m (B5, B6, B7, B8A, B11, B12) 60 m (B1, B9, B10)		2 m	27830 m	1000 m	100m
Spectral Range	432 – 2290 (nm)	432 – 2280 (nm)	400–1040 (nm)	10.3 - 11.3 (μm)	10.85 - 12 (μm)	10.6 - 12.51 (μm)
Temporal Resolution	5 days (Twin satellites)		1 day; 4.5 days	1 day	<1 day	16 days
Acquisition Date	24 May 2021 (Mucilage), 02-10 August 2021 (LU/LC)	25 May 2021		1990 - 2021	2018-2021	2018-2021

Sentinel-2 and Worldview-3 satellite images were used to detect different types of mucilage. Sentinel-2 satellite image has high spectral resolution with 5 days temporal resolution. Sentinel-2, a European Space Agency (ESA) mission, provides freely accessible satellite images with 10 m spatial resolution and 5 days temporal resolution (SUHET, 2015). Worldview-3 image has a high spatial resolution of 2 m, a crucial characteristic for effectively monitoring various types of mucilage.

To detect SST of the Sea of Marmara, NOAA's Climate Data Records (CDR), Sentinel-3 and Landsat-8 satellite data, which have different temporal and spatial resolutions, were used as satellite data. NOAA CDR provides global and daily "Optimum Interpolation 1/4° Daily SST (OISST)" data (retrieved from Google Earth Engine (GEE) platform) which has sea surface temperature and temperature anomaly bands with spatial resolution of 0.25°C (27830 m) since 1981 (Reynolds et al., 2008; Url-7). In order to be able to monitor spatial distribution of SST, Landsat-8, Sentinel-3 and NOAA Optimum Interpolation 1/4° Daily SST (OISST) Analysis Version 2 (NOAA OISST V2) data were selected for this study. Landsat-8 and Sentinel-3 satellite images have higher spatial resolution compared to NOAA OISST V2 data. Landsat-8 provides two thermal bands which are Band 10 and Band 11 that covers 10.6 to 12.51 μm region of the electromagnetic spectrum with 100 m spatial resolution since 2013 (Url-8). On the other hand, Sentinel-3 Sea and Land Surface Temperature Radiometer (SLSTR) data, which was retrieved from EUMETSAT website (Url-9), provides 1 km spatial resolution for SST analysis since May 2016 (Url-10). Selected cloud-free Sentinel-3 and Landsat-8 images were acquired on June, July and August. A total of 9 cloud-free Landsat-8, and a total of 9 cloud-free Sentinel-3 satellite images that were acquired on the same days on summer season between 2018 and 2021 were used.

Data from two sources, CORINE and Sentinel-2, were utilized for LU/LC detection. CORINE generated thematic maps for LU/LC which encompasses 44 different classes in 1990 and every six years starting from 2000 (Copernicus, n.d.-b). CORINE Land Cover (CLC) data that belongs to 1990, 2000, 2006, 2012 and 2018 were utilized. To detect LU/LC in 2021, the selected cloud-free Sentinel-2 images acquired between 2–10 August 2021 were downloaded from the Copernicus Open Access Hub website (ESA et al., n.d.).

2.2.2 Ancillary Data

In addition to satellite data, ancillary data including photographs and in-situ data were also utilized. Photographs from different resources were used to evaluate the mucilage in May, 2021, in İzmit Bay and verify the results that were obtained from the satellite images.

To verify SST results, two datasets of SST in-situ data which were obtained from the Turkish State Meteorological Service (TSMS) were utilized. The first one is in-situ daily SSTs that were acquired between 1990 and 2021 from the 16 stations whose locations are shown in Figure 2.3. The second one is monthly mean SSTs that were acquired between 2014 and 2020 (Url-13; Url-14; Url-15).

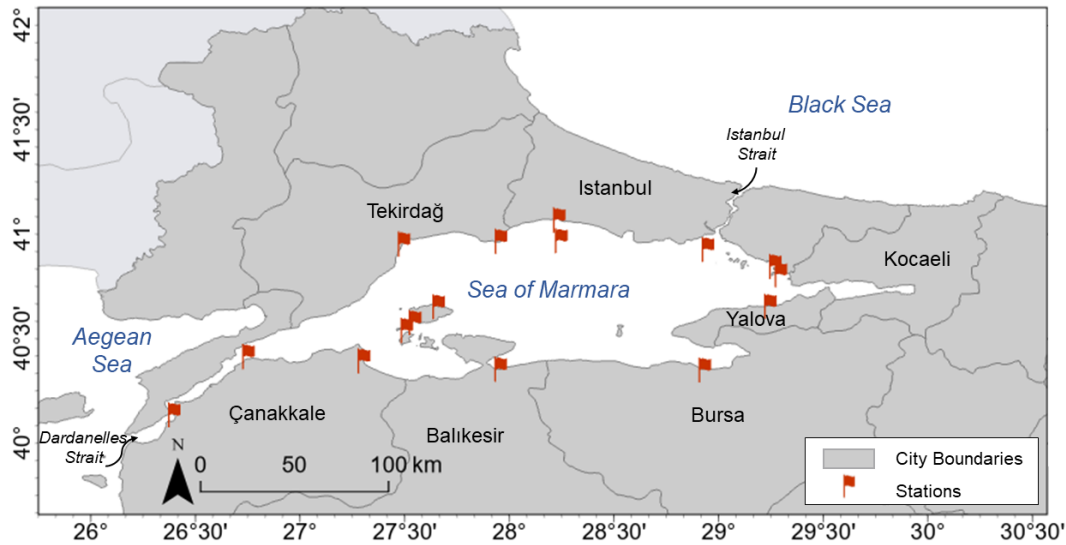


Figure 2.3 : The geographical location of the study area and the meteorological stations.

3. METHODOLOGY

In this study, three main steps were conducted. Firstly, detection of different colored mucilage types was conducted. Subsequently, the second and third steps involved investigating probable causes such as changes in SST and LU/LC. Throughout these stages, a multi-source data was used. For mucilage detection, both high-resolution (Worldview-3) and medium-resolution (Sentinel-2) images were utilized, resulting in the generation of thematic maps. Satellite data, including NOAA, Sentinel-3 and Landsat-8, were employed for SST detection, leading to the generation of time series for identifying trends and anomalies. In assessing land/sea interaction within LU/LC, both CORINE and Sentinel-2 data were used, resulting the generation of thematic maps. The methodology followed in this study is shown in the flow chart shown in Figure 3.1.

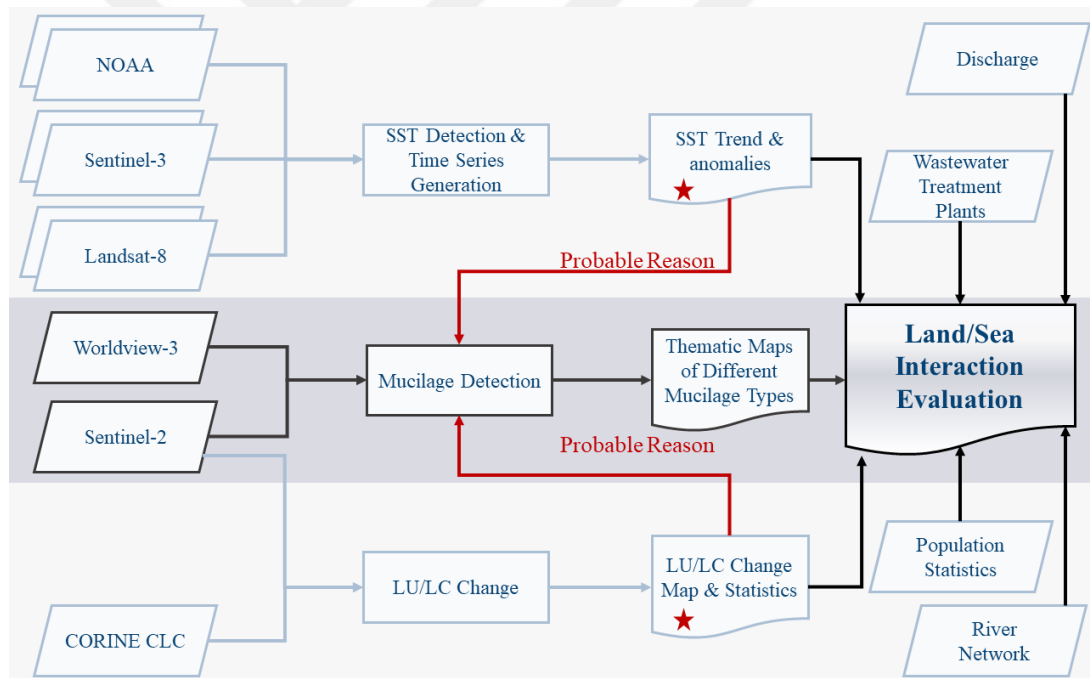


Figure 3.1 : Flow chart of the methodology.

3.1 Methodology of Detection of Mucilage Phenomenon by Satellite Images

The spectral characteristics and areal extents of different mucilage types in the İzmit Bay (Figure 3.2b) were detected by using medium- (Sentinel-2) (Figure 3.2c) and high-spatial resolution (Worldview-3) (Figure 3.2d) satellite images.

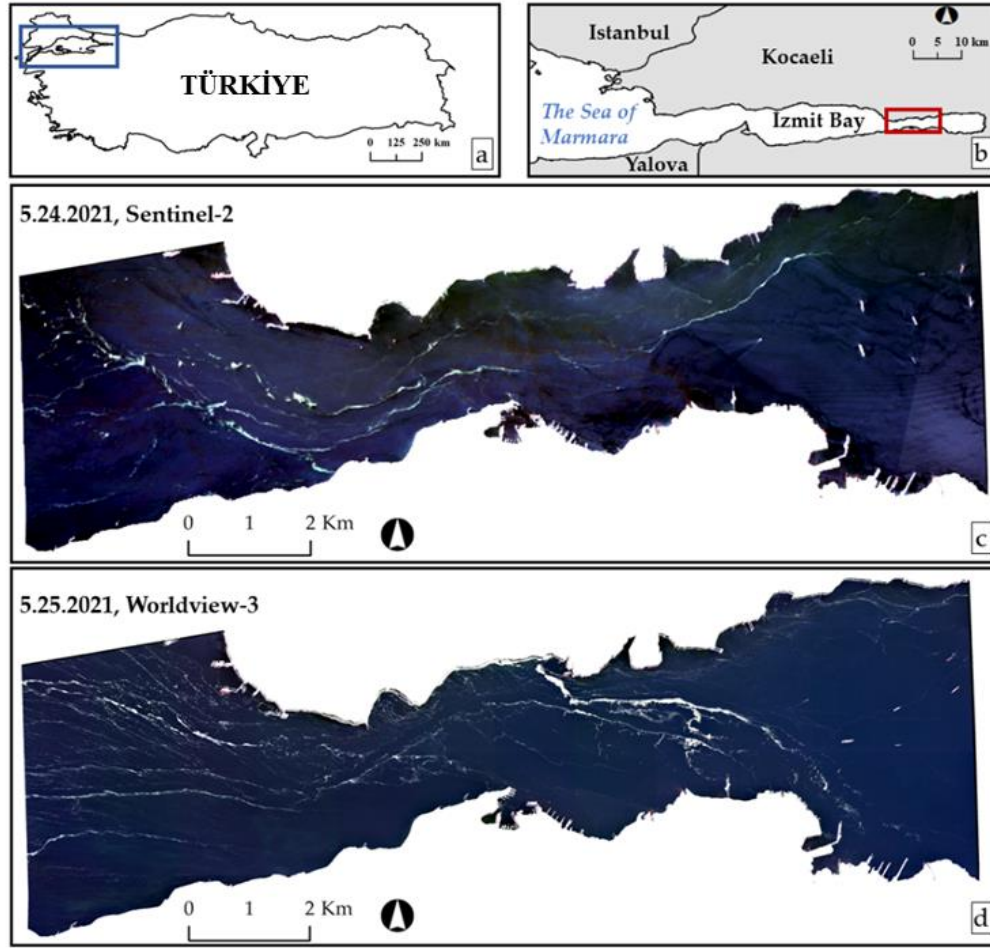


Figure 3.2 : Study area. a) The map of Türkiye with the dark blue box that showing the Sea of Marmara, b) the map of İzmit Bay with the red box represents the sub-region, c) natural color composition of Sentinel-2 satellite image from May 24, 2021, d) Worldview-3 satellite image from May 24, 2021, and May 25, 2021, respectively.

An overview of the identification process of mucilage classes is presented in Figure 3.3. The analysis is based on Sentinel-2 image acquired on May 24, 2021, and Worldview-3 image acquired on May 25, 2021, covering the İzmit Bay. The mucilage formation began in March 2021 and densified in May 2021. Thus, easily visible in photographs owing to the large contrast with the surrounding water (Figure 3.2). Initially, the satellite images were atmospherically corrected. Subsequently, spectral reflectance from different mucilage types was collected, followed by the application of ANOVA test. To evaluate satellite image's potential on this specific problem, their spectral and textural information were analyzed by using the in-situ photographs. In order to identify and to discriminate mucilage classes, SVM classifier was employed to these images separately and accuracy assessment was conducted.

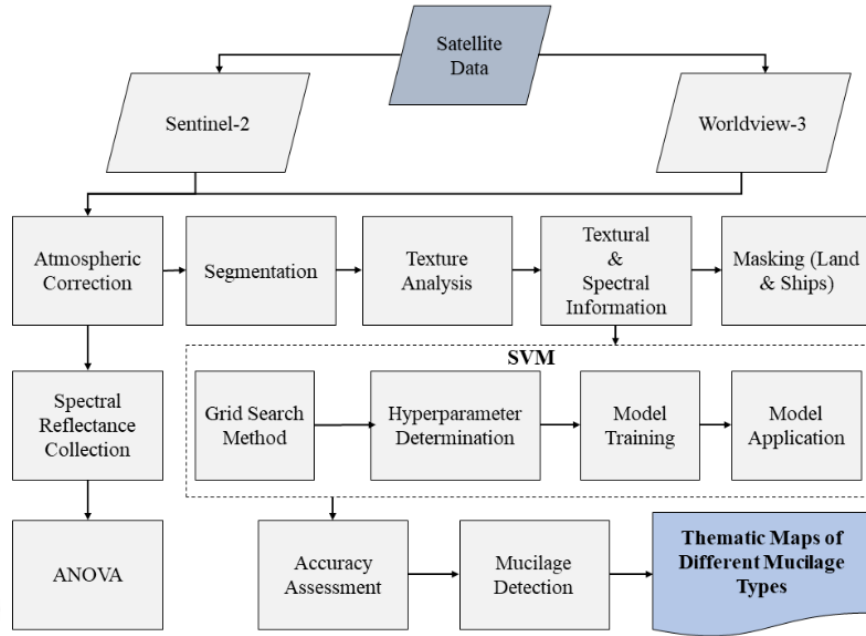


Figure 3.3 : Flow chart of the mucilage phenomenon detection.

Atmospheric correction is an important pre-process step to eliminate atmospheric effects and retrieve surface reflectance (Mather, 1999). As a first step, atmospheric correction was applied to the Worldview-3 satellite data. In this scope, digital number (DN) values were converted to radiance values by using Eq.3.1. Absolute scale factor and effective bandwidth values were obtained from the metadata file. After the radiance values were obtained, these values were converted to TOA (Top of Atmosphere) reflectance values by using Eq.3.2 (Kuester, 2016).

$$L = GAIN * DN \left(\frac{abscalfactor}{effectivebandwidth} \right) + OFFSET \quad (3.1)$$

$$\rho = \frac{L_{pixel,band} d_{ES}^2 \pi}{E_{\lambda_{band}} \cos(\theta_s)} \quad (3.2)$$

where

ρ : Top of atmosphere reflectance

$L_{pixel,band}$: Sensor radiance

d_{ES} : Earth Sun distance

θ_s : Solar zenith angle

$E_{\lambda_{band}}$: Averaged solar exoatmospheric irradiance

Physically-based atmospheric models were applied to Worldview-3 and Sentinel-2 satellite images in order to retrieve surface reflectance. After the surface reflectance

values were obtained, spectral reflectance collection was conducted. In this scope, spectral reflectance curves of different mucilage types were generated. In this study, three types of mucilage were considered. The first one, which was named as white mucilage, refers to dispersed mucilage. The white mucilage has smaller aggregates and has a spectral reflectance curve similar to water, but with higher reflectance especially between 600-900 nm. The second one, which was named as yellow mucilage, refers to accumulated mucilage. The yellow mucilage is formed from ageing aggregates that accumulated with the help of wind and currents. The third one, which was named as brown mucilage, refers to mucilage that have high organic matter concentration with ageing denser accumulations. Characteristics of different mucilage types in İzmit Bay were analyzed by Sentinel-2 and Worldview-3 satellite images with benefit from the opportunity of their spatial resolution capacity.

For the purpose of examining the spectral separability, spectral reflectance curves of these samples that belong to different types of mucilage was drawn by using Sentinel-2 satellite image and Worldview-3 satellite image as shown in Figure 3.5 and Figure 3.6, respectively. In order to compare the reflectance curves, the spectral range between 443-865 nm in the Sentinel-2 satellite data and the spectral range between 425–950 nm in the Worldview-3 satellite data was used. For the purpose of analyzing differences between spectral reflectance curves that belong to different mucilage types, the two-way Analysis of variance (ANOVA) test (Fisher, 1925) was applied. ANOVA, a statistical method, is utilized to compare means among three or more classes, determining if there exists a significant difference between them. The output of an ANOVA test includes an F-statistic along with a corresponding p-value. A significant p-value signifies notable distinctions among class means (MacFarland, 2012). In this test, different mucilage types were compared by considering two independent variables. Alpha value was considered as 0.05. The hypothesis tested was there is no significant difference between changes in spectral reflectance belong to different types of mucilage.

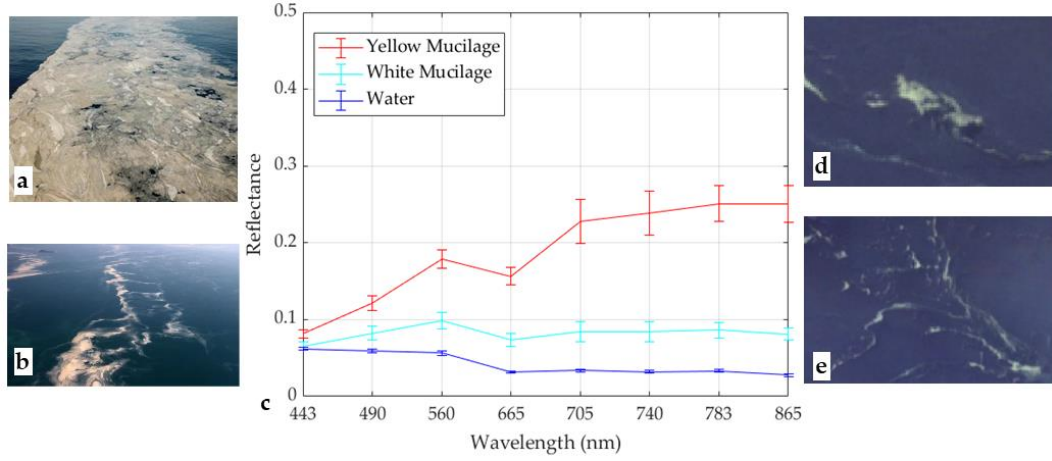


Figure 3.4 : Examples of different mucilage shown with representative photographs; (a) yellow mucilage (Url-17), and (b) white mucilage (Url-18); the Sentinel-2 satellite image of (d) yellow in open water on 24.05.2021, and (e) white mucilage in open water on 25.05.2021; c) Spectral reflectance curves of the yellow mucilage, the white mucilage and water that were retrieved from the Sentinel-2 satellite data.

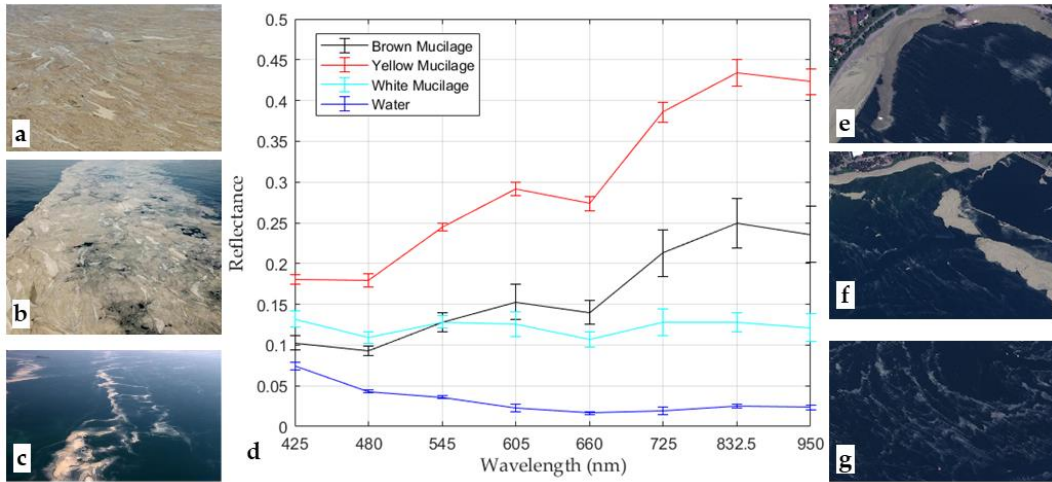


Figure 3.5 : Examples of different mucilage shown with representative photographs; (a) brown (Url-16), (b) yellow (Url-17), and (c) white mucilage (Url-18); the Worldview-3 satellite image of (e) brown in Kocaeli coast on 25.05.2021, (f) yellow in Kocaeli coast on 25.05.2021, and (g) white mucilage in open water on 25.05.2021; d) Spectral reflectance curves of the brown mucilage, the yellow mucilage, the white mucilage and water that were retrieved from the Worldview-3 satellite data.

When different mucilage covered areas were examined, different textural characteristics of the mucilage was observed. For the purpose of generating textural features, the image objects were generated by using multiresolution segmentation method (Baatz and Schäpe, 2000). In the next step, texture analysis was applied in order to distinguish the different types of textural mucilage features including a) contrast, b) dissimilarity and c) angular second moment. In addition to spectral features of the Worldview-3 and Sentinel-2 satellite images textural features were generated by

using the Gray-Level Co-occurrence Matrix (GLCM) method (Haralick et al., 1973). GLCM is a statistical technique utilized to quantify texture by investigating the spatial relationships of pixels (Zainal et al., 2013) and it has been widely used in various remote sensing applications such as agriculture monitoring (Tuzcu Kokal et al., 2021), LU/LC classification (Parracciani et al., 2024), above-ground biomass (Huong et al., 2023). GLCM offers information on the spatial distribution of intensities between neighboring pixels. It gives information about how often different pixel intensity combinations occur in an image. The relationships between reference and neighbor pixels are represented in a co-occurrence matrix (P_d) (Eq.3.3) (Zainal et al., 2013).

$$P_d[i, j] = n_{i,j} \quad (3.3)$$

$n_{i,j}$ refers to the number of times the pixel values (i, j) occur. The values of P_d are normalized using Eq.3.4 and the values range between 0 and 1 (Zainal et al., 2013).

$$N[i, j] = \frac{P[i, j]}{\sum_{i=1}^n \sum_{j=1}^n P[i, j]} \quad (3.4)$$

By using GLCM, various statistical features such as contrast, dissimilarity, and angular second moment are derived, providing information about the texture's characteristics. The formulas of contrast, dissimilarity, and angular second moment are provided in Eq.3.5, Eq.3.6 and Eq.3.7, respectively (Zainal et al., 2013; Kwak and Park, 2019).

$$\text{Contrast} = \sum_{i=1}^n \sum_{j=1}^n (i - j)^2 N[i, j] \quad (3.5)$$

$$\text{Dissimilarity} = \sum_{i=1}^n \sum_{j=1}^n |i - j| N[i, j] \quad (3.6)$$

$$\text{Angular second moment} = \sum_{i=1}^n \sum_{j=1}^n N^2[i, j] \quad (3.7)$$

The differentiated mucilage textures were used as the mucilage types described in this study. As there is an intense maritime traffic in the Sea of Marmara, ships and piers were masked. In the next step, spectral and textural features were defined in the input feature space and object-based classification technique was applied to Sentinel-2 and Worldview-3 satellite images.

In order to identify and to discriminate mucilage classes, SVM classifier was employed to these images separately. To evaluate their potential on this specific problem, their spectral and textural information were analyzed by using the in-situ photographs. Mucilage photographs in the İzmit Bay are shown in Figure 3.6. Figure 3.6a, c, taken on May 7, 2021, show thick accumulations of mucilage in the inner sections of small bays. The location of Figure 3.6b is close to industrial and residential areas and also in the study area of this study. In Figure 3.6d, the mucilage-covered area located in the

entrance of İzmit Bay, which is close to Topçular Ferry Pier, was observed in the field survey that was conducted on May 26, 2021. In the photograph in Figure 3.6e, which was taken on May 26, 2021, the mucilage-covered area can be seen on the offshore and coastal areas from the view of Osmangazi Bridge.

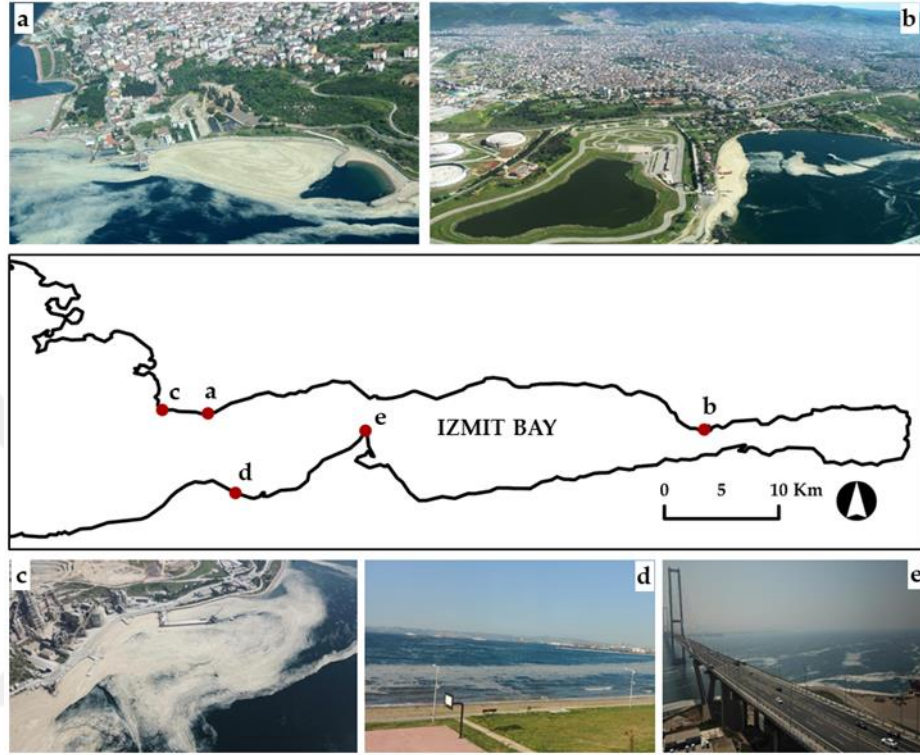


Figure 3.6 : Examples of mucilage appearances shown with the field photographs from different sites in İzmit Bay including a) the eastern side of the coast of Darıca (in Kocaeli), taken on May 7, 2021 (Url-19), b) the coast of Körfez (in Kocaeli), taken on May 7, 2021 (Url-19), c) the western side of the coast of Darıca (in Kocaeli), taken on May 7, 2021 (Url-17), d) nearby Topçular Ferry Pier taken on May 26, 2021, e) Osmangazi Bridge, on May 26, 2021.

SVM, which is a supervised statistical machine learning technique, was used in order to find an optimal separation hyperplane and separate the dataset into the predetermined number of classes (Mountrakis et al., 2011) with Radial Basis Function (RBF). SVM is one of the most commonly used Kernel-based machine learning algorithms for classification purposes was applied (Vapnik, 1979; 2013). Since the decision boundaries in SVM are generally not defined as a linear basis, the nonlinearity in SVM was overcome by projection of the dataset into a higher dimensional feature space, using kernel functions and a construction of a learn classification problem in that feature space (Pal & Mather, 2005; Mather and Tso, 2009). The projection process is shown in Figure 3.7 adapted from Mather and Tso, (2009).

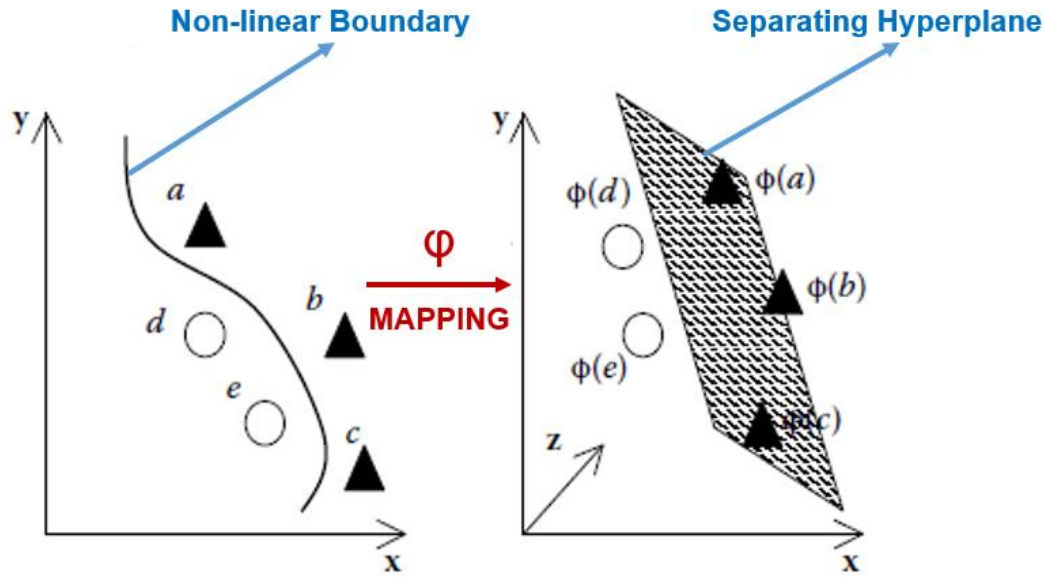


Figure 3.7 : Projection of the data into a higher dimension, adapted from Mather and Tso, (2009).

Selection of RBF is a commonly used kernel to apply SVM to nonlinear separated classes. The kernel used hyperparameters, as gamma and cost to maximize the margin. These parameters were defined by using grid search method (Mountrakis et al., 2011). The grid search method was applied by using the Scikit-Learn module of Python programming language (Pedregosa et al., 2011) for optimization of hyperparameter values. The model was applied by using optimized values. In the scope of the accuracy assessment, overall accuracy and kappa metrics were calculated (Congalton & Green, 2019).

3.2 Methodology of Sea Surface Temperature Detection Using Satellite Images

The methodology followed to detect SST is described in the flow chart shown in Figure 3.8. To address the SST variations of the Sea of Marmara in time, a comprehensive set of both field and satellite data regarding SSTs were obtained within the context of this study. The SST trend and its anomalies between the years 1990 and 2021 were detected by applying Seasonal-Trend decomposition procedure based on LOESS (STL) method to NOAA OISST V2 data. On the other hand, spatial SST distribution was detected with Landsat-8, Sentinel-3 and NOAA OISST V2 satellite data. SST results were verified with the in-situ data within the scope of accuracy assessment.

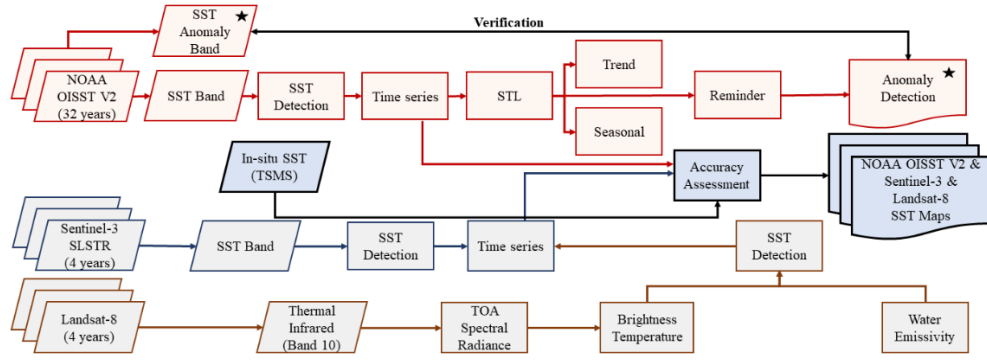


Figure 3.8 : Flow chart of the methodology used.

Change of SST spatial variations of the Sea of Marmara were also examined in detail with Sentinel-3 and Landsat-8 data as shown in the flow diagram of the methodology used (Figure 3.8). Sentinel-3 images were used to monitor the recent years by taking the advantage of covering the entire study area with a single frame. SST data retrieved from Sentinel-3 SLSTR observations were used to generate time-series data. On the other hand, Landsat-8 satellite image was also used to generate time-series. When both of the thermal bands of Landsat-8 were considered, Band 10 was found to be more appropriate for the SST calculation based on the study of Vanhellemont, (2020). As a first step, raw (Collection1-Tier 1 DN values) were converted to Top of Atmosphere (TOA) values by using Eq.3.8.

$$L\lambda = ML * Q_{cal} + AL \quad (3.8) \text{ (Url-11)}$$

where ML refers to band-specific multiplicative rescaling factor, Q_{cal} represents the quantized and calibrated standard product pixel values for Band 10, and AL represents the band-specific additive rescaling factor provided in metadata file.

After TOA radiance values for each pixel of the band were retrieved, Brightness Temperature (BT) values were calculated with band-specific thermal conversion constants (K_1 , K_2) in Celsius by using the Eq.3.9 (Url-11; Vanhellemont, 2020). As a last step, SST were calculated as emissivity corrected surface temperature (T_s) with sea surface emissivity values by using Eq.3.10 (Stathopoulou & Cartalis, 2007; Avdan & Jovanovska, 2016). The sea surface emissivity value was selected as 0.991 (Avdan & Jovanovska, 2016).

$$BT = \frac{K_2}{\ln[(K_1/L_\lambda)+1]} - 273.15 \quad (3.9)$$

$$Ts = \frac{BT}{\{1 + [(\lambda BT/\rho) \ln \epsilon]\}} \quad (3.10)$$

where λ refers to wavelength of emitted radiance, ε refers to emissivity value of sea, ρ is calculated by Eq.3.11.

$$\rho = h c / \sigma \mu m K \quad (3.11)$$

In the verification step, the results obtained by Sentinel-3 and Landsat- 8, which were acquired synchronically, were further compared. Besides, the SST values that were obtained with Landsat-8 and Sentinel-3 were compared with the in-situ measurements that were derived from Turkish State Meteorological Service. Accordingly, Root Mean Square Error (RMSE) and bias metrics were calculated by using Eq.3.12 and Eq.3.13 to assess accuracies.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (X_{obs,i} - X_{sens,i})^2}{n}} \quad (3.12)$$

$$Bias = \frac{1}{n} \sum_{i=1}^n (X_{obs,i} - X_{sens,i}) \quad (3.13)$$

where X_{obs} refers to the in-situ data, X_{sens} refers to the acquired data, n refers to number of the samples.

Time-series of SST of the Sea of Marmara was produced by using NOAA CDR OISST v02r01: Optimum Interpolation of SST from 1990 to 2021 in the GEE platform. For the purpose of detecting anomalies, STL (Cleveland et al., 1990) method was applied to the time-series data by using the formula that is given in Eq.3.14.

$$Y_v = T_v + S_v + R_v \quad (3.14) \text{ (Cleveland et al., 1990)}$$

T_v refers to trend component, S_v refers to seasonal component, R_v refers to remainder component.

The threshold value was determined as three times the standard deviation from the mean value of the retrieved remainder component to find the anomalies. Then, anomaly detected days were compared with the SST anomaly band of the NOAA OISST V2 for the purpose of verifying anomaly results.

3.3 Methodology of LU/LC Assessment of the Coastal Cities of the Sea of Marmara

LU/LC assessment of the coastal cities of the Sea of Marmara is composed of two main steps. The first step involves generating the 2021 LU/LC map. The second step combines 3rd hierarchical level of CLC nomenclature and detects LU/LC changes by comparing multi-temporal CLC data and produced 2021 LU/LC map. The flow chart

presented in Figure 3.9 illustrates the overall methodology implemented for the coastal cities along the Sea of Marmara situated within the Sea of Marmara Basin.

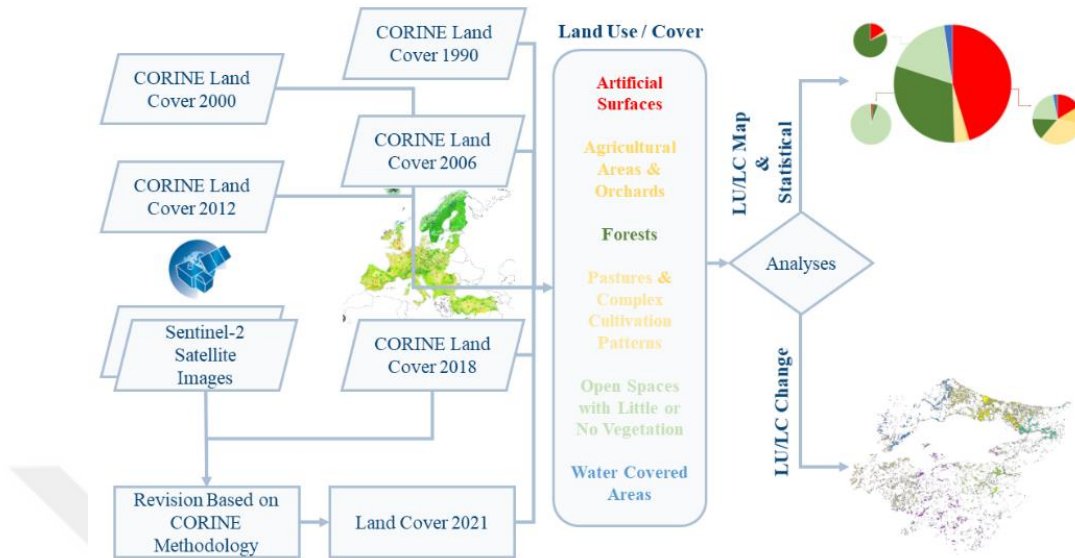


Figure 3.9 : The flow diagram of the methodology used (Sentinel logo was retrieved from the website of ESA (ESA, n.d.) and the CORINE image was retrieved from the CORINE website (Copernicus, n.d.-a)

The LU/LC classes of coastal cities in 2021 were derived by revising the CLC 2018 dataset. In this process, various data sources, such as stand maps acquired from Republic of Türkiye Ministry of Agriculture and Forestry General Directorate of Forestry (Url-20), Sentinel-2 imagery, and high resolution Google Earth images, were utilized. Cloudless Sentinel-2 images acquired between August 2nd and 10th, 2021 were utilized for this purpose. CORINE methodology was applied to Sentinel-2 satellite images to generate the LU/LC map for coastal cities along the sea in 2021 by referencing CLC 2018 data which is in vector format (Kosztra et al., 2019). The minimum mapping unit (MMU) considered for this analysis was 25 ha with a minimum linear width of 100 m. The scale used for the maps was 1:100 000. Additionally, a minimum change of 5 ha was used for calculating the areal changes (Sertel et al., 2018; Kosztra et al., 2019; Copernicus, n.d.-b; Copernicus, n.d.-c).

3rd hierarchical level of CLC nomenclature was investigated and 36 different levels of CLC data classes were detected for Tekirdağ, İstanbul, Kocaeli, Yalova, Bursa, Balıkesir and Çanakkale cities that are situated within the Sea of Marmara Basin. These classes were further combined in line with the characteristics of the study area. Considering the substantial size of the study area, the classes were united into 6 distinct classes to facilitate a general assessment and to simplify the results. These classes are

(1) artificial surfaces, (2) agricultural areas and orchards, (3) pastures and complex cultivation patterns, (4) forests, (5) open spaces with little or no vegetation, and (6) water covered areas.

The process of combining classes was applied to the CLC data acquired in 1990, 2000, 2006, 2012, 2018, and in the produced 2021 LU/LC map. Subsequently, a comparison process was conducted by using the maps within intervals of 1990-2000, 2000-2006, 2012-2018, 2018-2021 and the overall long-term glimpses covering 31 years (1990-2021) to detect intermediate and overall LU/LC changes in the coastal cities. The investigation of these changes was conducted separately for each city. To quantify the extent of the changed areas, area calculation was performed in the Geographic Information System (GIS) environment. Once the areas were calculated, distribution of LU/LC classes in 2021 was examined for the study area.

4. RESULTS

4.1 The Mucilage Detection Results

Mucilage formation, which is a global environmental problem, was observed in the Sea of Marmara as well as seen in Mediterranean Sea, the Adriatic Sea and the Gulf of Mexico in the past. Mucilage can occur in different types and forms.

In this study, the two-way ANOVA was applied in order to search whether there is a significant difference between the reflectances of different types of mucilage. ANOVA results belongs to Worldview-3 satellite image were shown in Table 4.1.

While Sentinel-2 satellite image was used to obtain an outline information of the study area, Worldview-3 satellite image was used to obtain detailed information about the characteristics of the mucilage types.

Table 4.1 : ANOVA test results of the Worldview-3 and Sentinel-2 images.

Satellite image	Source of variation	SS	df	MS	F	P-value	F-critical
Worldview-3	Samples	1.50	3	0.50	2621.84	1.1E-114	2.68
Sentinel-2	Samples	0.46	2	0.23	1395.06	1.13E-71	3.09

Based on the two-way ANOVA analyses using satellite data, three significantly different (P-value <0.05) mucilage was detected (Table 4.1). The spectral and textural information were utilized in the input feature space of the classification. For textural information three methods including the contrast, the dissimilarity and the angular second moment textural features were generated by applying GLCM method to the Worldview-3 and Sentinel-2 satellite images (Figure 4.1).

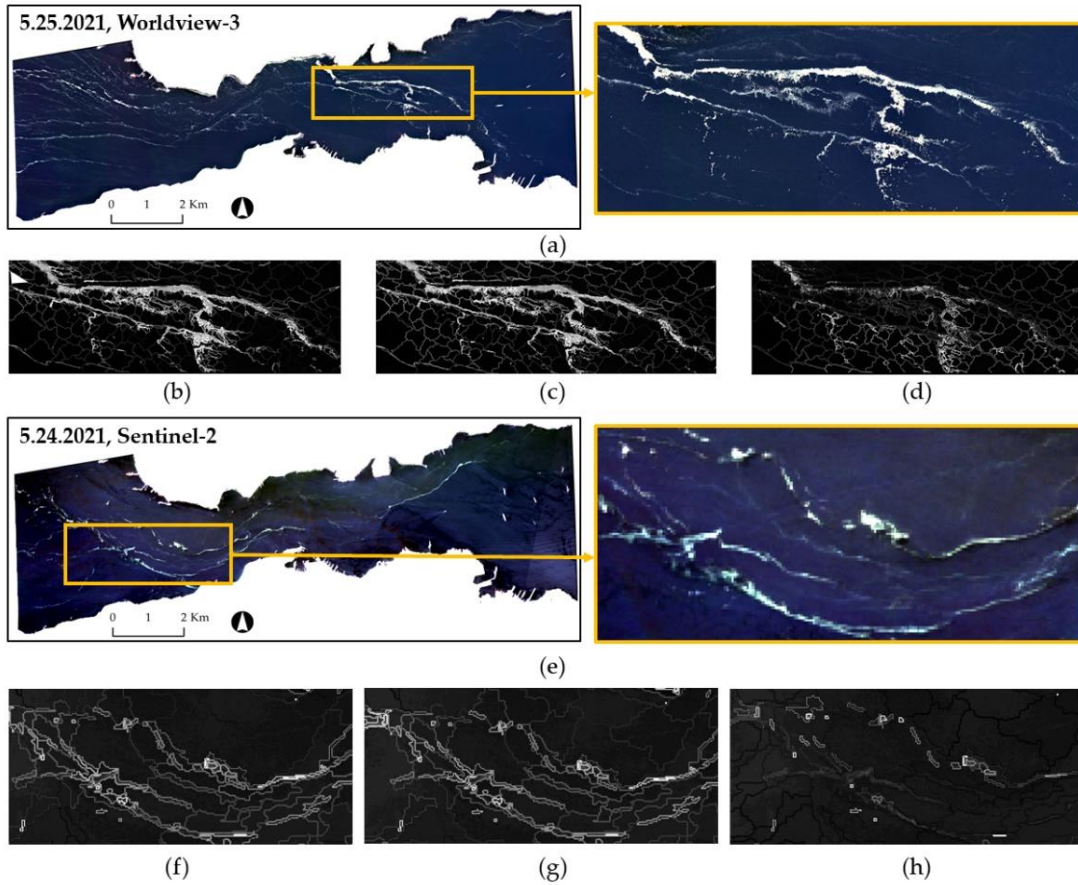


Figure 4.1 : Results of mucilage texture analyses performed on two pilot locations (a, e) in the İzmit Bay by using the Gray-Level Co-occurrence Matrix (GLCM) method (Haralick et al., 1973). The two study areas are shown orange boxes in a) Worldview-3 satellite image from May 25, 2021 and e) Sentinel-2 satellite image from May 24, 2021. The mucilage textures are characterized by using (b,f) Contrast, (c,g) Dissimilarity and (d,h) Angular Second Moment method described in GLCM method.

The SVM classification method was applied to Sentinel-2 satellite image to detect two different mucilage types, which are white mucilage and yellow mucilage. The produced thematic map was shown in Figure 4.2. The zoomed images were shown in order to monitor spatial variations of different mucilage types in Figure 6.4a-c and it was seen that mainly yellow mucilage accumulations are surrounded by white mucilage that have dispersed patterns.

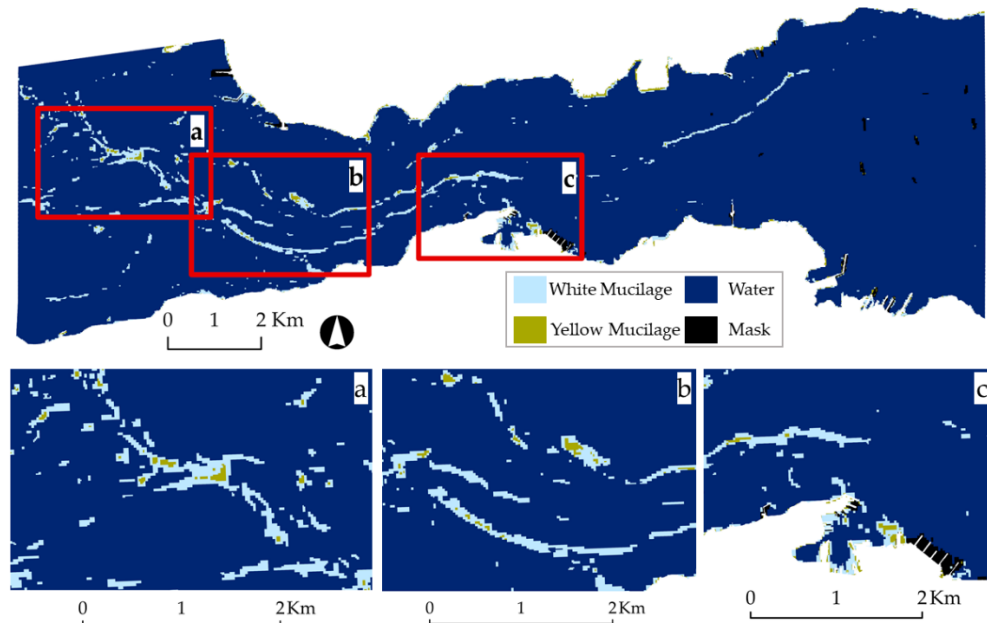


Figure 4.2 : The thematic map of the different mucilage types that was produced by applying SVM classification method to Sentinel-2 satellite image. The zoomed images to monitor spatial variations of different mucilage types in locations a), b), c).

Worldview-3 satellite image having higher spatial resolution compared to Sentinel-2 was used in order to detect mucilage accumulations with higher detail and accuracy. According to SVM classification results, three different mucilage types, which are white mucilage, yellow mucilage and brown mucilage were discriminated. The produced thematic maps were shown in Figure 4.3. Zoomed images were shown in order to monitor spatial variations of different mucilage types in Figure 6.5a-d. In general, yellow mucilage accumulations were surrounded by white mucilage that showed dispersed patterns. The results showed a similar pattern obtained from Sentinel-2 satellite image (Figure 4.2). The contribution of the Worldview-3 satellite image is detecting brown mucilage covered areas. In Worldview-3 satellite images, the brown mucilage accumulations were seen mostly in the coastal regions (Figure 4.3) and this accumulated brown mucilage covered areas could not be discriminated by using Sentinel-2 satellite image.

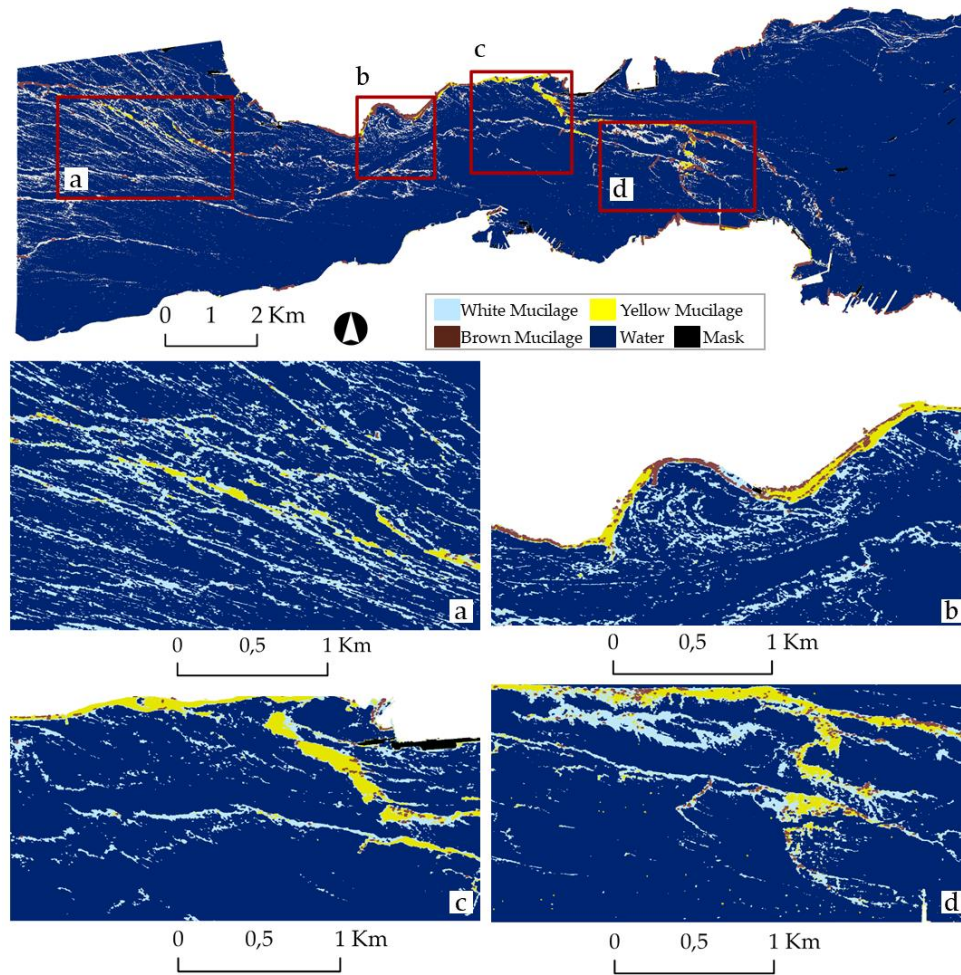


Figure 4.3 : The thematic map of the different mucilage types that was produced by applying SVM classification method to Worldview-3 satellite image. The zoomed images to monitor spatial variations of different mucilage types in locations a), b), c), d).

The results of areal extent of the classes from Sentinel-2 and Worldview-3 classification were shown in Table 4.2. When the areal extent of the classes was examined, it was seen that white mucilage covers the most area among all of the mucilage types in both satellite images. Higher areal coverage of the white mucilage is related to the less dense and dispersed characteristics of the freshly formed mucilage. In Worldview-3 satellite image, the brown mucilage covers the least area among all of the mucilage types. Brown mucilage covered the least area among the all the mucilage types as shown in Table 4.2. When Figure 4.2 and Figure 4.3 compared, it is seen that Sentinel-2 satellite data was incapable to detect brown mucilage areas due to its lower spatial resolution (Table 4.2).

Table 4.2 : Areal extents of the mucilage classes in İzmit Bay based on satellite data in May 2021. The corresponding study sites are shown in Figure 3.2.

Mucilage Class	Area (ha)	
	Sentinel-2	Worldview-3
White Mucilage	193	350
Yellow Mucilage	37	74
Brown Mucilage	-	11

In the scope of accuracy assessment, error matrixes were generated to assess overall accuracies and kappa statistics. Overall accuracies that were obtained from Sentinel-2 and Worldview-3 satellite images were calculated as 0.86 and 0.93, respectively. Kappa statistics that were obtained from Sentinel-2 and Worldview-3 satellite images were calculated as 0.79 and 0.90, respectively.

4.2 The SST Results

Thematic maps were produced by using Landsat-8 and Sentinel-3 and NOAA OISST V2 satellite data. Spatial SST distributions were extracted by using the Landsat-8 (Figure 4.4), Sentinel-3 (Figure 4.5) and NOAA OISST V2 (Figure 4.6) satellite data.

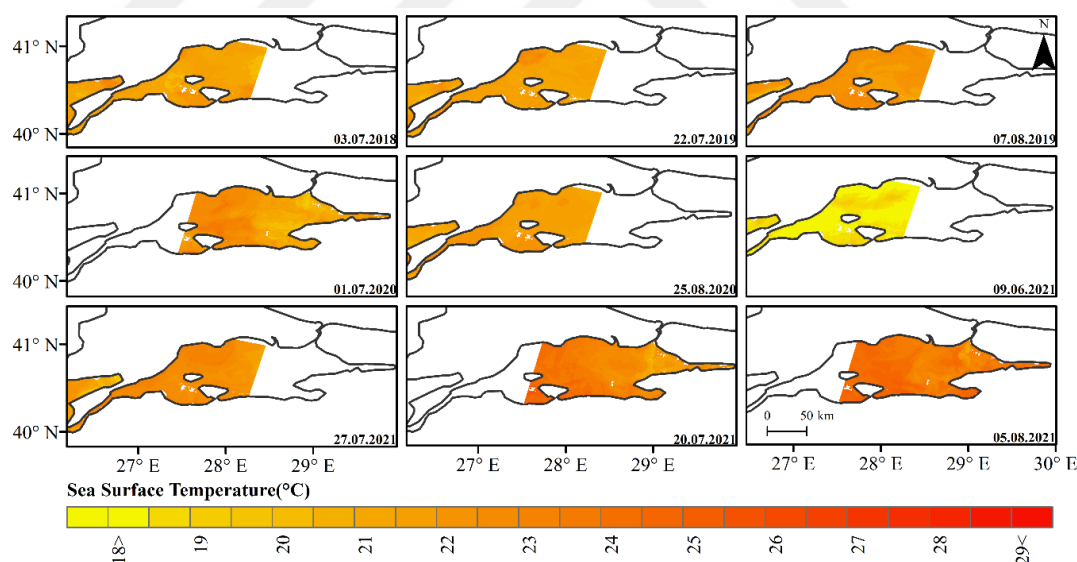


Figure 4.4 : SST maps retrieved from Landsat-8 satellite images.

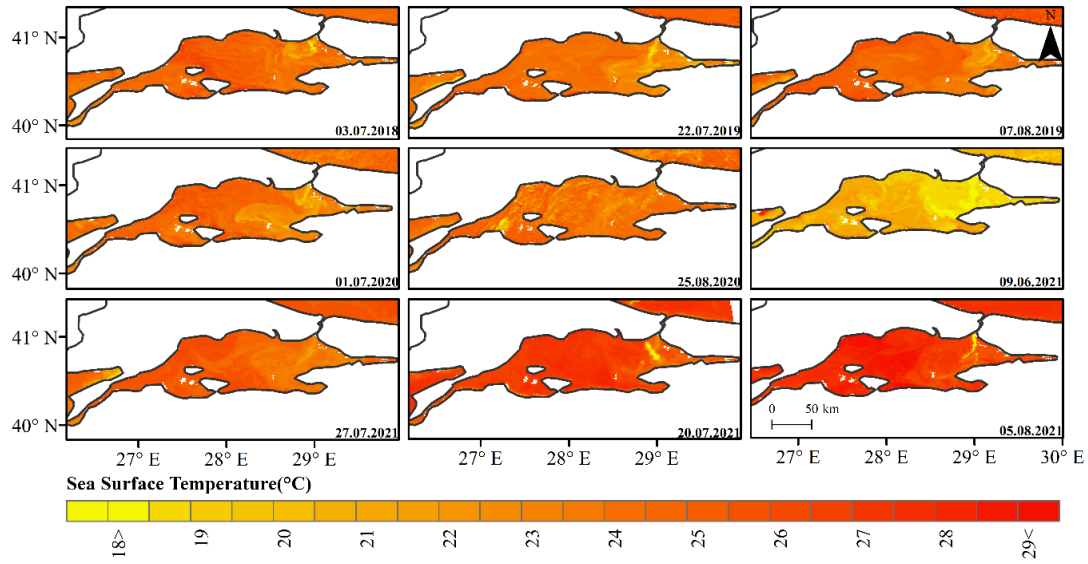


Figure 4.5 : SST maps retrieved from Sentinel-3 satellite images.

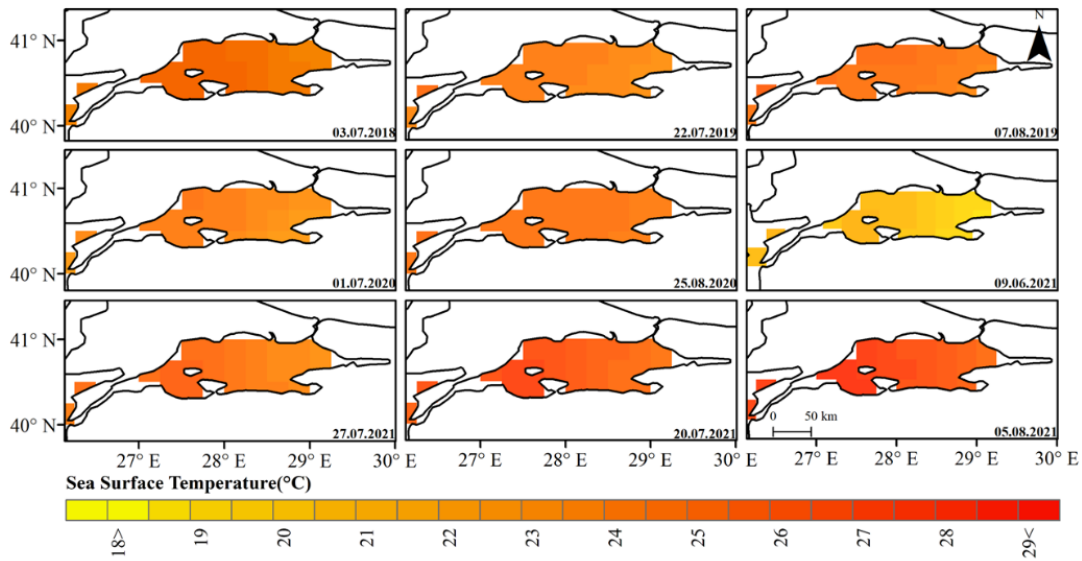


Figure 4.6 : SST maps retrieved from NOAA OISST V2 satellite images.

When Figure 4.4 and Figure 4.5 are examined, it is seen that consistent results were obtained by using synchronically acquired Sentinel-3 and Landsat-8 satellite images. Besides, the cold water that originated from the Black Sea via Istanbul Strait was detected as yellow color in the Northeastern part of the sea. While spatial SST variations can be detected by using the Landsat-8 (Figure 4.4) and Sentinel-3 (Figure 4.5) satellite images, these variations cannot be distinguished by using the NOAA OISST V2 (Figure 4.6) satellite data due to having coarse spatial resolution.

In the scope of accuracy assessment, monthly mean SST data were calculated from daily NOAA OISST V2 data and were compared with monthly mean SSTs that were

acquired between in 2014 and 2020 (Url-13; Url-14; Url-15). Moreover, the results that were obtained by using Landsat-8 and Sentinel-3 satellite images were linked with in-situ daily SSTs. RMSE and bias of NOAA OISST V2 data were calculated as 1.2°C and 0.3°C , respectively. Accordingly, RMSE values were found as 1.68°C and 1.19°C and bias values were calculated as 0.89°C and -0.25°C in the Landsat-8 and Sentinel-3 satellite image results, respectively. Calculated RMSE and bias values indicate that NOAA OISST V2, Sentinel-3 and Landsat-8 satellite data are proper data to monitor SST of the Sea of Marmara.

Detection of temporal SST variability was carried out by using NOAA data. The original NOAA OISST V2 dataset (Figure 4.7a) was decomposed to trend (Figure 4.7b), seasonal (Figure 4.7c) and residual (Figure 4.7d) components, it is seen that the time-series has an increasing trend, and the highest temperatures were recorded in 2020. Furthermore, approximately 2°C variations of SST were observed over the 32-year period. By applying the threshold values to residual component (Figure 4.7e), SST anomalies were detected and these days are represented by the red dots on the time-series data (Figure 4.7f) and are depicted in Table 4.3. It can be stated that anomaly detected days are detected especially in the recent years.

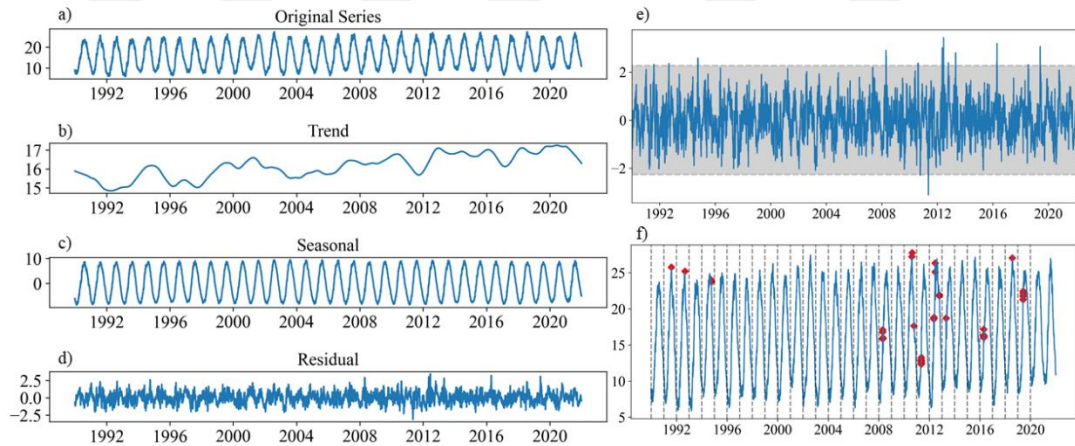


Figure 4.7 : a) Original series, b) trend component, c) seasonal component, d) residual component, e) threshold values are shown with gray color on the residual values, f) anomaly detected days are represented by the red dots on the time-series data.

Table 4.3 : Anomaly detected days.

Date	SST (°C)	Date	SST (°C)	Date	SST (°C)	Date	SST (°C)	Date	SST (°C)
5.08.1991	25.8	26.04.2008	16.0	9.05.2011	13.0	13.06.2012	26.3	21.04.2016	16.3
1.09.1992	25.2	27.04.2008	16.0	10.05.2011	12.7	14.06.2012	25.1	23.04.2016	16.3
3.10.1994	23.8	12.08.2010	27.3	11.05.2011	12.4	16.10.2012	21.9	22.07.2018	27.0
4.10.1994	24.0	13.08.2010	27.4	12.05.2011	12.4	17.10.2012	21.8	28.05.2019	21.3
5.10.1994	23.7	19.08.2010	27.8	13.05.2011	13.3	28.04.2013	18.7	29.05.2019	21.8
21.04.2008	17.1	20.08.2010	27.4	7.05.2012	18.6	29.04.2013	18.7	30.05.2019	21.8
22.04.2008	16.8	10.10.2010	17.6	8.05.2012	18.7	17.04.2016	16.0	31.05.2019	22.4
23.04.2008	15.9	6.05.2011	12.3	9.05.2012	18.8	18.04.2016	16.1	1.06.2019	22.1
24.04.2008	15.8	7.05.2011	12.7	10.05.2012	18.8	19.04.2016	16.2	5.06.2019	22.5
25.04.2008	15.9	8.05.2011	12.9	11.05.2012	17.9	20.04.2016	17.2		

The temperature anomaly band of the NOAA OISST V2 data was calculated by subtracting 30-year mean from the daily data (Url-21). In order to verify anomaly detection results, they were compared with the temperature anomaly band of the NOAA OISST V2 data as shown in Figure 4.8. The dates that were detected as anomalies with both of the datasets are shaded with gray color in Table 4.3.

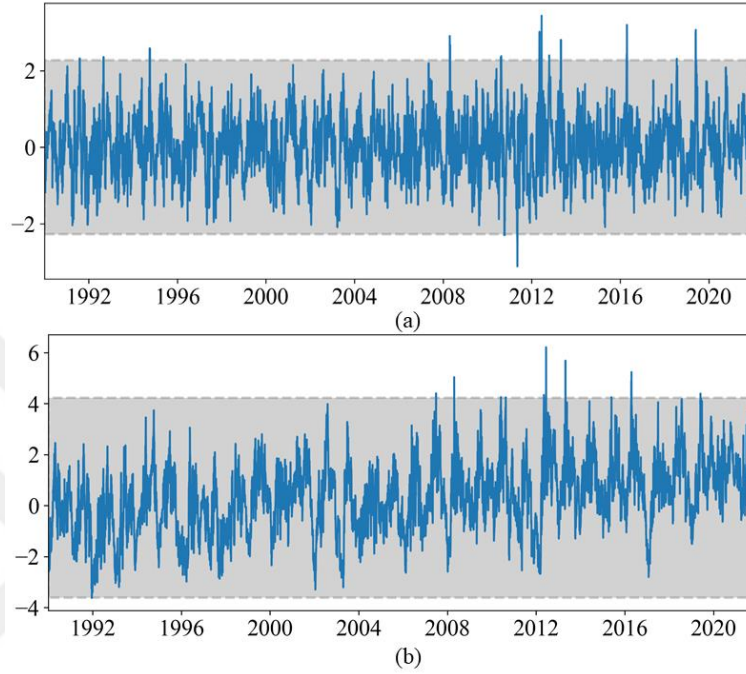


Figure 4.8 : a) The residual component that was obtained from STL method, b) anomaly band result of the NOAA OISST V2 data.

As can be seen from Figure 10a, the residual component is eliminated from the trend effect due to STL method. However, NOAA OISST V2 temperature anomaly band is under the increasing trend effect as shown in Figure 4.8b.

4.3 The LU/LC Results of CORINE

The most recent available CORINE data for the study area is CLC 2018 data. Considering the significant changes experienced by cities such as İstanbul, Kocaeli and Bursa, it is necessary to use more recent data than 2018. Furthermore, it is crucial for this recent data to align with CORINE datasets for comprehensive temporal analysis. Therefore, in this study, land use/land cover (LU/LC) classes that correspond to CORINE classes for 2021 were detected. Figure 4.9 illustrates the LU/LC of the coastal cities along the Sea of Marmara in 2021 along with the areal distributions of classes, which are artificial surfaces, agricultural areas and orchards, pastures and

complex cultivation patterns, forests, open spaces with little or no vegetation, water covered areas.

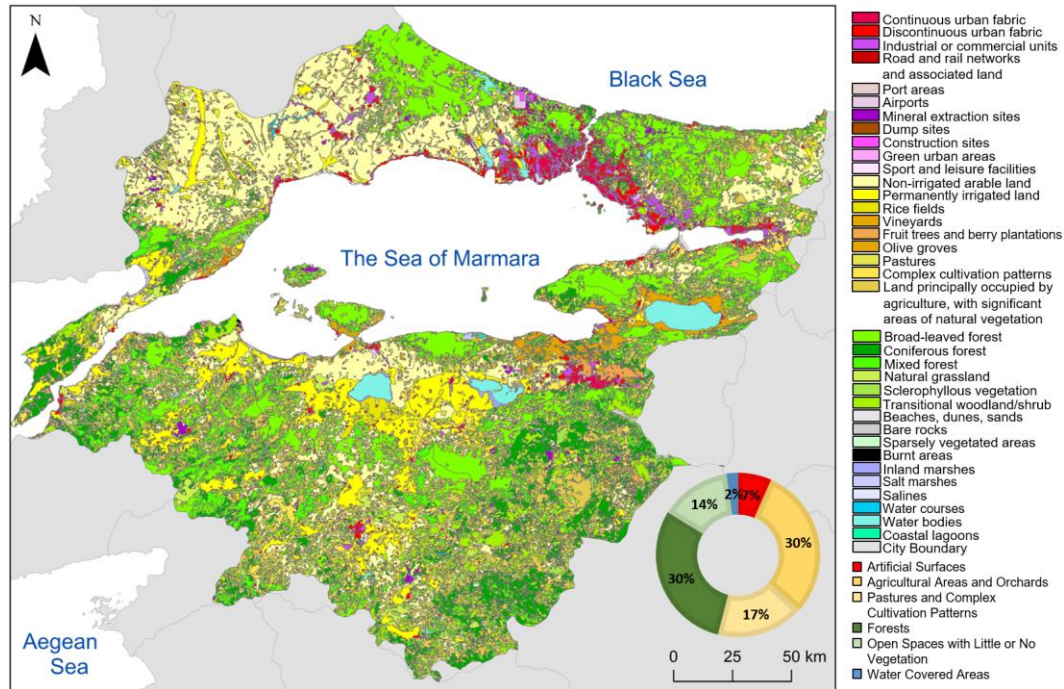


Figure 4.9 : Generated LU/LC map of coastal cities along the Sea of Marmara for 2021.

When examining the recently produced LU/LC map (Figure 6.11), it can be observed that the artificial surfaces (~285528 ha) including urban fabric, industrial and/or commercial units, transportation network and associated land, port areas, airports, construction sites, sport and leisure facilities are particularly massed in metropolitan cities of İstanbul, Kocaeli and Bursa. The areas primarily used for agricultural purposes (~1291573 ha) including agricultural areas, orchards, pastures, and complex cultivation patterns were predominantly concentrated in Balıkesir, Çanakkale, and Tekirdağ. Water covered areas were primarily focused on the boundaries of Bursa and Balıkesir covering an area of approximately 97859 ha. The distribution of the combined classes in the coastal cities is shown in Figure 4.10. In addition, LU/LC maps of each city are separately demonstrated in Figure 4.10a-g.

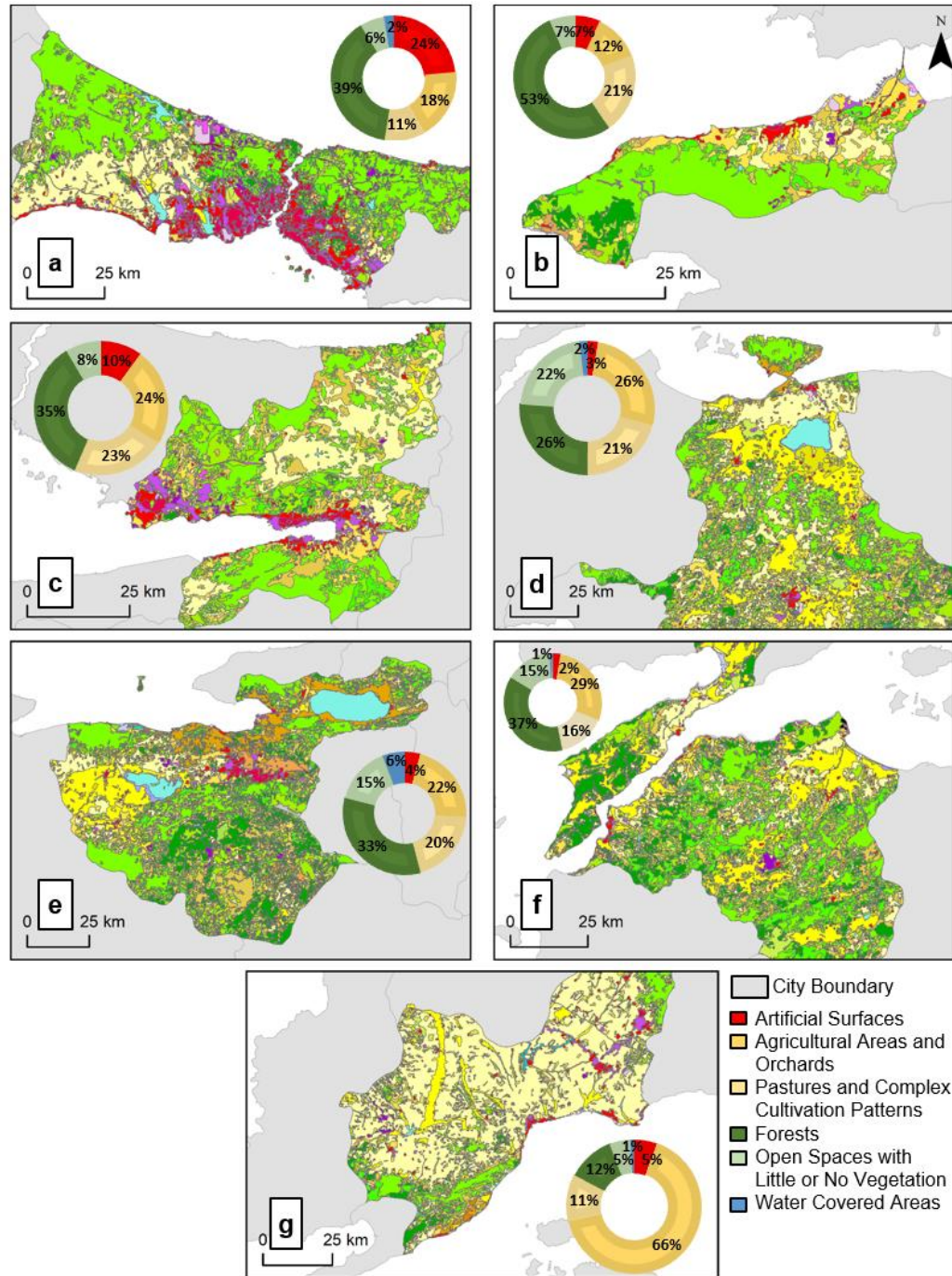


Figure 4.10 : LU/LC maps of 2021 and areal distribution of a) İstanbul, b) Yalova, c) Kocaeli, d) Balıkesir, e) Bursa, f) Çanakkale, and g) Tekirdağ.

Figure 4.10a reveals that forests cover 39% of İstanbul, with the second largest portion occupied by artificial surfaces by 24%. These artificial surfaces are notably concentrated along the Sea of Marmara. Similarly, forests cover a significant area in Yalova. More than half of the city land is covered by forests, while pastures and complex cultivation patterns contribute significantly, accounting to 21% (Figure 4.10b). Figure 4.10c demonstrates that forests cover 35% of Kocaeli. Agricultural areas and orchard class, and pastures and complex cultivation pattern class share

similar portions of 24% and 23%, respectively. Similar to İstanbul, artificial surfaces in Kocaeli, comprising of 10%, are prominently concentrated along the coast. Figure 4.10d demonstrates that the largest shares belong to the forest class and agricultural areas and orchard class, each addressing 26%, while artificial surfaces cover just 3% in Balıkesir. As seen in Figure 4.10e, forests cover 33% of Bursa. Additionally, agricultural areas and orchard class, and pastures and complex cultivation pattern class are nearly evenly distributed, making up 22% and 20% respectively. Among all cities that are shown in Figure 4.10, Bursa stands out with the largest portion of water-covered areas, making up 6% of its total area. Figure 4.10f highlights that forests dominate 37% of Çanakkale, and agricultural areas and orchard class account for the second largest portion of 29%. On the other hand, Tekirdağ stands out with 2/3 of its area covered by pastures and complex cultivation patterns (Figure 4.10g).

Due to the significant impact of LU/LC on the water quality of the Sea of Marmara, this study investigates the LU/LC changes of the coastal cities alongside across 6 sequential periods of 1990-2000, 2000-2006, 2006-2012, 2012-2018, 2018-2021 and 1990-2021.

To better understand the urban agglomeration, the location of the ports and industries were detected in the study. Furthermore, due to the significance of the interaction between land and sea, the lengths of the coastlines of each city along the sea were also examined. The percent distribution of these coastlines along with the locations of ports and main industries, which are important for the water quality of the sea (Öztürk et al., 2021), are illustrated in Figure 4.11a. Among the 7 cities that surround the Sea of Marmara, Çanakkale has the longest coastline of approximately 537 km followed by İstanbul with approximately 408 km. With a population of nearly half a million people (TURKSTAT, 2022a), the coastline of Çanakkale still remains sparsely populated. Although İstanbul comes the second with 23% share of the total coastline, it stands out with the highest urban density and exerting the greatest environmental impact on the sea. Balıkesir comes in third place with a 17% share of the total coastline, spanning approximately 303 km. The remaining cities have share of the total coastline under 10%. Tekirdağ, Bursa, Kocaeli, and Yalova span approximately 138 km, 147 km, 148 km, and 119 km, respectively.

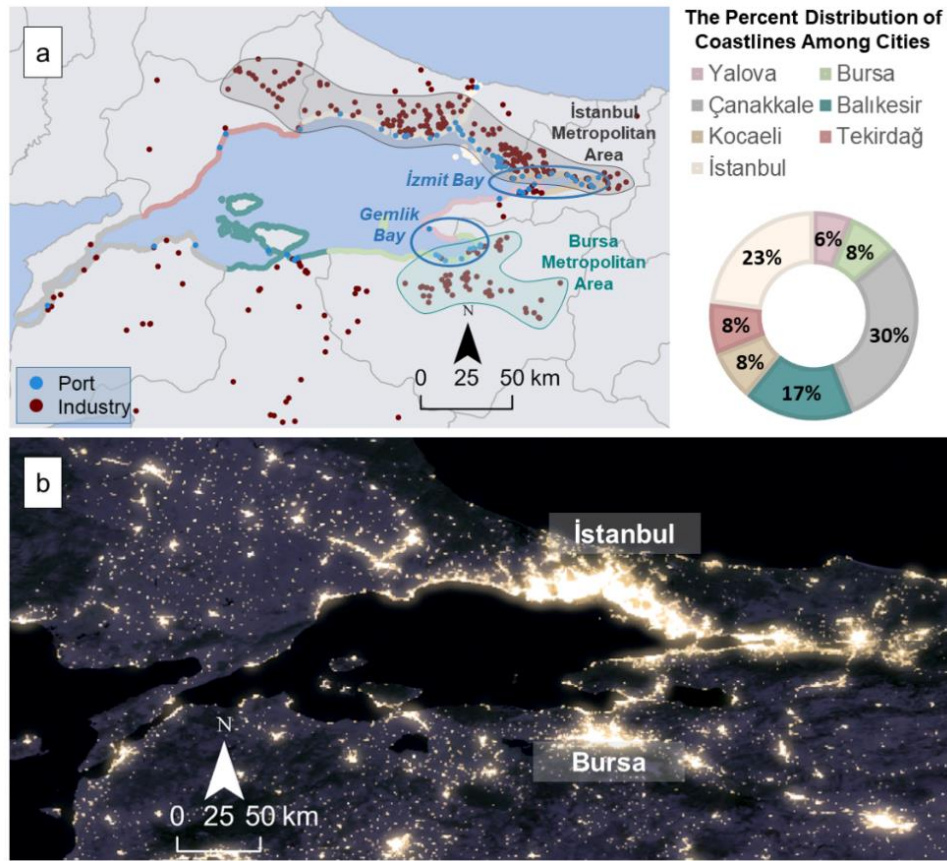


Figure 4.11 : a) Length of city coastlines along the Sea of Marmara with the location of ports and main industries. İstanbul Metropolitan Agglomeration is shown as dark grey area, Bursa Agglomeration is shown in green area, b) Night time view of city lights around the Sea of Marmara (NASA Worldview Snapshots, 2017).

The northern coast of the Sea of Marmara encompassing the shores of İstanbul, Kocaeli and Tekirdağ is home to one of the largest urban agglomerations in the world, with a population of more than 19 million people (TURKSTAT, 2022a; Caglayan et al., 2020). İstanbul Greater Metropolitan cluster, shown in dark grey filled region in Figure 4.11a, spans a length of approximately 220 km in east-west direction, and is gathered around the urban core of İstanbul (Kaygalak & Reid, 2016). On the southern coast of the sea, the urban agglomeration centered around the urban core of Bursa, shown in green filled region in Figure 4.11a, hosts more than 3 million people (TURKSTAT, 2022a). These two metropolitan clusters benefit from their special location as they are located on the crossroad of maritime lines between Black Sea and Mediterranean Sea, furthermore İstanbul Strait and Dardanelles bridge Asian and European continents. Densely industrialized İstanbul, Kocaeli, and Bursa metropolitan areas are directly connected to one of the busiest shipping lines in the world via ports located on the southern coast of İstanbul, İzmit Bay, and Gemlik Bay as shown in

Figure 4.11a. Due to their strategic location, these metropolitan areas along the Sea of Marmara are rapidly interconnected with each other through the development of new highways, high-speed train lines, and the busiest commuter ferry lines in the world (Lester, 2015). The map of roads and railways retrieved from Open Street Map (OSM) and ports is shown in Figure 4.12 (Url-12). Consequently, these metropolitan areas are in the process of forming a megalopolis belt area along the eastern coast of the Sea of Marmara, centered around multiple urban cores (Fang & Yu, 2017). The cluster of cities that forms this megalopolis around the coast of the sea can be best observed in the nighttime view of the city lights as shown in Figure 2.5b (NASA Worldview Snapshots, 2017; Uysal et al., 2018).

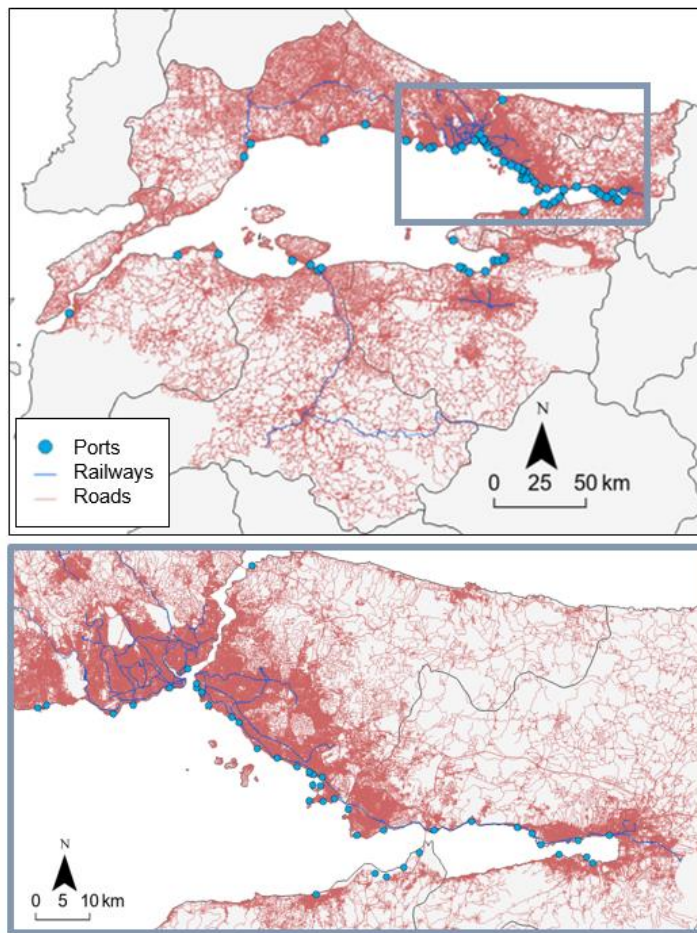


Figure 4.12 : The map of roads and railways retrieved from OSM (Url-12).

Comparison of the maps from 1990 to 2021 revealed the changes over a span of 31 years. LU/LC change of the coastal cities between 1990 and 2021 is illustrated in Figure 4.13.

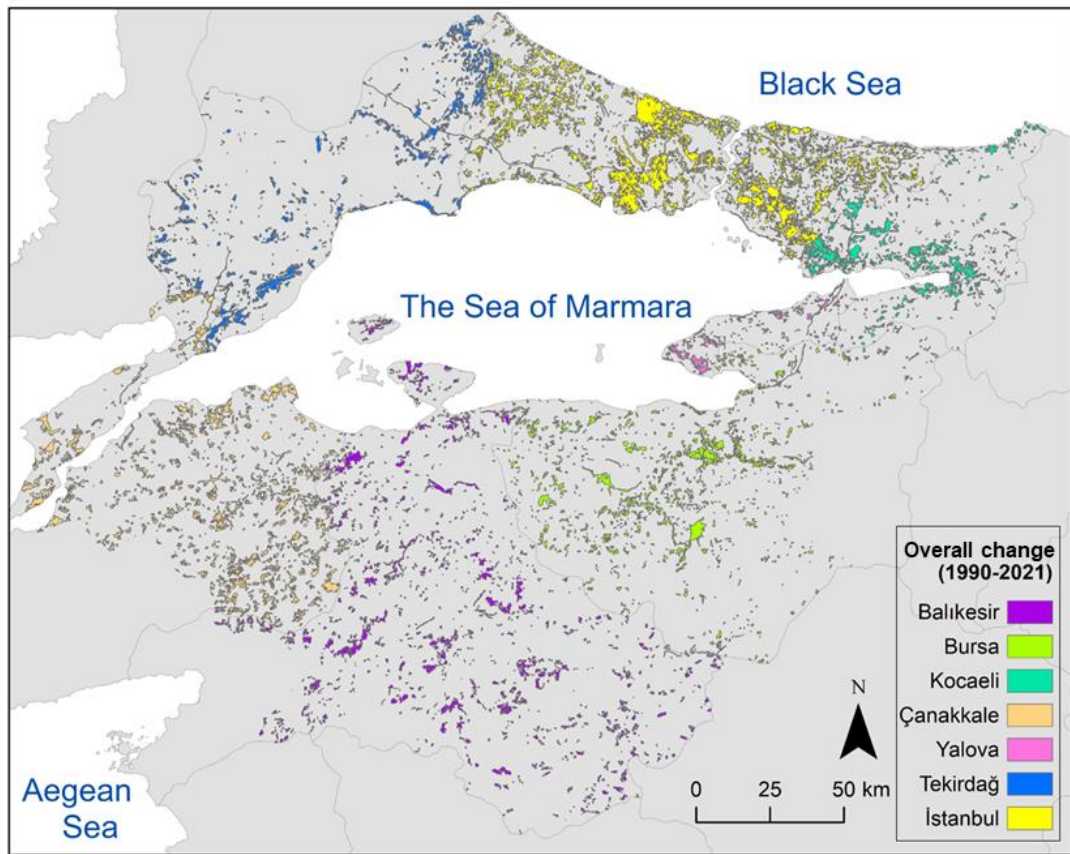


Figure 4.13 : Overall LU/LC change of the coastal cities between 1990-2021.

Between 1990 and 2021, İstanbul represented 36% of the overall LU/LC change. Following that, significant changes were observed in Çanakkale with 16%, and Balıkesir with 15%. Bursa contributed %12 to the change. Tekirdağ, Kocaeli, and Yalova contributed 11%, 8%, and 2%, respectively. Comparatively the most substantial changes that has occurred between the long inspection term are İstanbul, Çanakkale and Balıkesir; therefore, areal distributions of these remarkable changes among the 6 classes are focused on as depicted in Figure 4.14.

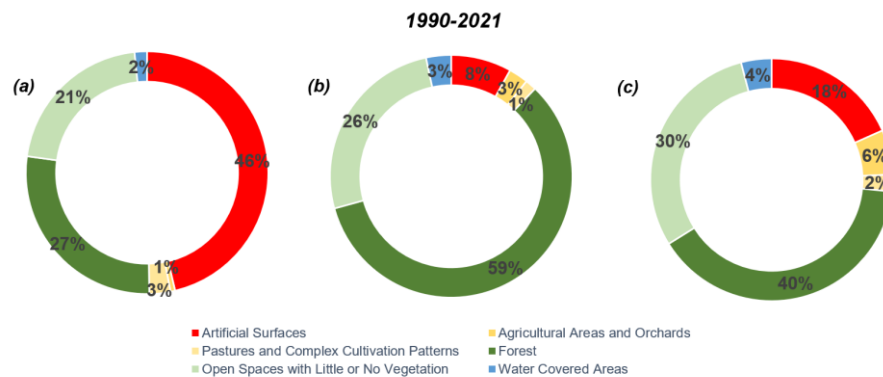


Figure 4.14 : LU/LC change per class during 1990 - 2021 in a) İstanbul, b) Çanakkale and c) Balıkesir.

Through analyzing Figure 4.14a, it becomes apparent that the most significant change in İstanbul between 1990-2021 occurred in the artificial surface with a share of 46%. Following that, secondary significant change was observed in the forest areas with 27%. On the other hand, the most significant changes were observed in forest areas in Çanakkale (Figure 4.14b) and Balıkesir (Figure 4.14c) with 59% and 40%, respectively. The secondary significant change in Çanakkale (Figure 4.14b) and Balıkesir (Figure 4.14c) were observed in the open spaces with little or no vegetation with a share of 26% and 30%, respectively.

In İstanbul, between 1990-2000, the most significant changes occurred in artificial surfaces. An area of approximately 35149 ha, comprising agricultural areas and orchards, pastures and complex cultivation patterns, forests, open spaces with little or no vegetation, water covered areas, was converted into other land use subclasses within artificial surfaces. This drastic change was inevitable as the city hosted a giant urban sprawl based on migration from the other cities due to employment opportunities. Following that, an area of 26566 ha of open spaces with little or no vegetation was converted into forests. This was also a must to keep the metropolitan area as a livable city.

From 2000 to 2006, the most substantial change was observed in the forested areas, accounting for 42% of the transformation, equivalent to an approximately 11800 ha of open spaces with little or no vegetation converted into forested regions. Over this period, İstanbul's population increased by around 12% (TURKSTAT, 2022a). In this period, an area of 3835 ha, encompassing agricultural areas and orchards, pastures and complex cultivation patterns, forests, open spaces with little or no vegetation, water covered areas, was converted into other land use subclasses within the artificial surfaces. During the period of 2006-2012, the population of İstanbul increased by again 12% (TURKSTAT, 2022a) and an area of 13498 ha encompassing all 6 combined class was converted into other land use subclasses within the artificial surfaces. Following that, nearly 10 000 ha of open spaces with little or no vegetation was converted into forest areas. During the period of 2012-2018, the population of the İstanbul increased by 9% (TURKSTAT, 2022a), and an area of 18249 ha comprising six combined classes was converted into other land use subclasses within the artificial surfaces. To assess the recent situation in İstanbul, the period from 2018 to 2021 was examined. Within this timeframe, the population of the city increased by 5% (TURKSTAT, 2022a) and approximately 67% of the change occurred in the artificial

surfaces. An area of 5839 ha across all of six combined classes converted into other land use subclasses within the artificial surfaces. Besides, 2369 ha area of forest was converted into open spaces with little or no vegetation. The most remarkable words that may be spent for Istanbul is that, the urban sprawl has continued in the all sequential terms of inspection pointing out the continuous interest to the city. The urban sprawl has also been accelerated through the migration to the city from Russia, Ukraine and some of the Asian, Middle East countries due to the unstable conditions they were facing (TURKSTAT, 2022b).

In Bursa, during the period from 2000 to 2006, the largest change amounting to 34%, was observed in the forest areas and open spaces with little or no vegetation. Additionally, an area of approximately 5880 ha of open spaces with little or no vegetation and forest areas, underwent a conversion process in Bursa. When examining the changes between 2018 and 2021, it was found that a total area of approximately 854 ha, consisting of agricultural areas and orchards, pastures and complex cultivation patterns, open spaces with little or no vegetation, and forests, had been converted to artificial surfaces. This recent conversion act is also due to the need to open new residential sides to house the new incomers to the city. Bursa also received a noticeable increase in the number of immigrants (TURKSTAT, 2022b).

In Kocaeli, where industrial activities were concentrated, except for the period between 2018 and 2021, the majority of changes were observed in the artificial surface class. During 2012-2018 and 2018-2021 periods, the most significant change occurred in open spaces with little or no vegetation. Totally, 5401 ha of forest-covered areas were converted into open spaces with little or no vegetation between 2012 to 2021. This variation is mostly to gain more space for establishing new residents.

In Yalova, during the periods of 1990-2000 and 2000-2006, the most significant change was observed in forested areas. In the periods of 2006-2012 and 2018-2021, the largest changes were observed in open spaces with little or no vegetation. The time period that observed the greatest change in artificial surface was 2012-2018, with an area of approximately 1154 ha. When examining more recent changes in Yalova, it was observed that the forest area, covering approximately 802 ha, underwent conversion to open spaces with little or no vegetation from 2018 to 2021.

In Balıkesir, while the most noticeable changes occurred in forested areas during the period from 1990 to 2000, significant changes were observed in open spaces with little or no vegetation during the periods between 2000 – 2006 and 2006 - 2012. The most

substantial change was observed during the period of 2018-2021 in artificial surfaces. From 2018 to 2021, an area of approximately 995 ha, there was a conversion of agricultural areas and orchards, pastures and complex cultivation patterns, forests, and open spaces with little or no vegetation into artificial surfaces.

In Çanakkale, during the first 3 periods, the most significant changes were observed in forested areas, whereas the largest change between 2012 and 2018, covering an area of approximately 2089 ha, occurred in open spaces with little or no vegetation. In the final period, the most substantial change was observed in artificial surfaces, where agricultural areas and orchards, pastures and complex cultivation patterns, forests, and open spaces with little or no vegetation were converted into artificial surfaces, totaling an area of approximately 1256 ha from 2018 to 2021.

In Tekirdağ, the most significant changes were observed in forests during the first 3 periods. However, the largest change occurred in artificial surfaces during the most recent 2 periods. An area of approximately 1427 ha, consisting of artificial surfaces, agricultural areas and orchards, forests, and open spaces with little or no vegetation, was converted into artificial surfaces from 2018 to 2021.

LU/LC changes in the coastal cities along the Sea of Marmara between 1990 and 2021 were tabulated in Table 4.4. The similar conditions of gaining more barren space for fulfilling the demand of more residential sites also prevail in all the coastal cities surrounding the Sea of Marmara. This actually is an expected situation all around the world as interest to residing in coastal cities rather than inner hinterlands has been favored throughout history (Pomianowski & Doburzyński, 2021; Hegazy, 2021).

Table 4.4 : LU/LC changes in the coastal cities along the Sea of Marmara between 1990 and 2021.

Year	City	Artificial Surfaces [ha]	Agricultural Areas and Orchards [ha]	Pastures and Complex Cultivation Patterns [ha]	Forest [ha]	Open Spaces with Little or No Vegetation [ha]	Water Covered Areas [ha]
1990	İstanbul	73081	115314	61154	221192	64356	10945
	Kocaeli	13672	83380	52226	131139	26481	213
	Yalova	2183	10323	17467	43286	5604	-
	Bursa	13801	198897	186394	276379	167019	49523
	Balıkesir	16910	263920	297154	293629	324625	19637
	Çanakkale	10502	168588	95538	206173	157136	3628
	Tekirdağ	15966	403556	90058	55792	51220	2266
	Total	146114	1243977	799992	1227590	796441	86211
2021	İstanbul	129259	100217	57889	212227	35082	12986
	Kocaeli	30701	72736	69470	107015	26390	980
	Yalova	5055	9922	16610	41921	5181	310
	Bursa	37410	195640	177363	294347	136557	50832
	Balıkesir	32655	321173	254548	317373	268546	21632
	Çanakkale	16213	183028	101374	236156	98792	5993
	Tekirdağ	34235	408856	68943	71429	30512	5126
	Total	285528	1291573	746196	1280469	601060	97859
Change (ha)		139414	47596	-53796	52879	-195381	11648
Change (%)		+95	+4	-7	+4	-25	+14

During 31-years between 1990 and 2021 (Table 4.4), significant changes were observed in the coastal cities' LU/LC. The most substantial increase amounting to 95% (Table 4.4) occurred in artificial surfaces. The reason is that the cities like İstanbul, Kocaeli and Bursa provide numerous job opportunities, education opportunities and own well-developed transportation systems (Demir et al., 2021; Satir et al., 2023). Besides, a 14% increase (Table 4.4) was recorded in the water covered areas, attributed to the construction of surface water collection structures such as dams, ponds and reservoirs especially in Istanbul. These constructions were necessary to meet the growing water demand of the densely populated cities, where industrial and agricultural facilities are intensified. Furthermore, these results provide clear evidence of the preservation of agricultural areas and orchards from 1990 to 2021. In addition, the implementation of greening activities has yielded positive outcomes in the forest areas. These regions experienced a notable increase of 4% (Table 4.4) between 1990 and 2021. On the other hand, a significant decline of 25% (Table 4.4) was observed in the open spaces with little or no vegetation. These areas underwent conversion into artificial surfaces from 1990 to 2021, following a similar trend seen in many cities worldwide (Cole et al., 2018). Another decrease was observed in pastures and complex cultivation patterns.

Furthermore, one of the results obtained by comparing the maps from 1990 and 2021 is the identification of more land reclamation areas over time. This study recognized a total land reclamation area of 2359 ha, with 1762 ha located along the Sea of Marmara coast and the remaining 597 ha along the Black Sea coast. Within the Sea of Marmara Region, the majority of the land reclamation areas were observed along Istanbul coasts. However, notable land reclamation areas were also detected along the coasts of Kocaeli and Yalova.

To assess the land-sea interaction more comprehensively, discharge, WWTPs (Wastewater Treatment Plants), current, and drainage network data were used as shown in Figure 4.15 (Meriç et al., 2018; Musaoğlu et al., 2022). Urban WWTPs are seen in city centers like İstanbul, İzmit, and Bursa. Domestic discharges are more concentrated in suburban areas, particularly around İstanbul, Bursa, and Kocaeli. While Industrial WWTPs were densified in İstanbul, İzmit Bay, Tekirdağ and Bursa, they are also seen in agricultural areas like as Susurluk Basin. Industrial, domestic and urban discharges are contributors to point source pollution. Pollution from these point sources can be transported to the Sea of Marmara via rivers. WWTPs located around

the sea impact water quality of the Sea of Marmara. Furthermore, the surface currents are depicted in the Figure 4.15, which lead to the spread of this pollution.

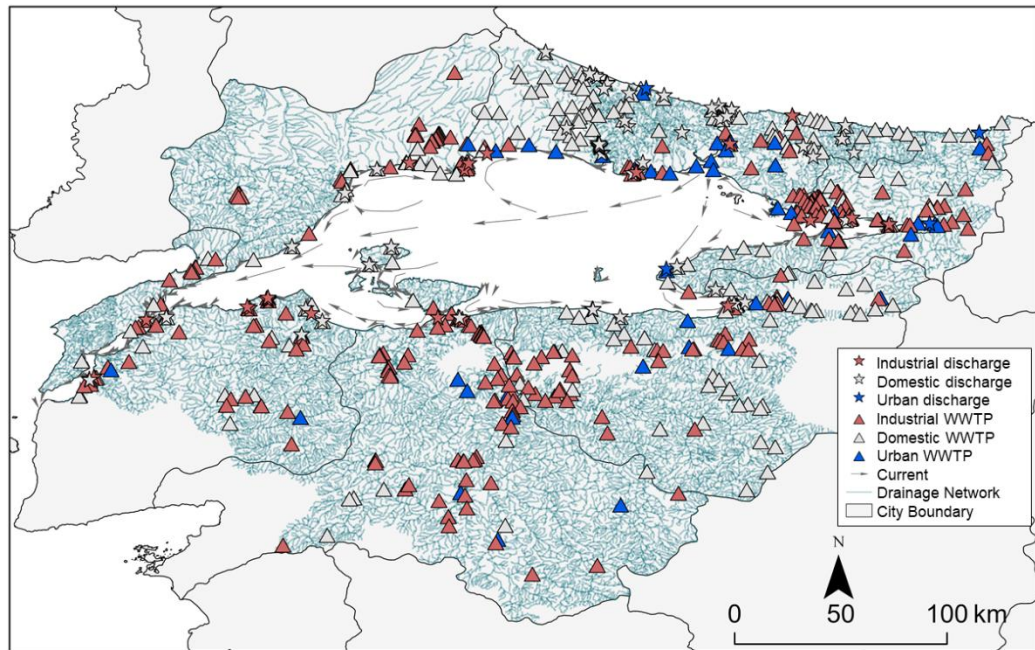


Figure 4.15 : Assessing land-sea interaction through discharge, WWTPs, currents, and drainage network data, adapted from the studies of Meriç et al. (2018) and Musaoğlu et al. (2022).

When all of the produced results and used ancillary data were compiled together, the land and sea interaction of the sea can be explained with the Figure 4.16.

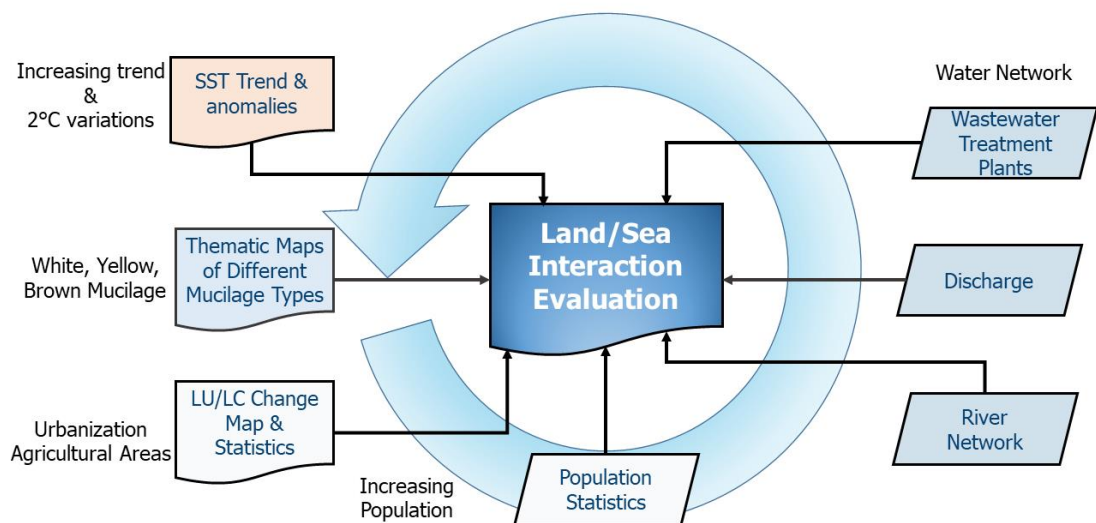


Figure 4.16 : The diagram illustrating the land and sea interaction.

The produced temporal LU/LC change maps reveal an expansion in both urban and agricultural areas. Accompanying this growth, there has been an increase in the

population within the Sea of Marmara region (TURKSTAT, 2022a). Pollutants originating from these urban and agricultural areas are carried via the river network and eventually discharged into the sea. In addition, pollutant loads from wastewater treatment plants are also carried through the water network to the sea. This situation is one of the reasons for the observed increase in SST. The study detected an increasing SST trend, characterized by variations of up to 2°C, which is one of the possible causes for the formation of the mucilage. This cycle is important in terms of evaluating the land and sea interaction.



5. DISCUSSION

This study elucidates detection of the white, the yellow and the brown mucilage accumulations in İzmit Bay region in the Sea of Marmara by using medium- (Sentinel-2) and high-spatial-resolution (Worldview-3) satellite images. The spectral reflectance curves of these stated three types of mucilage were clearly displayed and analyzed in detail. Based on the spectral information findings retrieved from multi-scale data, the areal extents of different mucilage types in İzmit Bay region were detected.

Structure and chemical content of the mucilage accumulations can change with time and with the increase of organic substance and pathogen concentrations they give off bad odor. Different mucilage types have different effects on the marine life in different regions in the world oceans. Further information on mucilage should be obtained to detect and pay special attention to the areas that need more urgent cleaning. Although there are case studies about the discrimination between mucilage and water covered areas (Acar et al., 2021; Abaci et al., 2022; Hu, 2022) and examining spectral reflectances of the mucilage in the Sea of Marmara (Hu et al., 2022), the areal extents and spectral characteristics of the different colored mucilage types, which are the white mucilage, the yellow and the brown mucilage, still remain unknown. This study presents further information on classifying mucilage based on its color characteristics by using the advantage of a high spatial resolution satellite image and also, shows the spectral reflectance curves of these different types of mucilage by using multi-scale satellite images. Utilization of high spatial resolution images is critical for the purpose of examining the characteristics of the different mucilage types.

Investigation of the spectral curves that belong to different types of mucilage is also important to differentiate mucilage and other pollution types such as marine debris as proposed by Hu et al., (2022). When the spectral reflectance curves of the mucilage (Figure 3.4 and Figure 3.5) were examined, it was seen that it has higher reflectance values than water covered areas especially in the region between 725 – 950 nm. In the study carried out by Hu et al., (2022) a decrease in the reflectance of the mucilage was observed around 670 nm, which was used to differentiate the mucilage from marine

debris. In this study, similar decrease in reflectance value around 665 nm and 660 nm was observed for all types of the mucilage with the Sentinel-2 image and Worldview-3 satellite image, respectively. While all of the three types of the mucilage can be detected by using Worldview-3 satellite image, only white and yellow mucilage types can be detected by using Sentinel-2 data because of having lower spatial resolution. After the two-way ANOVA test was applied, P-values in Table 4.1 show that there is a significant difference between spectral reflectance curves belong to different mucilage types.

In addition, although small accumulations of the mucilage cannot be detected by the Sentinel-2 satellite data, they can be detected by the Worldview-3 satellite image, so that higher accuracy values are obtained with the Worldview-3 data. Thus, Worldview-3 satellite image was found as an appropriate data to determine mucilage covered areas in higher detail. Besides, in the classification results that were shown in Figure 4.2 and Figure 4.3, it was seen that white mucilage was present mainly on offshore regions, while yellow and brown mucilage were present mainly on coastal areas. This observation can be explained with the accumulations of denser yellow and brown mucilage structures in the coastal regions by winds and currents. Current and wind data were obtained from the study of Ilicak et al. (2021) and Windy application (Url-22). During the ageing process of the yellow mucilage, organic substances and pathogen concentrations can increase, so that spectral reflectance of the mucilage changes (Mingazzini et al., 1995; Mecozzi et al., 2005), hence the brown mucilage forms within the yellow mucilage accumulations especially in semi-enclosed stagnant coastal regions that are less affected from the dispersing effects of the currents and winds. Besides, high spatial resolution enables discrimination of three different types of mucilage and smaller patches of white mucilage.

Besides the mucilage events in the recent decade, the Sea of Marmara has been also under effect of red tides (Turkoglu, 2013) and algal blooms (Turkoglu, 2016). Based on these past events, the Sea of Marmara and other similar water bodies may encounter with another phenomenon that was not observed in this region before. Furthermore, as proposed by Hu et al. (2022), mucilage phenomenon may be more common than detected. At this point, the findings about the spectral reflectance curves of different mucilage types contribute to the detection and monitoring efforts of different pollution events such as mucilage. As observed in this study, the white and the yellow mucilages

cover extensive areas especially in offshore regions, which necessitates remote sensing applications for detection.

To assess the land and sea interaction, investigation of LU/LC changes along the coastal cities in the Sea of Marmara is crucial. In the literature, urban growth in Istanbul was examined between 2006 and 2012 (Genel & Guan, 2021) and 1990 and 2018 (Bozkurt et al., 2023) using CLC datasets. In the current study, 2021 LU/LC classes, which are compatible with CORINE, were detected and a longer temporal span from 1990 to 2021 was considered to detect temporal changes more comprehensively. In the present study, similar findings were discovered regarding the increase in artificial areas in Istanbul closely paralleling the findings from the studies of Genel & Guan, (2021) and Bozkurt et al. (2023).



6. CONCLUSION

This chapter includes the conclusion part related to the findings of the marine mucilage and SST variations in the Sea of Marmara, and LU/LC of the surrounding land.

Satellite imageries are indispensable sources in order to bring the mucilage occurrence under control in a time and cost-effective way because of having capability to observe offshore areas with wide range of the electromagnetic spectrum. Mucilage has a viscous structure and can be dragged by the ships and can be seen as linear features in the satellite images. Thus, it can be distinguished by applying textural analysis to Sentinel-2 and Worldview-3 satellite images (Figure 4.1). A combination of spectral and spatial features was defined in the input space of the classification, leading to an improvement in the accuracy of the classification.

The classification results (Figure 4.2 and Figure 4.3) show that both Sentinel-2 and Worldview-3 satellite sensors were capable of discriminating mucilage from non-mucilage water. However, the spatial resolution of Worldview-3 provided better distinction between different mucilage types. While the spatial resolution of the Sentinel-2 data allows to discriminate white and yellow mucilage, the spatial resolution of the Worldview-3 data allows to discriminate all of the considered mucilage types. In particular, these three different types of mucilage can be detected effectively with spectral differences ranging from 725 to 950 nm. Therefore, near infrared region is the most proper region of the electromagnetic spectrum for discrimination of different types of mucilage and water. The accumulations of mucilage in coastal parts were detected more accurately by using Worldview-3 rather than Sentinel-2 satellite image. By using Worldview-3 satellite image higher accuracies were achieved due to higher spatial resolution when compared to Sentinel-2 data.

The SST, which is one of the possible causes of the mucilage formation, was investigated by using NOAA OISST V2, Sentinel-3 and Landsat-8 data. SST and SSTAs of the Sea of Marmara were comprehensively evaluated during the period of 1990 to 2021 by applying STL to NOAA OISST V2 data, and the SST results were

verified based on multi-source satellite images and in-situ measurements. Landsat-8 (RMSE = 1.68°C, bias = 0.89°C) and Sentinel-3 (RMSE = 1.19°C, bias = -0.25°C) satellite images were found as suitable data to monitor the study area.

Another probable cause of the mucilage formation, a detailed analysis was conducted to determine the LU/LC changes in the long-term (1990-2021) in coastal cities along the Sea of Marmara in this study. To this end, LU/LC detection was carried out for coastal cities along the Sea of Marmara in 2021, ensuring compatibility with CORINE classes. This compatibility is crucial for conducting temporal change analysis using CORINE CLC data. The LU/LC changes in the cities along the Sea of Marmara were investigated in different periods, which are 1990-2000, 2000-2006, 2006-2012, 2012-2018, 2018-2021 and 1990-2021 based on CLC dataset and on free Sentinel-2 satellite images. Based on the results, it was observed that while there is increase in artificial surfaces (95%), water covered areas (14%), agricultural areas and orchards (4%), and forests (4%), there is decrease in open spaces with little or no vegetation class (25%) and pastures and complex cultivation patterns class (7%) from 1990 to 2021. In addition, it was observed that 1762 ha area was detected as land reclamation areas along the coast from 1990 to 2021.

Comprehensive remote sensing applications to the water bodies may reveal new mucilage events and help to the scientific community for understanding of formation of mucilage and detection of regions that are prone to the mucilage phenomenon. Choosing the proper satellite image is important to achieve reliable insights in environmental monitoring. The main contribution of this study is comparing the capabilities of Sentinel-2 and Worldview-3 satellite images for the purpose of detecting different colored mucilage types. Sentinel-2 satellite data, with its capability to discriminate two different colored mucilage types, offers a cost-effective and valuable option that is sufficient for general mucilage monitoring purposes. Large swath width of Sentinel-2 data, which is freely available, offers opportunities for investigation of the extent of the mucilage coverage in a large region such as the Sea of Marmara. However, since WorldView-3 satellite data, which has capability to discriminate three different colored mucilage types ability to increase accuracy, is recommended for more detailed mucilage monitoring.

On the other hand, advantages of different types of satellites were also utilized to detect SST in this study. NOAA OISST V2 dataset is a feasible dataset for long-term SST

and SSTA detections since it has high temporal resolution. Although NOAA OISST V2 that has its own anomaly band, it is under the trend effect. Trend eliminated residuals can be obtained by applying STL method to NOAA OISST V2 data. Sentinel-3 data enables to monitor spatial SST variations in the entire sea with 1 km spatial resolution. Landsat has adequate spatial resolution to monitor SST distribution in detail, because of the swath width, the entire sea could not be simultaneously monitored. It is advisable to use the combination of multi source data to maximize the benefits of NOAA OISST V2, Sentinel-3 and Landsat data in SST detection.

Similar to choosing the proper satellite data, ensuring data consistency and standardization is crucial, particularly for LU/LC dynamics monitoring. Utilizing CORINE classes enables standardization in detecting LU/LC dynamics. This simplifies comparisons between LU/LC 2021, which was generated in this study, and forthcoming CLC 2024 data.

The practical methodology for detection of different types of mucilage, its possible causes like SSTA and increasing SST trend, and changes in LU/LC presented in this study can provide a valuable information in terms of environmental sustainability. Methodology followed in this study will be highly useful to detect land/sea interaction for especially developing countries and for particularly metropolitan cities where the urban sprawl is remarkable and irrepressible.



REFERENCES

- Abaci, B., Dede, M., Yüksel, S. E., & Yilmaz, M.** (2022). Mucilage detection from hyperspectral and multispectral satellite data. *Proc. SPIE 12094, Algorithms, Technologies, and Applications for Multispectral and Hyperspectral Imaging XXVIII*, 120940H.
- Acar, U., Yilmaz, O. S., Çelen, M., Ateş, A. M., Gülgen, F., & Balık Şanlı, F.** (2021). Determination of mucilage in the Sea of Marmara using remote sensing techniques with Google Earth Engine, *International Journal of Environment and Geoinformatics*, 8(4), 423–434.
- Ai, B., Wen, Z., Jiang, Y., Gao, S., & Lv, G.** (2019). Sea surface temperature inversion model for infrared remote sensing images based on deep neural network, *Infrared Physics and Technology*, 99, 231–239.
- Alcoverro, T., Conte, E., & Mazzella, L.** (2000). Production of mucilage by the adriatic epipelagic diatom *Cylindrotheca closterium* (Bacillariophyceae) under nutrient limitation, *Journal of Phycology*, 36(6), 1087–1095.
- Alparslan, E., Coskun, H. G., & Alganci, U.** (2009). Water quality determination of Küçükçekmece Lake, Turkey by using multispectral satellite data, *TheScientificWorldJournal*, 9, 1215–1229.
- Anderson, J. R., Hardy, E. E., Roach, J. T., & Witmer, R. E.** (1976). A land use and land cover classification system for use with remote sensor data, Geological Survey Professional, pp 964, United States Government Printing Office, Washington.
- Avdan, U., & Jovanovska, G.** (2016). Algorithm for automated mapping of land surface temperature using LANDSAT 8 satellite data, *Journal of Sensors*, 2016(1480307), 1–8.
- Baatz, M., & Schäpe, A.** (2000). Multiresolution Segmentation: An optimization approach for high quality multi-scale image segmentation. In: Strobl, J., Blaschke, T. and Griesbner, G., (Eds.), *Angewandte Geographische Informations-Verarbeitung* (pp. 12–23), XII, Wichmann Verlag, Karlsruhe, Germany.
- Bakr, N., & Afifi, A. A.** (2019). Quantifying land use/land cover change and its potential impact on rice production in the Northern Nile Delta, Egypt. *Remote Sensing Applications: Society and Environment*, 13, 348–360.
- Balkis, N., Atabay, H., Türetgen, I., Albayrak, S., Balkis, H., & Tüfekçi, V.** (2011). Role of single-celled organisms in mucilage formation on the shores of Büyükada Island (the Marmara Sea), *Journal of the Marine Biological Association of the United Kingdom*, 91(4), 771–781.
- Berthon, J. F., Zibordi, G., & Hooker, S. B.** (2000). Marine optical measurements of a mucilage event in the northern Adriatic Sea, *Limnology and Oceanography*, 45(2), 322–327.

- Beşiktepe, Ş. T., Sur, H. İ., Özsoy, E., Latif, M. A., Oğuz, T., & Ünlüata, Ü.** (1994). The circulation and hydrography of the Marmara Sea, *Progress in Oceanography*, 34(4), 285–334.
- Birhanu, L., Hailu, B. T., Bekele, T., & Demissew, S.** (2019). Land use/land cover change along elevation and slope gradient in highlands of Ethiopia, *Remote Sensing Applications: Society and Environment*, 16, 100260.
- Bolhuis, H., & Cretoiu, M. S.** (2016). The marine microbiome: An untapped source of biodiversity and biotechnological potential. In *In The Marine Microbiome; What is so special about marine microorganisms? Introduction to the marine microbiome—from diversity to biotechnological potential: Vol. Springer, Chamber* (pp. 3–20). Springer International Publishing.
- Bozkurt, S. G., Kuşak, L., & Akkemik, Ü.** (2023). Investigation of land cover (LC)/land use (LU) change affecting forest and seminatural ecosystems in Istanbul (Turkey) metropolitan area between 1990 and 2018, *Environmental Monitoring and Assessment*, 195(399).
- Caglayan, İ., Yeşil, A., Cieszewski, C., Gül, F. K., & Kabak, Ö.** (2020). Mapping of recreation suitability in the Belgrad Forest Stands, *Applied Geography*, 116, 102153.
- Chan, H. P., Konstantinou, K. I., & Blackett, M.** (2021). Spatio-temporal surface temperature variations detected by satellite thermal infrared images at Merapi volcano, Indonesia, *Journal of Volcanology and Geothermal Research*, 420, 107405.
- Chawla, I., Karthikeyan, L., & Mishra, A. K.** (2020). A review of remote sensing applications for water security: Quantity, quality, and extremes, *Journal of Hydrology*, 585, 124826.
- Chiggiato, J., Jarosz, E., Book, J. W., Dykes, J., Torrisi, L., Poulain, P. M., Gerin, R., Horstmann, J., & Beşiktepe, Ş.** (2012). Dynamics of the circulation in the Sea of Marmara: numerical modeling experiments and observations from the Turkish straits system experiment, *Ocean Dynamics*, 62, 139–159.
- Cleveland, R. B., Cleveland, W. S., McRae, J. E., & Terpenning, I.** (1990). STL: A seasonal-trend decomposition procedure based on loess, *Journal of Official Statistics*, 6(1), 3–73.
- Cole, B., Smith, G., & Balzter, H.** (2018). Acceleration and fragmentation of CORINE land cover changes in the United Kingdom from 2006–2012 detected by Copernicus IMAGE2012 satellite data. *International Journal of Applied Earth Observation and Geoinformation*, 73, 107–122.
- Colkesen, I., Kavzoglu, T., Sefercik, U. G., & Ozturk, M. Y.** (2023). Automated mucilage extraction index (AMEI): a novel spectral water index for identifying marine mucilage formations from Sentinel-2 imagery, *International Journal of Remote Sensing*, 44(1), 105-141.
- Congalton, R. G., & Green, K.** (2019). Assessing the accuracy of remotely sensed data: Principles and practices. CRC Press.

- Constantin, S., Doxaran, D. and Constantinescu, Ș.** (2016). Estimation of water turbidity and analysis of its spatio-temporal variability in the Danube River plume (Black Sea) using MODIS satellite data, *Continental shelf research*, 112, 14-30.
- Copernicus.** (n.d.-a). Copernicus Land Monitoring Service at a glance. Retrieved July 25, 2023, from https://land.copernicus.eu/pan-european/corine-land-cover/image_print
- Copernicus.** (n.d.-b). *CORINE Land Cover*. Retrieved July 25, 2023, from <https://land.copernicus.eu/pan-european/corine-land-cover>
- Copernicus.** (n.d.-c). *CORINE Land Cover nomenclature conversion to Land Cover Classification system*. Retrieved July 25, 2023, from https://land.copernicus.eu/eagle/files/eagle-related-projects/pt_clc-conversion-to-fao-lccs3_dec2010
- Copernicus.** (n.d.-d). *CORINE Land Cover Nomenclature Guidelines*. Retrieved July 25, 2023, from <https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines/html>
- Danovaro, R., Umani, S. F., & Pusceddu, A.** (2009). Climate change and the potential spreading of marine mucilage and microbial pathogens in the Mediterranean Sea. *PLoS ONE*, 4(9), e7006.
- De Lazzari, A., Berto, D., Cassin, D., Boldrin, A., & Giani, M.** (2008). Influence of winds and oceanographic conditions on the mucilage aggregation in the Northern Adriatic Sea in 2003-2006, *Marine Ecology*, 29(4), 469–482.
- Dela-Cruz, J., Middleton, J. H., & Suthers, I. M.** (2008). The influence of upwelling, coastal nutrients and water temperature on the distribution of the red tide dinoflagellate, *Noctiluca scintillans*, along the east coast of Australia, *Hydrobiologia*, 598, 59–75.
- Demir, E. İ., & Turkoglu, M.** (2022). Temporal variations of phytoplankton community and their correlation with environmental factors in the coastal waters of the Çanakkale Strait in 2018, *Oceanologia*, 64(1), 176–197.
- Demir, S., Basaraner, M., & Taskin Gumus, A.** (2021). Selection of suitable parking lot sites in megacities: A case study for four districts of Istanbul, *Land Use Policy*, 111, 105731.
- Di Gregorio, A., Henry, M., Donegan, E., Finegold, Y., Latham, J., Jonckheere, I., & Cumani, R.** (2016). Land Cover Classification System Software version 3, Food and Agriculture Organization of the United Nations, Rome.
- Dogan, E., Gazioglu, C., Okus, E., Gonenç, İ. E., Yüce, H., & Yücel, Z. Y.** (1998). Examination of the pollution in the West Black Sea by remote sensing technologies, *Turkish Journal of Marine Sciences*, 4(2), 87–101.
- Du, P., Xia, J., Zhang, W., Tan, K., Liu, Y., Liu, S.** (2012). Multiple classifier system for remote sensing image classification: A review, *Sensors*, 12(4), 4764-4792.

- Ekercin, S.** (2007). Water quality retrievals from high resolution IKONOS multispectral imagery: A case study in Istanbul, Turkey, *Water, Air, and Soil Pollution*, 183(1), 239-251.
- Ergül, H. A., Varol, T., & Ay, Ü.** (2013). Investigation of heavy metal pollutants at various depths in the Gulf of Izmit. *Marine Pollution Bulletin*, 73(1), 389–393.
- ESA.** (n.d.). Sentinel-2 mission logo. Retrieved July 25, 2023, from https://www.esa.int/ESA_Multimedia/Images/2015/01/Sentinel-2_mission_logo
- ESA, Copernicus, & Programme of the European Union.** (n.d.). Copernicus Open Access Hub. Retrieved July 25, 2023, from <https://scihub.copernicus.eu/dhus/#/home>
- Falt'an, V., Petrovič, F., Ot'ahel', J., Feranec, J., Druga, M., Hruška, M., Nováček, J., Solár, V., & Mechurová, V.** (2020). Comparison of CORINE land cover data with national statistics and the possibility to record this data on a local scale-case studies from Slovakia, *Remote Sensing*, 12(15), 2484.
- Fang, C., & Yu, D.** (2017). Urban agglomeration: An evolving concept of an emerging phenomenon. *Landscape and Urban Planning*, 162, 126–136.
- Fernández-Nóvoa, D., Costoya, X., deCastro, M., & Gómez-Gesteira, M.** (2021). Influence of the mightiest rivers worldwide on coastal sea surface temperature warming, *Science of the Total Environment*, 768, 144915.
- Fingas, M.** (2019). Remote sensing for marine management. In *World Seas: An Environmental Evaluation Volume III: Ecological Issues and Environmental Impacts* (pp. 103–119). Elsevier.
- Fisher, R. A.** (1925). *Statistical Methods for Research Workers*. Oliver and Boyd, Edinburgh, Scotland.
- Gallego, J., & Bamps, C.** (2008). Using CORINE land cover and the point survey LUCAS for area estimation, *International Journal of Applied Earth Observation and Geoinformation*, 10(4), 467 – 475.
- Gani, M. A., Sajib, A. M., Siddik, M. A., & Moniruzzaman, M.** (2023). Assessing the impact of land use and land cover on river water quality using water quality index and remote sensing techniques, *Environmental Monitoring and Assessment*, 195, 449.
- Ge, G., Shi, Z., Zhu, Y., Yang, X., Hao, Y.** (2020). Land use/cover classification in an arid desert-oasis mosaic landscape of China using remote sensed imagery: Performance assessment of four machine learning algorithms, *Global Ecology and Conservation*, 22, e00971.
- Genel, Ö. A., & Guan, C.** (2021). Assessing urbanization dynamics in Turkey's Marmara Region using corine data between 2006 and 2018, *Remote Sensing*, 13(4), 664.
- Genitsaris, S., Stefanidou, N., Sommer, U., & Moustaka-Gouni, M.** (2019). Phytoplankton blooms, red tides and mucilaginous aggregates in the urban Thessaloniki Bay, Eastern Mediterranean. *Diversity*, 11(8), 136.

- Gholizadeh, M. H., Melesse, A. M., & Reddi, L.** (2016). A comprehensive review on water quality parameters estimation using remote sensing techniques. *Sensors*, 16(8), 1298.
- Gigliotti, A.** (2013). *Extracting temporal and spatial distributions information about marine mucilage phenomenon based on Modis satellite images; A case study of the Tyrrhenian and the Adriatic Sea, 2010-2012 (MS Thesis), NOVA Information Management School (NIMS), Lisbon, Portugal.*
- Gobry, J. J., Twisa, S. S., Ngassapa, F., & Kilulya, K. F.** (2023). Impact of land-use/cover change on water quality in the Mindu Dam drainage, Tanzania, *Water Practice and Technology*, 18(5), 1086–1098.
- Gökaşan, E., Ergin, M., Özyalvaç, M., Sur, H. I., Tur, H., Görüm, T., Ustaömer, T., Batuk, F. G., Alp, H., Birkan, H., Türker, A., Gezgün, E., & Özturan, M.** (2008). Factors controlling the morphological evolution of the Çanakkale Strait (Dardanelles, Turkey), *Geo-Marine Letters*, 28, 107–129.
- Göksel, Ç., David, R. M., & Doğru, A. Ö.** (2018). Environmental monitoring of spatio-temporal changes in Northern Istanbul using remote sensing and GIS, *International Journal of Environment and Geoinformatics*, 5(1), 94–103.
- Göksel, Ç., Musaoğlu, N. and Kaya, Ş.** (2001). İstanbul Su Havzalarının Uydu Görüntüleri Kullanılarak Arazi Kullanım Değişimlerinin Zamansal Analizi, İSKİ, İstanbul Teknik Üniversitesi, İstanbul.
- Gupta, N., Mathew, A., & Khandelwal, S.** (2020). Spatio-temporal impact assessment of land use / land cover (LU-LC) change on land surface temperatures over Jaipur city in India, *International Journal of Urban Sustainable Development*, 12(3), 283–299.
- Hansen, M. C., Potapov, P. V., Pickens, A. H., Tyukavina, A., Hernandez-Serna, A., Zalles, V., Turubanova, S., Kommareddy, I., Stehman, S. V., Song, X. P., & Kommareddy, A.** (2022). Global land use extent and dispersion within natural land cover using Landsat data, *Environmental Research Letters*, 17, 034050.
- Haralick, R. M., Shanmugam, K., & Dinstein, I.** (1973). Textural features for image classification, *IEEE Transactions on Systems, Man, and Cybernetics*, SMC-3(6), 610–621.
- Hegazy, I. R.** (2021). Towards sustainable urbanization of coastal cities: The case of Al-Arish City, Egypt, *Ain Shams Engineering Journal*, 12(2), 2275–2284.
- Hu, C.** (2022). Sea snots in the Marmara Sea as observed from medium-resolution satellites, *IEEE Geoscience and Remote Sensing Letters*, 19, 1504905.
- Hu, C., Qi, L., Xie, Y., Zhang, S., & Barnes, B. B.** (2022). Spectral characteristics of sea snot reflectance observed from satellites: Implications for remote sensing of marine debris, *Remote Sensing of Environment*, 269, 112842.

- Huong, K. M., Rodríguez-Hernández, D. I., & Tuan, N. T.** (2023). Mapping the above-ground biomass of *Rhizophora apiculata* plantation forests using PlanetScope Imagery in Thanh Phu Nature Reserve, Vietnam, *Biology Bulletin*, 50(Suppl 3), S450-S461.
- İkis, D.** (2007). Temporal and Spatial Changes of Primary Productivity in the Sea of Marmara Obtained by Remote Sensing. MS Thesis, Middle East Technical University, Ankara, Türkiye.
- Ilicak, M., Federico, I., Barletta, I., Mutlu, S., Karan, H., Ciliberti, S. A., Clementi, E., Coppini, G., & Pinardi, N.** (2021). Modeling of the Turkish Strait system using a high resolution unstructured grid ocean circulation model, *Journal of Marine Science and Engineering*, 9(7), 769.
- Jang, J. C., & Park, K. A.** (2019). High-resolution sea surface temperature retrieval from Landsat 8 OLI/TIRS data at coastal regions, *Remote Sensing*, 11(22), 2687.
- Jing, Z., Chang, P., Shan, X., Wang, S., Wu, L., & Kurian, J.** (2019). Mesoscale SST dynamics in the Kuroshio-Oyashio extension region, *Journal of Physical Oceanography*, 49(5), 1339–1352.
- Kajtar, J. B., Hernaman, V., Holbrook, N. J., & Petrelli, P.** (2022). Tropical western and central Pacific marine heatwave data calculated from gridded sea surface temperature observations and CMIP6, *Data in Brief*, 40, 107694.
- Kavzoglu, T., Tonbul, H., Colkesen, I., & Sefercik, U. G.** (2021). The use of object-based image analysis for monitoring 2021 marine mucilage bloom in the Sea of Marmara, *International Journal of Environment and Geoinformatics*, 8(4), 529-536.
- Kaya, A. and Kizildere, M.** (2013). İstanbul'daki içme ve kullanma suyu havzalarındaki arazi kullanımı, Çevre Mühendisleri Odası İstanbul Şubesi.
- Kaya, Z., & Dervisoglu, A.** (2023). Determination of urban areas using Google Earth Engine and spectral indices; Esenyurt Case Study, *International Journal of Environment and Geoinformatics*, 10(1), 1–8.
- Kaygalak, I., & Reid, N.** (2016). The geographical evolution of manufacturing and industrial policies in Turkey, *Applied Geography*, 70, 37–48.
- Kim, H. C., Son, S., Kim, Y. H., Khim, J. S., Nam, J., Chang, W. K., Lee, J. H., Lee, C. H. and Ryu, J.** (2017). Remote sensing and water quality indicators in the Korean West coast: Spatio-temporal structures of MODIS-derived chlorophyll-a and total suspended solids, *Marine Pollution Bulletin*, 121(1-2), 425-434.
- Kosztra, B., Büttner, G., Hazeu, G., & Arnold, S.** (2019). Updated CLC illustrated nomenclature guidelines. Retrieved August 12, 2023, from https://land.copernicus.eu/user-corner/technical-library/corine-land-cover-nomenclature-guidelines/docs/pdf/CLC2018_Nomenclature_illustrated_guide_20190510.pdf

- Kuester, M.** (2016). Radiometric Use of WorldView-3 Imagery Technical Note. 1–12. Retrieved June 10, 2021, from https://dg-cms-uploads-production.s3.amazonaws.com/uploads/document/file/207/Radiometric_Use_of_WorldView-3_v2.pdf
- Kuroda, H., & Toya, Y.** (2020). High-resolution sea surface temperatures derived from Landsat 8: A study of submesoscale frontal structures on the Pacific shelf off the Hokkaido coast, Japan. *Remote Sensing*, 12(20), 3326.
- Kwak, G. H., Park, N.W.** (2019). Impact of texture information on crop classification with machine learning and UAV images, *Applied Sciences*, 9(4), 643.
- Lacaux, J. P., Tourre, Y. M., Vignolles, C., Ndione, J. A. and Lafaye, M.** (2007). Classification of ponds from high-spatial resolution remote sensing: Application to Rift Valley Fever epidemics in Senegal, *Remote Sensing of Environment*, 106(1), 66-74.
- Lamaro, A. A., Mariñelarena, A., Torrusio, S. E., & Sala, S. E.** (2013). Water surface temperature estimation from Landsat 7 ETM+ thermal infrared data using the generalized single-channel method: Case study of Embalse del Río Tercero (Córdoba, Argentina). *Advances in Space Research*, 51(3), 492–500.
- Lauer, D.T.** (1986). Applications of Landsat data and the data base approach. *Photogrammetric Engineering and Remote Sensing*, 52(8), 1193-1199.
- Lester, J.** (2015). A 2015 Comparison of Operational Performance: Washington State Ferries to Ferry Operators Worldwide. Washington State Department of Transportation Research Report. Retrieved August 12, 2023, from <https://rosap.ntl.bts.gov/view/dot/28870>
- Lins, R. C., Martinez, J. M., Motta Marques, D. D., Cirilo, J. A. and Fragoso, C. R.** (2017). Assessment of chlorophyll-a remote sensing algorithms in a productive tropical estuarine-lagoon system, *Remote Sensing*, 9(6), 516.
- MacFarland, T. W.** (2012). Two-way analysis of variance: statistical tests and graphics using R. Springer Science & Business Media.
- Malej, A., & Harris, R. P.** (1993). Inhibition of copepod grazing by diatom exudates: A factor in the development of mucus aggregates, *Marine Ecology Progress Series*, 96, 33–42.
- Massana, R., & Logares, R.** (2013). Eukaryotic versus prokaryotic marine picoplankton ecology. *Environmental Microbiology*, 15(5), 1254–1261.
- Mather, P. M.** (1999). Computer processing of remotely sensed images (pp. 87–88). John Wiley & Sons.
- Mather, P. ve Tso, B.** (2009). Classification Methods for Remotely Sensed Data, CRC Press.
- Mecozzi, M., Pietrantonio, E., Di Noto, V., & Pápai, Z.** (2005). The humin structure of mucilage aggregates in the Adriatic and Tyrrhenian seas: hypothesis about the reasonable causes of mucilage formation, *Marine Chemistry*, 95(3–4), 255–269.

- Meriç, E., Yokes, M. B., Yümün, Z. Ü., Eryılmaz, M., Yücesoy Eryılmaz, F.** (2018). Alien benthic foraminifers from Turkish Strait System, *International Journal of Environment and Geoinformatics*, 5(1), 68-75.
- Mingazzini, M., Colombob, S., & Ferrari, G. M.** (1995). Application of spectrofluorimetric techniques to the study of marine mucilages in the Adriatic Sea: preliminary results, *The Science of the Total Environment*, 165(1-3), 133-144.
- Monti, M., Welker, C., Dellavalle, G., Casaretto, L., & Fonda Umani, S.** (1995). Mucous aggregates under natural and laboratory conditions: A review, *Science of the Total Environment*, 165, 145-154.
- Moses, W. J., Gitelson, A. A., Berdnikov, S. and Povazhnyy, V.** (2009). Estimation of chlorophyll-a concentration in case II waters using MODIS and MERIS data—Successes and challenges, *Environmental Research Letters*, 4(4), 1-8.
- Morkoç, E., Okay, O. S., Tolun, L., Tüfekçi, V., Tüfekçi, H., & Legoviç, T.** (2001). Towards a clean Izmit Bay, *Environment International*, 26(3), 157-161.
- Mountrakis, G., Im, J., & Ogole, C.** (2011). Support vector machines in remote sensing: A review, *ISPRS Journal of Photogrammetry and Remote Sensing*, 66(3), 247-259.
- Mugo, R., Waswa, R., Nyaga, J. W., Ndubi, A., Adams, E. C., & Flores-Anderson, A. I.** (2020). Quantifying land use land cover changes in the Lake Victoria Basin using satellite remote sensing: The trends and drivers between 1985 and 2014, *Remote Sensing*, 12(17), 2829.
- Mujawdiya, R., Chatterjee, R. S., & Kumar, D.** (2022). MODIS land surface temperature time series decomposition for detecting and characterizing temporal intensity variations of coal fire induced thermal anomalies in Jharia coalfield, India, *Geocarto International*, 37(8), 2160-2174.
- Musaoğlu, N., Tanık, A. G., Yanalak, M., Gazioğlu, C., & Olğun Kıyak, N.** (2022). Bilgi Teknolojileri Kullanarak Marmara Denizi'ne Özgü Kirlilik Takip Sisteminin Altyapısının Oluşturulması. *The Scientific and Technological Research Council of Türkiye (TÜBİTAK) 1001 Project*, Project No: 121G142. [In Turkish].
- Mutlu, A. Z., Kazancı, B., Özçetin, A. Y., & Sarıyılmaz, F. B.** (2020). Akşehir gölü zamansal değişiminin bant oranlama yöntemleri ile belirlenmesi, *Türkiye Uzaktan Algılama Dergisi*, 2(1), 22-28.
- NASA Worldview Snapshots.** (2017). NASA Worldview Earthdata. Retrieved August 9, 2023, from <https://worldview.earthdata.nasa.gov/>
- Nguyen, L. H., Joshi, D. R., Clay, D. E., & Henebry, G. M.** (2020). Characterizing land cover/land use from multiple years of Landsat and MODIS time series: A novel approach using land surface phenology modeling and random forest classifier, *Remote Sensing of Environment*, 238, 111017.
- Okay, A., Mater, B., Artüz, B., Gürseler, G., Artüz, L., & Okay, N.** (2007). Bilimsel Açıdan Marmara Denizi. Türkiye Barolar Birliği Yayınları, İstanbul, Türkiye, 119.

- Orhon, D., Sözen, S., Kirca, V. S. O., Duba, S., Mermutlu, R., & Sumer, B. M.** (2021). Pollutant dynamics between The Black Sea and The Marmara Sea: Basis for wastewater management strategy, *Marine Pollution Bulletin*, 168, 112388.
- Ormeci, C., Sertel, E., & Sarikaya, O.** (2009). Determination of chlorophyll-a amount in Golden Horn, Istanbul, Turkey using IKONOS and in situ data, *Environmental Monitoring and Assessment*, 155(1–4), 83–90.
- Örmeci C., Müftüoğlu O., Gönenç E. İ., Doğan E., Musaoğlu N., Kaya Ş., & Göksel Ç.** (1995). Uydu verileriyle Batı Karadeniz'in durumu, *İ.T.Ü. Vakıf Dergisi*, 16, 22-25.
- Özalp, H. B.** (2021). First massive mucilage event observed in deep waters of Çanakkale Strait (Dardanelles), Turkey. *J. Black Sea/Mediterranean Environment*, 27(1), 49–66.
- Özonat, Ç.** (2017). Arazi Kullanım Değişikliklerinin İçme Suyu Havzaları Üzerindeki Etkilerinin Değerlendirilmesi: Elmalı Baraj Gölü Havzası Örneği, T. C. Orman ve Su İşleri Bakanlığı
- Öztürk, İ., Yanalak, M., Arslan, Ö., Koyuncu, İ., Dilekgürgen, E., Erşahin, M. E., & Türken, T.** (2021). Marmara Denizi'nde Deniz Salyası Sorunu ile İlgili Görüş ve Öneriler. İstanbul Teknik Üniversitesi. [In Turkish]
- Pal, M., & Mather, P. M.** (2005). Support vector machines for classification in remote sensing, *International Journal of Remote Sensing*, 26(5), 1007–1011.
- Parracciani, C., Gigante, D., Mutanga, O., Bonafoni, S., & Vizzari, M.** (2024). Land cover changes in grassland landscapes: Combining enhanced Landsat data composition, LandTrendr, and machine learning classification in google earth engine with MLP-ANN scenario forecasting. *GIScience & Remote Sensing*, 61(1), 2302221.
- Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., & Vanderplas, J.** (2011). Scikit-learn: Machine learning in Python, *The Journal of Machine Learning Research*, 12, 2825–2830.
- Pomianowski, A., & Doburzyński, S.** (2021). The importance of coastal cities and regions in selected European countries. *European Research Studies Journal*, XXIV(4), 578–589.
- Qu, L., Guan, L and Yang, M.** (2019). Comparison of Sentinel-3 SLSTR SST product with shipboard skin SST measurements. In IGARSS 2019-2019 IEEE International Geoscience and Remote Sensing Symposium, 8150-8153. <https://doi.org/10.1109/IGARSS.2019.8898085>.
- Reynolds, R.W., Banzon, V.F.NOAA CDR Program,** (2008). NOAA optimum interpolation 1/4 degree daily sea surface temperature (OISST) analysis, Version 2. NOAA National Centers for Environmental Information. <https://doi.org/10.7289/V5SQ8XB5>.
- Reynolds, R. W., Rayner, N. A., Smith, T. M., Stokes, D. C., & Wang, W.** (2002). An improved in situ and satellite SST analysis for climate, *Journal of Climate*, 15(13), 1609–1625.

- Salem, S. I., Higa, H., Kim, H., Kobayashi, H., Oki, K., Oki, T.** (2017). Assessment of chlorophyll-a algorithms considering different trophic statuses and optimal bands, *Sensors*, 17(8), 1746.
- Sarangi, R. K., & Devi, K. N.** (2017). Space-based observation of chlorophyll, sea surface temperature, nitrate, and sea surface height anomaly over the Bay of Bengal and Arabian Sea, *Advances in Space Research*, 59(1), 33–44.
- Sarı, E.** (2020) Kuzey Marmara Otoyolu Etkisiyle İstanbul Kuzey Ormanları Peyzaj Yapısında Meydana Gelen Değişimlerin Uydu Görüntüleri ve Peyzaj Metrikleri İle İncelenmesi (Master's thesis), Istanbul Technical University, Istanbul, Türkiye.
- Sarıyılmaz, F. B.** (2012). Zaman Serileri İle Değişim Analizi: İstanbul Sarıyer Örneği (Master's thesis), Istanbul Technical University, Istanbul, Türkiye.
- Sarıyılmaz, F. B.** (2017). Corine Sınıflandırmasının Sazlıdere Havzası Ölçeğinde Tematik Doğruluk Analizi (Doctoral dissertation), Istanbul Technical University, Istanbul, Türkiye.
- Sarıyılmaz, F. B., & Musaoğlu, N.** (2016). Uydu görüntülerinden üretilen arazi örtüsü/kullanımı haritalarında doğruluk analizi: LUCAS Metodolojisi, Uzaktan Algılama-CBS Sempozyumu (UZAL-CBS 2016), 5-7 Ekim 2016, Adana.
- Sarıyılmaz, F. B., Musaoğlu, N., & Uluğtekin, N.** (2017). Producing information for CORINE database by using classification method: A case study of Sazlıdere Basin, Istanbul. ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences, IV-4/W4, 357-362.
- Satir, O., Yeler, S. T., Donmez, C., & Paul, C.** (2023). Evaluating ecosystem service changes in a frame of transportation development in Istanbul, *Environmental Monitoring and Assessment*, 195, 801.
- Savun-Hekimoğlu, B., & Gazioğlu, C.** (2021). Mucilage problem in the semi-enclosed seas: Recent outbreak in the Sea of Marmara, *International Journal of Environment and Geoinformatics*, 8(4), 402–413.
- Sengupta, D., Chen, R., & Meadows, M. E.** (2018). Building beyond land: An overview of coastal land reclamation in 16 global megacities, *Applied Geography*, 90, 229–238.
- Sengupta, D., Choi, Y. R., Tian, B., Brown, S., Meadows, M., Hackney, C. R., Banerjee, A., Li, Y., Chen, R., & Zhou, Y.** (2023). Mapping 21st century global coastal land reclamation, *Earth's Future*, 11(2), e2022EF002927.
- Sertel, E., Musaoğlu, N., Alp, G., Yay Algan, I., Kaya, Ş., Yüksel, B., & Yılmaz, A.** (2018). 1:25000 ölçekli ulusal arazi örtüsü/kullanımı sınıflandırma sistemi ile HGK TOPOVT veritabanının karşılaştırılması, *Harita Dergisi*, 160, 34–46.
- SUHET.** (2015). SENTINEL-2 User Handbook. Retrieved August 12, 2023, from https://sentinel.esa.int/documents/247904/685211/Sentinel-2_User_Handbook

- Stathopoulou, M., & Cartalis, C.** (2007). Daytime urban heat islands from Landsat ETM+ and Corine land cover data: An application to major cities in Greece, *Solar Energy*, 81(3), 358–368.
- Stock, C. A., Pegion, K., Vecchi, G. A., Alexander, M. A., Tommasi, D., Bond, N. A., Fratantoni, P. S., Gudgel, R. G., Kristiansen, T., O'Brien, T. D., Xue, Y., & Yang, X.** (2015). Seasonal sea surface temperature anomaly prediction for coastal ecosystems, *Progress in Oceanography*, 137, 219–236.
- Sunar, F.** (1992). Water-quality assessment in the Izmit Bay using Landsat-TM image data, *The Photogrammetric Journal of Finland*, 13(1), 79–86.
- Syariz, M. A., Jaelani, L. M., Subehi, L., Pamungkas, A., Koenhardono, E. S., & Sulisetyono, A.** (2015). Retrieval of sea surface temperature over Poteran Island water of Indonesia with Landsat 8 TIRS image: A preliminary algorithm. *International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences - ISPRS Archives, XL-2/W4*, 87–90.
- Tadese, M., Kumar, L., Koech, R., & Kogo, B. K.** (2020). Mapping of land-use/land-cover changes and its dynamics in Awash River Basin using remote sensing and GIS. *Remote Sensing Applications: Society and Environment*, 19, 100352.
- Tassan, S.** (1993). An algorithm for the detection of the white-tide (“mucilage”) phenomenon in the adriatic sea using AVHRR data, *Remote Sensing of Environment*, 45(1), 29–42.
- Tas, S., Kus, D., & Yilmaz, I. N.** (2020). Temporal variations in phytoplankton composition in the north-eastern Sea of Marmara: potentially toxic species and mucilage event. *Mediterranean Marine Science*, 21(3), 668–683.
- Tas, S., & Yilmaz, I. N.** (2015). Potentially harmful microalgae and algal blooms in a eutrophic estuary in Turkey. *Mediterranean Marine Science*, 16(2), 432–443.
- Tırmanoğlu, B., İsmailoğlu, İ., Tuzcu Kokal, A., & Musaoğlu, N.** (2023). Yeni nesil multispektral ve hiperspektral uydu görüntülerinin arazi örtüsü / arazi kullanımı sınıflandırma performanslarının karşılaştırılması: Sentinel-2 ve PRISMA Uydusu, *Geomatik*, 8(1), 79–90.
- Tolun, L. G., Okay, O. S., Gaines, A. F., Tolay, M., Tüfekçi, H., & Kırath, N.** (2001). The pollution status and the toxicity of surface sediments in Izmit Bay (Marmara Sea), Turkey, *Environment International*, 26(3), 163–168.
- Tong, X. Y., Xia, G. S., Lu, Q., Shen, H., Li, S., You, S., Zhang, L.** (2020). Land-cover classification with high-resolution remote sensing images using transferable deep models, *Remote Sensing of Environment*, 237, 111322.

- TÜDAV (Türk Deniz Araştırmaları Vakfı)** (2017). 2017 Yılı Türkiye Denizleri raporu. Retrieved from <http://tudav.org/wp-content/uploads/2018/04/TUDAV_2017_Denizler_Raporu_s.pdf>, retrieved date: 01.02.2021.
- Turkoglu, M.** (2008). Synchronous blooms of the coccolithophore *Emiliana huxleyi* and three dinoflagellates in the Dardanelles (Turkish Straits System), *Journal of the Marine Biological Association of the United Kingdom*, 88(3), 433–441.
- Türkoğlu, M.** (2010). Temporal variations of surface phytoplankton, nutrients and chlorophyll a in the Dardanelles (Turkish Straits System): a coastal station sample in weekly time intervals. *Turkish Journal of Biology*, 34(3), 319–333.
- Turkoglu, M.** (2010). Winter bloom of coccolithophore *Emiliana huxleyi* and environmental conditions in the Dardanelles, *Hydrology Research*, 41(2), 104–114.
- Turkoglu, M.** (2013). Red tides of the dinoflagellate *Noctiluca scintillans* associated with eutrophication in the Sea of Marmara (the Dardanelles, Turkey), *Oceanologia*, 55(3), 709–732.
- Turkoglu, M.** (2016). First harmful algal bloom record of tytoplanktonic dinoflagellate *Prorocentrum lima* (Ehrenberg) F. Stein, 1878 in the Dardanelles (Turkish Straits System, Turkey), *Journal of Coastal Life Medicine*, 4(10), 765–774.
- Türkoğlu, M., & Erdoğan, Y.** (2010). Diurnal variations of summer phytoplankton and interactions with some physicochemical characteristics under eutrophication in the Dardanelles, *Turkish Journal of Biology*, 34(2), 211–225.
- Turkoglu, M., & Oner, C.** (2010). Short time variations of winter phytoplankton, nutrient and chlorophyll a of Kepez Harbor in the Dardanelles (Çanakkale Strait, Turkey), *Turkish Journal of Fisheries and Aquatic Sciences*, 10(4), 537–548.
- TURKSTAT.** (2022a). İstatistik Veri Portalı, Yıllara göre il nüfusları. Retrieved July 24, 2023, from <https://data.tuik.gov.tr/> [In Turkish].
- TURKSTAT.** (2022b). Uluslararası Göç İstatistikleri. Retrieved August 12, 2023, from <https://data.tuik.gov.tr/Bulten/Index?p=Uluslararası-Göç-İstatistikleri-2022-49457> [In Turkish].
- Tuzcu A., Dervişoğlu A., Musaoğlu N. and Tanık A. G.** (2019) Determination of land-use/cover and water turbidity of wetlands by using high resolution satellite image, International Symposium on Applied Geoinformatics (ISAG 2019), 1(1), 154-158.
- Tuzcu Kokal, A., İsmailoğlu, I., Musaoglu, N., & Tanik, A.** (2023). Detection of surface temperature anomaly of the Sea of Marmara. *Advances in Space Research*, 71(7), 2996–3004.
- Tuzcu Kokal, A., Olgun, N., & Musaoğlu, N.** (2022). Detection of mucilage phenomenon in the Sea of Marmara by using multi-scale satellite data. *Environmental Monitoring and Assessment*, 194, 585.

- Tuzcu Kokal, A., Sunar, A. F., Dervisoglu, A., Berberoglu, S.** (2021). The use of spectral and textural features in crop type mapping using Sentinel-2A Images: A case study, Çukurova Region, Turkey, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B3-2021, 117-122.
- Uysal, C., Maktav, D., & Small, C.** (2018). Mapping urban growth and its relation to seismic hazards in Istanbul, *Journal of the Indian Society of Remote Sensing*, 46(8), 1307–1322.
- Uysal, Z.** (2006). Vertical distribution of marine cyanobacteria *Synechococcus* spp. in the Black, Marmara, Aegean, and eastern Mediterranean seas, *Deep-Sea Research Part II: Topical Studies in Oceanography*, 53(17–19), 1976–1987.
- Vanhellemont, Q.** (2020). Automated water surface temperature retrieval from Landsat 8/TIRS. *Remote Sensing of Environment*, 237, 111518.
- Vapnik, V.** (1979). Estimation of dependences based on empirical data [in Russian]. Nauka, Moscow. Springer-Verlag, New York.
- Vapnik, V.** (2013). The nature of statistical learning theory. Springer Science & Business Media.
- Vogelmann, J. E., Howard, S. M., Yang, L., Larson, C. R., Wylie, B. K., & Van Driel, N.** (2001). Completion of the 1990s National Land Cover Data Set for the conterminous United States from Landsat Thematic Mapper data and ancillary data sources, *Photogrammetric Engineering and Remote Sensing*, 67(6), 650-662.
- Vollenweider, R. A., Giovanardi, F., Montanari, G., & Rinaldi, A.** (1998). Characterization of the trophic conditions of marine coastal waters with special reference to the NW Adriatic Sea: Proposal for a trophic scale, turbidity and generalized water quality index, *Environmetrics*, 9(3), 329–357.
- Wang, D., Pan, D., Wei, J.-A., Gong, F., Zhu, Q., & Chen, P.** (2016). Monitoring thermal discharge from a nuclear plant through Landsat 8. *Remote Sensing of the Ocean, Sea Ice, Coastal Waters, and Large Water Regions 2016*, 9999, 99991E.
- Wang, W., Yang, P., Xia, J., Huang, H., & Li, J.** (2023). Impact of land use on water quality in buffer zones at different scales in the Poyang Lake, middle reaches of the Yangtze River basin, *Science of the Total Environment*, 869, 165161.
- Weigand, M., Staab, J., Wurm, M., & Taubenböck, H.** (2020). Spatial and semantic effects of LUCAS samples on fully automated land use/ land cover classification in high-resolution Sentinel-2 data, *International Journal of Applied Earth Observation and Geoinformation*, 88, 102065.
- Yagci, A. L., Colkesen, I., Kavzoglu, T., & Sefercik, U. G.** (2022). Daily monitoring of marine mucilage using the MODIS products: a case study of 2021 mucilage bloom in the Sea of Marmara, Turkey, *Environmental Monitoring and Assessment*, 194, 170.

- Yalçın, B., Artüz, M. L., Pavlidou, A., Çubuk, S., & Dassenakis, M.** (2017). Nutrient dynamics and eutrophication in the Sea of Marmara: Data from recent oceanographic research, *Science of the Total Environment*, 601–602, 405–424.
- Yentur, R. E., Buyukates, Y., Ozen, O., & Altin, A.** (2013). The environmental and socio-economical effects of a biologic problem: Mucilage, *Marine Science and Technology Bulletin*, 2(2), 13–15.
- Zainal, Z., Ramli, R., & Mustafa, M.M.** (2013). Grey-level co-occurrence matrix performance evaluation for heading angle estimation of moveable vision system in static environment, *Journal of Sensors*, 624670, 1-6.
- Zarei, A., Shah-Hosseini, R., Ranjbar, S., & Hasanlou, M.** (2021). Validation of non-linear split window algorithm for land surface temperature estimation using Sentinel-3 satellite imagery: Case study; Tehran Province, Iran, *Advances in Space Research*, 67(12), 3979–3993.
- Zhang, Y., Chen, R., & Wang, Y.** (2020). Tendency of land reclamation in coastal areas of Shanghai from 1998 to 2015, *Land Use Policy*, 91, 104370.
- Zhang, Y., & Zhang, T.** (2016). Structure-guided unidirectional variation de-striping in the infrared bands of MODIS and hyperspectral images, *Infrared Physics and Technology*, 77, 132–143.
- Zhu, Z., Qiu, S., & Ye, S.** (2022). Remote sensing of land change: A multifaceted perspective, *Remote Sensing of Environment*, 282, 113266.
- Url-1** <<https://earthobservatory.nasa.gov/global-maps/MYD28M>>, date retrieved 28.05.2022.
- Url-2** <<https://download.gebco.net/>>, date retrieved 12.04.2024.
- Url-3** <https://ncics.org/ncics/pdfs/obs4MIPs/DOISST_TechNote_revisedNCEI.pdf>, retrieved date 29.05.2021.
- Url-4** <http://esamultimedia.esa.int/docs/S2-Data_Sheet.pdf>, date retrieved 05.06.2021.
- Url-5** <<https://directory.eoportal.org/web/eoportal/satellite-missions/c-missions/copernicus-sentinel-2>>, date retrieved 05.06.2021.
- Url-6** <<https://earth.esa.int/eogateway/missions/Worldview-3>>, date retrieved 13.06.2021.
- Url-7** <https://developers.google.com/earth-engine/datasets/catalog/NOAA_CDR_OISST_V2_1>, date retrieved 30.09.2021.
- Url-8** <https://www.usgs.gov/faqs/what-are-band-designations-landsat-satellites?qt-news_science_products=0#qt-news_science_products>, date retrieved 30.09.2021.
- Url-9** <<https://archive.eumetsat.int/>>, retrieved date 30.09.2021.
- Url-10** <<https://sentinel.esa.int/web/sentinel/missions/sentinel-3>>, date retrieved 30.09.2021.

- Url-11** <<https://www.usgs.gov/landsat-missions/using-usgs-landsat-level-1-data-product>>, date retrieved 29.09.2021.
- Url-12** <<https://www.openstreetmap.org/export#map=5/51.500/-0.100>>, date retrieved 26.04.2024.
- Url-13** <<https://www.mgm.gov.tr/FILES/resmi-istatistikler/denizSuyu/Marmara-DenizSuyu-Sicakligi-Analizi.pdf>>, date retrieved 30.09.2021. (in Turkish).
- Url-14** <<https://mgm.gov.tr/FILES/resmi-istatistikler/denizSuyu/Marmara-DenizSuyu-Sicakligi-Analizi-2019.pdf>>, date retrieved 30.09.2021. (in Turkish).
- Url-15** <<http://www1.mgm.gov.tr/FILES/resmi-istatistikler/denizler.pdf>>, date retrieved 30.09.2021. (in Turkish).
- Url-16** <<https://www.dha.com.tr/>>, date retrieved 28.12.2021.
- Url-17** <<https://haberglobal.com.tr/>>, date retrieved 28.12.2021.
- Url-18** <<https://www.ntv.com.tr/>>, date retrieved 03.07.2021.
- Url-19** <<https://www.sabah.com.tr/>>, date retrieved 28.12.2021.
- Url-20** <<https://cbs.ogm.gov.tr/vatandas/>>, date retrieved 14.04.2024.
- Url-21** <<https://www.ncdc.noaa.gov/oisst/optimum-interpolation-sea-sur-face-temperature-oisst-v20>>, date retrieved 30.09.2021.
- Url-22** <<https://www.windy.com/?41.068,28.982,5>>, date retrieved 21.10.2021.
- Url-23** <<https://www.usgs.gov/centers/eros/science/usgs-eros-archive-advanced-very-high-resolution-radiometer-avhrr-sensor>>, date retrieved 05.04.2024.
- Url-24** <<https://sentinels.copernicus.eu/web/sentinel/user-guides/sentinel-3-slstr/overview/geophysical-measurements/sea-surface-temperature>>, date retrieved 05.04.2024.
- Url-25** <<https://docs.sentinel-hub.com/api/latest/data/sentinel-3-slstr-l1b/>>, retrieved date 5 April 2024.

CURRICULUM VITAE

Name Surname : Aylin TUZCU KOKAL

EDUCATION :

- **B.Sc.** : 2017, İstanbul Technical University, Faculty of Civil Engineering, Department of Geomatics Engineering
- **M.Sc.** : 2019, İstanbul Technical University, Faculty of Civil Engineering, Department of Geomatics Engineering

PROFESSIONAL EXPERIENCE AND REWARDS:

- Since 2017 Working as a Research Assistant at Istanbul Technical University
- 2019 - 2023 Working as a scholarship student in the Istanbul Technical University Scientific Research Projects Office (BAP) under project number MGA-2019-41917
- 2019 - 2024 Working as a scholarship student in the Istanbul Technical University Scientific Research Projects Office (BAP) under project number MDK-2021-43054
- 2021-2022 Working as a scholarship student in the Scientific and Technological Research Council of Türkiye (TUBITAK) 1001 project under project number 121G142
- 2022 Grant Award by the Scientific and Technological Research Council of Türkiye (TUBITAK) 2214/A project under project number 1059B142200399
- 2023-2024 Working as a Visiting Scholar at Boston University

PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- **Tuzcu Kokal, A.**, Musaoğlu, N. 2021. Monitoring Chlorophyll-a and Sea Surface Temperature with Satellite Data Derived from Multiple Sensors, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B3-2021, 515-520.
- **Tuzcu Kokal, A.**, Olgun, N., Musaoğlu, N. 2022. Detection of Mucilage Phenomenon in the Sea of Marmara by Using Multi-scale Satellite Data, *Environmental Monitoring and Assessment*, 194, 585.
- **Tuzcu Kokal, A.**, İsmailoğlu, İ., Musaoğlu, N. 2022. Comparison of Landsat-9 and PRISMA Satellite Data for Land Use/Land Cover Classification, *ASPRS 2022 Annual Conference*, XLVI-M-2-2022, 197-201.

- **Tuzcu Kokal, A.**, Ismailoglu, I., Musaoglu, N., Tanik, A. 2023. Detection of surface temperature anomaly of the Sea of Marmara, *Advances in Space Research*, 71(7), 2996-3004.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Tuzcu, A.**, Dervisoglu, A., Musaoglu, N., Tanik, A. 2019. Determination of Land-Use/Cover and Water Turbidity of Wetlands by Using High Resolution Satellite Image, *The International Symposium on Applied Geoinformatics (ISAG 2019)*, 1(1), 154-158, Istanbul, Türkiye.
- Musaoglu, N., Dervisoglu, A., Yagmur, N., Bilgilioglu, B., **Tuzcu, A.**, Tanik, A. 2020. Assessing Contribution of Climate Change on Wetlands by Using Multi-temporal Satellite Data, In *Climate Change, Hazards and Adaptation Options*, 77-87, Springer, Cham.
- Yagmur, N., Tanik, A., **Tuzcu, A.**, Musaoglu, N., Erten, E., Bilgilioglu, B. 2020. Opportunities Provided by Remote Sensing Data for Watershed Management: Example of Konya Closed Basin, *International Journal of Engineering and Geosciences*, 5(3), 120-129.
- **Tuzcu Kokal, A.**, Sunar, A. F., Dervisoglu, A., Berberoglu, S. 2021. The Use of Spectral and Textural Features in Crop Type Mapping Using Sentinel-2A Images: A Case Study, Çukurova Region, Turkey, *The International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*, XLIII-B3-2021, 117-122.
- Tirmanoğlu, B., İsmailoğlu, İ., **Tuzcu Kokal, A.**, Musaoğlu, N. 2023. Yeni nesil multispektral ve hiperspektral uydu görüntülerinin arazi örtüsü/arazi kullanımı sınıflandırma performanslarının karşılaştırılması: Sentinel-2 ve PRISMA Uydusu, *Geomatik*, 8(1), 79-90.
- **Tuzcu Kokal, A.**, Kacıkoc, M., Musaoglu, N., Tanik, A. 2024. Remote Sensing Application in Water Quality of Lake Burdur, Türkiye, *Photogrammetric Engineering & Remote Sensing*, 90(2), 85-87.