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Research Article

Detection of chlorophyll a on the Black Sea Coast with Sentinel-2 Satellite

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ABSTRACT

It is costly and time-consuming to determine coastal pollution with ground measurements. One of the most basic parameters to determine pollution in these areas is Chlorophyll A. This study aims to investigate the determination of this parameter using Remote Sensing (RS) techniques. In the study, the Sentinel-2 satellite was used to determine the parameter Chlorophyll A in the coastal areas of the Black Sea. 19 algorithms were used in the application. The algorithms are related to luminance reflections and the 8 bands of the satellite were used for the study. An Artificial Neural Network model was published as the best result. Pollution was observed in the coastal areas of the Black Sea between 2021 and 2017. As a result of the analysis, it is possible to observe coastal pollution quickly, without cost and/or at very low cost, with RS techniques. In this sense, RS techniques are of great importance in detecting environmental pollution, and relevant algorithms should be developed and supported by local measurements.

Keywords: Chlorophyll A, Remote Sensing, Sentinel 2, Artificial Neural Network Model, pollution

Sentinel-2 Uydusu ile Karadeniz Kıyısında Klorofil A Tespiti

ÖZ

Kıyı kirliliğinin yer ölçümleri ile tespit edilmesi maliyetli ve zaman alıcıdır. Bu alanlardaki kirliliğin belirlenmesinde en temel parametrelerden biri Klorofil A'dır. Bu çalışma, bu parametrenin Uzaktan Algılama (UA) teknikleri ile belirlenmesini araştırmayı amaçlamaktadır. Çalışmada Karadeniz kıyı bölgelerinde Klorofil A parametresini belirlemek için Sentinel-2 uydusu kullanıldı. Uygulamada 19 algoritma kullanılmıştır. Algoritmalar parlaklık yansımaları ile ilgilidir ve çalışmada uydunun 8 band kullanılmıştır. En iyi model Yapay Sinir Ağ Modeli çıkmıştır. 2021-2017 yılları arasında Karadeniz kıyı bölgelerinde kirlilik gözlemlenmiştir. Yapılan analizler sonucunda UA teknikleri ile kıyı kirliliğinin kısa sürede, masrafsız ve/veya çok düşük maliyetle gözlemlenebileceği görülmüştür. Bu anlamda çevre kirliliğinin tespitinde UA teknikleri büyük önem taşımakta olup, ilgili algoritmalar geliştirilmeli ve yerel ölçümlerle desteklenmelidir.

Anahtar Kelimeler: Klorofil A, Uzaktan Algılama, Sentinel 2, Yapay Sinir Ağ Modeli, kirlilik

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1. INTRODUCTION

Water is essential for life. Given global population growth and environmental trends, the Environment Program UN estimates that 1.8 billion people will face water scarcity by 2025. Water means survival for the people and other species we depend on, making proper management of our water resources essential. Good decisions require good data[1]. Remote sensing (RS) makes it possible to collect temporal and spatial information over large areas, in a short period of time, and at specific intervals. Nowadays, more and more environmental pollution is detected with the help of remote sensing.
Some studies on water quality assessment using satellite imagery images are presented below;

In the study conducted by[2], a temporal analysis (Landsat 1975-1987) of Tuz Gölü was conducted in relation to the change of surface water quality. In this application, which is carried out using ISODATA algorithm, one of the remote sensing techniques, the current situation of the lake is studied using Terra Aster (2004) satellite data. The results obtained from the processed and interpreted satellite images show that the water quality of the lake has drastically decreased between 1975 and 2004.

Gholizadeh et al. [3], widely used approaches and sensors to assess and measure water quality parameters studied. The parameters include: Chlorophyll A (Chl-a), colored dissolved organic matter (CDOM), Secchi disc depth (SDD), turbidity, total suspended sediments (TSS), water temperature (WT), sea surface salinity (SSS).

A water quality measurement model based on multivariate probabilistic logic was developed. This model is based on[4] water quality parameters such as water turbidity, chlorophyll-a, vegetation index, and surface temperature described in the scientific literature, and probabilistic functions derived from the distribution of pixel values of these parameters are used. The procedure was applied to the Centla wetlands in southeastern Mexico. A qualitative scale for water quality assessment was proposed.

In the study conducted by [5], emote sensing and GIS applications were used to monitor water quality parameters such as suspended solids, phytoplankton, turbidity, and dissolved organic matter.

Following the early empirical approach developed by [6], he statistical relationship between spectral reflectance value and water quality parameter was evaluated. It can provide information on bands or wavelengths from spectral reflectance and has been shown to be suitable for this water quality parameter.

In the study conducted by[7] a direct method was developed to predict summer total phosphorus and chlorophyll A levels in a wide range of lakes. These two parameters were measured in 16 Iowa lakes, and phosphorus loading was estimated.

The measurement data used in the study were obtained from "Integrated Marine Pollution Monitoring Program" funded by the Turkish Ministry of Environment and Urbanization/General Directorate of EIA, Permit and Inspection/ Department of Laboratory, Measurement and coordinated by TUBITAK- MRC CC&S for the provisioning of the data used in this study[8]. he field measurements were conducted between 2017 and 2021 and the algorithms were applied to the satellite image with the measurement date. 19 algorithms were used for the application.

2. STUDY AREA and MATERIAL

The fact that the northern Anatolian mountains extend parallel to the coast of the Black Sea has prevented the formation of significant inlets and promontories on the southern shores of the Black Sea. This extension of the mountains has resulted in the Black Sea coast of Anatolia having a poor appearance in terms of roads providing access to the bays, gulfs and inner regions. It is an inland sea with an average depth of 1300 m, a width of 600 km, a length of 1200 km and a total area of about 423000 km^2. It extends east-west across the Balkan and Anatolian peninsulas, the Caucasus and the Eastern European platform. The Black Sea, which flows into the Mediterranean Sea through the straits of Istanbul and Çanakkale, represents one of the most important strategic points of Asia Minor. Moreover, the rich underground and surface resources of the areas around the Black Sea have increased interest in this sea since ancient times. All these characteristics have made the Black Sea a sea that determines the location of ports and plays an important role in trade activities[9]. The Google Earth image of the Black Sea Coast of the Study Area is shown in Figure 1.

It is mainly the process of pollution and eutrophication, accompanied by natural fluctuations and climate changes, which are shown by changes in the ecological system and resources of the Black Sea. However, the environmental crisis of the Black Sea is closely related to the unique features of the marine environment [10].

The Sentinel-2 satellite used for the study area is a multi-band satellite developed by the European Space Agency (ESA) under the Copernicus Land Monitoring

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Services. The satellite has 13 spectral bands and spatial resolutions of 10 m, 20 m, and 60 m. 11.

Figure 1. Google Earth image of the Study Area (Black Sea Coast).

3. CHLOROPHYLL A

The main problem affecting the health and integrity of coastal marine ecosystems is eutrophication. This is a process that not only leads to pollution or an increase in the supply of organic matter, but also increases the primary production of the ecosystem [12], which is a fundamental change in the energy base of the same by nutrients [13]. The eutrophication process leads to the gradual displacement of seagrasses and slow-growing macroalgae by fast-growing macroalgae and phytoplankton, and eventually to their dominance at high nutrient loads [14]. When eutrophication is high, it includes hypoxia events, foam events, nutrient imbalances, chlorophyll and toxic algae blooms, massive deaths of benthic animals and changes in species patterns and even community structure [15].

Chlorophyll A is found in algae and phytoplankton in surface waters. Chlorophyll A is one of the ecological indicators used to assess the ecological status of the marine environment. This pigment cell is used to extract energy from sunlight to produce oxygen to sustain life. Monitoring chlorophyll content is one way to monitor algae growth. High chlorophyll content means high nutrient content in surface water. Food causes algae to grow. When algae populations flourish, they collapse and die in response to changing ecological conditions. As a result, dissolved oxygen levels drop. High nutrient levels are an indicator of pollution from anthropogenic sources. Therefore, chlorophyll measurement can be considered an indicator of nutrient levels [16].

Chlorophyll A fluorescence from microalgae is a compelling indicator of dissolved water contaminant toxicity because it is easy to measure and responds quickly. While several Chl a fluorescence parameters have been studied, most studies have focused on single species and/or a narrow range of toxins [17].

Remote sensing data and technologies are efficient tools for monitoring extreme hydroclimatic events, water quality, and water quantity [18]. Chlorophyll A, colored dissolved organic matter, suspended solids (TSS), Secchi disc depth, and turbidity, which are water quality parameters, have been determined using remote sensing data [3, 18, 19]. Chlorophyll A concentration monitoring is possible by using reflected and absorbed sunlight information, which provides valuable information about the marine environment [20].

4.METHOD AND APPLICATION

Images from 2017 to 2021 were used for the application. 19 Algorithms were used, and correlation and regression analyzes were applied to Sentinel satellite images of 13 different dates. 19 satellite images were used in the models.

All Sentinel 2A and 2B images used in the study were acquired on the day of fieldwork. The ESA Snap program was used for the atmospheric correction. After atmospheric correction, all images were converted to RGB pixel size by applying the interpolation method.

After atmospheric correction and resampling, all images were geometrically corrected, i.e., the measurement points were positioned correctly. All images were converted to WGS-84 datum and coordinates in the UTM projection system.

The relationships between the measured values of 40 points in the models were examined according to the applied models. The analysis was performed with chlorophyll A readings from 38 points and fluorescence readings from 2 points.

A second measurement, which serves as an independent indicator of biological activity, uses a byproduct of photosynthesis: fluorescence emanating from the light-collecting complex of the photosystem II. Fluorescence is one of several quenching mechanisms for the excited state of chlorophyll A. The quantum yield of fluorescence varies primarily due to non-photochemical quenching effects by sunlight [21, 22] but can also be affected by nutrient stress [23, 24].

We used models; Multiple regression model, Polynomial regression model, Response surface regression model, Nas et al. (2007) [25], Tenjo et al. (2015) and Ruiz-Verdú et al. (2016) [26], Cândido et al. (2016) (1-7)[27], El-Magd and Ali (2008) (1-2) [28], Toming et al. (2016) [29], Watanabe et al. (2015) [30], Jaelani et al. (2016) [31], Lim and Choi (2015) [32], ANN (Artificial Neural Network Model) methods. Accuracy analysis was made by comparing the estimation methods, and the method giving the most accurate result was determined. The method and analysis results are

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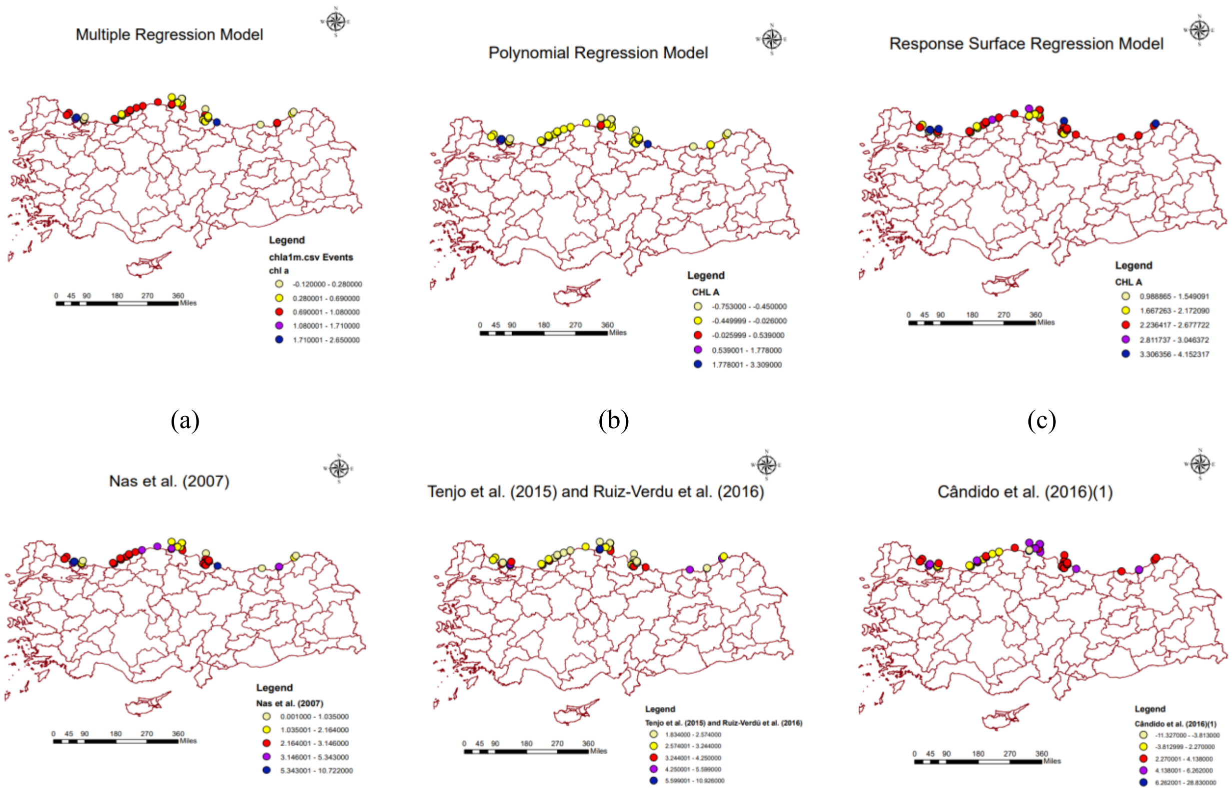
given in Table 1. According to the analysis result, the Chl a significance value gave more accurate results for the ANN model than the other models according to $p=0.00001<0.05$ p and R^2 value. As a result of the algorithm; Chlorophyll A inferences of the models are shown in Figure 2. The graphic analyzes of the models according to the measurement values are given in Figure 3.

Table 1. Chl A estimation methods and accuracy analyzes

Number	Sensor	Number of Variables	Number of Samples	Model	R	R^2	P
1	Sentinel 2	19	40	Artificial Neural Network Model	0.56601	0.32037	0.0001
2	Sentinel 2	19	40	Watanabe et al. (2015)[30]	0.4097	0.16785	0.0001
3	Sentinel 2	19	40	Cândido et al. (2016)(1)[27]	0.37727	0.14233	0.0001
4	Sentinel 2	19	40	Cândido et al. (2016)(2)[27]	0.34081	0.11615	0.0001
5	Sentinel 2	19	40	Cândido et al. (2016)(5)[27]	0.34081	0.11615	0.01831
6	Sentinel 2	19	40	Cândido et al. (2016)(3)[27]	0.31746	0.10078	0.0001
7	Sentinel 2	19	40	Cândido et al. (2016)(6)[27]	0.31746	0.10078	0.04805
8	Sentinel 2	19	40	Multiple Regression Model	0.29166	0.08506	0.0001
9	Sentinel 2	19	40	Toming et al. (2016)[29]	0.28602	0.08181	0.0001
10	Sentinel 2	19	40	Tenjo et al. (2015) and Ruiz-Verdu et al. (2016)[26]	0.26453	0.06997	0.0018
11	Sentinel 2	19	40	Nas et al. (2007)[25]	0.26446	0.06994	0.0001
12	Sentinel 2	19	40	Cândido et al. (2016)(4)[27]	0.25242	0.06371	0.14646
13	Sentinel 2	19	40	Cândido et al. (2016)(7)[27]	0.19373	0.03753	0.51982
14	Sentinel 2	19	40	Response Surface Regression Model	0.16606	0.02757	0.03024
15	Sentinel 2	19	40	Polynomial Regression Model	0.13977	0.01953	0.0001
16	Sentinel 2	19	40	El-Magd and Ali (2008) (1)[28]	0.08594	0.00738	0.00325
17	Sentinel 2	19	40	Jaelani et al. (2016)[31]	0.03495	0.00122	0.96082
18	Sentinel 2	19	40	Lim and Choi (2015)[32]	0.03495	0.00122	0.90085
19	Sentinel 2	19	40	El-Magd and Ali (2008) (2)[28]	0.00801	6.42E-05	0.01981



(a) (b) (c)

(d) (e) (f)

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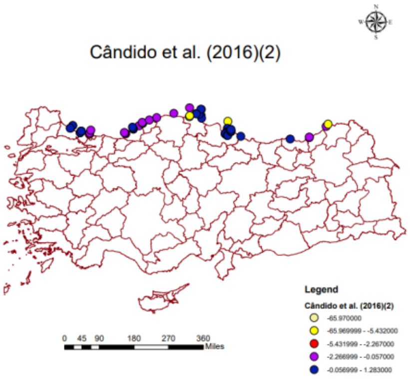

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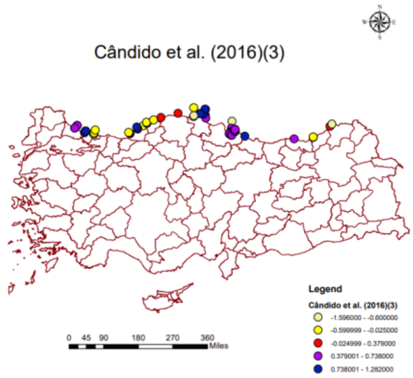

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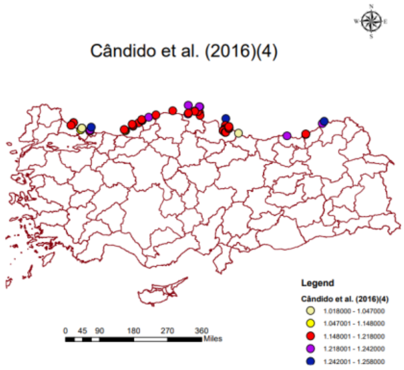

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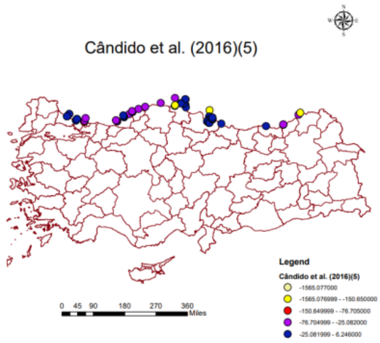

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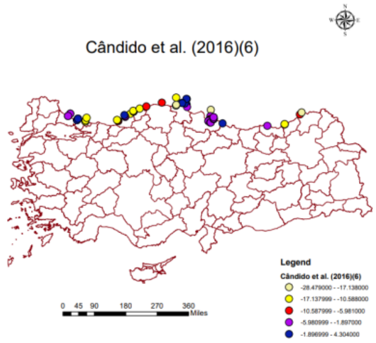

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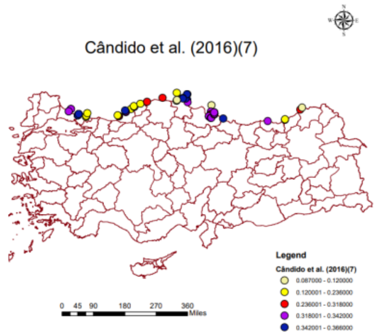

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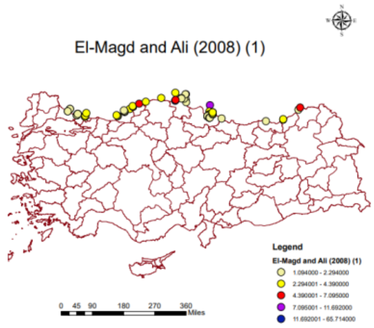

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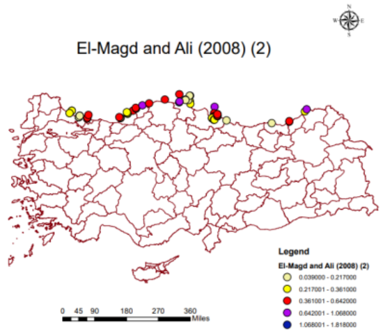

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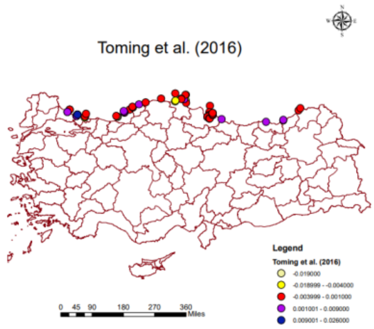

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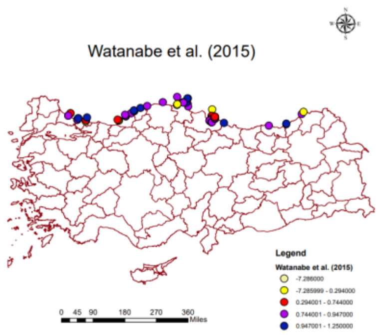

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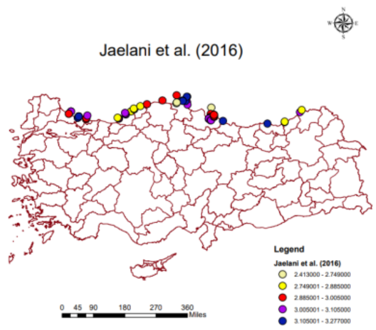

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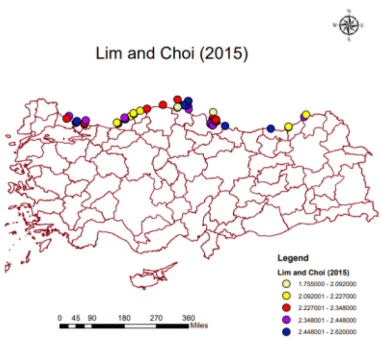

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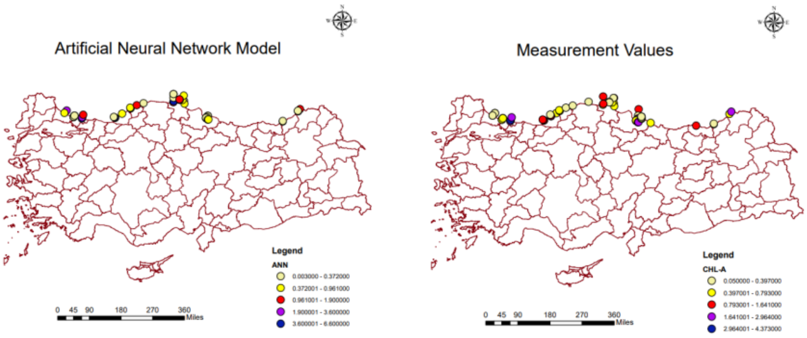
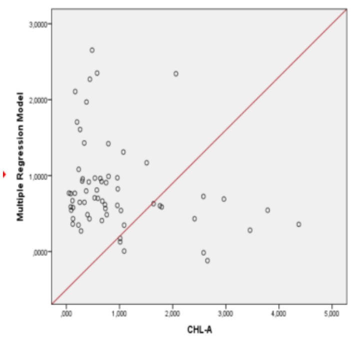


Figure 2. Chlorophyll A models; Multiple regression model (a), Polynomial regression model (b) , Response surface regression model (c) , Nas et al. (2007) [25] (d), Tenjo et al. (2015) and Ruiz-Verdú et al. (2016) [26] (e), Cândido et al. (2016)(1) [27] (f), Cândido et al. (2016)(2) [27] (g), Cândido et al. (2016)(3) [27] (h) Cândido et al. (2016)(4) [27] (i) Cândido et al. (2016)(5) [27] (j), Cândido et al. (2016)(6) [27] (k), Cândido et al. (2016)(7) [27] (l), El-Magd and Ali (2008) (m) [28] (l), El-Magd and Ali (2008) (2) [28] (n), Toming et al. (2016) [29] (o), Watanabe et al. (2015) [30] (p), Jaelani et al. (2016) [31] (q), Lim and Choi (2015) [32] (r), ANN (Artificial Neural Network Model (s) and Chlorophyll A measurement values (t)



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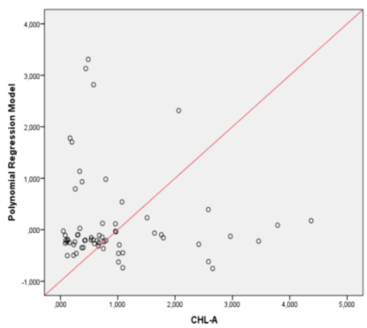

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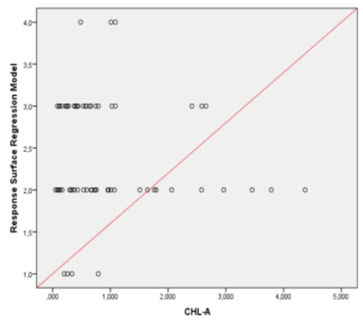

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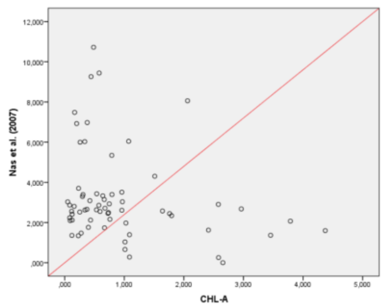

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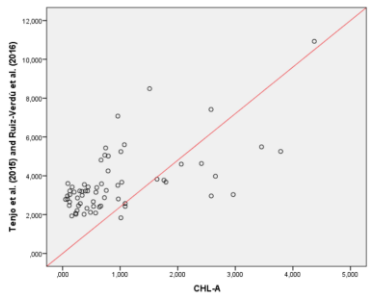

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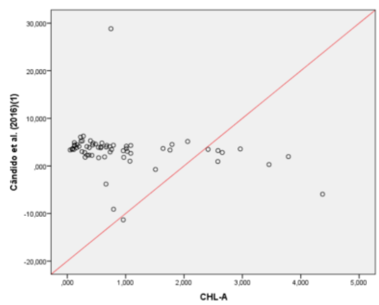

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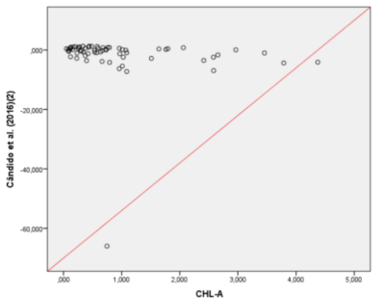

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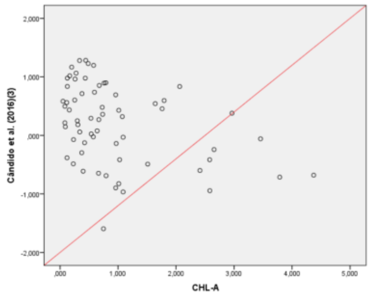

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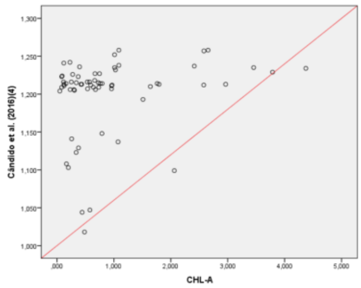

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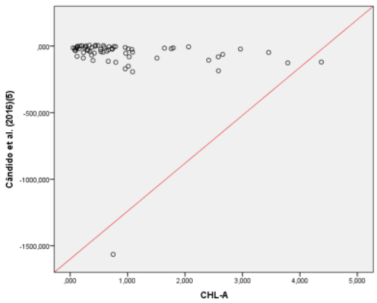

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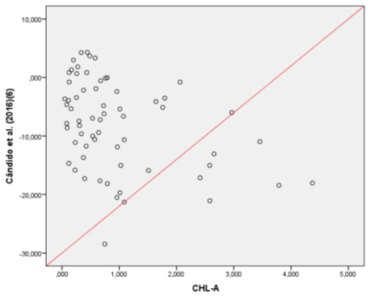

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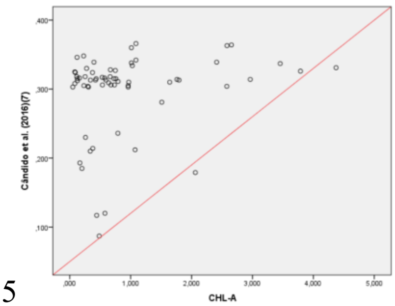

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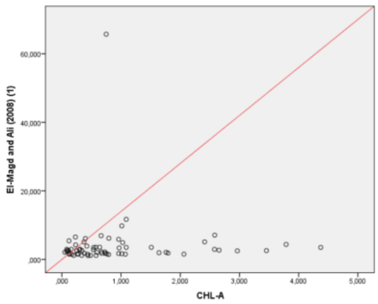

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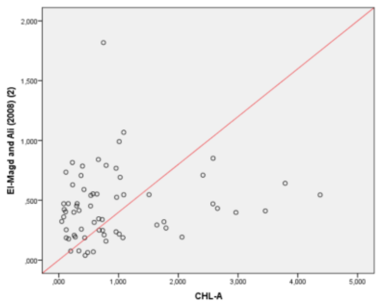

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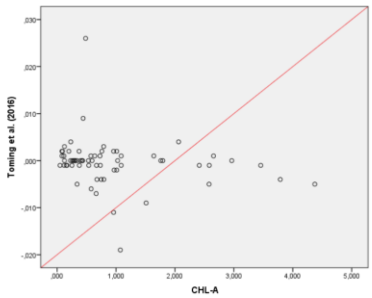

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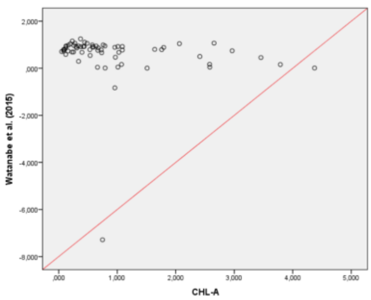

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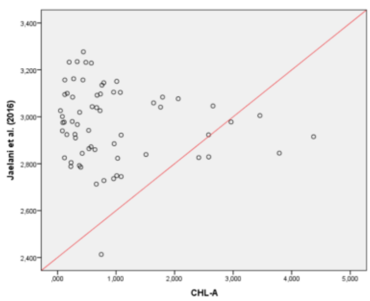

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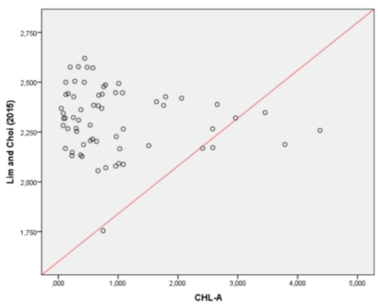

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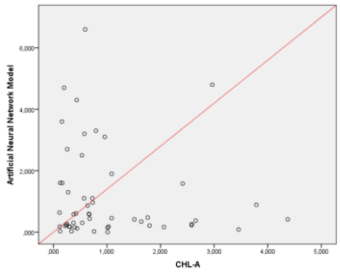

Figure 3. Chlorophyll A models; Multiple regression model (a), Polynomial regression model (b) , Response surface regression model (c) , Nas et al. (2007) [25] (d), Tenjo et al. (2015) and Ruiz-Verdú et al. (2016) [26] (e), Cândido et al. (2016)(1) [27] (f), Cândido et al. (2016)(2) [27] (g), Cândido et al. (2016)(3) [27] (h) Cândido et al. (2016)(4) [27] (i) Cândido et al. (2016)(5) [27] (j), Cândido et al. (2016)(6) [27] (k), Cândido et al. (2016)(7) [27] (l), El-Magd and Ali (2008) (m) [28] (l), El-Magd and Ali (2008) (2) [28] (n), Toming et al. (2016) [29] (o), Watanabe et al. (2015) [30] (p), Jaelani et al. (2016) [31] (q), Lim and Choi (2015) [32] (r), ANN (Artificial Neural Network Model (s) graphics

5.RESULTS

Between 2017 and 2021, measurements were made at 40 points in the coastal regions of the Black Sea, including summer and winter periods. At these terrestrial measurement points, the water quality of the Black Sea coast was monitored using remote sensing methods. 13 Sentinel-2 satellites were used for the study.

The most important parameter for determining water quality is Chlorophyll a. This is because chlorophyll has a relationship that is directly proportional to the reflectance of the surface. In this study, the parameter Chlorophyll A was investigated. 19 algorithms were used. An artificial neural network model was published as the best result. It was found that the proportions of Chlorophyll A, which are the main parameters of pollution, are higher in the Bosphorus and its coasts, on the shores of Sinop and around the Black Ereğli Sea than in other regions.

The Black Sea coast working area is rainy, windy and choppy in all seasons. For this reason, the steps of field measurement and satellite image processing are difficult. From many studies, it is easier to determine water quality in a closed area such as a lake than in open coastal areas. This is because the lake has a stagnant water surface and its parameters do not fluctuate much. In open areas, it is difficult to measure the parameters due to problems such as wind and waves. The parameters also have fluctuations.

It has been shown that it is possible to observe coastal pollution in a short time, without cost and/or at very low cost using remote sensing techniques. On-site measurement is costly and very time consuming. Moreover, measurement on the ground is not possible in all weather conditions. In this sense, remote sensing techniques are of great importance for pollution detection and are used in many studies.

6. CONCLUSION

Water quality parameters can vary depending on weather conditions, time, space, and many other factors. Repeated sampling to analyze periodic changes in water quality is expensive and time consuming. Remote sensing makes it possible to collect information over a wide range of areas and in a short period of time. As a result of the study, it was found that the capabilities offered by RS can be a solution to many problems faced by classical spatial methods that are widely used in water quality determination (such as mustilage), creating a more economical, faster, and labor-saving system for water quality determination projects by ensuring that the two methods work in harmony. These developments show that RS may be an alternative for water quality surveys in the future. Remote sensing technology has proven to be an effective method for monitoring pollution.

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Conflict of interest

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Authors declare that there is no a conflict of interest with any person, institute, company, etc.

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