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Employing Earth Observations and Artificial Intelligence to Address Key
Global Environmental Challenges in Service of the SDGs

A Dissertation by

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Chapman University

Orange, CA

Schmid College of Science and Technology

Submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy in Computational and Data Sciences

December 2019

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December 2019

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ABSTRACT

Employing Earth Observations and Artificial Intelligence to Address Key Global Environmental
Challenges in Service of the SDGs

by Wenzhao Li

Earth Observation (EO) data provides the capability to integrate data from multiple sources and helps to produce more relevant, frequent, and accurate information about complex processes. EO, empowered by methodologies from Artificial Intelligence (AI), supports various aspects of the UN's Sustainable Development Goals (SDGs). This dissertation presents author's major studies using EO to fill in knowledge gaps and develop methodologies and cloud-based applications in selected SDGs, including SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life below Water) and SDG 15 (Life on Land). For SDG 6, the study focuses on spatiotemporal water recharge pattern and interconnections between variables in the Nile watershed countries, highlighting the EO's potential to implement transboundary water cooperation (SDG 6.5.2). For SDG 11, the studies focus on the indicators of urbanization (SDG 11.a.1 and 11.1.1) and air quality (SDG 11.6.2). Utilizing EO datasets, the annual geographical and population weighted PM 2.5 level in Egypt are analyzed in 18 years. The Random Decision Forest is developed to predict the PM10 levels in Cairo. Additionally, a cloud-based impervious surface classifier based on fully convolution neural networks (FCNN) is trained to monitor the urbanization in five Nile basin cities between 2013 and 2019. For SDG 14, the studies focus on the marine pollution (SDG 14.1.1) through monitoring and exploring the atmospheric and meteorological factors regulating algal blooms, as well as its primary productivity in the Red Sea.

For SDG 15, the mangrove changes over the Western Gulf region is quantified using multi-indices and machine learning models to protect the local threatened species (SDG 15.5.1). The MENA is investigated concerning changes of land coverage using harmonic analysis of vegetation index (SDG 15.1.1). Finally, the dissertation also summarizes the SDG researches the author involved, including 1) air pollutant in the MENA region; 2) dust impact on rainfall 3) aerosols' impact on snowfall; 4) oil spill modelling to help proper mitigation; 5) vegetation in the sea turtle nesting Islands; and 6) EO of Mediterranean seagrass *Posidonia Oceanica*.

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1 Introduction

1.1 Goals of this Research

On the historical 70th anniversary of the United Nations (UN) in September 2015, the heads of state and delegates gathered and adopted the 2030 Agenda for Sustainable Development in three dimensions — economic, social, and environmental— in a balanced and integrated manner, which represents a milestone in our progress towards international development cooperation. This comprehensive sustainability framework was built on the basis of the historical experiences of human society and a shared expectation for the next 15 years.

The 17 Sustainable Development Goals (SDGs) incorporate various social, economic, environmental, and developmental aspects, which consist of 169 targets and 230 indicators, and have been endorsed by all countries with respective national implementation plans for their different and very diverse development context. It can be concluded that the SDGs constitute a vast system that is complicated, diverse, dynamic, and interconnected, where the success to achieve one goal is often linked to solving issues associated with other goals. However, the implementation of the agenda faces several challenges from a scientific perspective, including data deficiency, imperfect methods, interconnected and mutually constrained targets, diverse localization issues, and other problems restricting the pace of progress. There are four major challenges in the implementation of the 2030 Agenda for Sustainable Development, including: (1) missing data and the evolution of SDG indicators, (2) complementary and non-complementary interconnections between different Sustainable Development Goals (SDGs), (3) complicated and

varied problems in quantifying and monitoring indicators within different national and local contexts, and (4) difficulties in modeling indicators to monitor SDGs. Particularly, the main challenge in monitoring progress relates to the lack of data available for the development of indicators, and this lack of data has been identified for more than half of indicators.

As an important aspect of technological innovation today, the Earth Observation (EO) plays an important role to mitigate the shortage of in-situ data availability by providing reliable, updated and cost-effective data as solutions in a global or regional scales. In addition, the EO data is characterized by massive quantity, multiple sources, multi-temporal, multi-dimensional heterogeneous structure, and high complexity. The study of EO data in support of SDGs therefore requires powerful computing capabilities and advanced analytical methods. Recent advancement in artificial intelligence (AI) methodologies, computing and information technology and especially availability of remote sensing data, have provided an opportunity to monitor the SDG related indicators (e.g. vegetation, urban and marine habitats) from regional to global scales on a consistent and regular basis. The advantages of cloud computing including the parallel computing offer near unlimited computer processing capabilities, as well as free access to a large volume of EO data already stored in the remote cloud drives. In recent years, there has been an emerging increase in high-performance cloud computing platforms, such as the NASA Earth Exchange (NEX), Amazon Web Service (AWS) and Google Earth Engine (GEE).

The main goal of the research on EO for SDGs include converting EO Data into SDG-related information, providing decision support for SDG implementation, constructing an AI-driven and cloud computing-integrated system for SDG indicators, and investigating the inter-linkages among different components of the Earth system. We have preliminarily sorted out 14

indicators from four SDGs as a priority. The four SDGs include: SDG 6 (Clean Water and Sanitation), SDG 11 (Sustainable Cities and Communities), SDG 14 (Life below Water), and SDG 15 (Life on Land). The dissertation presents author's seven major studies of EO on the development of SDG indicators and sustainability assessments in the above-mentioned four SDGs. These cases provide in-depth, systematic research and evaluation results on the selected SDGs and indicators by means of data, method models, and decision support. The dissertation also summarizes the other SDG researches the author involved. It can be seen that EO as a new scientific methodology has started demonstrating its great value and potential for application in monitoring and evaluating SDGs. The report concludes with a summary of the author's major progress in EO and AI research for SDGs and future research priorities.

1.2 2030 Agenda for Sustainable Development

The 2030 Agenda for Sustainable Development was adopted by all United Nations (UN) Member States in 2015. This agenda seeks to build on the Millennium Development Goals and complete what they did not achieve. The agenda includes 17 Sustainable Development Goals (SDGs), 169 targets, and 232 indicators all aimed at establishing principles of sustainable development in national policies. The research proposed in this dissertation addresses four of these goals. In particular, SDG 6 concerning SDG 6 clean water and sanitation, SDG 11 concerning sustainable cities and communities, SDG 14 concerning life below water, and SDG 15 concerning life on land.

1.3 SDG 6

The objective of SDG 6 is to “Ensure availability and sustainable management of water and sanitation for all”. To achieve this, SDG 6 asserts eight different targets. Table 1-1 shows selected targets and the associated indicator(s). Target 6.5 asserts, “By 2030, implement integrated water resources management at all levels, including through transboundary cooperation as appropriate.” The research proposed in this dissertation performs two functions to contribute to this target. First, it informs countries in the Nile watershed for the urgent need of water resources management and cooperation. Second, this research provides a methodology of using cloud computing platform Google Earth Engine to perform multiple experiments to study the water recharge pattern in the Nile watershed. Both contribute to the indicator 6.5.2, “Proportion of transboundary basin area with an operational arrangement for water cooperation”. In addition to these direct implications of this research there are several indirect impacts. For example, this research contributes to the indicator 6.6.1 behind target 6.6, “Change in the extent of water-related ecosystems over time” by the studying the interconnection between multiple hydrological variables in the basin-scale water ecosystem. Another example shows this research can be used to inform target 6.4, “By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity” by informing policy makers in the Nile Delta region to improve the groundwater use efficiency, as stated in the indicator 6.4.1, “Change in water-use efficiency over time”.

Table 1-1: Selected SDG 6 Targets and Indicators

Targets	Indicators
6.4 By 2030, substantially increase water-use efficiency across all sectors and ensure sustainable withdrawals and supply of freshwater to address water scarcity and substantially reduce the number of people suffering from water scarcity	6.4.1 Change in water-use efficiency over time 6.4.2 Level of water stress: freshwater withdrawal as a proportion of available freshwater resources
6.5 By 2030, implement integrated water resources management at all levels, including through transboundary cooperation as appropriate	6.5.1 Degree of integrated water resources management implementation (0–100) 6.5.2 Proportion of transboundary basin area with an operational arrangement for water cooperation
6.6 By 2020, protect and restore water-related ecosystems, including mountains, forests, wetlands, rivers, aquifers and lakes	6.6.1 Change in the extent of water-related ecosystems over time

1.4 SDG 11

The objective of SDG 11 is to “Make cities and human settlements inclusive, safe, resilient and sustainable”. To achieve this, SDG 11 asserts ten different targets. Table 1-2 shows selected targets and the associated indicator(s). Target 11.1 asserts, “By 2030, ensure access for all to adequate, safe and affordable housing and basic services and upgrade slums.” The research proposed in this dissertation performs state-of-art machine learning algorithm- Fully Convolution Neural Networks (FCNN) model to identify and monitor the slums in the Nile watershed cities, as well as the world’s biggest slum- Orangi Town, Karachi, Pakistan, to contribute to this target. First, the research informs countries in the Nile watershed for the urgent need of urban planning and disaster risk reduction to control the slums growth. It contributes to the indicator 11.b.1, “Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030.” Second, similar to what has been done for Target 6.5 (water management), this research also provides a case of using cloud computing platform Google Earth Engine to contribute the sustainable urbanization in the Nile watershed. It contributes to the indicator 11.1.1, “Proportion of urban population living in slums, informal settlements or inadequate housing”, as well as the indicator 11.a.1, “Proportion of population living in cities that implement urban and regional development plans integrating population projections and resource needs, by size of city.” This research also finds the urban expansions in the developed regions while the model is limited to identify slums/rural areas and their changes. This may be due to the biases introduced for the difference between training data from developed countries (i.e. United States) and developing countries in the Nile watershed. It reveals the situation of data and technology inequality among the developed and developing countries. Therefore, the study suggests future cooperation and support to the developing countries to achieve

SDGs, as it is stated in the indicator 11.c.1, “Proportion of financial support to the least developed countries that is allocated to the construction and retrofitting of sustainable, resilient and resource-efficient buildings utilizing local materials.” Additionally, the Target 11.6 asserts, “By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management.” In the Cairo metropolitan region, the research makes use of the Random Decision Forest (RDF) model to convert satellite-based AOD and other meteorological parameters to predict PM₁₀. The study also shows annual population weighted and geographic mean PM_{2.5} for all of Egypt using GWR datasets to compare with monthly MERRA-2 datasets (min, max, and mean values) of PM_{2.5} dust AOD and sea salt AOD, as well as surface air temperature and wind speed during the period from the year 1998 to 2016. These works can improve the knowledge of air pollutant variability and intensity in the Cairo and MENA region for decision makers to operate proper mitigation strategies. It contributes to the indicator 11.6.2, “Annual mean levels of fine particulate matter (e.g. PM_{2.5} and PM₁₀) in cities (population weighted).”

Table 1-2: SDG 11 Targets and Indicators

Targets	Indicators
11.1 By 2030, ensure access for all to adequate, safe and affordable housing and basic services and upgrade slums	11.1.1 Proportion of urban population living in slums, informal settlements or inadequate housing
11.6 By 2030, reduce the adverse per capita environmental impact of cities, including by paying special attention to air quality and municipal and other waste management	11.6.1 Proportion of urban solid waste regularly collected and with adequate final discharge out of total urban solid waste generated, by cities 11.6.2 Annual mean levels of fine particulate matter (e.g. PM2.5 and PM10) in cities (population weighted)
11.a Support positive economic, social and environmental links between urban, peri-urban and rural areas by strengthening national and regional development planning	11.a.1 Proportion of population living in cities that implement urban and regional development plans integrating population projections and resource needs, by size of city
11.b By 2020, substantially increase the number of cities and human settlements adopting and implementing integrated policies and plans towards inclusion, resource efficiency, mitigation and adaptation to climate change, resilience to disasters, and develop and implement, in line with the Sendai Framework for Disaster Risk Reduction 2015–2030, holistic disaster risk management at all levels	11.b.1 Number of countries that adopt and implement national disaster risk reduction strategies in line with the Sendai Framework for Disaster Risk Reduction 2015–2030 11.b.2 Proportion of local governments that adopt and implement local disaster risk reduction strategies in line with national disaster risk reduction strategies
11.c Support least developed countries, including through financial and technical assistance, in building sustainable and resilient buildings utilizing local materials	11.c.1 Proportion of financial support to the least developed countries that is allocated to the construction and retrofitting of sustainable, resilient and resource- efficient buildings utilizing local materials

1.5 SDG 14

The objective of SDG 14 is to “Conserve and sustainably use the oceans, seas and marine resources for sustainable development”. To achieve this, SDG 14 asserts ten different targets.

Table 1-3 shows some of these targets and the associated indicator(s). Target 14.1 asserts, “By

2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution.” The research proposed in this dissertation performs two studies to contribute to this target. First, it observes an anomalously high chlorophyll-a (Chl-a) event (>2 mg/m³) during June 2015 in the South Central Red Sea (17.5° to 22°N, 37° to 42°E). The analysis suggests that a combination of factors controlling nutrient supply contributed to the anomalous phytoplankton growth. Second, the following research considers the various factors that regulate nutrients supply in the Red Sea, as well as the data quality issue of the Ocean Color Climate Change Initiative (OC-CCI) dataset due to the inclusion of different datasets. Both of these researches contribute to the indicator 14.1.1, “Index of coastal eutrophication and floating plastic debris density”. In addition to these direct implications of this research there are several indirect impacts. For example, this research contributes to the indicator 14.2.1 behind target 14.2, “By 2020, sustainably manage and protect marine and coastal ecosystems to avoid significant adverse impacts, including by strengthening their resilience, and take action for their restoration in order to achieve healthy and productive oceans” by the studying the nutrient exchange between phytoplankton growth and coastal coral reefs ecosystems. Another example shows this research can be used to inform target 14.5, “By 2020, conserve at least 10 per cent of coastal and marine areas, consistent with national and international law and based on the best available scientific information” by informing policy makers in the Red Sea coastal countries to increase the protected areas, as stated in the indicator 14.5.1, “Coverage of protected areas in relation to marine areas”.

Table 1-3: SDG 14 Targets and Indicators

Targets	Indicators
14.1 By 2025, prevent and significantly reduce marine pollution of all kinds, in particular from land-based activities, including marine debris and nutrient pollution	14.1.1 Index of coastal eutrophication and floating plastic debris density
14.2 By 2020, sustainably manage and protect marine and coastal ecosystems to avoid significant adverse impacts, including by strengthening their resilience, and take action for their restoration in order to achieve healthy and productive oceans	14.2.1 Proportion of national exclusive economic zones managed using ecosystem-based approaches
14.5 By 2020, conserve at least 10 per cent of coastal and marine areas, consistent with national and international law and based on the best available scientific information	14.5.1 Coverage of protected areas in relation to marine areas

1.6 SDG 15

The objective of SDG 15 is to “Protect, restore and promote sustainable use of terrestrial ecosystems, sustainably manage forests, combat desertification, and halt and reverse land degradation and halt biodiversity loss”. To achieve this, SDG 15 asserts twelve different targets. Table 1-4 shows some of these targets and the associated indicator(s). Target 15.1 asserts, “By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements.” The research proposed in this dissertation performs two functions to contribute to this target. First, it uses the enhanced vegetation index (EVI) as an indicator of this drying trend over the MENA region the past 20 years. The harmonic analysis model is used for comparison with observation data to reveal trends in some capital cities within the MENA region. For the Saudi Arabia region, the soil moisture products, vegetation and precipitation-based products were assessed to monitor and predict the variability of vegetation

distribution. Second, the research conducts the change detection analysis on mangrove forests along the Saudi Arabian coast of the WAG for the years 2000, 2010 and 2018 using Landsat 7 & 8 data. A new method is employed to identify and analyze submerged mangrove forests distribution via a submerged mangrove recognition index (SMRI) and Normalized Difference Vegetation Index (NDVI) in Abu Ali Island. The vegetation and land use from the research contributes to the indicator 15.1.1, “Forest area as a proportion of total land area”, indicator 15.2.1, “Progress towards sustainable forest management” and indicator 15.3.1, “Proportion of land that is degraded over total land area”. Mangroves forests present as an important habitat for large coastal communities and species of high biodiversity, yet they are increasingly threatened by natural pressure and anthropogenic activities. The study contributes to the indicators 15.1.2, “Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type” and 15.5.1, “Red List Index”. Additionally, since the mangroves locate in both land and coastal regions, the research of mangrove change detection also contributes to the targets as stated in SDG 14.2 and 14.5.

Table 1-4: SDG 15 Targets and Indicators

Targets	Indicators
15.1 By 2020, ensure the conservation, restoration and sustainable use of terrestrial and inland freshwater ecosystems and their services, in particular forests, wetlands, mountains and drylands, in line with obligations under international agreements	15.1.1 Forest area as a proportion of total land area 15.1.2 Proportion of important sites for terrestrial and freshwater biodiversity that are covered by protected areas, by ecosystem type
15.2 By 2020, promote the implementation of sustainable management of all types of forests, halt deforestation, restore degraded forests and substantially increase afforestation and reforestation globally	15.2.1 Progress towards sustainable forest management
15.3 By 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation- neutral world	15.3.1 Proportion of land that is degraded over total land area
15.5 Take urgent and significant action to reduce the degradation of natural habitats, halt the loss of biodiversity and, by 2020, protect and prevent the extinction of threatened species	15.5.1 Red List Index

1.7 Sendai Framework for Disaster Risk Reduction

The Sendai Framework for Disaster Risk Reduction aims for: “The substantial reduction of disaster risk and losses in lives, livelihoods and health and in the economic, physical, social, cultural and environmental assets of persons, businesses, communities and countries.” To this end, the research presented in this dissertation addresses the livelihoods and health and in the economic, and environmental assets of persons, businesses, communities, and countries. Specifically, the slums urbanization is a key social and environmental challenge in the developing countries. The slums and low-income rural habitats are more vulnerable to the diseases, wars and environmental

disasters. Therefore, the research is critical to monitor these communities for improved urban planning and disaster risk deduction. The air quality observation and modeling is also helping the MENA cites to improve the urban health standards. In addition, the primary resource of many countries is their marine environment such as the mangrove and costal reefs ecosystems. These ecosystems provides considerable services to human communities with ecological and economic values for income (tourism or otherwise) and sustenance (through fishing, research, or otherwise). They also have environmental functionality to protect shoreline from storms, erosion, and sedimentation for local human communities. Therefore, the research presented in the dissertation is critical to the lives, livelihoods, and health of local communities economically, socially, culturally, and environmentally. Particularly with respect to the MENA regions including the urban habitats which are challenged by the rapid population growth and air pollutions, as well as villages in the Red Sea and the Gulf regions which rely on the tourist and fishery income from the mangrove and coral reefs and for subsistence, the results of this research are imperative to inform policy and decision making.

1.8 World Economic Forum: The Global Risks Report

The Global Risks Report is an annual evaluation by the World Economic Forum which looks at the foremost risks facing the world [2]. These risks range from weapons of mass destruction to terrorist attacks to financial crisis. There are several methods by which the World Economic Forum reports on these risks. One such methodology is a visualization called the Global Risks Landscape. This visualization plots each primary global risk on a scale by likelihood on the x-axis and impact on the y-axis. Therefore, global risks that are higher on the plot represent a larger impact while global risks that are to the right of the plot represent a larger likelihood. In 2019, all

environmental risks were represented in the first quadrant as both most likely and most impactful, Figure 1-1.

Figure 1-1: World Economic Forum Global Risks Landscape.

The failure of climate-change mitigation and adaptation was both the second most likely risk and second highest impact risk. Furthermore, the extreme weather events are the in the highest likely risk with the third highest impact risk. This dissertation directly addresses the extreme weather events, such as air pollution, algal blooms, extreme drought and induced water shortage,

as well as indirectly investigates the failure of climate-change mitigation and adaptation risk outlined in the World Economic Forum Global Risks Report. Specifically, the research proposed identifies the impact that climate-change is having on the ocean primary productivity and air qualities, as well as the mangrove coastal ecosystems as most biodiverse marine ecosystems and among the most biodiverse ecosystems in the world. This research also is an evaluation of the changing cover across a large extent of land/water coverage including coastal/land forest detection and therefore provides valuable information for the governments and businesses addressed in the Global Risks Report. Providing this insight provides data for these organizations to call attention to the need for natural disaster and climate-change mitigation and adaptation.

2 First Study: Earth Observation and Cloud Computing in support of Two Sustainable Development Goals for the River Nile Watershed Countries

2.1 Introduction

The Nile is a major north-flowing river through eleven countries in the Northeastern Africa, these countries from south to north are Tanzania, Uganda, Rwanda, Burundi, the Democratic Republic of the Congo, Kenya, Ethiopia, Eritrea, South Sudan, Republic of the Sudan and Egypt. With an estimated length ranging between 5,499 km and 7,088 km, it is the longest river in Africa and widely regarded as the longest river in the world [1]. The Nile serves as the primary water source to downstream nations namely, Sudan and Egypt [2]. However, water stress/scarcity are expected because of limited water to meet various irrigation needs of the Nile basin nations, as well as hydraulic engineering projects among the countries such as hydropower dams being built in Sudan (Merowe dam), Ethiopia (Grand Renaissance dam) and Uganda (Karuma dam) as well as other stressors driven by climate change. It is noted that these projects will not reduce the tensions between countries but possibly introduce more challenges, bringing the uncertainty of the future economic development and regional stability. Additionally, the local water measurements of Nile are outdated and limited. For example, the latest records of stations in Global Runoff Data Centre (https://www.bafg.de/GRDC/EN/01_GRDC/grdc_node.html) dataset date back to 1984.

Countries in the Nile are undergoing rapid population growth and urbanization. Seven Nile basin countries are expected to double their populations between 1995 and 2025 [3]. Most of the countries have agriculturally-based economies, and rapid population growth will further pressure the natural resources and often contribute to environmental stress. The limited financial resources and technological abilities of the majority of these nations results in them being unable to properly take mitigation actions [3]. Additionally, rapid urbanization is anticipated in the Nile countries due to the increasing movement of people from rural to urban areas associated with population growth and poverty. On one hand, the rapid urbanization is driven by the labor migration and development of industry. On the other hand, the unplanned urban regions often lack the infrastructure and institutions needed to adequately supply adequate water and provide sanitation, as well as reliable housing and public transportation, in order to protect human and environmental health. The migrated population form or join the low-income communities (slum urbanizations) that are especially impacted by inadequate environmental services and by water and air pollution. The situation is typical in the Nile countries, since the ongoing South Sudanese civil war has sent at least over 2 million people migrating neighboring countries as refugees [4]. The uncontrolled growth (from 245,000 in 1956 to more than 7 million in 2012) of Sudan's capital Khartoum has resulted in 50 per cent of residents are living in informal and squatter settlements on the outskirts of the city [5].

On the historical 70th anniversary of the United Nations (UN) in September 2015, the heads of state and delegates gathered and adopted the 2030 Agenda for Sustainable Development [6]. This comprehensive sustainability framework was built on the basis of the historical experiences of human society and a shared expectation for the next 15 years. The 17 Sustainable Development Goals (SDGs) incorporate various social, economic, environmental, and

developmental aspects, which consist of 169 targets and 230 indicators [7], and have been endorsed by all countries with respective national implementation plans for their different and very diverse development context. It can be concluded that the SDGs constitute a vast system that is complicated, diverse, dynamic, and interconnected, where the success to achieve one goal is often linked to solving issues associated with other goals. In order to achieve the SDGs and effectively assess their progress with the full strength of science, technology, and innovation (STI), the United Nations (UN) has established the “Technology Facilitation Mechanism” (TFM) [8]. Presently, a pressing priority of TFM is to make breakthroughs towards Tier II indicators (methods established but with poor data) and Tier III indicators (methods under development with either poor data or no data). Fortunately, the Earth Observation (EO) plays an important role to mitigate the shortage of in-situ data availability by providing reliable, updated and cost-effective data as solutions in a global or regional scales [9]. In addition, the EOs are characterized by massive quantity, multiple sources, multi-temporal, multi-dimensional heterogeneous structure, and high complexity. The study of EO data in support of SDGs therefore requires powerful computing capabilities and advanced analytical methods. Recent advancement in image-processing methodologies, computing and information technology and especially availability of remote sensing data, have provided an opportunity to monitor the SDG related indicators (e.g. vegetation, rainfall and marine habitats) from regional to global scales on a consistent and regular basis [10–14]. The advantages of cloud computing including the parallel computing offer near unlimited computer processing capabilities, as well as free access to a large volume of EO data already stored in the remote cloud drives. In recent years, there has been an emerging increase in high-performance cloud computing platforms, such as the NASA Earth Exchange (NEX), Amazon Web Service (AWS) and Google Earth Engine (GEE) [15]. GEE is widely used for the environmental research in the Nile watershed

and adjacent regions [10,16–20]. It is characterized as an easily accessible and user-friendly front-end platform providing a convenient environment for interactive data representation and algorithm development. The GEE directly accesses the Google’s cloud resources to undertake all the processing and analysis, which does not require large processing powers of computers or expensive software. It is a tool that allows researchers from developing countries (e.g. Nile Basin countries) to have the same ability to undertake state-of-art studies as those in the most advanced nations. Considering the urgent situation of water data availability and urbanization stress in the Nile Basin countries, the EO and cloud computing evidently appear to be one of the priorities to help achieve the SDG goals.

This paper demonstrates the intersection between EO, cloud computing and related technologies and demonstrates how they contribute to the assessment of two SDGs in the Nile watershed countries, namely SDG 6 “clean water and sanitation” and SDG 11 “sustainable cities and communities”. This is carried out through studying the water resources using multiple hydrological variables, as well as the changing detection of the changing percentage of impervious surface areas in five major Nile basin cities using advanced algorithms implemented on the cloud-computing platform.

2.2 Materials and Methods

2.2.1 Study Area

In this study, we investigate seven countries in the River Nile watershed, namely, Egypt, Sudan, South Sudan, Ethiopia, Uganda, Kenya and Tanzania, which totally occupy up to 97% of the areas of the watershed calculated from the shapefile accessed from the Nile Basin Initiative

(<https://www.nilebasin.org/>) (Table 2-1). Sudan has the biggest size (33.92%) compared to other countries, while both South Sudan and Uganda have the entire territories within the watershed (Fig. 2-1). Five capital cities among the countries are located in this region, namely: Cairo, Khartoum, Juba, Addis Ababa and Kampala. The following section will study and address their changes of impervious surface in recent years.

Table 2-1: The countries in the Nile watershed under investigation in this research

Country	Capital City	Calculated Area (km ²)	Percentage
Egypt	Cairo	232,522.1	8.98%
Sudan	Khartoum	878,440.2	33.92%
South Sudan	Juba	638,825.2	24.67%
Ethiopia	Addis Ababa	360,680.9	13.93%
Uganda	Kampala	239,450.5	9.25%
Kenya	Nairobi	112,661.4	4.35%
Tanzania	Dodoma	72,724.7	2.81%
Nile watershed	N/A	2,589,724.4	100.00%

Figure 2-1: The map of countries in the Nile watershed region and the selected capital cities (Cairo, Khartoum, Juba, Addis Ababa and Kampala) in this study.

2.2.2 Hydrological Datasets and Methods

NASA-USDA Global Soil Moisture Dataset

The NASA-USDA Global soil moisture dataset [21–24] include information of surface and subsurface soil moisture, soil moisture profile (%), as well as surface and subsurface soil moisture anomalies represented as unitless and standardized values (negative/positive either refers to drier/wetter than normal conditions, respectively) computed using a 31-days moving window. The dataset has spatial resolution of $0.25^{\circ} \times 0.25^{\circ}$ at global scale and temporal resolution of 3 days. This dataset is generated through the data assimilation approach, which employs a modified two-layer Palmer model using a 1-D Ensemble Kalman Filter (EnKF) to integrate the satellite-derived Soil Moisture Active Passive (SMAP) Level 3 soil moisture observations. This approach turns out to be helpful to improve the model-based soil moisture predictions, particularly for the Nile watershed region which lacks good quality hydrological measurements.

Climate Hazards Group Infrared Precipitation with Station Dataset

Precipitation dataset is obtained from the Climate Hazards Group Infrared Precipitation with Station (CHIRPS) dataset (version 2.0) [25]. CHIRPS is a 30+ year quasi-global rainfall dataset, which is developed by United States Geological Survey (USGS) in collaboration with the Earth Resource Observation and Science center (<https://www.usgs.gov/centers/eros>). The dataset incorporates 0.05° resolution satellite imagery with in-situ station data with temporal resolution as pentad (i.e. the first 5 pentads in a month have 5 days and the last pentad contains all the days from the 26th to the end of the month) to create gridded precipitation time series for trend/correlational analysis and drought/flood monitoring.

Famine Early Warning Systems Network Land Data Assimilation System dataset

The evapotranspiration (ET) and runoff data is obtained from the Famine Early Warning Systems Network (FEWS NET) Land Data Assimilation System (FLDAS) [26,27]. The FLDAS is designed particularly to assist the food security investigations for the developing countries with sparse data accessibility. In this research, the version of FLDAS dataset used in this study is the Noah version 3.6.1 surface model with downscaled CHIRPS-6 hourly precipitation inputs using the NASA Land Surface Data Toolkit (<https://lis.gsfc.nasa.gov/software/ldt>). The model uses a combination of the new version of Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) data and CHIRPS for the data forcing purpose. The dataset provides monthly records with spatial resolution of 0.1 arc degrees. Besides, the total runoff is computed from the sum of surface storm runoff (Q_{s_tavg}) and baseflow-groundwater runoff (Q_{sb_tavg}). The unit of the FLDAS data is translated from $kg\ m^{-2}\ s^{-1}$ to $mm\ s^{-1}$ to match the units used in precipitation ($mm/pentad$) and soil moisture (mm) datasets.

GRACE Monthly Gravitational Anomalies dataset

GRACE Tellus Monthly Mass Grids [28–30] provides monthly gravitational anomalies relative to a 2004-2010 time-mean baseline. The dataset uses the units of "Equivalent liquid water thickness" (LWE) which represent the deviations of mass in terms of vertical extent of water in centimeters. The Gravity Recovery and Climate Experiment (GRACE) mission operated from April, 2002 to June, 2017. The GRACE satellites measure the spatial and temporal variability in the earth's gravity field and the monthly gridded terrestrial water storage (TWS) products are available from the NASA Jet Propulsion Laboratory (JPL) Tellus website

(<https://grace.jpl.nasa.gov/data/get-data/monthly-mass-grids-land/>) on 1 horizontal resolution grids and global coverage. The unit is GRACE data is also translated from centimeters to mm.

Harmonic analysis is a method involving the representation of functions or signals as a superposition of elementary waves. In this study, to estimate the variation of multiple hydrological factors (e.g. precipitation), we build the harmonic model $H(t)$ with elements of a constant band (β_0), a linear term of slope (β_1) and harmonic terms of amplitudes (β_2 , β_3 , β_4 and β_5). The term β_1 , associated with the linear part of the factor, represents the increasing/decreasing trend, whereas a constant band β_0 represents the extent of consistency of the time series. Moreover, f represents the fundamental frequency. The β_1 of the harmonic analysis can show linear trend of a series regardless of the seasonal variations. The value β_1 shows the monthly trend in the Nile watershed. Positive value presents increasing trend, and negative value decreasing.

$$H(t) = \beta_0 + \beta_1 t + \beta_2 \cos(2\pi ft) + \beta_3 \sin(2\pi ft) + \beta_4 \cos(4\pi ft) + \beta_5 \sin(4\pi ft) \quad (1)$$

The precipitation, ET, surface soil moisture, runoff and LWE products are used to generate the changing trend map of the Nile watershed region during May 1st, 2013 till October 20th, 2019, as well as lag correlation analysis using their anomalies value X_a calculated as:

$$X_a = X - \bar{X} \quad (2)$$

with X as the monthly value and $\bar{X}$ as the monthly mean value.

In the previous comparative global study of water availability in the major river basins [31], the basin averaged water balance was estimated through the equation (3) and compared to the GRACE water LWE anomaly:

$$P - ET - R = \Delta S \quad (3)$$

where precipitation (P), ET, runoff (R), and change in surface and subsurface water storage ΔS are monthly and basin averaged values for each of the basins. The left-hand variables can be estimated from the satellite observations or model outputs, while the right-hand ΔS is estimated through the GRACE observations. The difference between P-ET-R and ΔS represents other factors related to human activities, such as of exploitation of groundwater in the basin for agricultural or industrial purposes. All the data used in this research is accessed from the Google Earth Engine platform through sampling of random points (200 to 300 points according to the country size) within the overlapped region of both Nile watershed and countries' territories.

2.2.3 Landcover and Land Use Datasets

USGS Landsat 8 Surface Reflectance

The Landsat 8 Surface Reflectance Tier 1 dataset [32] observed from OLI/TIRS sensors is used in this research. The imagery has been atmospherically corrected by the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS). It includes the per-pixel saturation mask and cloud, shadow, water and snow mask from C Function of Mask (CFMASK). The data is available since April 11th, 2013 and generated by Google using a Docker image supplied by USGS. The images contain 5 visible and near-infrared (VNIR) bands of 30 m resolution, 2 short-wave infrared (SWIR) bands of 30 m resolution processed to orthorectified surface reflectance, and two thermal infrared (TIR) bands of resampled 30 m resolution for processed to orthorectified brightness temperature. In this study, we utilized Landsat 8 imagery composites of the period during May 1st to October 20th, 2013 and May 1st to October 20th, 2019 for the five capital cities in order to compare the changes of the percentage of impervious surfaces. The

imagery composites are generated through rigorous cloud masking and quality assurance, as well as transformation of temperature unit from Kelvin to Celsius.

The National Land Cover Database

The National Land Cover Database (NLCD) [33] is a land cover database based on 30-m Landsat imageries. It includes 8 epochs (1992, 2001, 2004, 2006, 2008, 2011, 2013 and 2016), in which the 1992 data not directly comparable to the later epochs since it is generated from unsupervised classification method while other editions are based on the imperviousness data layer for the urban classes and on a decision-tree classification for the rest classes. The dataset is generated by the Multi-Resolution Land Characteristics (MRLC) Consortium, a partnership of federal agencies led by the U.S. Geological Survey. However, the dataset only covers the regions of continental US for each of the eight epochs, plus separate images for Alaska, Hawaii, and Puerto Rico in 2001 and 2011. In this study, the training model is built with inputs from the NLCD parameter (NLCD2016) representing the percent of the pixel covered by developed impervious surface of the year 2016.

Cloud Computing and Deep Learning Modeling of Impervious Surfaces

The modeling approach in this study is built on the infrastructure provided by the Google's full-stack geospatial modeling and analysis platform: 1) Google Earth Engine as the geospatial analysis platform; 2) Earth Engine Data Catalog as the geospatial data achieve that can be accessed and analyzed in the cloud computing platform; 3) TensorFlow as the machine learning platform to implement models design; 4) AI Platform as to build and run the models and 5) Colab as the Jupyter notebook server for the workflow development. Firstly, the Earth Engine request the

training data from the Earth Engine Data Catalog stored in the cloud storage. Secondly, the cloud storage finds the training data and sends it to the AI Platform, while the AI Platform receives the model designed by the TensorFlow and its APIs programmed in the Colab server. When the model is built completely, GEE can access the model to make predictions through its new functionality API of `ee.Model.fromAIPlatformPredictor` and output the results. This update of GEE's API to have new integration with Google Cloud's AI Platform expands its modeling scalability and enhances its analytical capabilities. The traditional APIs in the GEE include the machine learning algorithms such as Decision Trees, K-Means and Support Vector Machine. However, these methods have limited capability to extract information from high dimensional (number of bands $>> 3$) imagery about not just the spectral values from one pixel, but spatial patterns of many pixels (i.e. the spatial context) represented as big patches of pixels (e.g. 256×256). Therefore, the fully convolutional neural networks (FCNNs) are designed to handle these difficulties. FCNN contains one or more convolutional layers, in which inputs are neighborhoods of pixels. Therefore, it learns from patches of data, instead of single pixels, resulting in a network that is not fully connected, but is suited to identifying spatial patterns. In this study, the FCNN model is trained from patched-based training data from NLCD dataset and predicts a continuous $[0, 1]$ output in each pixel from 256×256 neighborhoods of pixels to show the percentage of the impervious surface levels. The example provided in the Colab document (https://colab.research.google.com/github/google/earthengine-api/blob/master/python/examples/ipynb/UNET_regression_demo.ipynb) shows the details of how to export patches of data to train the network and how to overtile image patches for inference, to eliminate tile boundary artifacts. The Landsat 8 surface reflectance data has been processed to have bands' value scaled to $[0, 1]$ for both seven reflectance data and two thermal temperatures between 0 to 100 Celsius. Therefore, the processed Landsat 8 composite

image in 2016 is ready to be trained with the NLCD impervious surface as an objective field. The training patches are obtained from cities across the continental US shown in Fig. 2-2a (red as training regions and blue as evaluation regions). Total 20,000 and 8,000 patches are used for training and evaluation, respectively. The modelling process took 1 day 6 hour and 57 mins, and the process is displayed in the Figure 2-2b.

Figure 2-2: a) Locations of the sampling polygons on the United States map, red for training polygons, blue for evaluation. The map on the right bottom shows the impervious surface percentage (red as 100% and green as 0%) region of the Metropolitan Los Angeles; b) The charts of the modeling process regards of loss function and root mean squared error for the training (upper) and evaluation (lower) datasets..

2.3 Results

2.3.1 Comparison of Changing Trends Among Multiple Hydrological Parameters

Figure 2-3 illustrates the changing trends of multiple hydrological factors (precipitation, ET, surface soil moisture, runoff and LWE) over the Nile watershed calculated based on harmonic analysis during the period between the years 2002 – 2017, (2010 - 2017 for surface soil moisture due to data availability). It is observed that the changing trends of precipitation and ET are very similar due to FLDAS having CHIRPS rainfall as model input. The trends show an increase in the Sudan, South Sudan and most regions in Uganda and Tanzania. Noted decreasing change is also calculated in the Sudan and South Sudan and Ethiopia region. Surface soil moisture has increased for most of the watershed except some regions in South Sudan and Uganda. The Nile Delta region has an increase of surface soil moisture in much of the basin which corresponds to an increase in precipitation. Decreasing LWE may correspond to the impacts of overexploitation of groundwater to meet the increasing agriculture needs. The precipitation, ET and runoff are stable for the northern part of Nile watershed but with decreasing LWE. Increasing LWE is found in Sudan, Ethiopia, Uganda, Kenya and Tanzania but not South Sudan. The runoff values stay the same for most of the watershed yet have an increasing trend in the limited regions of South Sudan, Ethiopia, Kenya and Uganda, while having some overlapping regions with decreased surface soil moisture.

Figure 2-3: Monthly changing trends of multiple hydrological factors (precipitation, ET, surface soil moisture, runoff and LWE) over the Nile watershed calculated based on harmonic analysis of the periods between the years 2002 - 2017 (Note: surface soil moisture trend is calculated using the accumulative value of the period 2010 – 2017).

2.3.2 The Relationship Between the Groundwater Variability and Multiple Hydrological Parameters

Figure 2-4 shows positive correlations between multiple parameters (surface soil moisture, ET, runoff and precipitation) and LWE. However, such relationship is not plausible for the low p-value for most of the region, except: 1) positive relationship between surface soil moisture and LWE in Uganda; 2) positive relationship between ET and LWE in Uganda and Kenya but negative in boundary parts in Ethiopia and Sudan; 3) positive relationship between runoff and LWE in areas of Ethiopia, South Sudan and Uganda; and 4) positive relationship precipitation and LWE in areas of Sudan and Egypt.

Figure 2-4: The correlation map (correlation coefficient and p-value) between monthly anomalies values of LWE and other hydrological factors (precipitation, ET, surface soil moisture, runoff) over the Nile watershed calculated based on Pearson correlation analysis of the periods between the years 2002 - 2017 (2010 - 2017 for surface soil moisture).

In Figure 2-5, the time series analysis of the sampled locations is used to compare LWE and P-ET-R (precipitation minus ET and runoff) over the Nile watershed and the included countries (Egypt, Ethiopia, Kenya, South Sudan, Sudan, Tanzania and Uganda) during the period from 2002 till 2017.

Nile watershed exhibits seasonal variations of P-ET-R and LWE during the years, with the lowest LWE after 2011 but highest during fall of 2014, showing a trend of increase since 2011. Egypt shows low variability of P-ET-R for its limited precipitation. Besides, the LWE level stays below zero showing continuous groundwater loss. The situation is significant for the year 2012. The loss of the groundwater are very likely due to the overexploitation. Ethiopia shows a strong lag correlation between P-ET-R and LWE. The peaks of P-ET-R occur several months ahead of peaks of LWE. This lag relationship can also be seen in South Sudan and Sudan. The LWE variability of Ethiopia is higher than Sudan but lower than South Sudan. For Kenya, Uganda and Tanzania, the seasonal variations of LWE and P-ET-R are not as strong as those shown in Ethiopia, South Sudan and Sudan. LWE in the three countries demonstrates a decreasing trend during 2003-2006 and an increasing trend during 2011-2016. Additionally, the P-ET-R shows a general pattern of double peaks during spring and fall annually.

Figure 2-5: The time series line charts to compare LWE and P-ET-R (precipitation minus ET and runoff) over the Nile watershed and the countries (Egypt, Ethiopia, Kenya, South Sudan, Sudan, Tanzania and Uganda) during the period between 2002 and 2017.

Figure 2-6 shows the correlation maps of correlation coefficient (Corr) and p-value between P-ET-R and LWE up to 3 months lags. The Corr value for the regions with p-value higher than 0.05 (red color) is not considered plausible. In the case of lag=0, the positive relationship is found near the south of Egypt. South Sudan, some parts of Ethiopia and Uganda demonstrate a negative relationship, which may be due to the coincidence between high LWE and low precipitation seasons. In the case of lag=1, only some regions of Sudan and Ethiopia show a weaker positive relationship between P-ET-R and LWE. However, for lags value of 2-3 months, the strong positive connections between P-ET-R and LWE are illustrated in the most of the regions in South Sudan, Ethiopia and southern part of Sudan, indicating the recharge process to the groundwater. This result also matches the observed relationship between the peaks of P-ET-R and LWE in Sudan, South Sudan and Ethiopia in Figure 2-5.

Figure 2-6: The correlation maps (correlation coefficient and p-value, up to 3 months lags) between LWE and P-ET-R (precipitation minus ET and runoff) over the Nile watershed calculated based on Pearson correlation analysis of the periods between the years 2002 – 2017.

2.3.3 The Change Detection of Impervious Surface Among multiple Selected Cities Between 2013 and 2019

Figure 2-7 shows the Landsat-8 true color composite images and corresponding impervious surface maps classified by the FCNN model. To compare the changes between the year 2013 and 2019 among five capital cities in the Nile watershed, Table 2-2 shows the ratio of highly impervious surface (value > 50%) areas for the years of 2013 and 2019 and the changes Δ . Three

cites (Khartoum, Addis Ababa and Kampala) illustrate an expansion in the percentage of impervious surface to some extent, with additional red or yellow colored regions. For Cairo, the ratio unexpectedly decreased since the additional impervious surface areas are seen at the eastern region at the New Cairo City. It may be due to the classifier cannot identify some regions of human habitats as it is observed that massive regions of human habitats are not marked as impervious surface (red arrows). Similarly, the community of the southern outskirts of the Khartoum (red rectangle) is also missed. For Juba, the decreased ratio may result from the dramatic changes of the settlements and constructions in the context of South Sudanese Civil War since December 2013.

Figure 2-7: The Landsat-8 true color composite images and corresponding impervious surface (red as 100% and green as 0%) maps in the year 2013 and 2019, for the selected cities including Cairo, Addis Ababa, Juba, Kampala and Khartoum.

Table 2-2: The changes of impervious surface areas (value > 50%) in selected cities

City	2013	2019	Δ
Cairo	14.4%	12.3%	-2.1%
Khartoum	10.6%	23.7%	13.1%
Juda	12.2%	11.4%	-0.8%
Addis Ababa	39.1%	44.5%	5.4%
Kampala	14.9%	25.4%	10.5%

To further explore the cause of misclassification of impervious surface in the Cairo region, Figure 2-8 is created to show the surface reflectance signatures of the samples (selected locations shown on the left of Figure 2-8) in four types of land categories, namely, human habitats not marked as high impervious surface (Unmarked Habitat), human habitats marked as high impervious surface (Marked Habitat), barren areas with human habitats and vegetations (Barren) and vegetations areas such as croplands or grasslands (Vegetation). The barren surface shows a highest surface reflectance over B2-B7, while vegetation surface has high B5 (Near Infrared) in contrast to B4 (Red). However, the unmarked and marked habitats only have slight differences of surface reflectance values in the bands B6 (Shortwave Infrared 1) and B7 (Shortwave Infrared 2). All land types, as expected, showed similar behavior over the brightness temperature bands (B10 and B11) since these bands can be used to calculate spectral index for a body in case of non-thermal radiation which doesn't apply here.

Figure 2-8: The surface reflectance for four types of landcover in the Cairo and adjacent region, including human habitats not marked as high impervious surface (Unmarked Habitat), human habitats marked as high impervious surface (Marked Habitat), barren areas with human habitats and vegetations (Barren) and vegetations areas such as croplands or grasslands (Vegetation).

2.4 Discussion

The impact on groundwater recharge under various climate change scenarios has been investigated by previous studies [34]–[36], which commonly concluded that the amount of groundwater is decreasing, especially in the Northern Africa and Middle East regions. For the Nile basin, our results of ΔS as P-ET-R shows a slightly different pattern compared with what was presented in the previous study. This may due to the choices of different hydrological datasets (e.g. TRMM vs CHIRPS datasets for precipitation, GLDAS vs FLDAS for runoff, MODIS vs FLDAS for ET). Besides, this study also directly compared the P-ET-R monthly anomalies values and the LWE values through correlational analysis (Fig. 2-6). The approach used both time series analysis, correlation maps (up to 3 months lags) to show the spatial water transport, and recharge pattern

among different regions in the Nile watershed. It is suggested that the pattern is dependent on the ecosystem, topology and climate of the basin. It is also noted that the magnitude of the P-ET-R is much larger for water-rich basins such as Amazon and Mekong than Nile [31]. The study validates the use of P-ET-R to show the spatial and temporal variability as it reflects the increase or decrease in the water storage in coordination with GRACE Equivalent liquid water thickness, especially for some countries such as Ethiopia, Sudan and South Sudan (Fig. 2-5). To sum up, the Nile basin countries should improve cooperation of the usage of and protection of the water resources as it is stated in the SDG Indicator 6.5.2: “Proportion of transboundary basin area with an operational arrangement for water cooperation”.

Figure 2-7 shows clear expansions of urban areas of three of the selected cities through targeting the impervious surfaces. This approach provides a tool to monitor the urbanization procedure through the SDG Indicator 11.a.1 “Proportion of population living in cities that implement urban and regional development plans integrating population projections and resource needs, by size of city”. However, the model trained from the US data sources cannot identify some parts of the human habitats in Cairo and Khartoum as the impervious surfaces. The spectral signatures between the marked and unmarked regions also do not show significant difference to clearly discriminate them. It is known that the model does not simply use the spectral differences as the parameters but also include the imagery context or texture. Therefore, it is possible that the training data from US cities lack certain texture or types of impervious surface, which are common in Cairo or other cities. It is suggested that both unmarked regions in Cairo and Khartoum are the towns with similar constructions and homogeneous texture and materials. It is also found that for the entire Nile Delta region, many towns or villages are also classified as non-impervious surface (Figure 2-9 regions A-E), where the percentage value of impervious surfaces is even lower than

surrounding crop fields (also seen in Figure 2-7). Additionally, the difference between the low-income community (rural and slum areas) (characterized with homogeneous houses and imagery textures) and high-income community (characterized with high urban greening and diverse buildings) can also alter the model outputs. For instances, Figure 2-10 shows the classified impervious surface of Karachi, Pakistan and its slum - Orangi Town (red square region), which is regarded as the largest slum in the world with estimated population from 1.5 to 2.4 million. Orangi Town has houses of similar structure and homogeneous texture. It is apparent that the model does not mark the Orangi Town while the adjacent region with rich heterogeneous textures (right bottom corner cross the red line) can be classified. It is reasonable to speculate that such typical texture of impervious surface is not included in the US training datasets. However, such high-resolution impervious surface datasets are only limited in the US cities. This situation reflects a data inequality between developed and developing countries that even the results of modeling approach to help investigate the developing countries can be biased. Extensive model optimization and tuning is need to effectively monitor the slums settlement as required by SDG Indicator 11.1.1: “Proportion of urban population living in slums, informal settlements or inadequate housing”.

Figure 2-9: The Landsat-8 true color composite image and corresponding impervious surface map in the year 2019 for the Nile Delta region with its unmarked towns (A, B, C, D, E) shown in the high resolution satellite images in Google Map.

Figure 2-10: The Landsat-8 true color composite image and corresponding impervious surface map in the year 2019 for the Karachi, Pakistan. Red line separates the marked high impervious region from the its biggest slum named Orangi Town (red rectangle) shown in the high resolution satellite image in Google Map.

According to UN's 2019 SDG report [37], "The lack of accurate and timely data on many marginalized groups and individuals makes them "invisible" and exacerbates their vulnerability.

While considerable effort has been made to address these data gaps over the past four years, progress has been limited.“ Reports from UN and Chinese Academy of Sciences [38] also highlighted that, only about 45% of indicators are supported by both methods and data, about 39% have methods but lack data, and some 16% have neither standard methods nor data. Therefore, the data and methodology lagging becomes a bottleneck that the full implementation of the 2030 SDGs will be hampered if these issues are not effectively resolved. In the model training experience, the Google Cloud Platform (GCP) charged \$25.99 to generate the model within 31 hours. It is a relatively inexpensive for the researchers with limited financial capacity, considering GCP also provides \$300 credit for new users which covers all the cost. Our case here shows an example of tackling the data/methodology bottleneck of SDG studies with EO data and cloud computing in an economical (free of charge) approach. Therefore, further advancement and applications of EO and cloud computing should be explored to empower the effective assessment, data availability and monitoring of each and all SDG targets and indicators essential to ensure the achievement of SDGs.

2.5 Conclusion

This study presents the EO and cloud computing solutions to support the SDG 6 “clean water and sanitation” and SDG 11 “sustainable cities and communities” in the seven Nile watershed countries. Multiple SDG indicators are studied including: the transboundary water cooperation (6.5.2), urban and regional development under population growth (11.a.1) and slums monitoring (11.1.1). The results clearly show the connections between multiple hydrological parameters and spatial/temporal groundwater recharge patterns in the region. Besides, an advanced deep-learning impervious surface classifier using fully convolution neural networks (FCNN) was trained on top of the cloud platform to monitor the urbanization procedure in the selected five cities

during the period 2013 to 2019. Clear urban expansions are observed in the developed regions while the classifier is limited to identify slums/rural areas and their changes. This may due to the biases introduced for the difference between training data from developed countries (i.e. United States) and developing countries in the Nile watershed. Therefore, the authors suggest future North-South and South-South cooperation to solve the data inequality among the countries, as well as the development of methods to fully use the advancement of EO and cloud computing to achieve SDGs.

3 Second Study: Studying the Impact on Urban Health over the Greater Delta Region in Egypt Due to Aerosol Variability Using Optical Characteristics from Satellite Observations and Ground-Based AERONET Measurements

3.1 Introduction

Air pollution is reported as one of the most severe environmental problems for the Greater Delta region of Egypt [39]–[41]. Over the past few decades, Egypt has been introduced to numerous activities, including unplanned urbanization, air polluting industries, and energy production that contributed to excessive air pollution with gases, particulates, and aerosols at levels often exceeding the World Health Organization (WHO) guidelines [41], [42]. The Greater Delta region, especially its largest city, Cairo, is a densely populated region with all of the above activities that requires a better understanding of its atmospheric aerosol characteristics considering its high aerosol loading, as well as recently more frequent emerging aerosol events occurring at all seasons, which is different from past years [39], [41]. On the other hand, the rural and suburban

parts of the Nile Delta have higher ventilation due to the mass of agricultural land together with higher wind speeds [43]. As it is similar to other developing countries, there are diverse sources of air pollution in Egypt; however, comparing to industrialized countries, the formation and levels of coal ash, mineral dust, and other small particles in Egypt is more pronounced [44]. The key variables for air quality are nitrogen dioxide (NO₂), carbon monoxide (CO), sulfur dioxide (SO₂), suspended particulate matter (SPM), lead (Pb), and ozone (O₃) [45]. Such levels of dust, fine particles, and soot are reported to be more characteristic in Egypt than those found in industrialized countries, which is due to the industries and traffic within downtown Cairo and its surrounding regions emitting particles incessantly throughout the year [46]. It is worth noting that over the past two decades, there has been a seasonal air pollution episode locally known as the “black cloud”. The black cloud is a dark smoke and haze that covers the Greater Cairo and the Nile Delta [47], [48]. This episode has been associated with commonly known illegal local practices of burning rice husk leftovers after the growing season together with other contributing factors [39], [40], [44], [47], [49], [50]. In 2007, the World Bank characterized the air quality in Cairo as the “worst” in the world with regard to particulate matter concentration [51]. Much higher and frequent air pollution episodes were recorded recently in Cairo, threatening the public health of its over 20 million population [41], since human lungs can be severely damaged by the dust, the tiny soot fragments, and pollutant particulates [52]. Besides the emission of air pollutants, naturally, Cairo is at the apex of the Nile Delta that is bounded by the Mokattam Hills and the western heights. During the strong spring wind events, the Mokattam Hills produce large concentrations of airborne sand [44], [53].

A study of aerosol profiles in Cairo and Alexandria found that it includes “pollution-like”, “background pollution” and “dust-like” components [48], [50]. For further understanding of the

aerosol profile, it is necessary to analyze the chemical composition of aerosols which is found to be highly dominated by mineral dust over $100 \mu\text{gm}^{-3}$ in winter and spring, comparing to over $50 \mu\text{gm}^{-3}$ in summer and autumn [54]. Natural dust storms also play a role in the level of the aerosols particularly in the “Khamsin” period [55]–[57]. Moreover, dust deposition over water bodies, while traveling across continents, affects different marine habitats such as those of the Red Sea, the Mediterranean Sea and the Atlantic Ocean [14], [58]–[60].

From the above, it is evident that the frequent aerosol activities in Cairo and the Greater Delta region require detailed investigation of their characteristics, optical properties, and dynamics. For that purpose, we are expanding the usage of the well-established and the most influential aerosol observation network, the Aerosol RObotic NETwork (AERONET). AERONET is a ground-based aerosol network set up by National Aeronautics and Space Administration (NASA) and LOA-PHOTONS Centre National de la Recherche Scientifique (CNRS) and is significantly extended by associates from national offices, foundations, colleges, singular researchers, and accomplices. The system comprises an excess of 500 globally distributed sun and sky-scanning automated radiometers. AEROENT data is characterized by its high frequency (every 15 min) and low uncertainty observations. It provides long-term and continuous spectral properties of aerosols derived by the Sun photometer; its data products have three available levels (Level-1.0 (unscreened), Level-1.5 (cloud-screened and quality controlled), and Level-2.0 (quality-assured)) based on their different processing of cloud screening and quality control. Both cloud-screened and quality control have been applied to the Level-2.0 dataset, whereas the Level-1.5 dataset is only processed with cloud-screened but without quality assurance. Level-1.0 has neither cloud screening nor quality control. Therefore, Level-2.0 is regarded as the most accurate dataset, and thus is used in this research.

On October 2004, Cairo University hosted an AERONET sun photometer for air quality assessment followed by another campaign conducted by the Egyptian Meteorological Authority (EMA) from April 2005 until March 2006. Since April 2010, EMA has been routinely maintaining the third AERONET site, which was named EMA2 until now. As mentioned before, AERONET measurements occur several times a day and provide various products that are used for air quality assessment. However, the AERONET datasets in Cairo are relatively lacking (only since 2004), also considering the four-year missing observations between 2006–2010. To overcome this limitation, various remotely sensed data collected on board satellites are used and have been proven to be effective tools to achieve a regional/global and temporal characterization of aerosols, playing a key role in studying the horizontal variation of aerosols in the Greater Delta region. Several algorithms have been developed using: for example, POLarization and Directionality of the Earth's Reflectances (POLDER), Moderate Resolution Imaging Spectroradiometer (MODIS) (both on board the Terra and Aqua satellites), Ozone Monitoring Instrument (OMI) (on board the Aura satellite), Multi-angle Imaging Spectroradiometer (MISR) (on board the Terra satellite), and Sea-viewing Wide Field-of-view Sensor (SeaWiFS) (on board the SeaStar satellite)) [61]–[65], to retrieve the global aerosol optical depth (AOD). For example, MODIS and the MISR are the most commonly used sensors to observe AOD. Using these satellite data and ground-based observations, many studies have been investigated to reveal the mechanism of the increased pollution and dust activities in Cairo [40], [46]–[49], [53], [54], [66]–[69]. Additionally, the remotely sensed AOD products have been developed and applied to estimate the concentration of fine particulate matters (such as PM₁₀ and PM_{2.5}) for the air quality research [70]–[73].

However, the accuracy of satellite aerosol products is challenged by diverse uncertainties, including cloud contamination, complex surface in different regions, and the different retrieving

process among aerosol models [61], [62], [74]–[77]. Therefore, satellite measurements need to be validated using ground-based observations, such as AERONET dataset, to make the best use of their aerosol related products for the Cairo region [78]–[80].

Hence, this paper focuses on the classification of different aerosol microphysical and optical properties using AERONET data while evaluating the best remotely sensed aerosol datasets through cross-validation against the in situ measurements from the AERONET observations. We also investigate and compare the typical aerosol emerging episodes in each season to describe their different origins and composition, as well as their impacts on the human health.

3.2 Materials and Methods

3.2.1 Study Area

The area of study geographically covers the Nile Delta, which is bounded by the Mediterranean Sea to the north, the Western Desert to the west, the Eastern Desert and Sinai to the east, and the Nile Valley to the south. The area is approximately 35,000 km² and includes major urbanized cities such as Cairo, Alexandria, and Tanta. However, the majority is rural areas and agricultural land. The Nile Delta is a typical arcuate delta with Cairo City in the apex. It accommodates about 55% of the population and it secures the food for the population via agriculture (Figure 3-1).

Figure 3-1: Nile Delta area of study and four main cities (Cairo, Alexandria, Tanta, and Port Said) in each Delta corner and center (background remotely sensed image from Google Earth).

3.2.2 AERONET and Satellite Aerosol Products

The ground-based AERONET aerosol-related products were collected from the sites in Cairo area, including: Cairo University (30.026167°N, 31.207317°E), Egyptian Meteorological Authority (EMA) (30.080767°N, 31.290067°E), and EMA2 (30.080767°N, 31.290067°E). Here, we used some of the AERONET products addressing aerosol characteristics, namely, spectral-based values of aerosol optical depth (AOD), single scattering albedo (SSA), aerosol size distribution, and Ångström exponent (AE) with a temporal variability component. The spectral deconvolution algorithm (SDA) [81] applied to the AOD analysis calculates the fine mode fractions to the total aerosols (FMF) by yielding fine and coarse aerosols at a standard wavelength of 500 nm. This parameter proves to be a quite effective indicator of the size distribution of the

observed aerosols. It is known that high AE values present a higher abundance of finer aerosol particles, while a set of low AE values corresponds to aerosols with coarser particle sizes [50]. The aerosols in fine mode are mostly generated from gas-to-particle conversion [82], while, carbonaceous and sulfate aerosols are generated from biomass burning and urban/industrial activities. On the other hand aerosols in coarse mode are mainly from mineral dust or sea salt [50]. Therefore, either a decrease in the number of larger particles or an increase in the number of smaller particles can cause an increase in the value of AE and FMF. All the products are accessed from the AERONET Data Synergy Tool (https://aeronet.gsfc.nasa.gov/cgi-bin/bamgomas_interactive).

Monthly AOD Version 3 Level-2.0 data [83] collected at EMA is used to validate the AOD retrievals from the multiple satellite sensors using the Multi-sensor Aerosol Products Sampling System (MAPSS) [84]. The MAPSS provides a direct cross-validation between the aerosol products from multiple spaceborne sensors and well-characterized co-located AERONET ground-based data through generating spatial statistics such as linear regression analysis (number of observations, outliers, the coefficient of determination denoted as R^2 , root mean square deviation as RMSE), with flexible options (including/excluding outliers, quality control). The sensors used in the validation process are listed in the Table 3-1.

Table 3-1: The spaceborne sensors validated against observations of the Egyptian Meteorological Authority (EMA) station. MODIS: Moderate Resolution Imaging Spectroradiometer, MISR: Multi-angle Imaging Spectroradiometer, POLDER3: POLarization and Directionality of the Earth's Reflectances, SeaWiFS: Sea-viewing Wide Field-of-view Sensor, OMI: Ozone Monitoring Instrument.

Stations	Period of Available Data	Number of Observation	Outliers
Aqua MODIS	13 April 2005–21 March 2006	66	2
MISR	1 May 2005–19 January 2006	23	0
Terra MODIS	13 April 2005–22 March 2006	68	2
POLDER3	14 April 2005–21 March 2006	57	4
SeaWiFS	14 May 2005–6 February 2006	11	0
OMI	13 April 2005–22 March 2006	118	1

Here, we used the data provided from the stations of EMA (April 2005–March 2006) and Cairo University (October 2004–March 2005) for cross-validation purposes and the time series analysis, although with a shorter record, while not using observations from the EMA2 station for cross-validation but only for time series analysis. This is because the EMA2 station, although with a longer record (April 2010 until now), is not included in the MAPSS system that is used for the evaluation of satellite products. The validation result will be presented in Section 3.1 as the scatter plots of AERONET AOD against satellite AOD with key linear regression parameters, filtering outlier values with the quality control option. Additionally, we also demonstrate the advantage of using the satellite-derived aerosol plumes analysis from the MISR Interactive eXplorer (MINX) tool [85], [86], to obtain AERONET-like aerosol products such as spectral-based AOD, AE, and SSA.

EMA2 daily spectral based AOD observations at multiple bands (340 nm, 380 nm, 440 nm, 500 nm, 675 nm, 870 nm, and 1020 nm) as well as FMF and AE at band 550 nm are used to determine typical aerosol patterns in Cairo through the K-means classification method. The aerosol

information collected at EMA2 is also used to analyze the aerosol properties of the four typical AOD episodes for each season (DJF=Dec-Feb, MAM=Mar-May, JJA=Jun-Aug, SON=Sep-Nov). The episodes are selected based on the AERONET aerosol Level-2.0 data during the available observation periods: Cairo University (October 2004–March 2005), EMA (April 2005–March 2006), and EMA2 (April 2010–March 2017). For each episode, NASA’s Goddard Space Flight Center (GSFC) seven days Back-kinematic trajectory analysis product [87], [88] generated twice a day (00 UTC and 12 UTC), is used to compute simple air parcel backward trajectories to analyze the aerosol tracking for origin attribution. Following their traveling path, the aerosols’ vertical structure and subtypes are observed and measured by CALIOP (Cloud-Aerosol Lidar with Orthogonal Polarization) [89], [90] on-board the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) mission. The CALIOP profile range from the earth surface to 40 km with high spatial resolution of 30-60 m in the vertical and 333 m in the horizontal. CALIPSO data has shown potential application for the human health assessment. For example, the synergy usage of MODIS, CALIPSO and AERONET observations demonstrated the evidence of the transport mechanisms of *Candida* fungus which causes the annual spike Kawasaki disease in Japan [91].

3.2.3 Environmental Indicators Related to Public Health

UV Aerosol Index

Ultraviolet (UV) rays form a type of electromagnetic radiation spectrum with wavelengths from 10 nm to 400 nm, which are longer than X-rays but shorter than visible light. The studies revealed that a long exposure to the UV rays causes serious public health problems, such as cataracts and other damage to the eye [92]. About 65% to 90% of melanoma of the skin, which

accounts for three-fourths of all skin cancer deaths, was also reported to be caused by UV rays [93], [94]. On the other hand, UV rays also impacts the vitamin D circulation, which is reported as a protective factor against rectum and colon cancer [95].

In this study, the Ultra-Violet Aerosol Index (UVAI) is accessed from the Level-3 daily global TOMS-Like Total Column Ozone gridded product OMTO3d [96] at 1-degree spatial resolution. The UVAI is an index that detects the presence of UV-absorbing aerosols, which are calculated as the difference between the observations and model calculations of absorbing and non-absorbing spectral radiance ratios. The negative or small values of UVAI represent non-absorbing aerosols or clouds, while larger positive values represent absorbing aerosols such as dust or smoke. Here, we analyze the UVAI variations during the selected aerosol episodes to demonstrate the impact of aerosols on UV exposure.

Solar Spectral Radiation and Modeling Datasets

As we know, the incoming shortwave solar radiation together with the radiation reflected, absorbed, and emitted by the Earth system make up the Earth's radiation budget. Larger atmospheric aerosol particles scatter and absorb some of the shortwave radiation, leading to atmospheric warming. The heated atmosphere in turn emits longwave infrared radiation, some of which reaches the Earth surface, which can increase the land surface temperature and change the surface air humidity. Besides the previously mentioned urbanization impacts (e.g., land surface modification), a portion of the outgoing longwave radiation (OLR) from the Earth's surface is absorbed by greenhouse gases (e.g., water vapor), which in turn contributes to the "Urban Heat Island" effects, posing more impact on the public health of the inhabitants in the greater Cairo region.

To investigate the aerosols' impact on the solar radiation and air temperature, we used the Global Land Data Assimilation System (GLDAS) version 2.1 dataset [102] for the radiation analysis. GLDAS uses advanced land surface modeling to generate optimal fields of land surface fluxes and states through assimilating both satellite and ground-based observational data products. In this research, we used the Google Earth Engine [103] tool to obtain and process GLDAS products, including specific humidity ($Q_{air_f_inst}$ in the unit of kg/kg) (the ratio of water vapor mass to total moist air parcel mass), air temperature ($T_{air_f_inst}$ in the unit of Kelvin), downward longwave radiation flux ($LW_{down_f_tavg}$ in the unit of W/m²), downward shortwave radiation flux ($SW_{down_f_tavg}$ in the unit of W/m²), wind speed ($Wind_f_inst$ in the unit of m/s), average surface skin temperature ($AvgSurfT_inst$ in the unit of K), net longwave radiation flux (Lw_{net_tavg} in the unit of W/m²), pressure ($P_{surf_f_inst}$ in the unit of Pa), and net shortwave radiation flux (Sw_{net_tavg} in the unit of W/m²). Google Earth Engine proved to be an effective cloud online computing and analysis tool for the environmental research in Egypt and the Middle East and North Africa regions [10], [58], [59].

In order to assess the role of aerosol-related impacts and their connection to air pollution in the study region, the gridded data of the Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) is used in this research. The MERRA-2 dataset is an atmospheric reanalysis dataset produced by the National Aeronautics and Space Administration (NASA) and released by NASA Global Modeling and Assimilation Office (GMAO) in 2017. The monthly means of the “Dust Extinction AOT 550 nm—PM_{2.5}”, “Sea Salt Extinction AOT 550 nm”, “Surface Air Temperature”, and “Surface Wind Speed”, as well as daily mean of “Total Aerosol Extinction AOT 550 nm” at $0.5^\circ \times 0.625^\circ$ resolution covering the period from the year 1998 to 2016 are obtained and processed [104], [105].

PM10 and PM2.5 Datasets

The PM10 dataset is provided by the Egyptian Environmental Affairs Agency (EEAA), including the hourly observations in eight locations (Abuzabal, Shubra, Qualaly, AlainyPH, Abasseya, NasrCity, NewEgypt, and Helwan) of the Greater Cairo region during 2018. In addition, to show the annually PM2.5 variability in Egypt, satellite-based geographically weighted regression (GWR) PM2.5 product [106] is used and obtained from the Socioeconomic Data and Applications Center (SEDAC) (<https://sedac.ciesin.columbia.edu/data/set/sdei-global-annual-gwr-pm2-5-modis-misr-seawifs-aod/data-download>).

3.3 Results

3.3.1 Validation of Satellite Sensors for Aerosol Analysis in Cairo

Here, the fitness of various satellite aerosol products in measuring Cairo's regional aerosol conditions is investigated as compared with AERONET measurements during 2004–2006. The AOD products of POLDER3 (Figure 3-2d), SeaWiFS (Figure 3-2e), and OMI (Figure 3-2f) are less dependent on AERONET measurements ($R^2 < 0.5$). This inconsistency may result from the lower efficiency of AOD retrieval algorithms, or limited observations (e.g., only 13 observations for SeaWiFS). However, the updated products (e.g., merged Dark Target and Deep Blue MODIS Collection 6.1) of Aqua MODIS (Figure 3-2a) and Terra MODIS (Figure 3-2c) [107]–[111], as well as MISR (Figure 3-2b) have achieved a high consistency with AERONET measurements (R^2

>0.6). Therefore, these products are validated to study the aerosol variability along with AERONET products, especially over the Mediterranean region [112], [113]. Moreover, the MISR could provide an analysis of aerosols plumes microphysics. Aerosol products such as AE, SSA, and AOD fraction by particle can disclose the particle properties of the plumes during their moving over the region. For example, Figure 3-2g–j show aerosol-related histograms of a plume over Egypt on 14 September 2008. Optical depth bars (Figure 3-2g) contain different spectral bands, as exhibited by the different colors, which represent the composition of different pollution sources. This aerosol plume has high SSA (>0.95) (Figure 3-2i), which indicates generally a cooling effect to the land surface [114]. High AE value (>1.7) validates the sources from industrial pollution and biomass burning (Fig. 3-2h). Over industrial regions, such as North America and Europe, or urban centers (our case), the SSA is identified to be about 0.98 caused by large supplements of black carbon and sulfate from biomass burning (Fig. 3-2i) [115], whereas SSA is lower over the dusty regions, such as Sahara Desert. The histogram in Figure 3-2j illustrates the fraction of the green-band optical depth values by different particle sizes: small (blue bar at 0.7), medium (green bar near 0), and large (red bar at 0.3), which shows that this plume is mainly composed of small aerosol particles. Figure 3-2j also indicates the non-existence of spherical particles, as no purple bar appears in this figure. It is worth noting that the data samples for MISR are also relatively small, but given the high consistency shown by the MISR, and the effective application of MISR in the Cairo region for aerosol analysis [39], [40], we still employ MISR in the research.

Figure 3-2: Scatter plots of Cairo Aerosol Robotic Network (AERONET) aerosol optical depth (AOD) observations as to AOD data from (a) Aqua MODIS, (b) MISR, (c) Terra MODIS, (d) POLDER3, (e) SeaWiFS, and (f) OMI in EMA and Cairo University stations. Aerosol histograms with no cloud contamination where color indicates band for (g) optical depth, (h) Ångström exponent, (i) single scattering albedo (SSA), and (j) Tau (AOD) fraction by particle over Egypt on 14 September 2008.

3.3.2 Time-Series Analysis of AERONET and Multi Sensors

Figure 3-3 shows the monthly AOD values over the Cairo area, as displayed from a time series analysis of Terra MODIS (Figure 3-3a), Aqua MODIS (Figure 3-3b), MISR (Figure 3-3c), and AERONET (Figure 3-3d) from 2000 until 2018. The obvious periodic characteristics are indicated in Figure 3-3—high AOD values occur in summer and low in winter, which also could be found from the AERONET measurements. The AOD variability as depicted from the time series of Terra MODIS and Aqua MODIS is more coherent, since both datasets are retrieved with same retrieval algorithms. Some emerging AOD events recorded by MISR (such as March 2003, which is located by a black circle) are not found in the Terra MODIS and Aqua MODIS series. Therefore, to choose the typical seasonal emerging AOD events, months with high AOD values agreed by all three datasets are selected for analysis, including June 2013 (summer), January 2014 (winter), March 2014 (spring), and September 2015 (fall), which are marked by the red arrows.

Figure 3-3: Time series plot of AOD in Cairo during 2000 to 2018 for (a) Terra MODIS, (b) Aqua MODIS, (c) MISR, and (d) AERONET, respectively. Red arrows point to the high AOD anomalies indicated during June 2013 (summer), January 2014 (winter), March 2014 (spring), and September 2015 (fall).

In Figure 3-4, the red arrows show the dates of the aerosol emerging events for the selected months, which are 8 June 2013, 2 January 2014, 3 March 2014, and 9 September 2015. They are either the highest AOD values observed during the month (such as 9 September), or the date of one of the highest record of the month (such as 3 March), which could be considered as the main contributor to the emerging monthly AOD value for the month. Detailed analysis for each event will be discussed in Section 3.3.

Figure 3-4: Time series of AERONET monthly AOD during (a) June 2013, (b) January 2014, (c) March 2014, and (d) September 2015. Red arrows point to the high AOD anomalies events during each month: 8 June, 2 January, 3 March, and 9 September, respectively.

3.3.3 Analysis of Seasonal Aerosol Emerging Episodes

In Figure 3-5, the SDA time series show the starting times for seasonal aerosol soaring are: 14 UTC at 8 June 2013, 09 UTC at 2 January 2014, 11 UTC at 3 March 2014, and 12 UTC at 9 September 2015. Both fine and coarse aerosols were contributors to the total aerosol amount, as indicated by the aerosol composition analysis. However, the total aerosols at 2 January 2014 is mainly composed of fine aerosols, whereas coarse aerosols (mainly dust from sandstorms) are the dominant aerosol component for the other three events.

Figure 3-5: Time series of AERONET Daily 500-nm AOD spectral deconvolution algorithm (SDA) retrievals during (a) 8 June 2013, (b) 2 January 2014, (c) 3 March 2014, and (d) 9 September 2015, respectively. Black/blue/red lines represent total/coarse/fine aerosols, respectively.

In Figure 3-6, most of the aerosol particles measured during the 2 January 2014 event fall in the radius range of 0.1 to 1 μm (fine aerosols), and some fell into the radius range of 1 to 10 μm (coarse aerosols). This result indicates that the Cairo region is affected by aerosols with a complex mixture of air pollution types during autumn, when biomass burning contributes to a background of urban pollution and desert dust [39]. In addition, the aerosol particles in the other three emerging events are sized in the range of 1 to 10 μm , which is close to the size of dust. It's worth noting that

the aerosol size distribution of 10 September 2015 is used to substitute the missing observations during 9 September 2015, considering that the aerosol particles measured in both dates have similar properties.

Figure 3-6: Size distributions of aerosols during (a) 8 June 2013 (b) 2 January 2014, (c) 3 March 2014, and (d) 10 September 2015, respectively. Lines in different colors represent different observations during the day.

Figure 3-7 demonstrates the aerosols' transportation path (GSFC back trajectory maps in Figure 3-7a–d) and their composition (CALIPSO aerosol subtypes in Figure 3-7e–h) for each of the seasonal aerosol episodes. The subtypes product was not available for 3 March 2014; therefore, both Figure 3-7g,h are presenting the 9 September 2015 case, since the two origins are clear. Figure 3-7a shows that the aerosols episode during 8 June 2013 originated from Libya and Algeria,

extending to the Western Desert (blue 700 hPa and light purple 850 hPa paths), while the other aerosols extend from regions in southern and western Europe traveling across the Mediterranean Sea (dark purple 950 hPa). This is confirmed in the highlighted region of Figure 3-7e, showing that aerosols were mainly composed of mineral dust and partially polluted dust and dusty marine particulates. Figure 3-7b also illustrates the aerosols during 2 January 2014 originating from the same regions, while the dark purple path (950 hPa) shows some aerosols crossing closely to the water surface of the Mediterranean Sea, potentially transporting water vapor and other marine aerosols. This is also confirmed in the highlighted region of Figure 3-7f, showing that aerosols mostly were classified as marine, dusty marine, and polluted continental/smoke, with a small portion of dust in higher altitudes. Figure 3-7c clearly shows that aerosols originated and were even “stirred up” in the western deserts; therefore, it is valid to speculate that these aerosols are mostly composed of mineral dusts. It is worth noting that the CALIPSO data is not available to access during the 3 March 2014. Figure 3-7d demonstrates the two components of dust east and west origins for the 9 September 2015 episode: one from the western desert (light purple path) and another from the Mesopotamia and Mediterranean region (dark purple and blue paths). Figure 3-7g,h show that both sides were dominated mainly by mineral dust, while the marine and polluted dust might come from the Mediterranean and nearby regions. It is plausible to conclude that the western deserts of North Africa are the main origins for the selected seasonal aerosol events, while the existence of contributors from the Mediterranean and eastern regions cannot be ignored for their characteristic types and properties.

Figure 3-7: Back-trajectories analysis during (a) 8 June 2013, (b) 2 January 2014, (c) 3 March 2014, and (d) 9 September 2015, respectively, as well as the Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observation (CALIPSO) aerosol subtype classifications for the same scenes (a,b,d) with their associated highlighted region of interest: (e) red box: the Greater Delta and

Mediterranean region (at 00:06 to 00:19 UTC 6 June 2013); (f) red box: the Greater Delta and Mediterranean region (at 00:05 to 00:19 UTC 2 January 2014); (g) red box: the Mesopotamia region (at 23:24 to 23:37 UTC 3 March 2014) and (h) blue box: the Egypt's Western Desert region (at 11:14 to 11:27 UTC 9 September 2015). The missing CALIPSO aerosol subtype analysis for 3 March 2014 (c) due to data unavailability.

In order to investigate the aerosols' impact on the human living environment, such as air temperature, UV exposure, solar radiation, and humidity, Figure 3-8 illustrates the variation of listed parameters for the selected seasonal aerosols episodes. The higher values of UVAI during the events in Figure 3-8a,g,j show the increased UV absorption, indicating the dusts' protective ability to excessive skin UV exposure. Figure 3-8d shows the lower UVAI values throughout the whole periods, indicating the limited capability of marine-dominated aerosols to the UV absorption. A pronounced negative relationship between air temperature and humidity is suggested by Figure 3-8b,h,k. This is because dust storms are drying the air and warming the temperature. However, it is noticeable that in Figure 3-8b, the humidity bounced back to regular values. This may resulted from the effects of the marine aerosols depicted in Figure 3-7e. The negative relationship is also clear between longwave and shortwave radiations, especially in Figure 3-8i,l showing rise of longwave radiation and fall of the shortwave radiation values. In contrast to the marine aerosols, the dust aerosols are suggested to absorb or scatter the shortwave radiation and then emit the longwave radiation to warm up the land surface, while fortunately decreasing the humidity and thus not making the warming effect even worse. Figure 3-8 also demonstrates the seasonal differences among the listed parameters, highlighting the relatively moderate environment during the winter season with lower temperature, humidity, and solar radiation.

Figure 3-8: The Ultra Violet Aerosol Index (UVAI) (a,d,g,j), air temperature, and specific humidity (b,e,h,k), shortwave (SW) and longwave (LW) radiation (c,f,i,l) values recorded before and after five days for each aerosol episode: 8 June 2013 (a–c); 2 January 2014 (d–f); 3 March 2014 (g–i); and 9 September 2015 (j–l).

3.3.4 Aerosol Patterns In Cairo

As shown in Section 3.3, aerosol patterns, namely types and sources, are different in the Greater Cairo region, posing divergent impacts on the UVAI and air temperature that indirectly relate to human health. The dataset of AOD in multiple spectral bands is calibrated from Cairo EMA2 from 2010 to 2017 with as many as 2219 observations. The unsupervised K-means algorithm is used to classify AOD measurements with different bands (340–1640 nm), FMF, and AE, since the aerosol types can be conjectured from their different optical properties [48], [50]. The result shows five different patterns of aerosols, represented by the five kinds of clusters summarized in Table 3-2, in which Cluster 1 indicates a clear, low AOD atmospheric environment. Its values for each band are low but its AE value is high, representing fine aerosols. Cluster 2 represents less severe aerosol events composed of fine aerosols such as industrial pollution and sea salt. Cluster 3 also represents less severe aerosol events, but mainly consists of coarse aerosols. This could be known by its low FMF and AE values, indicating rich dust composition. Cluster 4 represents severe aerosol events induced mainly by fine aerosols (such as the event during 2 January 2014), because of its high values in the 340–500 nm bands, and high values of both FMF and AE to show that the aerosols are mainly composed of finer particles. This pattern is indicating the “pollution-like” mechanisms of aerosols both from air pollution and mixtures with other type of small size aerosols, as previously discussed [48], [50]. Finally, Cluster 5 represents the severe events caused by the coarse aerosols (mainly dust storms), which is characterized by a high value in each of the bands, and both low FMF and AE values. This pattern is matching the “dust-like” mechanisms of aerosol released by wind erosion in the Sahara [48], [50].

Table 3-2: AERONET AOD bands, fine mode fraction (FMF), Ångström exponent (AE), and number of instances values for five clusters.

K-Means Clusters	Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5
Classified Aerosol Types	Clear Day	Light Fine Aerosol	Light Mixed Aerosol	Heavy Pollution-Like	Heavy Dust-Like
AOD 340 nm	0.42	0.75	0.59	1.31	1.58
AOD 380 nm	0.37	0.68	0.55	1.23	1.55
AOD 440 nm	0.31	0.57	0.51	1.10	1.50
AOD 500 nm	0.27	0.49	0.48	1.00	1.48
AOD 675 nm	0.19	0.33	0.42	0.75	1.43
AOD 870 nm	0.15	0.25	0.39	0.59	1.40
AOD 1020 nm	0.14	0.21	0.37	0.51	1.36
AOD 1640 nm	0.10	0.14	0.29	0.33	1.16
FMF 500 nm	0.57	0.70	0.32	0.68	0.19
AE 500 nm	1.18	1.27	0.51	0.90	0.16
# of Instances	1115	729	285	80	10

3.3.5 Connection between Particulate Matters, Aerosol's Optical Characteristics, and Meteorological Parameters

Figure 3-9a–c exhibits the relationships between PM10 and aerosol's optical characteristics, using MODIS Aqua and Terra AOD daily observations and MERRA-2 model outputs, during the periods from 1 January 2018 to 31 December 2018. Eight PM10 stations, with hourly data, were included to generate the daily PM10 averages used here. The difference in the data acquisition frequency of satellite-based AOD observations against the hourly PM10 data collection accounts for lack of a direct relationship. Hence, using MODIS-based AOD values to represent daily PM10 might be problematic, since PM10 values vary greatly during the day, while the MODIS sensors can only capture AODs in limited time periods. On the other hand, a weak positive relationship was found between the modeled MERRA-2 AOD and PM10. This connection indicates that the PM10 value could be converted based on MERRA-2 outputs along with other meteorological parameters. Additionally, the AERONET observations provide more reliable

evaluation for the relationship between the aerosol optical characteristics and PM10. Therefore, the AOD and Ångström exponent (AE) daily values are collected from the AERONET EMA2 Station in different spectral bands (1020 nm, 870 nm, 675 nm, 500 nm, 440 nm, 380 nm, and 340 nm) for the same period. Figure 3-9d demonstrates the positive relationship between PM10 and AOD at 1020 nm, which is the AOD that is mostly related to PM10 among all the bands. In contrast, Figure 3-9e shows the negative relationship between AE at 340/440 nm and PM10, showing the strong linkage between PM10 and coarse aerosols. It suggests that the AOD and AE observations can be used to estimate the extent of PM10 pollutions.

To be able to model PM10 data, machine learning methods are applied here to achieve better accuracy estimation of PM10 values from the MERRA-2 AOD along with multiple meteorological parameters obtained from the GLDAS model. The dataset has total 364 observations, where each observation has 10 input parameters namely: (MERRA-2_AOD, month, AvgSurfT_inst, LWdown_f_tavg, Lwnet_tavg, Psurf_f_inst, SWdown_f_tavg, Swnet_tavg, Tair_f_inst, and Wind_f_inst). These fields were used to generate the modeled PM10, which was then validated against the objective field (ground-based daily PM10). The dataset is randomly split by the ratio (9:1) into a training dataset (327 observations) and testing dataset (37 observations), respectively. We built various supervised machine learning models, each assigned different parameters, including 97 random decision forests, one decision tree, one linear regression, and two artificial neural networks. The models use R2 values and MAE (mean absolute error) as the training metrics and cross-validation for the evaluation process. The selected best models of each model category are listed in Table 3-3. Among them, the best Random Decision Forest achieves the best performance with highest R2 value (0.58825) and lowest MAE (27.37317). Therefore, this model was selected to predict the PM10 values based on the aforementioned input parameters

using the testing dataset. The comparison between the predicted PM10 and actual PM10 values is illustrated in Figure 3-9f. The result demonstrates the higher R2 value (0.43) than all of the R2 values in Figure 3-9a–e, which shows the improvement of the predictability using AOD with meteorological parameters. Since this approach only deploys lower temporal (daily) and spatial resolution (MERRA-2 of $0.5^\circ \times 0.625^\circ$ and GLDAS of $0.25^\circ \times 0.25^\circ$), it promotes potential further optimizations by using finer spatial and temporal resolution inputs.

Figure 3-9: The relationship between the daily average of PM10 and multiple products: (a) MODIS Aqua AOD; (b) MODIS Terra AOD; (c) Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) AOD; (d) AERONET AOD at 1020 nm; (e) AERONET Ångström exponent (AE) at 340 nm/440 nm; (f) predicted PM10 values from the Random Decision Forest model output.

Table 3-3: The selected model per category. MAE: mean absolute error

Ranking	Algorithm Name	R ²	MAE
1	Random Decision Forest	0.58825	27.37317
2	Artificial Neural Network	0.37955	29.91710
3	Linear Regression	0.28848	28.41857
4	Decision Tree	0.25115	37.64001

Figure 3-10 shows the average annual PM_{2.5} for all of Egypt using GWR datasets to compare with monthly MERRA-2 datasets (min, max, and mean values) of PM_{2.5} dust AOD and sea salt AOD, as well as surface air temperature and wind speed during the period from the year 1998 to 2016. Since the majority of Egypt is covered with depopulated desert regions, the population weighted PM_{2.5} is apparently lower than the geographic mean PM_{2.5} for all the types of PM_{2.5} components. However, with dust and sea salt excluded, the population-weighted PM_{2.5} is higher than that of the geographic mean due to the PM_{2.5} particles mainly coming from civilization, such as industrial and transport emissions and burnt agriculture waste. The black arrows point to the 2010 PM_{2.5} including dust and sea salt, showing the impact of anomalous high temperature, particularly during cool months, on the rising of PM_{2.5} dust aerosols. The black circles suggest the relationship between both record-breaking hot months and emergently increased PM_{2.5}, regardless of the dust and sea salt components. The red arrows show the severely high PM_{2.5} in 2006, which is explained by the excessively numerous fire events during the “black cloud” season [40], [41].

Figure 3-10: Egypt's average annual population weighted and geographic mean PM2.5 using geographically weighted regression (GWR) datasets to compare with monthly MERRA-2 datasets (min, max, and mean values) of PM2.5 dust AOD and sea salt AOD, as well as surface air temperature and wind speed during the period from 1998 to 2016.

3.4 Discussion

The consequence of the accelerated economic growth of Egypt in the past decades makes Cairo the largest city of Africa with more than 20 million people, as well as one of the most air-polluted mega cities globally [116], which puts people living in urban areas into a more vulnerable situation of environment-related and public health issues. Additionally, the pollution over such a dense population severely impacts not only the residents but also tourists from many countries.

The factors deteriorating air quality include natural sources from the surrounding deserts and anthropogenic sources such as vehicles, industries, agriculture waste burning, and even the formation of secondary aerosols [53]. The complexity of identifying the pollution types, sources, and trajectories is even enhanced by Cairo's special geographical and meteorological characteristics, which introduces complications in the managerial strategies. However, the period of the worst air quality condition over Cairo is identified in the fall season, when the wind currents are weak [47], [53]. The warmer and lighter air mass stays over the colder air to make the bowl-like Cairo even more stagnant without air movement, trapping the air pollutant close to the ground. This high ambient concentration of air pollutants is known as the "black cloud". The rare appearance of rainstorms in this season makes the situation even more severe. It also brings public debates around the major contributors to the locally known "black cloud" episode—urban pollutants (industries and vehicles) or agriculture waste burning, which is banned by the government. The study [40] found that smoke from the agriculture waste contributed to the urban air pollution as well as from the open fires generated at sunset (when it is less likely to get observed), which is the worst time for Cairo's air quality. Besides, it is reported that Cairo's increased ozone during summer is transported from Europe [117] and the CO increases as a result of the Khamsin events and industrial pollution [14]. A study also showed that the anticyclone flow of the Asian summer monsoon can transport the pollution from Asia towards Africa [118]. These studies suggest that the urban air quality control needs efforts from urban, rural, and even international collaborations. Moreover, other significant effects of aerosols (e.g., effects on the visibility, the nutrient balance, and acidity of soil) have also been reported [119], [120].

As it is illustrated in Figure 3-10, the rapid increase of air temperatures, possibly driven by climate changes, can intensify both the AOD and PM_{2.5} in Egypt. The usage of machine learning

to improve the estimation and prediction of meteorological parameters, such as precipitation, has been validated in the previous research. On the other hand, the tropospheric aerosols can both alter the direct and indirect radiative forcing to the Earth's surface as the feedback to impact the warming process [121]. However, the knowledge of the aerosols' characteristics and sources is critical not only for human health, but also for the understanding of their interaction with regional and global climate change, particularly the radiation balance of the Earth's system. For instance, the direct global dust-climate feedback is calculated as approximate range of -0.04 to $+0.02$ $\text{Wm}^{-2} \text{K}^{-1}$, which can potentially shape the major dust sources of the future climate, as has likely occurred in the past [122], [123]. The absorption of SW and LW radiation, as well as scattering LW radiation back to the Earth's surface, causes a dust-warming effect, which results from the coarse dust and is intensified by the bright surfaces, such as the desert region of the Middle East [124], [125]. In contrast, the scattering of SW radiation induces cooling effect, which results from the fine dust and is enhanced over the dark surfaces [125]. However, past investigations of the responses of dust cycle to the climate changes yielded divergent results, because of many uncertainties of parameters in quantifying the dust-climate feedbacks [124], [126]–[130]. Therefore, there is no solid consensus on whether the dust activities will enhance or weaken future climate changes [129]–[132]. Recently, a study investigated the annual patterns and episodes of the Cairo's air pollution using satellite-based measurements from the tropospheric emission spectrometer (TES) on board the Aura [41] to demonstrate multiple pollutants' seasonal variation.

3.5 Conclusion

This study extends the work with more accurate ground-based AERONET observations focusing on the atmospheric aerosols. In this research, the combination of AERONET ground-based and satellite observations (e.g., MISR and Aqua and Terra MODIS) are used to study different compositions of aerosol loadings over Cairo and Nile Delta during a near 20-year period from 1999 to 2018. Our analysis validated the better performance of MISR and MODIS sensors in observing local aerosol events in Cairo. Aerosol products from the AERONET portal (such as SDA and the GSFC model) as well as CALIPSO aerosol subtypes tool are used to study the emerging aerosol episodes for each season. The result indicates that during the spring, fall, and summer, the selected aerosols events are caused by dust-related storms, whereas during winter, pollution and marine-related finer aerosols could also lead to severe aerosol conditions. The seasonal episodes also revealed the unassociated impacts on human health through altering the UV exposure, air temperature, humidity, and solar radiation intensities. Aerosols in different conditions (clear, fine, coarse, and mixed aerosols) are well distinguished using a multi-band AOD spectrum, as well as derived AE and FMF products using the K-means method over AERONET observations. The PM_{2.5} is indicated to be connected with air temperature and aerosol activities over the Egypt region. The Random Decision Forest model has been proved to improve the accuracy of estimating PM₁₀ based on AOD and meteorological parameters, while future work is suggested to develop advanced algorithms to optimize the air quality predictions that are critical to human health.

4 Third Study: Synergistic Use of Remote Sensing and Modeling to Assess an Anomalously High Chlorophyll-a Event during Summer 2015 in the South Central Red Sea

4.1 Introduction

The Red Sea is a narrow meridionally-elongated oceanic basin, surrounded by arid land and desert separating Northern Africa from the Arabian subcontinent [133]. The basin extends to about 30°N in the Gulf of Suez and the Gulf of Aqaba (Eilat) and terminates to the south at the straits of Bab al Mandeb at approximately 12.5°N. The length of the Red Sea is roughly 2250 km, with a maximum width of 355 km and a maximum depth of 3,040 m; although the average depth is 490 m [134], [135]. The Red Sea has no river inflow or stream sources and has a high evaporation rate at more than 210 cm/yr [136] and a precipitation rate of less than 100 mm/yr [137], [138], resulting in the highest salinity of any major tropical oceanic basins [136]. Salinity increases from 36.5‰ in the far southern region to 40–41‰ towards the northern part [139]. It is noteworthy that below the pycnocline (205–300 m), the entire Red Sea basin has water with extremely uniform temperature and salinity, with values of 21.6 and 40.6 practical salinity unit (psu) ‰, respectively [140]–[142].

The Red Sea has extremely high biodiversity, with more than 1,400 species of fish and over 300 species of coral, many of them unique to the region [143], [144]. The area is economically important, with over 100,000 tons of fish reportedly caught each year, representing an annual value of over \$200 million (US) [145]. The high temperature and salinity of the water also make the Red Sea an important natural laboratory for understanding the effects of climate change, especially on coral reefs [146], [147]. Interestingly, the entire Red Sea is considered to be oligotrophic, lacking in several important nutrients including nitrate, ammonium, phosphate, and silicate, and supporting levels of chlorophyll-*a* (Chl-*a*) less than 2.6 mg m^{-3} (or, equivalently, 2.6 g L^{-1}) [148]. However, recent studies using both satellite and *in situ* observations have challenged this simple notion by identifying regions with Chl-*a* concentrations and nutrient levels higher than traditional oligotrophic thresholds [149]–[152].

In this study, we consider a phytoplankton bloom that occurred in the South Central Red Sea (17.5° – 22.0° N, 36° – 43° E) in late June 2015. In this particular case, the Chl-*a* anomaly observed by the Moderate Resolution Imaging Spectroradiometer (MODIS) instrument on the Aqua satellite was 2.65 mg m^{-3} above the monthly mean value (3.05 mg m^{-3} compared to 0.40 mg m^{-3}) for the period from 2002 to 2017—an outlier of 3.5 standard deviations from the mean. To better understand the conditions and possible causes of this unique event, we used a wide range of oceanographic and meteorological datasets, including Chl-*a* concentrations, sea surface temperature (SST), sea surface height (SSH), mixed layer depth (MLD), ocean current velocity, aerosol optical depth (AOD), and dust aerosol optical depth (DAOD), obtained from different sensors and models. The results show that this event is anomalous in multiple ways and suggests temporal relations between geophysical parameters that may be important for understanding the behavior of Chl-*a* events in the Red Sea.

4.2 Materials and Methods

4.2.1 Study Area

In this study, we first partitioned the Red Sea into four different meridional domains at specific latitudinal boundaries based on the abundance and spatiotemporal distribution of surface Chl-*a* following the approach of Raitso et al. [149]. The four regions, from north to south, are designated the Northern Red Sea (NRS), the North Central Red Sea (NCRS), the South Central Red Sea (SCRS), and the Southern Red Sea (SRS) (Figure 4-1, Table 4-1) [149].

This subdivision is important because the northern Red Sea and southern Red Sea have different climatology due to the influence of the Arabian Ocean monsoon [153]. The NRS does not exhibit a monsoon effect, with winds from the north-northwest the entire year [140], [153]. South of 20°N, during the Northeast Monsoon (Nov-Feb), the winds blow from the south-southeast, and during the Southwest Monsoon (Jun-Sep), the winds blow from the northwest to north-northwest [153]. This change in the prevailing winds affects the occurrence of dust storms over the Red Sea, as well as SST and salinity, especially in the southern part of the basin [139], [141], [154].

Table 4-1: Four Regions of the Red Sea; NRS: Northern Red Sea; NCRS: North Central Red Sea; SCRS: South Central Red Sea; SRS: Southern Red Sea

Region Number	Region Name	North End	South End
1	NRS	27.7°N	25.5°N
2	NCRS	25.5°N	22°N
3	SCRS	22°N	17.5°N
4	SRS	17.5°N	12.8°N

Figure 4-1: Moderate Resolution Imaging Spectroradiometer (MODIS) Aqua chlorophyll-a Chl-a (mg m⁻³) monthly averaged Level-3 composite for the Rea Sea from July 2002 to May 2017. The four regions consecutively from north to south are the NRS, NCRS, SCRS and SRS.

Figure 4-2: Hovmöller latitude-time plot for the four regions of Red Sea from January 2012 to December 2015. (Left) Chl-a (mg m^{-3}) merged Level-3 Ocean Color Climate Change Initiative (OC-CCI) 4 km monthly data, (Right) MODIS-Aqua Chl-a (mg m^{-3}) Level-3 4 km monthly data. The individual rows correspond to: (a) Northern Red Sea (NRS) (b) North Central Red Sea (NCRS) (c) South Central Red Sea (SCRS) (d) Southern Red Sea (SRS). Note the difference in the scales between the left and right sets of panels.

4.2.2 Chlorophyll Data

Terra and Aqua MODIS Data

Chl-*a* concentrations derived from satellite ocean color retrieval algorithms are good indicators of phytoplankton biomass in the surface layer [149], [155]. Among the satellite sensors that routinely provide global Chl-*a* retrievals are the MODIS instruments onboard the National Aeronautics and Space Administration (NASA) Terra and Aqua satellites. The Terra satellite, launched in 1999, is in a sun-synchronous orbit, with an equatorial crossing time of 10:30 LT. The Aqua satellite, launched in 2002, is also sun-synchronous, with an equatorial crossing time of 13:30 LT. Together, the two sensors provide nearly daily global coverage. In the past, the MODIS-Terra instrument had calibration issues that caused unacceptably large uncertainties in ocean color retrievals [156]. However, these have been addressed in the most recent reprocessing of the MODIS-Terra data through cross-calibration with the Sea-viewing Wide Field-of-view Sensor (SeaWiFS) instrument [157]. Operational Chl-*a* retrievals from MODIS-Aqua were evaluated against *in situ* data for the northern part of the Red Sea and the results for this region were found to be comparable to the performance of the algorithm in other parts of the world [158]. MODIS-Terra and Aqua Chl-*a* retrievals have also been evaluated against retrievals from SeaWiFS in the Arabian Sea, where it was found that MODIS-Aqua underestimated the Chl-*a* in the open ocean by less than 20%, but MODIS-Terra underestimated the Chl-*a* by about 30% [159]. However, it is important to recognize that the mission objective for SeaWiFS was an error less than 35%, so the MODIS-Terra Chl-*a* results are acceptable [160]. We also include both MODIS-Terra and MODIS-Aqua Level-3 data in our analysis because using both sensors significantly improves the coverage from one sensor alone due to sun-glint avoidance and changes in cloudiness [161], [162], and issues have been identified with the coverage of MODIS-Aqua alone, particularly in the

southern Red Sea [163]. In this work MODIS-Terra and Aqua Level-3 Chl-*a* data version 2014 at 4-km resolution are used [164], [165] (Table 4-2). The Terra data includes a monthly composite of Chl-*a* concentration in June 2015 for its anomalous behavior, a monthly climatology composite of Chl-*a* concentration of June during 2000 to 2016 for comparison and annual composite Chl-*a* concentration for comparison. The Aqua data include a 16 years averaged monthly composite of Chl-*a* concentration from 2002 to 2017, and a monthly composite of Chl-*a* concentration from 2012 to 2016 (Table 4-2).

Table 4-2: The characteristics and source of data used in this study. OC-CCI: Ocean Color Climate Change Initiative; GHRSSST: Group for High Resolution Sea Surface Temperature; ASCAT: Advanced Scatterometer; OSCAR: Ocean Surface Current Analyses Real-time; MLD: mixed layer depth; SSH: sea surface height; AOD: aerosol optical depth; HYCOM: HYbrid Coordinate Ocean Model; SST: sea surface temperature.

Data Name	Product	Level	Spatial Resolution	Temporal Resolution	Web Link
MODIS Chl- <i>a</i> (Terra & Aqua)	MOD21/MYD21	3	4 km	Monthly	https://oceancolor.gsfc.nasa.gov/cgi/l3
OC-CCI V3 data	OC-CCI Chl- <i>a</i>	3	4 km	Daily/Monthly	https://www.oceancolour.org/portal
SST	GHRSSST	4	0.05°	Daily	http://apdrc.soest.hawaii.edu/las/v6/constrain?var=11674
Wind	ASCAT	2	0.25°	Daily	http://apdrc.soest.hawaii.edu/las/v6/dataset?catitem=11683
Ocean Surface Current	OSCAR	4	1/3°	5-day	http://apdrc.soest.hawaii.edu/las/v6/constrain?var=2136
HYCOM Model	MLD	-	1/12°	Daily	http://apdrc.soest.hawaii.edu/las/v6/constrain?var=10471
	SSH	-	1/12°	Daily	http://apdrc.soest.hawaii.edu/las/v6/constrain?var=10472
MODIS AOD (Terra & Aqua)	MOD04/MYD04	2	3 km	Daily	https://worldview.earthdata.nasa.gov/

The Ocean Color Climate Change Initiative (OC-CCI) Data

Due to the importance of phytoplankton in the Earth system, ocean color is recognized as an essential climate variable (ECV) [166]. Long-term monitoring of ocean color, and particularly Chl-*a*, requires a time series of quality-controlled data generated from multiple instruments and multiple algorithms. The Ocean Color Climate Change Initiative (OC-CCI) dataset has been produced by the European Space Agency (ESA) to address this need [166]. The dataset merges retrievals from SeaWiFS; MODIS-Aqua; the MEdium Resolution Imaging Spectrometer (MERIS), which flew on Envisat-1; and the Visible Infrared Imaging Radiometer Suite (VIIRS), which flies on the Suomi National Polar-orbiting Partnership (NPP) satellite [167]. Critical steps for achieving data consistency include band-shifting and empirical bias correction [166]–[168]. The OC-CCI dataset has been used by other researchers in the Red Sea and shows good consistency with *in situ* observations along with substantially improved coverage, particularly for the southern region [158], [162], [163]. In this work, we used daily and five-day composites of Level-3 OC-CCI Chl-*a* data at 4 km resolution from June 25 to 29, 2015 [169] (Table 4-2). It is noteworthy that the performance of two Chl-*a* algorithms (OCI and OC3) were evaluated against MODIS-Aqua and *in situ* chlorophyll data. The results showed that the performance of the algorithms in Red Sea was comparable with their performance in other oligotrophic regions in the global ocean, supporting the use of ocean color data in the Red Sea. Moreover, it was mentioned that the two empirical algorithms (OC4 and OCI) systematically overestimated chlorophyll when compared with the *in situ* data [158].

4.2.3 Oceanography and Meteorology Data

Sea Surface Temperature (SST) Data

For this study we acquired daily SST information from 21 June to 29 June 2015 at 0.05° resolution from the Group for High Resolution Sea Surface Temperature (GHRSSST) Operational Sea Surface Temperature and Sea Ice Analysis (OSTIA) daily data (Table 4-2). OSTIA uses satellite data provided by the GHRSSST project, blending data from sensors including the Advanced Very High Resolution Radiometer (AVHRR), the Advanced Along Track Scanning Radiometer (AATSR), the Spinning Enhanced Visible and Infrared Imager (SEVIRI), the Advanced Microwave Scanning Radiometer for -EOS (AMSR-E), the Tropical Rainfall Measuring Mission (TRMM) Microwave Imager (TMI), as well as in situ data from drifting and moored buoys [170]–[172].

Wind Data—ASCAT Global Wind Field L3 Data

Gridded, daily-averaged surface wind and wind stress fields at 0.25° resolution were obtained on 24 June 2015 from objectively interpolated wind fields from the Advanced Scatterometer (ASCAT) on the European Organisation for the Exploitation of Meteorological Satellites (EUMETSAT) meteorological operational platform (Metop)-A and -B polar orbiting satellites [173] (Table 4-2). The fields use the ASCAT observations as well as meteorological analyses from the European Centre for Medium-Range Weather Forecasts (ECMWF) [174].

Ocean Surface Current Data

Ocean surface current data at 0.33° resolution available at five-day intervals, from 17 to 21 June, 22 to 26 June, 27 June to 01 July 2015, were obtained from the Ocean Surface Current Analysis Real-time (OSCAR) project [175], [176] (Table 4-2). OSCAR uses sea surface height gradients and ocean surface vector wind fields to calculate velocities fields in the global ocean surface derived from geostrophy, Ekman dynamics, and thermal wind assumptions [177].

Mixed Layer Depth (MLD) and Sea Surface Height (SSH)

Daily information regarding the MLD and SSH at 0.08° resolution from 21 to 30 June 2015 was obtained from the three dimensional, real time, HYbrid Coordinate Ocean Model (HYCOM) [178] (Table 4-2). The HYCOM model uses the Navy Coupled Ocean Data Assimilation (NCODA) system to incorporate information from satellite altimeters and SSTs, as well as data from ocean floats and buoys through the application of a three-dimensional variation (3DVAR) scheme.

Aerosol Optical Depth (AOD) and Dust Aerosol Optical Depth (DAOD) Data

Atmospheric aerosols – specifically mineral dust which contains iron (Fe), phosphorus (P), and other micronutrients – have been postulated to play an important role in the fertilization of the global oceans, especially in nutrient-limited areas such as oligotrophic seas. In order to assess the potential roles of aerosols and dust in the Red Sea, we acquired the Collection 6, MODIS 3 km AOD data (Table 4-2). For time series analysis of both AOD and DAOD in the region, we used

the NASA Goddard Online Interactive Visualization ANd aNalysis Infrastructure (Giovanni) tool [179] to obtain the monthly mean Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) AOD and DAOD fields at $0.5^\circ \times 0.625^\circ$ resolution. MERRA-2 assimilates AOD from the Advanced Very High Resolution Radiometer (AVHRR) instruments, the Multi-angle Imaging SpectroRadiometer (MISR) instrument on Terra, as well as MODIS-Terra and MODIS-Aqua, among other satellite and ground-based sensors. Giovanni was also used to obtain the MODIS-Aqua Chl-*a* concentrations on a monthly basis at 4 km resolution for similar temporal analyses.

4.3 Results

4.3.1 Chl-*a* Climatology in the Red Sea and Anomaly Identification

In order to visualize the temporal and spatial variability of Chl-*a* in the Red Sea we constructed latitude-time Hovmöller plots from both OC-CCI and MODIS-Aqua monthly datasets from January 2012 to December 2015. These are shown in Figure 4-2 for the four regions in Figure 4-1 and listed in Table 4-1. Note these are similar to the latitude-time plots of Acker et al., but the axes have been switched. Due to the large north-south differences in the magnitude of Chl-*a* in the Red Sea, the OC-CCI data (left panels) have been plotted on a logarithmic scale using different ranges for each domain. The MODIS-Aqua data (right panel), on the other hand, are displayed using a linear scale that is constant for the four domains, which helps highlight the overall changes in the Chl-*a* concentrations. However, the scale difference did not affect the matching of blooms' occurrences in the same regions using both datasets. Note that, while the OC-CCI dataset includes

MODIS-Aqua, due to differences from band shifting and empirical bias correction, the specific values of Chl-*a* in the left and right sets of panels are not directly comparable, but it is only the relative temporal and spatial changes that are important. Figure 4-2 also demonstrates the coverage differences between the blended OC-CCI dataset and the MODIS-Aqua dataset alone. White regions with missing data are much more prevalent in MODIS-Aqua plots for the SRS and SCRS and have been discussed by previous authors. It is noteworthy that an anomalous Chl-*a* outbreak was quite evident from both datasets in region 3 (SCRS) near 19.5°N to 17.5°N during the summer of 2015.

Both sets of panels in Figure 4-2 show the strong seasonal pattern in Chl-*a* in the Red Sea with increased concentrations in boreal winter (December–January) and decreased concentrations in boreal summer (June–August). The anomalous feature of interest appears in the SCRS in the summer of 2015 as a band of enhanced Chl-*a* values (warm colors) that is easier to identify in the MODIS-Aqua data, but is also apparent in the OC-CCI dataset. While other researchers have identified peaks in Chl-*a* concentrations in May or June, especially in the southern Red Sea, it is both the timing and magnitude of this anomaly that attracted our interest.

To better represent the magnitude and timing of the Chl-*a* anomaly, we next constructed monthly time series of the average Chl-*a* concentration in the four regions of the Red Sea using the MODIS-Aqua data, as shown in Figure 4-3a. The stacked bars clearly show the relative contribution of each of the regions to the overall Chl-*a* concentration in the basin, with the SRS being the largest contributor, and the SCRS being the second largest. The >3 mg m⁻³-high Chl-*a* anomaly in June 2015 stands out clearly with the overall Chl-*a* load reported for the entire Red Sea

being even greater than what is observed in the winter months. The SCRS is by far the largest contributor to the Chl-a amount for the June 2015 event.

Figure 4-3: Time series analysis of chlorophyll-a concentration in the Red Sea. (a) Area average of MODIS Aqua Chl-a concentration (mg m^{-3}) monthly data from January 2012 to December 2016 over four regions of Red Sea (b) South Central Red Sea daily OC-CCI Chl-a concentration (mg m^{-3}) from 1 June to 7 July for each year from 2012 to 2016.

Even finer temporal resolution is displayed in Figure 4-3b, which plots the daily Chl-a concentration from the OC-CCI dataset averaged just over the SCRS for 1 June to 7 July for the years 2012 to 2016. Since the OC-CCI dataset has been demonstrated to have good consistency with in situ observations in the Red Sea, we have more confidence in the numeric values of the Chl-a concentrations. The reported Chl-a concentration on 29 June exceeds 1 mg m^{-3} , compared to the regional mean for this time period, which hovers around 0.3 mg m^{-3} . The four highest

values of Chl-*a* for the SCRS occurred in 2015 on 29 June, 24 June, 27 June, and 28 June, in order of decreasing magnitude from 1.08, 0.77, 0.67 and 0.61 mg m⁻³ respectively. Only a single high value from 30 June 2014 prevents 1 July 2015 from being the next highest value.

The spatial structure of the anomalous late-June 2015 event is demonstrated in Figure 4-4. Panel (a) shows the Chl-*a* composite for the Red Sea from the OC-CCI data for June 26 to June 29. The dashed box encloses the SCRS. The highest Chl-*a* values are seen in this region, particularly in the southeast portion of SCRS domain. The northwest portion of the domain shows low Chl-*a* values surrounded by somewhat higher values and apparently associated with an eddy structure. Such eddies have previously been identified in satellite observations of Chl-*a*, and the existence of large, persistent eddies was identified in hydrographic surveys of the region as far back as 1993. The dominance of the Chl-*a* features from June 26 to June 29 is clearly shown in Figure 4-4b, which displays the mean Chl-*a* concentrations for the Red Sea from the OC-CCI dataset for the entire month of June 2015. Consistent with the results in Figure 4-3b, the anomalies from the end of the month are superimposed on a background of lower values. The change in the Chl-*a* values due to averaging over a longer time period is not readily apparent in the selected color scale, which was chosen to be consistent throughout the figure. Figure 4-4c shows the mean Chl-*a* values for June 2015 from MODIS-Terra. Recall that MODIS-Terra is not included in the OC-CCI dataset, but the Chl-*a* values show good consistency with MODIS-Aqua Chl-*a*, although there might be some bias in the Red Sea. The agreement between the OC-CCI monthly mean Chl-*a* values (Figure 4-4b) and the MODIS-Terra Chl-*a* values (Figure 4-4c) is acceptable, with the MODIS-Terra data showing regionally higher values of Chl-*a* and a greater frequency of missing data, indicated by the white regions. The inclusion of the MODIS-Terra Chl-*a* data is motivated by a desire to extend the Chl-*a* time series back as far as possible. The SeaWiFS instrument ceased

operation in December 2010 and so cannot be used for this purpose. The MODIS-Aqua time series begins in 2002, but the MODIS-Terra dataset extends back to 2000, so we use MODIS-Terra to construct the Chl-*a* climatology for June using data from 2000 to 2015 as shown in Figure 4-4d. The spottiness of the satellite retrievals, especially in the SRS is evident in this figure. However, it is also apparent that the features observed in June 2015 are not expected climatologically. Finally, Figure 4-4e displays the annual mean Chl-*a* concentrations from MODIS-Terra for 2015 as a basis for comparison. The overall distribution of Chl-*a* from MODIS-Terra closely resembles the yearly climatology derived from both SeaWiFS and MODIS-Aqua (Figure 4-1). The annual observations clearly show the lack of dominance of this bloom, which confirms our assumption of being an anomaly and hence worth the investigation.

Figure 4-4: Chl-*a* concentrations in the Red Sea for different time periods (a) The OC-CCI Chl-*a* (mg m^{-3}) merged level-3 5-day composite, from 25 June 2015 to 29 June 2015, (b) the OC-CCI Chl-*a* merged level-3 monthly composite for June 2015, (c) the MODIS Terra Chl-*a* level-3 monthly composite of June 2015, (d) the MODIS Terra Chl-*a* level-3 monthly climatology composite for June for all years from 2000 to 2015 and (e) MODIS Terra Chl-*a* level-3 4-km annual composite for 2015.

4.3.2 Temporal and Spatial Variations of Chl-a Concentration-Related Factors

In order to understand the physical processes and the factors influencing phytoplankton growth related to the significant Chl-a anomaly observed in the SCRS in late June 2015, we consider a wide range of oceanographic and meteorological data as summarized in Section 2. Figure 4-5 presents a daily overview from 21 June to 30 June 2015 of four of these factors: (a) Chl-a concentrations from OC-CCI, (b) the MLD and (c) SSH from HYCOM simulations, and (d) the SST from OSTIA.

Figure 4-5: Daily variability from 21 June until 30 June 2015 for (a) Chl-a, (b) mixed layer depth (MLD), (c) sea surface height (SSH), (d) sea surface temperature (SST).

For the whole region, we deduced an increasing SST trend with the clear declining MLD and SSH trends from June 21 to June 25 (blue and red arrows in Figures 4-5 b, c & d). This general

behavior become more stable during the latter days, June 26–30, indicating the beginning of a new increasing cycle. Starting with the Chl-*a* figures in the left-most panel (Figure 4-5a), the anomaly appears most clearly on June 24 and 29, with some evidence of enhancement on the later date, consistent with the results shown in Figure 4-3b. However, the temporal development of the Chl-*a* anomaly is difficult to make out due to the large fraction of missing data, indicated by the white areas. Inspection of the MODIS-Terra and Aqua true color imagery and AOD retrievals for this time period show elevated AOD due to blowing dust, which is persistent in this season [180], [181], as well as high clouds and AOD and Chl-*a* retrieval exclusions due to sun-glint. The eddy appears in the northwestern portion of the SCRS on June 22, as evidenced by a ring of elevated Chl-*a*. The Chl-*a* signal in this ring intensifies later in the period (June 27-29), contributing to the overall anomaly seen in the Chl-*a* data. There is also some evidence of another, smaller eddy centered around 18°N, 40°E in the observations from June 29.

In Figure 4-5b, the MLD indicates the vertical region within the ocean that has relatively uniform properties due to the effects of surface wave-generated turbulence. The MLD is particularly important to phytoplankton in the Red Sea because deepening the mixed layer can make nutrients from lower level waters available for use. A number of studies in the Red Sea have shown that phytoplankton concentrations in the Red Sea typically reach a maximum around a depth of 80 m, rather than at the surface, due to the oligotrophic nature of the surface water. In Figure 4-5, the deepest MLD appears along an axis slightly to the east of the central portion of the Red Sea. The maximum MLD, around 40 m according to the HYCOM model appears on June 22, with the values getting shallower on succeeding days. There is also evidence of multiple eddies, especially along the western portion of the basin. Such eddies are common in the area, and have been implicated in increases in phytoplankton by a number of authors.

Satellite altimeters are capable of measuring SSH with a vertical precision of a few centimeters. The HYCOM model assimilates this information to provide continuous spatial fields of SSH, which has been used to identify eddy circulations in the Red Sea. Cyclonic eddies (rotating counterclockwise in the northern hemisphere) are associated with anomalously low SSH, while anti-cyclonic eddies (rotating clockwise in the northern hemisphere) are associated with anomalously high SSH. Figure 4-5c shows the largest SSH along the eastern part of the Red Sea. The SSH in this region slowly decreases from 23 to 26 June, and then show a slight increase toward the end of the period. Since SSH is unlikely to reflect changes in currents in this region, especially the intrusion of intermediate waters from the Gulf of Aden (GAIW) to the south, the signal in this part of the map likely reflects day-to-day changes in the SST. A triplet of local SSH anomalies in the eastern part of the basin likely indicate the presence of large-scale eddies. A diffuse region of locally higher SSH is generally coincident with the ring of enhanced Chl-a, which is especially apparent on 27 June centered around 20.5°N, 38.5°E. This suggests that the enhanced Chl-a is associated with the border of an anticyclonic eddy. Two additional regions of locally lower SSH are also apparent throughout the time period to the southeast of the larger area of higher SSH. On 22 June these are centered around 19°N, 39°E and 18°N, 39.75°E. The reduction in the SSH indicates these are cyclonic eddies.

The SST field (Figure 4-5d), shows less spatial structure than the other geophysical variables. On a large scale, the obvious features are higher SSTs in the southeastern part of the Red Sea and lower SSTs in the northwestern part. In the northwest, in particular, cooler SSTs are gradually replaced by somewhat warmer SSTs through the time period. The main feature in this part of the basin is a large area of cooler SSTs surrounded by a ring of slightly higher SSTs. On 22 June, the core of this feature is near 20°N, 38°E. This feature is likely associated with the region

of enhanced SSH mentioned above in connection with the ring of enhanced Chl-a attributed to an anticyclonic eddy. Anticyclonic mesoscale features in the ocean, normally creating surface convergence that pushes water down, are expected to be associated with fewer nutrients in the mixed layer and enhanced SSTs—and are thus commonly known as warm-core eddies. The SST data in Figure 4-5d indicate this anticyclonic feature is associated with locally cooler SSTs, even though the SSH is elevated. This is a second anomaly associated with the anomalous Chl-a event in June 2015.

The anticyclonic nature of the large eddy near 20°N, 38°E on June 22 is confirmed by the clockwise rotation of the composite surface current vectors from OSCAR shown in Figure 4-6. This figure shows two eddies that are persistent features throughout the time period. However, it is likely that the 0.33° resolution of the OSCAR data is insufficient to resolve the pair of cyclonic eddies apparent in the higher resolution SSH data. The formation of an eddy dipole in the western Red Sea near 19°N with a cyclonic eddy to the *north* and an anticyclonic eddy to the *south* has been attributed to the influence of a wind jet associated with the Tokar Gap, which is active throughout the boreal summer and a large source of atmospheric dust.

Figure 4-6: Ocean Surface Current Analysis Real-time (OSCAR) third-degree resolution ocean surface currents (m s^{-1}) for (a) 17 to 21 June, (b) 22 to 26 June, (c) 27 June to 1 July 2015.

Figure 4-7 shows clearly the Tokar Gap wind jet was active during this time period. The MODIS-Terra true color image from 23 June shows a pronounced dust plume emanating from the vicinity of Tokar and extending out over the Red Sea. This is facilitated by strong winds blowing from west to east caused by large land/ocean temperature gradients that occur in this area predominantly in July. The ASCAT surface wind stress field from June 24 indicates that the winds that produced the dust uplift were likely also affecting the sea surface during this time. While the Tokar Gap wind jet was clearly active, at least during a portion of the time period of interest, comparison of the ASCAT surface wind stress field in Figure 4-7 and the surface current vectors in Figure 4-6 shows that the winds were acting in opposition to the movement of the surface water. This decoupling of the surface wind stress and the surface currents has been noted previously by Churchill et al. [181], who implicated the effects of diurnal surface heating, which would be particularly pronounced in June in the SCRS.

Figure 4-7: The Tokar Wind Jet represented by (Left) MODIS-Terra true-color composite image of a dust event induced by the Jet on 23 June 2015 and (Right) Advanced Scatterometer (ASCAT) Level 3 wind field stress (pascal) on 24 June 2015.

It is remarkable that the region centered around 21.5°N, 37.5°E exhibits low Chl-a, low SST and high SSH simultaneously during the period of study since this is in opposition to the circulation as manifested by the sea surface currents (Figure 4-5 and Figure 4-6). Our results show clearly that this anticyclonic eddy influences the biological production in the Red Sea more than the meridional circulation, in agreement with other studies

4.3.3 Other Factors Contributing to the Chl-a Concentration Variability in the South Central Red Sea

The previous section describes a number of geophysical features directly associated with the Chl-a anomaly observed at the end of June 2015 in the SCRS. To explore the physical causes for this event, we constructed a monthly time series of Chl-a from MODIS-Aqua for the SCRS for the period from July 2002 to April 2017 using the NASA Giovanni tool. Using Giovanni, we also extracted monthly time series of MODIS-Terra and Aqua AOD. AOD and DAOD from the MERRA-2 reanalysis, and the MODIS-Aqua SSTs for the same region and time period. After this, the data were de-seasonalized and the monthly anomalies were calculated by subtracting the

appropriate monthly mean values from each month. Calculation of the seasonal mean and seasonal variance for July showed that the June 2015 event was 3.5 standard deviations above the monthly mean for June calculated from the full Chl-a dataset (including the anomaly itself). Relative to the overall variance of the entire Chl-a dataset for all months, the June 2015 was 11.9 standard deviations above the monthly mean. The MODIS-Aqua mean value for June for the entire time period was 0.4 mg m^{-3} , compared to 2.7 mg m^{-3} for June 2015.

Figure 4-8 shows a portion of this time series for the Chl-a and SST from MODIS-Aqua and the DAOD from MERRA-2. In order to put the results on the same scale, the anomaly values have been scaled to their maximum value (i.e., the maximum anomaly will have a value of 1.0). The red box shows the time period from April to June 2015 when both the DAOD and Chl-a had their largest anomalies for the entire data record from July 2002 to April 2017. Note that the SST has a very large negative anomaly in April 2015 as well, although this is not the largest anomaly in the dataset.

Figure 4-8: Time series of scaled anomalies for the SCRS for Chl-*a* and SST from MODIS-Aqua and dust aerosol optical depth (DAOD) from MERRA-2. The red box indicates the period from April to June 2015 including the largest anomalies in both DAOD and Chl-*a*.

Other authors have investigated the (instantaneous) monthly correlation between various geophysical variables and Chl-*a* in the Red Sea. However, Figure 4-8 is suggestive of a strong *lag* correlation of two months between DAOD anomalies and Chl-*a* anomalies and SST anomalies and Chl-*a* anomalies for the SCRS. This lag correlation is explored further in Figure 4-9. Here we calculated the correlation for the entire dataset for lags of zero to six months. Although we considered other variables, the only significant relationships were found for DAOD and Chl-*a* and SST and Chl-*a*. Significance was determined by considering the standard error of a pure white noise process, which goes as $1/\sqrt{N}$, where N is the number of samples. Monthly DAOD and SST anomalies are essentially uncorrelated with Chl-*a* anomalies with a lag of zero, with values of +0.02 and -0.04, respectively. At two months lag, however, both DAOD and SST anomalies have statistically significant correlations with the Chl-*a* anomalies with correlation coefficients exceeding three times the expected error for a white noise process. These relationships essentially vanish for longer lags.

Figure 4-9: Monthly lag correlation between dust aerosol optical depth (DAOD) and Chl-a (solid) and SST and Chl-a (dot-dashed). Dashed lines show the limits of three standard deviations for a white noise process. The red box shows that the 2-month lag correlations exceed this level for both relationships.

Note that Figure 4-9 shows statistical relationships constructed from nearly 15 years of MODIS-Aqua data, so the two month lag apparent in Figure 4-8 is simply one example of the persistent relationship between DAOD and Chl-a and SST and Chl-a. Furthermore, because these relationships are statistical in nature, it is not possible to attribute cause and effect, only that the anomalies in DAOD and SST lead the anomalies in Chl-a by two months. The fact that DAOD and SST show opposite relationships with the same lag suggests that a third geophysical variable, such as wind speed, might actually be the controlling factor. For example, it is found strong (instantaneous) monthly correlations between Chl-a and wind and SST and wind. This is area ripe for further investigation.

4.4 Discussion

Seasonal winds and the thermohaline circulation are the most significant factors governing the circulation in the Red Sea circulation. For the southern portion of the Red Sea, exchange of water with the Gulf of Aden (GA) to the southeast is particularly important. The structure of this circulation pattern is depicted in Figure 4-10. During boreal winter, southeasterly winds force the surface water to flow northward from the GA into the Red Sea, meanwhile, the deep layer of the Red Sea outflow water (RSOW) flows outward to the GA (Figure 4-10, top). During the summer, the winds shift and the surface layer flows outward into the GA. Meanwhile, the nutrient rich layer of Gulf of Aden intermediate water (GAIW) flows into the Red Sea and goes northwards to replace the outflow surface water (Figure 4-10, bottom).

Figure 4-10: Sketch of the two circulation patterns in the Strait of Bab El Mandeb in the southern Red Sea. (Top) winter circulation. (Bottom) summer circulation. SW: surface water; GAIW: Gulf of Aden intermediate water; RSOW: Red Sea outflow water. (This figure is taken from [2] and used with permission).

Churchill et al. hypothesized that it is the nutrient-laden GAIW through its interaction with eddy circulations is the source for nutrients for the coral reefs and phytoplankton in the southern

Red Sea in the summer. The Chl-*a* anomaly of late June 2015, the largest observed in the SCRS in the MODIS-Aqua dataset, was related to eddy circulation patterns evident in the MLD, SSH, and SST fields from various observations and models. The largest regions of Chl-*a* anomaly are clearly associated with cyclonic eddies located around 19°N, 39°E. Such eddies cause upwelling – a process known as eddy pumping– which brings up nutrients from lower in the water column, likely associated with the GAIW. However, other processes are likely at work causing the Chl-*a* anomalies in this region, as evidenced by the behavior of the anomalous “cold-core” anticyclonic eddy. Interestingly, this eddy interacts with the Chl-*a* anomalies in a way that is consistent with a normal, “warm-core” anticyclonic eddy, that having a ring of enhanced Chl-*a* around its center. This ring is likely associated with counterrotation outside the main eddy or other mesoscale effects not resolved in our datasets.

A persistent anticyclonic eddy has been observed in this region in previous studies. However, the existence of the Tokar Gap wind jet observed in the MODIS imagery suggest that a simple model for the generation of an eddy dipole caused by surface wind stress may not be appropriate in this situation. More complex models have been able to simulate long-lived anticyclonic eddies in other seasons, but the question of why this particular eddy appears to have a cold core in the SST data remains an area for future investigation.

Also suggestive is the evidence for a two-month lag in the correlation between DAOD and SST anomalies and Chl-*a* anomalies. Time lags of one to three months have been observed between dust events and phytoplankton blooms in the Arabian Sea and the Indian Ocean. The question of the residence time of dust and the release of bioavailable Fe in the oceanic mixed layer

is an important research question, and these results might provide an important clue for oligotrophic waters like the Red Sea.

In this regard, we here acknowledge the limitations of our study and the need for more investigation into other possible anomalies in other time periods. Also, the nutritious nature of dust events needs to be investigated more thoroughly to quantitatively assess contribution of dust deposition to ocean primary production.

4.5 Conclusion

Under normal conditions, the Red Sea basin experiences an increased phytoplankton blooms during boreal winter (from December to January), and a decline in the frequency of blooms during summer (from June to August). However, we identified an anomalous Chl-a event in late June 2015 whose mechanisms have been investigated through a combination of a suite of remote sensing and modeling datasets. Factors contributing to this event include upwelling processes driving the convective vertical nutrient transfer as well as eddy circulation driving the horizontal advection of nutrients. The anticyclonic eddy centered around 20°N completely blocked the forward flow of colder, nutrient-rich water from the Gulf of Aden in the south, leading to low Chl-a concentration north of the eddy. The results demonstrate that physical processes, particularly eddies, through their interaction with the nutrient rich Gulf of Aden intermediate water, control the spatial distribution of patterns of biological production within the South Central Red Sea. We believe that wet deposited aerosols with possible bioavailable nutrients (Fe in particular), spreading on the Red Sea surface, could potentially enhance the process of phytoplankton growth and productivity, but with a lag time on the order of two months, although other geophysical

processes might be more fundamental, such as changes in the winds. We will investigate these findings further using data from sample collections in the Red Sea that we are in the process of acquiring.

5 Fourth Study: An Assessment of Atmospheric and Meteorological Factors Regulating Red Sea Phytoplankton Growth

5.1 Introduction

There has been much recent scientific interest in ocean color observations and biological productivity issues in the Red Sea region [148], [182]–[199]. The Red Sea is surrounded by deserts and other arid land and has no river inflow or stream sources. Its high evaporation rate (>210 cm/yr) [200] and low precipitation rate (<100 mm/yr) [137], [138] result in the Red Sea having the highest salinity of any major tropical oceanic basin [20]. Furthermore, the region is well-known for its extremely high biodiversity with more than 300 species of coral and 1400 species of fish [143], [201]. Fisheries are economically important to this area, as over 100,000 tons of fish are reportedly caught each year [145]. The high temperature and salinity of the water also make the Red Sea an important natural laboratory for understanding the effects of climate change, especially on coral reefs [146], [147], [202].

Overall, the Red Sea is considered oligotrophic, as its surface waters are deficient in several important nutrients including nitrate, ammonium, phosphate, and silicate, resulting in low levels of chlorophyll-a (Chl-a) (< 2.6 mg/m³) [148]. However, the basin has a significant north-south gradient in nutrient content regulated by the meridional flow [14], and a distinct seasonality with

maximum surface water Chl-a concentrations seen during the winter time, and minimum concentrations during the summer [184]. Recent studies using both in situ and satellite observations have also identified regions with higher Chl-a concentrations and nutrient levels than the traditional oligotrophic threshold of 2.6 mg/m³ [148], [184], [191], [192]. Locally elevated levels of Chl-a and surface nutrients have been attributed to interactions among oceanic gyres, particularly in the southern portion of the Red Sea [148], [184], [191], [192], as well as aerial deposition of micro-nutrients, for example iron (Fe), by wind-blown dust [203].

In an attempt to better understand the relationships among oceanic circulation and atmospheric deposition on Chl-a amounts and nutrient levels in the Red Sea, a recent study examined an anomalously high Chl-a event (>2 mg/m³) that occurred in June 2015 in the South Central Red Sea (17.5° to 22°N, 37° to 42°E) [199]. The analysis suggested that a combination of factors contribute to anomalous phytoplankton events in this portion of the Red Sea basin. These factors include horizontal transfer of upwelling water through eddy circulation and possible mineral fertilization from atmospheric dust deposition. Notably, a lag correlation analysis revealed a statistically significant two-month positive lag correlation between dust anomalies and Chl-a anomalies using the MODIS-Aqua dataset. A similarly significant two-month negative lag correlation was identified between SST anomalies and Chl-a anomalies [199].

In this study, we further explore the relationships between Chl-a and other potentially important environmental factors in the Red Sea region, including dust aerosol optical depth (DAOD), SST, and wind speed for the period from September 1997 to December 2016. The role of dust is further elucidated through examination of dust sources, dust properties, and the vertical profile of dust in the region.

5.2 Materials and Methods

5.2.1 Data

Ocean Color Climate Change Initiative (OC-CCI) Chlorophyll-a Data

In this study the Ocean Color Climate Change Initiative (OC-CCI) Level-3 Chl-a dataset version 3.1 at 4-km resolution is used, which extends from September 1997 to December 2016. The OC-CCI dataset is produced by the European Space Agency (ESA) and merges Chl-a retrievals from the Sea-viewing Wide Field-of-view Sensor (SeaWiFS); the MODerate resolution Imaging Spectroradiometer (MODIS) on the Aqua satellite; the MEdium Resolution Imaging Spectrometer (MERIS), which flew on Envisat-1; and the Visible Infrared Imaging Radiometer Suite (VIIRS), which flies on the Suomi National Polar-orbiting Partnership (NPP) satellite [167]. Critical steps for achieving data consistency within the OC-CCI dataset include band-shifting and empirical bias correction to match MERIS, MODIS, and VIIRS data with SeaWiFS, and then merging the datasets together to compute uncertainty estimates per pixel [167], [168], [204]. The OC-CCI dataset has been widely used to address ocean related processes using various optical parameters [167], [198], [204]–[207]. For the Red Sea region, in particular, the OC-CCI dataset has been demonstrated to have good consistency with in situ observations along with substantially improved coverage, particularly for the southern portion of the basin, enabled by blending data from multiple satellite instruments [188], [194], [208].

MODIS-Aqua SST Data

MODIS-Aqua Global Level 3 Mapped Thermal SST product relies on information derived from the 11 and 12 μm thermal infrared (IR) bands (MODIS channels 31 and 32). SST data is available for both daytime and nighttime overpasses for different averaging periods, ranging from daily to annual, gridded at $0.041^\circ \times 0.041^\circ$ resolution [209]. For this study, we utilized the monthly MODIS-Aqua Daytime SST data product for the period from July 2002 to May 2017 from the latest released version 2014.0.

Advanced Very High Resolution Radiometer (AVHRR) Pathfinder SST Data

The 4 km Advanced Very High Resolution Radiometer (AVHRR) Pathfinder Version 5 SST dataset is a reanalysis of historical AVHRR data that has been improved using extensive calibration, validation, and other information to yield a consistent, research quality time series for global climate studies [210], [211]. The collection of National Oceanic and Atmospheric Administration (NOAA) satellite platforms that is used in the AVHRR Pathfinder SST time series includes NOAA-7, NOAA-9, NOAA-11, NOAA-14, NOAA-16, NOAA-17, and NOAA-18. In this study, we used the monthly daytime SST data for the time period from September 1997 to June 2002 to extend our analysis farther back in time than is possible with the MODIS-Aqua SST dataset alone, and to provide better temporal consistency with the OC-CCI dataset. As a check, we compare the AVHRR SST data and the MODIS Aqua SST data from July 2002 to December 2009 in order to characterize the systematic observational differences between the two datasets. We

adjust these differences to produce a combined SST dataset for the Red Sea that extends from September 1997 to December 2016.

Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) Dust Reanalysis Data

The Modern-Era Retrospective analysis for Research and Applications version 2 (MERRA-2) is an atmospheric reanalysis dataset extending from January 1980 to present produced by the National Aeronautics and Space Administration (NASA) based on historical analysis using the Goddard Earth Observing System Model, Version 5 (GEOS-5) with its Atmospheric Data Assimilation System (ADAS), version 5.12.4. In order to assess the role of dust-related impact in the Red Sea, we use the NASA Goddard Online Interactive Visualization AND aNalysis Infrastructure (GIOVANNI) tool [212] to obtain and process the monthly mean MERRA-2 data, including the field “Dust Scattering AOT 550 nm,” which we designate as dust aerosol optical depth (DAOD) [213], as well as “Dust Dry Deposition” for “Bin-1” through “Bin-5” and “Dust Wet Deposition” “Bin-1” through “Bin-5”, and “Surface Wind Speed” [214]. All the MERRA-2 data used is at $0.5^\circ \times 0.625^\circ$ resolution.

Multi-Angle Imaging SpectroRadiometer (MISR) Aerosol Optical Depth (AOD) Data

The Multi-angle Imaging SpectroRadiometer (MISR) instrument has been operational on the NASA Terra satellite since early 2000 and it provides observations of the daytime portion of the Earth from nine viewing directions in four spectral bands with an instrument swath of 400 km.

In this research, we use the monthly MISR (MIL3MAE.004) AOD product at 558 nm, which is gridded at 0.5° spatial resolution [215], to investigate the relationship between dust aerosols and Chl-a events in the Red Sea. Studies have shown that MISR AOD retrievals over desert sites tend to have better agreement with Aerosol Robotic Network (AERONET) ground-based measurements than MODIS, especially for low AODs, and MISR provides a useful complement to MODIS AODs by capturing individual aerosol events, while still reproducing the overall aerosol climatology [216].

Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO)

AOD Data

The Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) satellite [217] has flown in formation with the sun-synchronous, near-polar A-train constellation of Earth observing satellites since 28 April 2006. Developed as a collaboration between the French space agency Centre National d'Etudes Spatiales (CNES) and NASA, the main scientific objective of the CALIPSO mission is to provide range-resolved information on the vertical distribution of aerosols and clouds. The Cloud Aerosol Lidar with Orthogonal Polarization (CALIOP) instrument uses a two-wavelength elastic backscatter Nd:YAG laser that transmits linear polarized light at 532 nm and 1064 nm, coupled with a receiver telescope of 1 m diameter that measures the perpendicular and parallel components of the attenuated backscatter at 532 nm and the total attenuated backscatter at 1064 nm [218]. The CALIOP Level 2 (L2) data includes information on the aerosol and cloud backscatter coefficient at 532 nm and 1064 nm and the particle depolarization ratio at 532 nm [219]. Both aerosol and cloud profile datasets are provided at 5 km horizontal and

60 m vertical resolution, for an altitude range up to 8.3 km above mean sea level (AMSL). The CALIPSO Version 3 (V3) algorithm discriminates aerosols into six subtypes: (i) clean marine, (ii) dust, (iii) polluted continental, (iv) clean continental, (v) polluted dust, and (vi) smoke [220]. The CALIPSO algorithm further assigns a specific Lidar Ratio (LR) to each aerosol subtype, which can be used in conjunction with the retrieved backscatter coefficient profiles for the derivation of the extinction coefficient profiles at various levels within the atmosphere [221].

Dust aerosol and the optical properties of dust have been extensively studied using CALIOP data [222]–[224]. In the present study, the CALIOP V3 L2 Aerosol Profile product is implemented to derive pure dust extinction coefficient profiles over the Red Sea for the period 2007 to 2015. The Climatological Dust Extinction coefficient profiles (Clim-DE) dataset, reported at $1^\circ \times 1^\circ$ spatial resolution, are also used [225]. The Clim-DE dataset is based on the CALIPSO pure dust product [226] and the ESA-LIVAS climatology (via <http://lidar.space.noa.gr:8080/livas/>). The Clim-DE product has been used in previous studies to investigate the vertical structure of Saharan dust transport over Europe [227] and the three-dimensional features of the dust burden over East Asia [228].

5.2.2 Methods

To investigate the variation of dust deposition and its impact on oceanic production in the Red Sea region, a multi-sensor approach was used to evaluate Chl-a variability associated with dust deposition using DAOD and other environmental parameters such as wind speed and SST. Using the MODIS-Aqua Chl-a product, Li et al. [199] revealed a two-month lag correlation positive dust anomalies and high Chl-a anomalies, as well as a two-month lag correlation between negative SST anomalies and high Chl-a anomalies. In this work, we use the OC-CCI dataset to

further test and validate the results obtained from [199]. Moreover, this research explores the possible factors contributing to the influence of aeolian dust on summertime phytoplankton blooms in the Red Sea by investigating other dust-related factors, namely, wind speed, dust sources, and dust deposition type.

A time-averaged map of Chl-a concentration for the Red Sea was generated with OC-CCI data from September 1997 to December 2016 (Figure 4-1). The map shows the same meridional pattern of Chl-a concentration as in previous research [199] – high values appear near the entrance of Gulf of Aden in the south and along nearby coastal areas; the northern Red Sea (20° N to 28° N) is lower in Chl-a than the southern Red Sea (13° N to 20° N), while the region south of the Farasan Islands (13° N to 17° N) has higher Chl-a amounts than the region just to the north (17° N to 20° N). Note, however, that the range of Chl-a values (0.15 to 2.15 mg/m³) from the OC-CCI dataset is smaller than the range reported for the MODIS-Aqua dataset (0.1 to 5 mg/m³) [199]. Based on the abundance and spatiotemporal distribution of surface Chl-a, in Figure 5-1, we partition the Red Sea into four domains at specific, integer latitudinal boundaries for convenience. The four regions, from north to south, are designated the Northern Red Sea (NRS) (28° N to 24° N), the North Central Red Sea (NCRS) (24° N to 20° N), the South Central Red Sea (SCRS) (20° N to 17° N), and the Southern Red Sea (SRS) (17° N to 13° N). Note that these designations are slightly different than those used in previous studies [199].

Figure 5-1: Ocean Color Climate Change Initiative (OC-CCI) Chl-a (mg m^{-3}) Level 3 monthly OC-CCI Chl-a data averaged for the Red Sea from September 1997 to December 2016. The four regions labeled consecutively starting from the north to south are the Northern Red Sea (NRS), North-Central Red Sea (NCRS), South-Central Red Sea (SCRS), and Southern Red Sea (SRS)

For each of the four regions, time series analyses of the nearly 20 years (September 1997 to December 2016) monthly data for Chl-a, DAOD, SST, and wind speed were performed using scaled values, anomalies, and lag (cross) correlation. The scaled values, SV , are calculated by finding the mean of the entire time series, x_m , subtracting this from each monthly value, x_i , and

then normalizing the result by the mean of the time series. Formally, this is represented by the equation:

$$SV = \frac{x_i - x_m}{x_m} = \frac{x_i}{x_m} - 1 \quad (1)$$

The use of the SV allows for time series of different variables to be represented on a similar scale and reveals potential long-term trends in the data, which are represented as deviations from the mean of the time series, x_m .

Due to the large seasonality in the Red Sea, it is often helpful to consider the monthly anomalies, as given by:

$$a_i = x_i - \bar{x} \quad (2)$$

where $\bar{x}$ is the mean value that is calculated for that month from the entire dataset. To make the different datasets comparable, the monthly anomalies are scaled by σ , the standard deviation of the values for that month, which we term the Z-score:

$$\text{Z-score} = \frac{a_i}{\sigma} = \frac{x_i - \bar{x}}{\sigma} \quad (3)$$

In order to uncover the relationships between two different parameters, both standard correlation and lag (cross) correlation analyses were done. The standard (Pearson) correlation coefficient, r , between two time series of variables, x and y , with N elements can be expressed as:

$$r = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} = \frac{\text{Cov}(x, y)}{\sigma_x \sigma_y} \quad (4)$$

where, Cov is the covariance function, and σ_x and σ_y represent the standard deviation of the x and y time series, respectively. The correlation coefficient can assume values between -1 and $+1$, with -1 representing perfect anti-correlation and $+1$ representing perfect correlation. Finally, as in [199], we consider the lagged (cross) correlation $r(k)$, for lag k , which is given by:

$$r(k) = \frac{\sum_{i=1}^{N-k} (x_i - \bar{x})(y_{i+k} - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} = \frac{\text{ccvf}(x, y)}{\sigma_x \sigma_y} \quad (5)$$

where, ccvf is the cross-covariance function.

When creating cross-correlations maps, all of the data are re-gridded to the same resolution using a bi-linear re-gridding algorithm. These maps reflect the relationships between phytoplankton—represented by Chl-a—and other atmospheric and oceanic factors in different regions within Red Sea. Lagged correlation maps, in particular, are used to attempt to uncover the mechanisms that are underlying the residence times of dust in the Red Sea and the release of bioavailable Fe into the oceanic mixed layer and its resulting effects on ocean productivity [229], [230].

5.3 Results

5.3.1 Time Series of Scaled Values for Chl-a, DAOD, and SST

The time series of the SV for three of the datasets, Chl-a from OC-CCI (green), DAOD from MERRA-2 (blue), and SST from blended AVHRR and MODIS-Aqua data (red) are shown in Figure 4-2 for the different regions of the Red Sea depicted in Figure 4-1.

Figure 5-2: Time series of scaled values (see Equation (1)) for Chl-a, dust aerosol optical depth (DAOD) (MERRA-2 Dust Scattering AOT in 550 nm), and sea surface temperature (SST) for the four regions of the Red Sea represented in Figure 5-1.

A strong seasonal variation in all of the variables is immediately apparent, but is clearest in the SST data. In all four regions, the SST is lowest near the beginning of the calendar year (January–February), and highest in near the end of boreal summer and the beginning of boreal autumn (August–October). Close inspection reveals small, but systematic differences from one region to the next. The SST cools off slightly earlier in the SRS and warms slightly later, especially

relative to the NRS. The magnitude of the SST SV is largest in the NRS and smallest SCRS, meaning that larger deviations from the mean are seen in the NRS.

There is also strong seasonality to dust events, particularly in the SRS, as shown in the time series of SV for DAOD. Visually, there is also good correspondence between the SV for DAOD and SST in the SRS, with elevated levels of DAOD corresponding to periods of elevated SST and decreased levels of DAOD corresponding to periods of lower SST. This relationship becomes progressively weaker to the north, with the NRS sometimes showing elevated DAOD events when the SST is near the mean value (SV near zero). The peak in the DAOD in the NRS tends to occur in the late boreal spring (April–May), with negative SV in the autumn. These results indicate that different mechanisms are responsible for dust generation in the northern parts of the Red Sea as compared to the southern regions.

The SV of Chl-a shows strong seasonality in the NRS, where Chl-a anomalies appear to be nearly perfectly anticorrelated with SST anomalies, meaning that low SSTs correspond to high Chl-a, and vice versa. The other portions of the Red Sea fail to show such a strong relationship. In the NCRS, positive SV values of Chl-a can correspond to positive (2002), negative (2007, 2007), and near zero (2010) SV values for SST. Visually, there appears to be little relationship with DAOD in the NRS. In the SCRS, the SV for Chl-a seems to follow a six-month cycle, with a peak in January and another around June. This relationship is also apparent in the SRS. Positive SV values for Chl-a correspond well to positive SV values for DAOD, but with SV values that are near zero for SST. Finally, in the SRS, positive SV values in Chl-a lead the maxima in SV values for SST slightly, and again correspond nearly perfectly with positive SV values for DAOD.

When considering the largest positive excursions in SV for Chl-a, we note that these occur mainly in the southern part of the Red Sea, with the summers of 2011, 2010, 2005, and 2003 having strong events that are larger in magnitude than the typical wintertime Chl-a enhancements. Note that the Chl-a event that was identified in the MODIS-Aqua dataset in summer 2015, and was discussed in detail in Li et al. [199], does not rank as one of the largest Chl-a events in the OC-CCI dataset, but is visible as one of the few outliers in the later part of the time series for the SCRS. The large positive Chl-a events in 2011, 2005, and 2003 are significant in both the SCRS and the SRS, but have small or even negative SV in the NCRS and NRS. The 2010 summertime event in the SCRS is weak in the SRS, but is the largest event in the NCRS. The second largest event in the NCRS is in October 2002, and it appears to be confined primarily to this region.

5.3.2 Time Series of Z-Scores for Chl-a, DAOD, and SST

The large seasonality evident in all four regions of the Red Sea in SST, DAOD, and Chl-a in Figure 5-2 tends to obscure significant monthly anomalies in these parameters. For this reason, we show the Z-scores over the different regions of the Red Sea in Figure 5-3. Recall that the Z-scores represent the monthly values, with the long-term monthly mean subtracted, and divided by the standard deviation of the monthly values (see Equation (3)). A Z-score that is equal to one represents a monthly value that differs from the long-term mean by one standard deviation. If the data are normally distributed, then the expectation is that 95% of the data will have a Z-score ≤ 2 , and only 0.3% of the data will have a Z-score > 3 . Of the three parameters, the only one that appears to be nearly normally distributed is the SST. Chl-a and DAOD Z-scores are skewed positive in all four regions, meaning that positive anomalies are more likely than negative anomalies.

The SST anomalies tend to be positive prior to 2002 in both the SCRS and SRS, with a notable negative anomaly in the later part of 2000. Other negative anomalies are apparent in 2011 and 2012 in all of the regions, with the intervening years showing small anomalies of both signs. The end of the SST record in 2015/2016 shows positive anomalies that may be related to the powerful El Niño in 2016, that made it the warmest year on record, with the World Meteorological Organization Provisional Statement on the State of the Climate noting that 2013–2017 could be the warmest five-year period on record [231].

Figure 5-3: Time series of Z-scores (see Equation (3)) for Chl-a, DAOD (MERRA-2 Dust Scattering AOT in 550 nm), and SST for the four regions of the Red Sea represented in Figure 5-1.

The DAOD anomalies appear to be primarily negative prior to mid-2000. This happens to be when MODIS-Terra data became available, so the inclusion of this dataset into the MERRA-2 DAOD reanalysis time series likely introduces temporal inhomogeneity. With the exception of a

few positive outliers, and the time period between 2010 and 2012, there is no clear pattern to the DAOD anomalies, especially late in the time series. The large positive DAOD anomaly in 2000 occurs in all four regions and it is correlated with a strong negative SST anomaly. However, when comparing across the regions, the largest DAOD anomaly corresponds to the smallest SST anomaly, and vice versa. Other DAOD anomalies appear in late 2010 and 2013 in all four regions, but there does not seem to be any relationship with SST. Finally, the large DAOD anomaly in 2015 only occurs in the SRS and SCRS, where it correlates well with a negative SST anomaly, but there is no DAOD anomaly at all in the NCRS or the NRS.

Even more than the DAOD dataset, the Chl-a Z-score time series shows clear temporal inhomogeneity. Visually, it is possible to separate the Chl-a time series into three distinct periods that are common to all four regions. The first period is prior to mid-2002, where the negative anomalies dominate in all the regions, with the exception of a single peak event in the NCRS and NRS in late 1998. Also notable in this time period are the gaps in the time series in the SCRS and SRS. Table 5-1 lists the time period of each of the four sensors used to construct the OC-CCI Chl-a dataset [31].

Table 5-1: Information of the Sensors Used in the OC-CCI Dataset.

Sensor Number	Sensor Name	Start Time	End Time
1	SeaWiFS	September 1997	December 2010
2	MODIS (Aqua)	July 2002	On-going
3	MERIS	April 2002	April 2012
4	VIIRS	January 2012	On-going

According to Table 5-1, prior to mid-2002 only the SeaWiFS sensor was used to generate the OC-CCI Chl-a time series, meaning that persistent clouds or dust could obscure the underlying water surface, resulting in a data gap. The introduction of additional sensors helped mitigate this

issue [188], [194], [208]. The second time period runs from mid-2002 to early 2012 and is characterized by primarily positive Chl-a anomalies. Only the NRS shows any significant negative anomaly during this period, which occurs in early 2010. Table 5-1 shows that MERIS was no longer included in the OC-CCI Chl-a dataset after April 2012, due to the loss of contact with the Envisat-1 platform. Around the same time, the VIIRS data began to be included. The loss of MERIS and the inclusion of VIIRS corresponds to the third period evident in the time series, which is characterized by primarily negative Chl-a anomalies. Notable exceptions are a strong positive anomaly at the beginning of 2014 that can be seen in all four Red Sea regions, and another large anomaly at the beginning of 2015, which seems to be confined to the SCRS and SRS. The June 2015 event discussed in detail in [199] is apparent in the Z-score time series, but only in the SCRS.

The time series shown in Figure 5-3 are suggestive of relationships among these three variables, particularly in the SCRS and, to a lesser extent, the SRS, as discussed in our earlier work [199]. However, the temporal inhomogeneities apparent in both the Chl-a time and DAOD series indicate that caution must be exercised before drawing too strong conclusions from these particular datasets. We explore the representativeness of the datasets for different time periods in our later discussion (Section 3.3).

5.3.3 Comparison of Sensors Used in OC-CCI Data

When comparing the monthly means of Chl-a between MODIS and OC-CCI a low bias in OC-CCI relative to MODIS-Aqua at large Chl-a values was observed with high outliers in the mean for low Chl-a values. Looking at the monthly median values the low bias remained, but the high bias is more or less eliminated. We believe that MERIS is the cause of this bias and for that we decided to run a comparative analysis between Chl-a, obtained from the OC-CCI data, against

SST, DAOD and wind observations and anomalies during three different periods amongst the sensors listed in Table 5-1. These three periods represents data before MERIS (1998-2002), during MERIS (2003-2011) and after MERIS (2012-2016). Figures 5-4a-c, show correlation maps (lag = 0) of SST, DAOD and WINDSPEED with Chl-a for each of the stated periods against the whole entire period (1998-2016). Similar behavior across the different time periods should be normal and is expected, however, cases with discrepancies inconsistent behavior will be discussed and highlighted in the following.

Over the entire time period 1998-2016, SST and Chl-a observations exhibit a consistent negative correlation during the three different periods (Figure 5-4a1), whereas the anomalies (Figure 5-4a5) of both the northern and southern-most regions of the Red Sea stood out owed to the upwelling of cooler and nutrient-rich seawater and the induction of a cool and nutrient-rich current from Gulf of Aden, respectively. However, during the period 1998-2002, the central Red Sea region (19°N-23°N) exhibited a low correlation presented by the white colored area (Figure 5-4a2) while the SST and the Chl-a anomalies experienced a positive correlation (Figure 5-4a6) due to the influence of eddy activity, a behavior that is also observed during the period 2012-2016 (Figure 5-4a8).

A consistent correlative behavior between wind speed and Chl-a observations is clear during all the time periods, where the northern Red Sea exhibits a negative correlation while middle and southern Red Sea exhibits a positive correlation (Figures 5-4b 1-4). This is attributed to the fact that summer seasons experience strongest periods of wind speed that can drive the Gulf of Aden currents into the Red Sea, leading to the phytoplankton bloom of the central and southern regions. While the northernmost region shows phytoplankton blooming mainly during the winter

period due to weaker wind. For wind speed and Chl-a anomalies, the entire region exhibits a positive correlation (Figures 5-4b 5-8). An exception is observed during 1998-2002 (Figure 5-4b6), where the northern and central Red Sea (19°N - 23°N) exhibited a different correlative behavior from the other periods. This can be attributed to the influence of wind stirring up the seawater to enhance nutrient mixing and the eddy activities over the two regions, respectively.

As for the DAOD and Chl-a, it is rather complicated because of the lack of observations during major dust events which make it hard to conclude a definitive correlative behavior. However, we observed an overall negative correlation between DAOD and Chl-a observations (Figures 5-4c 1-4) during all time periods, but with rather exceptional positive correlations in the coastal and southern regions of the Red Sea. This positive correlative behavior is not clear during the period 2012-2016 (Figure 5-4c4) mainly because the Chl-a summer observations are insufficient due to major dust events. It is also noteworthy that during 1998-2002, the negative correlation in 23°N - 25°N was stronger than that of 2003-2011, something that we need to look into to better understand it. For DAOD and Chl-a anomalies (Figure 5-4c 5-8), a positive correlative behavior is observed over the whole region with a very strong positive correlation in the NRS during 2012-2016 (Figure 5-4c8), which may be attributed to eddy's or wind stirring up influence (Figure 5-4b8) or wet deposition.

In conclusion it is quite clear that the three different outlined periods more or less behaved similarly when compared to the entire period's behavior namely during 1998-2016. This finding strongly support the validity of using OC-CCI Chl-a data to study its correlative behavior with SST, wind speed and DAOD.

Figure 5-4: Cross Correlation analysis at lag 0 for actual values and anomalies of SST (a1–a8), WINDSPEED (b1–b8) and DAOD (c1–c8) (MERRA-2 Dust Scattering Aerosol Optical Depth (AOT) in 550 nm) with Chl-a, for entire period (1998–2016) (first column), before MERIS (1998–2002) (second column), during MERIS (2003–2011) (third column), and after MERIS (2003–2011) (fourth column).

5.3.4 Anomaly Comparison of Chl-a Concentration and Other Factors for June 2010

Figure 5-5 shows the monthly anomaly, a_i (see Equation (2)), maps in the Red Sea for June 2010 for Chl-a, SST, and AOD, as well the related meteorological parameters dust dry and wet deposition, and wind speed. The latter three parameters are taken from the MERRA-2 reanalysis. June 2010 was selected because it has a large positive Chl-a anomaly, which is particularly apparent in the NCRS and SCRS time series (see Figure 5-3).

Figure 5-5: Monthly anomaly maps of (a) Chl-*a*, (b) SST, (c) AOD (MISR), (d) Dust dry deposition, (e) Dust wet deposition, and (f) Wind Speed for June 2010.

The map of the Chl-*a* anomaly field in Figure 5-5a shows a large area of high Chl-*a* at around 16°N in the SCRS, with a somewhat smaller positive anomaly around 22°N in the NCRS. Note the large region of missing data between about 17° and 18°N, which could be due to persistent clouds or dust. The SST anomalies in Figure 5-5b show the expected correlation in the SCRS with low SSTs in the area of elevated Chl-*a* amounts. In the NCRS, however, the SST anomalies are slightly positive. The AOD anomaly map in Figure 5-5c shows slightly elevated AODs at around 0.1 over most of the Red Sea during June 2010. Higher AOD anomalies are seen around 19°N, centered near Port Sudan, Sudan. Interestingly, negative AOD anomalies are more directly associated with the positive Chl-*a* anomaly in the SCRS. The dust dry deposition map in Figure 5-5d shows small positive anomalies over most of the region, with the exception of the extreme southern Red Sea. The dust wet deposition in Figure 5-5e, in contrast, has a large positive anomaly in both the SCRS and SRS, with larger positive anomalies along the eastern coastline. Comparison with Figure 5-5a shows that the positive Chl-*a* anomalies are not well correlated with the increased wet deposition in these regions, however. Finally, the wind speed anomalies in Figure 5-5f show

the distinct signature of the wind jet that is associated with the Tokar Gap, which is discussed in terms of its relation to the Chl-*a* anomaly in June 2015. In this case, the axis of elevated wind speeds corresponds well with the missing data in the Chl-*a* map in Figure 5-5a.

5.3.5 Correlation Analysis of Chl-*a* Anomalies with SST and DAOD Anomalies

To further investigate the relationships between SST and the MERRA-2 DAOD with Chl-*a*, the correlation coefficients, r (see Equation (4)), for the anomalies in these parameters for each month and each region within the Red Sea are given in Table 5-2.

Table 5-2: SST/Chl-*a* and DAOD/Chl-*a* monthly anomaly correlation coefficients for the four Regions of Red Sea. Light blue indicates negative correlation between -0.5 and -0.7 , dark blue indicates negative correlation < -0.7 . Light red indicates positive correlation between $+0.5$ and $+0.7$. Dark red indicates positive correlation $> +0.7$.

		NRS	NCRS	SCRS	SRS
January	SST/Chl- <i>a</i>	-0.562	-0.268	-0.496	-0.703
	DAOD/Chl- <i>a</i>	+0.244	+0.407	+0.310	+0.314
February	SST/Chl- <i>a</i>	-0.639	-0.355	-0.785	-0.592
	DAOD/Chl- <i>a</i>	+0.473	+0.669	+0.670	+0.678
March	SST/Chl- <i>a</i>	-0.617	-0.341	-0.618	-0.592
	DAOD/Chl- <i>a</i>	+0.138	+0.736	+0.479	+0.294
April	SST/Chl- <i>a</i>	-0.301	+0.042	+0.266	-0.138
	DAOD/Chl- <i>a</i>	+0.243	+0.588	-0.160	-0.027
May	SST/Chl- <i>a</i>	-0.151	-0.410	-0.419	-0.497
	DAOD/Chl- <i>a</i>	0.597	+0.436	+0.370	+0.360
June	SST/Chl- <i>a</i>	+0.122	-0.091	-0.223	-0.296
	DAOD/Chl- <i>a</i>	+0.531	+0.521	+0.528	+0.122
July	SST/Chl- <i>a</i>	+0.102	-0.263	-0.484	-0.672
	DAOD/Chl- <i>a</i>	+0.020	+0.250	+0.651	+0.674
August	SST/Chl- <i>a</i>	-0.083	+0.391	+0.015	-0.099
	DAOD/Chl- <i>a</i>	+0.147	+0.294	+0.219	+0.442
September	SST/Chl- <i>a</i>	-0.182	-0.096	-0.464	-0.339
	DAOD/Chl- <i>a</i>	+0.509	+0.562	+0.526	+0.431
October	SST/Chl- <i>a</i>	-0.107	+0.292	-0.228	-0.339
	DAOD/Chl- <i>a</i>	+0.647	+0.103	-0.017	+0.260
November	SST/Chl- <i>a</i>	-0.256	+0.034	-0.392	-0.705
	DAOD/Chl- <i>a</i>	-0.030	+0.169	+0.578	+0.500
December	SST/Chl- <i>a</i>	-0.319	-0.151	-0.542	-0.569
	DAOD/Chl- <i>a</i>	+0.095	+0.083	+0.269	+0.212

Significant negative correlations (< -0.5) are colored blue and significant positive correlations ($> +0.5$) are shaded red. Absolute values that are greater than or equal to 0.5 are shaded in light colors, and absolute values greater than 0.7 are shaded in darker colors. These limits are chosen because the coefficient of determination, r^2 , is 0.25 for $r = 0.5$ and approximately 0.5 for $r = 0.7$. This means that 25% and 50% of the association is explained by a linear relationship between the terms for these two thresholds, respectively. This same information is plotted in Figure 5-6 as a monthly time series for the SST/Chl-*a* anomaly relationship (Figure 5-6a) and the DAOD/Chl-*a* anomaly relationship (Figure 5-6b).

Figure 5-6: Time series plot of monthly anomaly correlation coefficients for the four regions of the Red Sea; (a) SST/Chl-*a*; (b) DAOD (MERRA-2 Dust Scattering AOT in 550 nm)/Chl-*a*.

As seen in Table 5-2, and Figure 5-6, SST anomalies are typically negatively correlated with Chl-*a* anomalies, while DAOD anomalies are positively correlated with Chl-*a* anomalies. These relationships are not unexpected, as phytoplankton tends to thrive in relatively cooler environments, while dust deposition can provide necessary nutrients, including Fe, which helps to foster phytoplankton growth, particularly in oligotrophic waters, like the Red Sea. The correlation with the largest magnitude is -0.785 , found between SST anomalies and Chl-*a* anomalies in February in the SCRS. This is followed closely by the large positive correlation of $+0.736$ between DAOD anomalies and Chl-*a* anomalies in March in the NCRS. Other significant negative

correlations are found in the SRS between SST anomalies and Chl-a anomalies in January and November.

When considering the overall temporal structure of the correlations between SST and Chl-a anomalies that are shown in Figure 5-6a, the relationships are similar for the NCRS, SCRS, and SRS, while the NRS behaves differently. The June and July correlations in the NRS achieve their highest (positive) values, and have their largest (negative) correlations in February and March. The other regions also have large (negative) values in February and March, with much smaller absolute correlations in April, then increasingly negative correlations in May, June, and July. This behavior may reflect the boreal summer intrusion of cooler waters from the Indian Ocean through the Gulf of Aden in the south, but the magnitude of the monthly correlation is rather small between SST and Chl-a in all four regions in the summertime.

The correlation between DAOD anomalies and Chl-a anomalies in Figure 5-6b shows a different pattern than Figure 5-6a. First, the NRS has large positive correlations in February, May, and October. The SCRS and SRS are nearly identical, with the exception of June, which may be due to the residual issues in the SRS due to clouds or persistent dust in this month. The correlation in these two regions peaks in February, falls rapidly in April, peaks again in July, then falls in October, but peaks again in November. The NCRS shows characteristics of both the NRS and the two southern regions with a broad peak in correlation centered on March, declining until July–August, with a second peak in the correlation in September.

February and March are the months that are showing the largest number of significant correlations in all regions, while August is the only month that shows no significant correlations. Significant positive anomaly correlations between DAOD and Chl-a outnumbered the significant

negative anomaly correlations between SST and Chl-a. With the exception of February and March, the former tend to be concentrated in the boreal summer months, while the latter are more frequent in the boreal winter. Finally, the number of months with significant anomalies of either sign is largest is the SRS (9), followed by the SCRS (8), the NRS (7), and the NCRS (5). Note, however, that these results are at least partly due to the selection of the threshold for significance.

5.3.6 Lag (Cross) Correlation Maps of SST, Wind Speed, and DAOD with Chl-a

In [199], we discovered a clear two-month lag correlation between Chl-a and DAOD anomalies using a MODIS data. To expand this major finding through the longer time and to gain further understanding of how the factors discussed here influence Chl-a, the MERRA-2 data of DAOD and Surface Wind Speed as well as MODIS Aqua SST data are re-gridded to 4km spatial resolution with linear re-gridding algorithm. This re-gridding algorithm is already applied and presented in Figure 5-4a–c. Through the current lag analysis, SST & Chl-a observations, and anomalies exhibits a gradually changing behavior (Figure 5-7(a1–8)). For instance, we found that the negative correlation between Chl-a and SST of the northern region gradually flips to a positive correlation at lag 3 due to a seasonal change (Figure 5-7(a1–4)). Moreover, the lag 3 map (Figure 5-7(a4)) shows a south-north positive trend implying on the inflow of the nutritious waters from the Gulf of Aden to the Red Sea environment. Slowly dissipating/increasing behavior in the anomalies of Chl-a and SST is observed as we move from 0 to 3 months lag (Figure 5-7(a5–8)). It is worth noting that the SST/Chl-a anomalies (Figure 5-7(a5–8)) use MODIS Aqua SST data during the period of 2003 to 2016, whereas the SST/Chl-a anomalies' plot during the period of 1998 to 2002 uses the AVHRR SST data (Figure 5-4(a6)).

Figure 5-7: Cross Correlation maps of actual observations and anomalies for SST (a1–a8), WINDSPEED (b1–b8) and DAOD (c1–c8) (MERRA-2 Dust Scattering AOT in 550 nm), with Chl-a for a time lag of 0 month (first column), lag of one month (second column), lag of two months (third column), and lag of three months (fourth column).

The northern region of the Red Sea shows an increasing negative behavior from lag 0 to 3 months lag between the Chl-a and wind speed observations (Figure 5-7(b1–4)). This finding shed the light of the decline of the wind driven vertical mixing with seasonal change. On the other hand, a declining positive correlative behavior from 0 to 3 months lag is clearly observed over the northern and southern Red Sea regions between the wind speed & Chl-a anomalies (Figure 5-7(b5–8)).

It is quite evident that the Red Sea environment exhibits a consistent negative correlative behavior between the Chl-a and the DAOD observations (Figure 5-7(c1–4)) with clear positive correlative exceptions dominating the southern region and the coastal areas. This can be cautiously attributed to possible deposition scenarios. However, it is noteworthy that the Chl-a and DAOD anomalies shows a positive correlation at zero lag (Figure 5-7(c5)) and moving north-south trend from lag 1 to lag 3 (Figure 5-7(c6–8)). The exceptional positively correlated round-shaped area at SCRS at lag-2 (Figure 5-7(c7)) agrees with the findings of [199] that showed the bloom at the same region during June 2015 because of the eddy's contribution as well as the Tokar gap dust event. This indicates that the bloom of June 2015 was so profound to dominate the correlation plot, showing that the two-month lag high correlation may have resulted from this event. However, all of the plots are all about the statistical relationship, not necessarily proving the causation between the observations.

5.3.7 Calipso-Based 3D Climatology of Desert Dust Aerosol over the Red Sea

In addition to the horizontal variability of AVHRR and MODIS Aqua SST, MERRA-2 Dust Reanalysis Data, MISR AOD, and OC-CCI Chl-a product, the CALIPSO based ESA-EARLINET LIVAS Pure-Dust and Clim-DE products are used to understand the structure of dust

aerosol layers over the study domain. The combined use of Pure Dust AOD and Clim-DE products provides the full three-dimensional desert dust aerosols over the Red Sea. Figure 5-8 shows the seasonal spatial patterns of CALIPSO columnar Dust AOD (DAOD) at 532 nm, over the Red Sea and the surrounding areas averaged for December–February (DJF), March–May (MAM), June–August (JJA), and September–November (SON) between 01/2007 and 12/2015. It must be clarified that the seasons have been defined based on the temporal and spatial characteristics of Aeolian dust activity over the Red Sea [190], [232]. From the geographical distributions of DAOD, it is revealed that the dust activity over the Red Sea peaks in summer, while it diminishes during winter. Moreover, a strong north-to-south and west-to-east DAOD increasing gradient is apparent over the study domain, throughout the year. The maximum DAODs (up to 0.5) are recorded over the southern parts of the Red Sea and Saudi Arabia in summer and spring, respectively. In autumn (SON), DAODs do not exceed 0.3, while in winter (DJF), the minimum DAODs (less than 0.1) throughout the year are observed over the eastern parts of the Sahara Desert.

Figure 5-8: Geographical distribution of the mean Cloud-Aerosol Lidar and Infrared Pathfinder Satellite Observations (CALIPSO) Dust AOD at 532 nm, for the three-month averages: December to February (DJF), from March to May (MAM), from June to August (JJA), and from September to November (SON), for the period 01/2007–12/2015.

In order to illustrate the vertical distribution of dust aerosols over the Red Sea, the seasonal extinction coefficient profiles (Clim-DE), which were averaged over the period 2007–2015, have

been produced for each sub region (NRS, NCRS, SCRS, SRS). As indicated in Figure 5-9, throughout the year, the main portion of dust aerosols is confined in the lowest troposphere (lower than 1 km), with maximum Clim-DE values ranging from 0.08 (Figure 5-9d) to 0.24 (Figure 5-9o) km^{-1} , depending on the sub region. Mean dust extinction coefficient gradually decreases with height, reaching values that are less than 0.01 km^{-1} up to 6 km^{-1} . Furthermore, elevated dust aerosol layers (2–5 km) are evident mainly between March and August and for latitudes southern to 20°N, encompassing the SCRS and SRS regions, while during autumn and winter, dust aerosol layers are in general suppressed below 5 km height. Among the sub regions, the highest extinction coefficients are found during MAM in the northern domains (NRS and NCRS), while the corresponding values in SCRS and SRS are observed during JJA. The synergistic implementation of the mean DAOD product (Figure 5-7) and the climatological extinction coefficient profiles (Figure 5-9) provides an insight regarding the seasonal variation of dust aerosols three-dimensional distribution above the Red Sea.

Figure 5-9: CALIPSO seasonal mean pure dust climatological extinction coefficient profiles at 532 nm (in km^{-1}) for the regions NRS (a–d), NCRS (e–h), SCRS (i–l), SRS (m–p), and for the three month averages: December to February (DJF), from March to May (MAM), from June to August (JJA), and from September to November (SON), for the period 01/2007–12/2015.

The strong spatial and temporal variability of DAOD across the study domain is driven by the geographical features as well as on the different meteorological mechanisms favoring dust mobilization and uplifting over arid areas of the eastern Saharan Desert and the Arabian Peninsula [233], [234]. Dust generating dynamical processes include meteorological mechanisms of different scales, such as cyclones and anticyclones [62,63], Nocturnal Low-Level Jets [237], [238] and Haboobs [239], [240]. Between February and April, mid-latitude Mediterranean cyclones associated with cold fronts passages result in a long-range transport of Saharan dust aerosol towards the northern Red Sea [232], [241]. By contrast, during summer the major sources of dust aerosols are the Arabian Peninsula deserts (An-Nafud, Ad-Dahna, Rub-Al-Khali) and the local

sources of Eritrea and the Republic of Sudan. Under favorable synoptic conditions, dust events take place over the southern Red Sea [181], [232]. In addition, the dust aerosol transport and deposition processes are highly dependent on the local topography in the vicinity of the Red Sea. At the northern parts (NRS, NCRS) the less complex surface elevation and the flatter topography allow the free transport of dust aerosol plumes. On the contrary, in the southern parts of the Red Sea (SCRS, SRS) mountain ridges along both the African and Arabian Peninsula coastlines confine dust aerosol flows creating persistent dust layers for extended periods [196]. The removal processes of dust aerosol particles include both dry and wet deposition [242], [243]. Dry deposition (or gravitational settling) is the predominant removal mechanism of mineral particles from the atmosphere in the north Red Sea (NRS, NCRS), while over its southern parts wet deposition plays a key role [241]. The higher dust aerosol load over the southern part of Red Sea [190] in combination with the predominance of wet removal processes results in an increased dust aerosol deposition and input to the southern parts of the Red Sea with respect to its northern parts.

5.4 Discussion

In this work, we studied a combination of atmospheric and meteorological factors, including SST, dust deposition (DAOD), and wind activities regulating Red Sea phytoplankton growth using 20 years (1997–2016) observation and reanalysis data. We discovered a bias in the OC-CCI data owed to the data merge from different sensors leading to some inconsistency over different time periods. The systematic high bias values occurred mainly during the service period of MERIS sensor. We presented this issue of inconsistency in the time series variation of Chl-a in Figure 5-3 and discussed it in Section 3.3. To overcome this problem, we divided the data into three periods: before MERIS (1998–2002), during MERIS (2003–2011), and after MERIS (2012–

2016), and compared each time frame with the entire time period (1998–2016). Our results confirmed that except for the central Red Sea during (1998–2002) and for NRS during (2012–2016), the correlation maps of most Red Sea regions match those of the entire time period. This is an important conclusion that supports the validity of using OC-CCI data for the long-term correlative analysis that is the focus of this work. An evident negative relationship between Chl-a and SST anomalies is observed and a major decline in Chl-a is correlated with the warmer waters of 2015 and thereafter. Hence, we argue against previous research proposing that the warmer climate conditions could make the Red Sea ecosystem more productive, since phytoplankton could not get underlying nutrition. The vertical analysis of dust aerosol optical depth proved that DAOD is a reliable indicator of dust deposition over the Red Sea ecosystem. We found that dust deposition contributed at different extents over different regions of the Red Sea to the Chl-a anomalies. This is clear from the positive correlation between DAOD and Chl-a at different lags. It is noteworthy that the SCRS exhibits a two-month lag, thus confirming the impact of the anomalous event during June 2015. However, not all of the dust events could induce phytoplankton blooms, due to the varying nature of the dust sources. For instance, SRS received more wet deposition as compared to the NRS (see Figure 5-5), resulting in more bioavailable nutrient (e.g., Fe, Si) for ocean ecosystems. Meanwhile, the positive correlation between wind speed and Chl-a verified that preferred wind patterns could enhance the horizontal intrusion of nutrient-rich water to the southern Red Sea. We found that stronger winds brought more nutritious water from Gulf of Aden into the Red Sea (see SRS in Figure 5-4(b5–8)). Furthermore, strong wind also enhanced vertical mixing, thus bringing deeper water that is nutrient rich to be brought into the euphotic zone. This is clear from the positive correlation between Chl-a and wind speed anomalies over the northernmost Red Sea as shown in Figure 5-4(b8). Ocean circulation is a quite important factor

influencing the phytoplankton blooms distribution. Hence, it is expected that the inflow of nutrient-rich seawater from the Gulf of Aden can affect most regions of the Red Sea, including NCRS, SCRS, and SRS. Our 19 years analysis showed a similar monthly correlation variability between Chl-a and SST anomalies for the central and southern regions, but not for the NRS, suggesting the role that the inflow played here (See Figure 5-6a). Moreover, since mesoscale anti-cyclonic eddies affect phytoplankton blooms through transferring nutrients and/or Chl-a to the open waters in the central Red Sea, our cross correlation maps showed the eddies' role, resulting in the October 2002 bloom that was reported in (see Figure 5-4(a2,a6,b2,b6)) and the June 2015 bloom reported (see Figure 5-7, Chl-a and DAOD anomalies at lag 2). The CALIPSO AOD climatology supported the dust contribution to the Chl-a, as discussed above and showed by the positive correlation coefficients (Table 5-2), since the dust activity peaked during summer and diminished during winter (see Figure 5-8). The extinction coefficient vertical profiles validated the dust aerosols contribution since the elevated dust layers (2–5 km) were evident during summer season mainly over the SCRS and SRS regions (see Figure 5-9).

5.5 Conclusions

This study considers a combination of different factors that are regulating nutrient supply in the Red Sea environment that may contribute to the observed anomalous phytoplankton outbreaks. We found that the Red Sea environment experienced, as expected, a negative correlation between SST and Chl-a observations. This negative correlation is plausible since phytoplankton normally blooms during winter. However, we also found that this negative relationship still holds between SST and Chl-a anomalies, with few exceptions that can be attributed to some eddy activities or possible wet dust deposition. It is clear that anomalously

cooler water, either from upwelling or intruding current from Gulf of Aden, could bring nutrients leading to enhanced phytoplankton blooming. On the other hand anomalously warmer water experiences reduced phytoplankton blooming because of nutrients shortage that is induced by stronger stratification and reduced mixing layer depth. This is evident from the extremely high SST anomalies paired with extremely low Chl-a anomalies during 2015–2016. Hence, we believe that warmer climate conditions could make the Red Sea ecosystem less productive. The extent of the June, 2010 anomalous event over the entire Red Sea environment made it quite interesting and it was deeply investigated. A combination of factors, ranging from SST anomalies, wet and dry dust deposition, and elevated wind speeds all contributed to the extent of that event. The strong north-to-south, west-to-east increasing gradient of the DAOD explains the higher dust activity on the southern regions of the Red Sea environment during summer and spring seasons that agrees with the higher productivity. This is evident from the correlation maps between Chl-a and DAOD anomalies at specifically two and three months lags over the southern Red Sea yet still with some contributions to the other regions as well at 0 lag. Our multi sensor approach together with the correlative analyses enhanced our understating of varying contributing atmospheric and meteorological factors into the phytoplankton blooms. Further research will be conducted for specific cases of anomalous blooms over the Arabian Gulf to investigate the regional extent of contributing factors to other neighboring water bodies.

6 Fifth Study: Synergistic use of Remote Sensing and Modeling for Estimating Net Primary Productivity in the Red Sea with VGPM, Eppley-VGPM and CbPM models Intercomparison

6.1 Introduction

Marine primary productivity is the rate at which photosynthetic organisms (mainly phytoplankton) produce organic compounds in the marine ecosystem. The net primary productivity (NPP) is considered the main indicator of the biogeochemical cycle since nearly half of global photosynthetically fixed carbon is derived from ocean phytoplankton [244], [245]. Therefore, accurate estimation of NPP is of great significance in the assessment and studies of fisheries source management, marine ecology systems and climate processes [246]. However, traditional ship-based in situ measurements are limited in their ability to capture the large-scale spatial and temporal dynamics of NPP, and are time consuming and expensive [247], [248]. Fortunately, satellite-borne sensors can address these shortcomings through their routine observations of the dynamics of the ocean surface, providing fundamental means for estimating oceanic NPP on large spatiotemporal scales [249]–[252]. Such observations help in accurately assessing the PP which, quantifies the amount of fixed carbon from photosynthesis processes [253]. Many satellite-based NPP models have been proposed in recent years and are categorized by type as i) chlorophyll-based, ii) carbon-based and iii) phytoplankton absorption-based models

[254] that will be further discussed in section II.B; or according to their complexities as i) wavelength resolved (WR), ii) depth resolved (DR), iii) wavelength integrated (WI), iv) time integrated (TI) and v) depth integrated (DI) [255]–[265]. These models have undergone extensive validation and accuracy assessment, through campaigns such as the Primary Productivity Algorithm Round Robin (PPARR), resulting in usage and conversion of remotely sensed environmental variables into PP [247], [258], [266]–[269]. It was found that the NPP data estimated from satellite based methods failed to show the seasonal variabilities and temporal trends in selected tropical regions (e.g., the tropical Pacific) [266], and underestimated the total PP [269]; moreover complex NPP models did not improve NPP estimates relative to simpler models [258].

Compared to other tropical regions, fewer studies exist that estimate PP for the Red Sea, and those that exist cover limited areas [270]. This is partly due to scarcity of oceanographic data because of the few surveys conducted in the waters of the Red Sea, although its marine resources are shared by eight countries (Saudi Arabia, Egypt, Sudan, Eritrea, Yemen, Israel, Jordan and Djibouti, in order of area of territorial waters). The extreme paucity of in situ data highlights the need for better estimates of PP in the Red Sea environment. Previous work from the King Fahd University of Petroleum and Minerals (KFUPM) undertook several multidisciplinary cruises in the Red Sea measuring physical and chemical parameters that could impact the PP in Saudi Arabian waters [270]–[274].

The Red Sea is a narrow, marginal oceanic basin in the northwest Indian Ocean. This basin extends from the Straits of Bab al Mandeb at 12.5°N in the south and branches off to 30°N in the Gulf of Aqaba (Eilat) to the northeast and the Gulf of Suez to the northwest. The Red Sea is 2250 km in length and 355 km in maximum width [135], [275]. Its seawater volume is approximately

233,000 km³, occupying an area of 4.51×10⁵ km² with a maximum depth of 3040 m and an average depth of 490 m [270]. The Red Sea has the highest salinity of any major tropical oceanic basin due to its lack of river inflow, low precipitation rate (<100 mm/year) [137], [138] and high evaporation rate (>210 cm/year) [276]. Because of its high salinity and temperature, the Red Sea becomes a natural laboratory to examine the responses of phytoplankton and coral reefs to the impacts of climate change [11], [277]–[279]. The Red Sea can be conveniently divided into four major geographic regions [11], [199]. From north to south these are designated the Northern Red Sea (NRS) (28°N to 24°N), the North Central Red Sea (NCRS) (24°N to 20°N), the South Central Red Sea (SCRS) (20°N to 17°N), and the Southern Red Sea (SRS) (17°N to 13°N) (Fig. 6-1)

The Red Sea is characterized by meridional circulation, which involves the southward flow of dense waters from the northern basin along the basin bottom to the Gulf of Aden (GA), as well as compensatory flow from GA into the Red Sea, which includes the movement of subsurface Gulf of Aden Intermediate Water (GAIW) for part of the year (summer-autumn) and surface waters for the rest (winter-spring) [275]. Traditionally, the Red Sea is defined as an oligotrophic water body with surface chlorophyll-a (Chl-a) <2.6 mg/m³ with an increasing north-south gradient [276], [280]. However, recent studies showed the Red Sea's biomass and PP are significantly influenced by eddy activities [281]. These eddies bring nutrient rich subsurface GAIW to the surface, stimulating notable phytoplankton blooms. In addition, the phytoplankton diversity in the Red Sea is quite high with at least 463 identified phytoplankton species [270]. Therefore, the notion of low levels of PP in the oligotrophic waters of the Red Sea needs to be reconsidered.

For example, over six million tons of dust is deposited into the Red Sea each year [270]. Summer dust storms are common along both coastlines, carrying phytoplankton-needed nutrients

to the oligotrophic waters in the NRS and NCRS. However, frequent dust storms also block satellite observations of large areas of the SCRS and SRS [11], [199], resulting in limited availability of ocean color data for NPP modelling, especially from late boreal spring to early fall. Additionally, large and unevenly distributed dust has an effect on the energy balance of the Red Sea. This asymmetric effect may exert a significant influence on the regional atmospheric and oceanic circulations [180] and may impact the PP.

In this study we apply three different global NPP models to the Red Sea region namely, the Vertically Generalized Production Model (VGPM), the Eppley-VGPM (abbr. as Eppley) and the Carbon-based Productivity Model (CbPM) [256], [265], [282], to understand the PP as well as PP regulating factors and trends. Although having in-situ measurements for quantifying the models' skill is ultimately desired, model inter-comparison still allows us to identify either the environmental conditions or the different satellite derived parameters contributing to the models' different results and divergence.

6.2 Background

6.2.1 Study Region

In this work we are addressing the NPP estimation over different regions of the Red Sea. For each region, 16 sample points were used to collect different parameters, represented by identical colors (red: NRS, green: NCRS, blue: SCRS, olive: SRS) (Fig. 6-1). The performance of ocean color NPP models in deeper waters (>250 m) was significantly better, because these models were more challenged in coastal Case-2 waters than open Case-1 waters. The influence of local-scale variability can be minimized by selecting data over the Red Sea and omitting coastal Case-2

waters where suspended inorganic particle loads can be particularly high. Therefore, the samples were selected based on their location and water column depths (> 600 m), assuming these areas represent Case-1 waters.

Figure 6-1: The samples collected in the Red Sea, represented by colors (red: NRS, green: NCRS, blue: SCRS, olive: SRS), where the water depth > 100 meters.

6.2.2 NPP Models

As noted previously, there are three different types of NPP models that will be discussed here: i) chlorophyll-based, ii) carbon-based and iii) phytoplankton absorption-based.

Chlorophyll-based Model

The generalized chlorophyll-based NPP model can be written as:

$$NPP = \varphi \cdot chl \cdot E \quad (1)$$

$$\varphi = \phi \cdot a_{ph}^* \quad (2)$$

with NPP and φ denoting PP and chlorophyll-normalized photosynthesis rate, which is in turn represented in (2) by the product of chlorophyll-specific absorption coefficients (a_{ph}^*) and the efficiency factor for the energy conversion of each absorbed photon to the production of organic carbon (ϕ); chl is the chlorophyll concentration and E is the absorbed photon energy. Since light changes spectrally with depth after penetrating the sea surface, it is notable that these two factors, depth and wavelength, must be accounted for while estimating E . Therefore, a common wavelength resolved (WR) model addressing this issue is implemented in (1) and is represented here as:

$$NPP(z) = \int \varphi(z) \cdot chl(z) \cdot E(\lambda, z) d\lambda \quad (3)$$

$$E(\lambda, z) = E(\lambda, 0)e^{-K(\lambda) \cdot z} \quad (4)$$

with $NPP(z)$, $\varphi(z)$, $chl(z)$ and $E(\lambda, z)$ representing the PP, chlorophyll-normalized photosynthesis rate, chlorophyll concentration as a function of depth and absorbed photon energy at water depth z and wavelength λ . $E(\lambda, 0)$ represents the surface spectral light energy with its spectral diffuse attenuation coefficient $K(\lambda)$, which is also calculated from chl for Case-1 waters. The photosynthesis of the whole water column (aka NPP) can then be derived from the integration of $NPP(z)$ over depth.

The VGPM [282] is a chlorophyll-based model whose photosynthesis rate is expressed as a function of water depth and photosynthetically active radiation (PAR). The VGPM estimates water column integrated productivity NPP as:

$$NPP = chl \cdot P_{opt}^B \cdot h_{PAR} \cdot f(E) \quad (5)$$

$$f(E) = \frac{c_1 \cdot PAR}{PAR + c_2} \cdot z_{eu} = \frac{0.66125 \cdot PAR}{PAR + 4.1} \cdot z_{eu} \quad (6)$$

with the chlorophyll concentration (chl), the maximum daily net PP within a given water column (P_{opt}^B) (in mg carbon fixed per mg chlorophyll per hour), daily hours of light (h_{PAR}) and a volume function $f(E)$ that relies on the empirical parameters ($c_1 = 0.66125$, $c_2 = 4.1$) to express the vertical decrease in PAR and the euphotic depth (z_{eu}) (practically defined as the depth where the solar radiation is 1% of its surface value).

The P_{opt}^B is also derived by an empirically parametrized sea surface temperature (SST)-dependent polynomial equation:

$$P_{opt}^B = -3.27 \cdot 10^{-8} SST^7 + 3.4132 \cdot 10^{-6} SST^6 - 1.348 \cdot 10^{-4} SST^5 + 2.462 \cdot 10^{-3} SST^4 - 0.0205 SST^3 + 0.0617 SST^2 + 0.2749 SST + 1.2956 \quad (7)$$

The Eppley-VGPM is a modified version of the VGPM, which only replaces the 7th degree polynomial expression of P_{opt}^B with the exponential function presented in [259], [283] given as:

$$P_{opt}^B = 1.54 \cdot 10^{0.0275 \cdot SST - 0.07} \quad (8)$$

Carbon-based Model

The estimation of phytoplankton biomass recently became possible because phytoplankton carbon biomass could be estimated from the total particulate backscattering coefficient, owing to their covariance with light scattering properties [284]–[290]. Moreover, the phytoplankton growth rates are now estimated from Chl-a to carbon ratios because the particle backscattering coefficient (b_{bp}), the absorption of phytoplankton pigments, and the absorption of colored dissolved organic carbon can be obtained by applying spectral matching algorithms simultaneously to satellite data [291]–[293]. After applying the algorithms, the CbPM model is developed [256], [265] in which the NPP is presented as:

$$NPP = C \cdot \mu \cdot f(E) \quad (9)$$

with phytoplankton carbon (C) derived empirically from its relationship to the measured b_{bp} :

$$C = 13000 \cdot (b_{bp} - 0.00035) \quad (10)$$

and phytoplankton growth rate (μ), which is based on the $chl:C$ ratios:

$$\mu = \mu_{max} \cdot f(N, T) \cdot g(I_g) \quad (11)$$

$$g(I_g) = 1 - e^{-5 \cdot PAR_{ML}} \quad (12)$$

where μ_{max} is the maximum growth rate; $f(N, T)$ refers to the nutrient and temperature stress and $g(I_g)$ describes reductions in growth rate with decreasing light at the mixed layer light level (PAR_{ML}). Furthermore, the $f(N, T)$ is expressed empirically as parametrized $chl:C$ ratios for the satellite observation ($Chl:C_{sat}$) and nutrient replete conditions ($Chl:C_{N,Tmax}$), which can also be derived from PAR_{ML} [8] as shown in (13) and later modified by introducing ε as the intercept [265] as given in (14):

$$f(N, T) = \frac{Chl:C_{sat}}{Chl:C_{N,Tmax}} = \frac{Chl:C_{sat}}{0.022 + 0.023 \cdot e^{-3 \cdot PAR_{ML}}} \quad (13)$$

$$f(N, T) = \frac{Chl:C_{sat}^{-\varepsilon}}{Chl:C_{N,Tmax}^{-\varepsilon}} \quad (14)$$

Finally $f(E)$, the volume function, describes the light change through the water column as:

$$f(E) = I_0 \cdot e^{\frac{-k_{490} \cdot MLD}{2}} \quad (15)$$

where I_0 is the cloud-corrected PAR just below the water surface, k_{490} is the light attenuation coefficient at 490 nm and MLD is the mixed layer depth.

Phytoplankton absorption-based Model

Estimation of chlorophyll concentration in this model is based on the remote sensing reflectance (R_{rs}) just above the surface. R_{rs} can be directly derived based on the ratio between water leaving radiance (Lw) and downwelling irradiance just above the surface (Ed+). Moreover, the R_{rs} is usually obtained from the total absorption coefficient (a) and the backscattering coefficient (b_b). Two main things to be considered to accurately derive spatially and temporally varying Chl-a from R_{rs} : 1) Remove the influence of detritus/CDOM and particles and 2) Take into

account the spatial/temporal variation of a_{ph}^* . However, the change of b_b is relatively weaker than a in the water [253], therefore the R_{rs} is largely dependent on a , hence, allowing chlorophyll concentration to be retrieved from a_{ph} . Since from (2) a_{ph}^* is the ratio of the phytoplankton absorption coefficient (a_{ph}) and chl , combining (2) and (3) results in a modified and more generalized model presented as:

$$NPP(z) = \int \phi(z) \cdot a_{ph}(\lambda, z) \cdot E(\lambda, z) d\lambda \quad (16)$$

The new model expressed by (16) eliminates the need for a_{ph}^* estimation, used previously in (3), hence avoiding a major source of uncertainty in the NPP calculation. On the other hand, the new model makes significant use of the a_{ph} value that is directly derived from R_{rs} , a methodology that has been well developed and evaluated [294]–[302].

Here we selected three, chlorophyll and carbon based, models and performed inter-comparisons to investigate the seasonal to decadal trends of the NPP in the Red Sea region. The used models are VGPM, Eppley and CbPM, that share the same temporal resolution of 8-day & monthly and spatial resolutions of $1/12^\circ$ (9 km). To account for the longest possible temporal variability over the Red Sea domain, data derived from SeaWiFS, MODIS and VIIRS sensors, spanning the periods 1998–2002, 2003–2018, and 2012–2018, respectively, were used. All three NPP model estimates are available via the website provided by Oregon State University (OSU). The phytoplankton absorption-based model is not used here as, to the best of our knowledge, there are no standard NPP products of a_{ph} from satellite ocean-color sensors yet.

6.3 Data and Methods

6.3.1 Model and Satellite Data

Different NPP related parameters are obtained from the European Space Agency's GlobColour merged products using SeaWiFS, MERIS, MODIS Aqua, VIIRS and OLCI-A sensors (<http://hermes.acri.fr/index.php?class=archive>) to explore relationships using multilinear regression analysis.

These merged products are generated by different averaging techniques namely AV: simple averaging, AVW: weighted averaging, AN: analytical from other L3 products or by the Garver-Siegel-Maritorena (GSM) model method that uses the normalized reflectances at the original sensor wavelengths, without inter-calibration [303]. The performance of these weighting methods depends mainly on the surrounding environmental conditions representing water types, geographical region and glint/aerosol conditions. Hence, different parameters are investigated here for possible NPP interplay including: 1) Angström exponents at 550 nm (over land & water) (A550) from MODIS [304] and MERIS [305] datasets; 2) particulate inorganic carbon (PIC) (mol/m³) generated from the original National Aeronautics and Space Administration (NASA) algorithms (2-band look-up table and 3-band algorithm at high concentrations) [306], [307]; 3) particulate organic carbon (POC) (mol/m³) generated from the original NASA algorithm (correlation of band ratios) [308]; 4) aerosol optical thicknesses at 550 nm (T550) (over land & water) calculated from A550 [309]; 5) PAR (einstein/m²/day) [310] indicating the photon flux density from 400 to 700 nm for photosynthesis; 6) particulate backscattering coefficient (BBP) (b_{bp} in II.2) (m⁻¹) at 443 nm generated from the GSM merging algorithm [303]; 7) the diffuse attenuation coefficient (m⁻¹) (KD490) of the downwelling irradiance at 490 nm as an indicator of

the turbidity of the water column, which is computed from corresponding merged chlorophyll products [311]; 8) MLD (m) provided by Global HYbrid Coordinate Ocean Model (HYCOM) [312] and downloaded from OSU website.

In order to assess the possible role and impact of dust on the NPP over the Red Sea, the monthly Modern-Era Retrospective Analysis for Research and Applications Version 2 (MERRA-2) atmospheric reanalysis data, including Dust Extinction AOT at 550 nm, Wind speed, and Angström Exponent are used. In addition, SST and Chl-a (mg/m³) were obtained from NASA's Ocean Color Web site (<https://oceancolor.gsfc.nasa.gov/>). The MERRA-2 data extend from January 1980 to present and are produced by NASA based on historical analysis using the Goddard Earth Observing System Model, Version 5 (GEOS-5) with its Atmospheric Data Assimilation System (ADAS), version 5.12.4 [214], [313].

The phytoplankton absorption coefficient $a_{ph}(\lambda)$ averaged at wavelengths λ_s , which determines the amount of radiant energy captured by the phytoplankton community has been suggested to be more related to PP than Chl-a [314]–[316]. In this study, we spectrally averaged the a_{ph} (APH), over the available wavelengths ranging from 412 nm to 670 nm, derived from the Ocean Color CCI (OC-CCI) dataset [317] using the Quasi-Analytical Algorithm (QAA) [298], and then compared the results with the NPP derived from the three previously mentioned models. Table 6-1 lists all the datasets used in this work.

6.3.2 Comparison with Climate Indices

It has been noted that NPP can be influenced by varying climatic patterns [269], [318], [319] in different geographical areas other than the Red Sea. We analyzed different climate indices

for their impact on the NPP products derived from the previously mentioned models. Table 6-2 summarizes and describes the used climate parameters including: the North Atlantic Oscillation (NAO), the North Pacific Gyre Oscillation (NPGO), the Multivariate ENSO Index (MEI), the Pacific Decadal Oscillation (PDO) and the Dipole Mode Index (DMI).

Table 6-1: Summary of data in the study

Name	Temporal Resolution	Spatial Resolution	Data Source
VGPM Eppley CbPM	8-day Monthly	9 km	OSU: http://www.science.oregon-state.edu/ocean.productivity/
A550 PIC POC T550 PAR BBP KD490	8-day	4 km	GlobColour: http://hermes.acri.fr/index.php?class=archive
MLD	8-day	9 km	OSU
VGPM Eppley CbPM	8-day Monthly	9 km	OSU
APH412	8-day	4 km	OC-CCI: https://www.oceancolour.org/
Dust AOD AE Windspeed	Monthly	0.5°x0.625°	MERRA-2: https://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/
SST Chl-a	8-day Monthly	4 km	NASA Ocean Color: https://oceancolor.gsfc.nasa.gov/

To determine the possible impact of these climate indices and their relationship with NPP, we applied correlation analysis to the 12-month moving average of NPP anomalies in the four regions of the Red Sea domain against the different indices, as well as the 12-month moving average, as shown in Table 6-2. The NPP monthly anomaly is denoted as (am) [269]:

$$a_m = x_m - x_t \quad (17)$$

with x_m representing the NPP data during month m and x_t the monthly average over the entire time series. The 12-month moving average for each a_m was calculated by taking the average value from a_m to a_{m+11} , then the monthly anomalies were scaled by the standard deviation of the values for that month (σ_m) to obtain the Z_{score} :

$$Z_{score} = \frac{a_m}{\sigma_m} = \frac{x_m - x_t}{\sigma_m} \quad (18)$$

6.3.3 Correlative maps between Chl-a and NPP products

For the purpose of finding the relationship between Chl-a and NPP for each model, we developed correlation maps that show the standard correlation using the Pearson correlation coefficient (r) in the range from -1 (anti-correlation) to $+1$ (perfect correlation), between these two monthly time series x and y , with N elements as:

$$r = \frac{\sum_{i=1}^N (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^N (x_i - \bar{x})^2} \sqrt{\sum_{i=1}^N (y_i - \bar{y})^2}} = \frac{\text{Cov}(x, y)}{\sigma_x \sigma_y} \quad (19)$$

with Cov being the covariance function, $\bar{x}$ and $\bar{y}$ the average and σ_x and σ_y the standard deviations for x and y , respectively.

Table 6-2: Summary of climate indices

Abbreviation	Name	Definition	Data Source
NAO	North Atlantic Oscillation	The NAO measures a climate pattern of North Atlantic Ocean fluctuations by the difference of atmospheric pressure at sea level (SLP) between the Icelandic Low and the Azores High.	http://www.cpc.ncep.noaa.gov/products/precip/CWlink/pna/nao.shtml
NPGO	North Pacific Gyre Oscillation	NPGO is a climate pattern that presents as the 2 nd dominant mode of Empirical Orthogonal Function of sea surface height variability (2 nd EOF SSH) in the Northeast Pacific.	http://www.o3d.org/npgo/
MEI	Multivariate El Niño/Southern Oscillation (ENSO)	The MEI is the bi-monthly time series of the leading combined EOF of five different variables, namely, SLP, SST, surface wind of combined zonal and meridional components, and outgoing longwave radiation (OLR), over the tropical Pacific basin (30°S-30°N and 100°E-70°W).	http://www.cdc.noaa.gov/people/klaus.wolter/MEI
PDO	Pacific Decadal Oscillation	The PDO is the leading EOF of mean SST anomalies during November through March for the Pacific Ocean to the north of 20°N latitude.	http://jisao.washington.edu/pdo
DMI	Dipole Mode Index	DMI represents the intensity of the Indian Ocean Dipole by anomalous SST gradient between the western equatorial Indian Ocean (50°E-70°E and 10°S-10°N) and the south eastern equatorial Indian Ocean (90°E-110°E and 10°S-0°N).	https://stateoftheocean.osmc.noaa.gov/sur/ind/dmi.php

6.4 Results

6.4.1 Relationship between NPP and multiple parameters

Statistical multilinear regression is applied to investigate the relationships between a set of variables (A550, MLD, T550, PAR, BBP, KD490, SST and Chl-a) and the responding NPP model values in each region for both MODIS-Aqua (MODISA) and VIIRS sensors. These relationships are presented by P-values of each variable in the four subregions of Red Sea (Fig. 6-2).

Figure 6-2: The P-values of the variables (A550, MLD, T550, PAR, BBP, KD490, SST and Chl-a) and the responding NPP model values, calculated from the multilinear regression model in each subregion (NRS, NCRS, SCRS and SRS) from both MODIS-Aqua (MODISA) and VIIRS sensors.

Figure 6-2 only shows the statistically insignificant variables P-values bigger than 0.05) for each dataset. The larger (insignificant) P-value suggests that changes in the variables are not associated with changes in the NPP values. Both A550 and T550 are the mostly appeared variables while SST does not appear in any of the subregions. However, there are also some insignificant variables such as Chl-a and PAR (CbPM NPP), BBP and MLD (Eppley and VGPM NPP), as well as KD490 (CbPM, Eppley and VGPM NPP) particularly in the SCRS and SRS. Additionally, the Fig. 6-3 presents the adjusted coefficient of determination (R^2) for the multilinear regression model to show the proportion of the variance in the NPP dataset that is predictable from the variables. This figure shows that: 1) both VGPM and Eppley NPP products are notably related to

Figure 6-3: The relationship between the combination of the values of variables (A550, MLD, T550, PAR, BBP, KD490, SST and Chl-a) and the responding NPP model values, which is represented by the R^2 values of multilinear regression model in each subregion (NRS, NCRS, SCRS and SRS) from both MODIS-Aqua (MODISA) and VIIRS sensors.

variables than that of CbPM, where the variables can explain most of the variance in the VGPM-VIIRS dataset ($R^2 > 0.8$) but fail to demonstrate that of CbPM-MODISA dataset ($R^2 < 0.2$); and 2) the NPP values in SCRS are generally less related to the variables compared to other regions of the Red Sea.

According to the equations in section III and results from Figs. 6-2&3, the scatterplots to show the relationships between NPP products and selected variables (BBP, PAR, SST, MLD), including the spectral averaged a_{ph} (APH), are illustrated in Fig. 6-4. The concentration of Chl-a is set by color levels. The increasing gradient in NPP from north to the south of Red Sea is generally consistent in all the three NPP models. However, the CbPM NPP has a lower median value in the SCRS than in the NCRS and NRS. Unreasonable low values (<100) also appear in the CbPM NPP products. In Fig. 6-4a, a wider BBP value range (0-0.004 m^{-1}) exists in SRS than the other regions (0-0.002) for both VGPM and Eppley products and the high values ($\text{BBP} > 0.003 \text{ m}^{-1}$) correspond to greater Chl-a and NPP values, while such a relationship does not exist in CbPM products. In general, the NRS has greater PAR values than the southern Red Sea (Fig. 6-4b). In the SCRS and SRS, high VGPM and Eppley NPP values are usually observed at the PAR range 40-45 $\text{einstein}/\text{m}^2/\text{day}$, as well as 55-60 $\text{einstein}/\text{m}^2/\text{day}$ but with many missing Chl-a values. Similar to BBP, PAR has no linear relationship with CbPM products in all regions. In Fig. 6-4c, median values of SST are higher in the NRS than the SRS. The VGPM product shows an apparent negative relationship with SST in the NRS, NCRS, and SCRS. The Eppley product shows a positive relationship in the SRS due to the settings of equation (7). Certain high NPP values are observed in the SCRS within SST ranging from 25 to 28 degrees, implying the impact of eddy activities. A positive relationship is found between MLD and VGPM NPP, particularly in regions with low Chl-a values (purple and blue dots in Fig. 6-4d). However, some high Chl-a and NPP values co-occur with the lowest MLD ($< 20 \text{ m}$) for both VGPM and Eppley products in the SCRS. The median value of MLD in the SRS is much lower ($\sim 25 \text{ m}$) than the three other regions ($\sim 35 \text{ m}$). There is an increasing gradient of APH median value along NRS ($< 0.01 \text{ m}^{-1}$) to SRS (> 0.03

m-1) (Fig. 6-4e). The positive relationship with APH and VGPM and Eppley NPP is also noted, especially in the SCRS and SRS, but not in the CbPM product.

Figure 6-4: The scatter plot (with colored Chl-a values) between NPP products (in log2 scale) and a) BBP, b) PAR, c) SST, d) MLD and e) APH (in log10 scale). Grey points refer to missing Chl-a values and red delta values refer to Chl-a > 2mg/m3. Boxplots are to show ranges and median value for NPP and variables.

6.4.2 Comparison between NPP products between sensors

The Red Sea was observed by both MODIS Aqua and VIIRS sensors during the year 2012 till 2018, which made it plausible for their 8-days Chl-a and the NPP products to be near identical. Correlation maps between multiple MODIS and VIIRS products, including Chl-a and NPP models (CbPM, Eppley and VGPM) during the same period are presented in Fig. 6-5. As shown in Fig. 6-5a, the Chl-a products from both MODIS and VIIRS sensors have strong correlation values ($r > 0.6$) for most regions of the Red Sea in the periods, with a decreasing gradient from north to south. The highest correlation ($r > 0.8$) observed in the SCRS are related to strong eddy activities. However, this relationship is not pronounced in the SRS ($r < 0.6$). The correlation map of CbPM NPP products in Fig. 6-5b demonstrates a mismatch between MODIS and VIIRS sensors. Only moderate correlation ($r \sim 0.5$) was observed in the NRS, while other regions show low correlation ($r < 0.3$) or even negative correlation in the SRS. This result goes against the hypothesis that coherency should remain within CbPM products. On the contrary, Eppley products show great consistency between MODIS and VIIRS sensors ($r > 0.9$) in all regions (Fig. 6-5c). The maps presented in the Fig. 6-5d exhibit a similar gradient pattern as shown in Fig. 6-5a, indicating the deciding role of Chl-a for VGPM products, yet the eddy-induced strong correlation in SCRS disappears.

The variations of each NPP product are shown in the time series for all the regions from 1997 to 2018 (Fig. 6-6). This figure suggests that the difference between SeaWiFS and MODIS remotely sensed data were not related to the NPP values. The NPP values before 2002 (SeaWiFS-based) are systematically lower than those after 2002 (MODIS-based), as presented in the CbPM time series. The intercepts of linear equations in the new Fig. 6-6 show the base levels of NPP for each region as a clear increasing gradient from north to south Red Sea. The southern Red Sea has more volatile NPP values than the north (significant gaps between maximum and minimum values). For VGPM and Eppley, the highest values commonly exist in the SRS (e.g., high values

Figure 6-5: Correlation map between MODIS and VIIRS products, including 8days Chl-a, CbPM NPP, Eppley NPP and VGPM NPP.

during May-1998 can be due to the strong ENSO event), with some exceptions such as high NPP events in the SCRS during the summer of 2015, which resulted from an eddy-driven phytoplankton event in the SCRS. However, the CbPM derived NPP is more variable than VGPM and Eppley, with many extremely low values in the SCRS and SRS. In general, NPP values are estimated as highest in Eppley and lowest in VGPM, yet CbPM tends to overestimate NPP values in NRS and NCRS, even higher than those in SCRS. CbPM and other two NPP models indicate different

trends: CbPM shows a rapid increase of NPP in SRS (2.25 mg C m⁻² day⁻¹ month⁻¹) but VGPM and Eppley exhibit a decreasing trend (1.37 and 1.91 mg C m⁻² day⁻¹ month⁻¹, respectively).

6.4.3 Environmental Forcing for the NPP trend

The variation of environmental forcing including SST, wind speed, Dust AOD and Angström Exponent (AE) are presented the Fig. 6-7. This figure shows that SST has increased for all four regions since 2003. For instance, the NRS has an annual increase of 0.0041 °C per month, meaning a ~0.78 °C increase from 2003 to 2018. In addition, seasonal patterns of wind speed in

Figure 6-6: Time series (values including SeaWiFS during the year 1997-2001 and MODIS: 2002-2018) to show trends for EPPLEY, VGPM and CbPM NPP for each region. The solid lines refer the mean value among the observations, whereas the shaded area shows the maximum and minimum value.

the NRS, NCRS and SCRS are not as apparent as in the SRS, which has the highest wind speeds in boreal winter and lowest wind speeds in summer (May or June), yet with a lower peak within

(usually July). The wind speed in SRS is negatively correlated ($r = -0.47$) with dust AOD and positively with AE ($r = 0.16$). Decreasing trends of windspeed are observed in the NRS and NCRS, whereas increasing trends are found in the SCRS and SRS. Moreover, AOD values show an increasing trend since 2014 for the NRS, SCRS, and SRS, especially during the summer seasons. This may be due to the highest temperature ever recorded occurring from 2015 to 2018, which were the top four warmest years in the global temperature record. Unlike wind speed, the AE in all the regions shows strong seasonality, as well as an increasing trend.

6.4.4 Teleconnections between NPP and climate indices

Correlation analysis between NPP (on average, max, and min) anomalies values and the moving average values of multiple climate indices are shown in Table 6-3. The highlighted values have been validated by the Pearson significance test ($P\text{-value} < 0.05$). Here, positive correlation exists between MEI/PDO indices and CbPM values in the NRS, NCRS, and SCRS. However, such strong connections are not observed in the VGPM and Eppley models. All the NPP products are generally not responsive to the DMI and NAO indices, but seem more reactive to NPGO, while showing opposite relationships: CbPM is negatively correlated to NPGO, yet VGPM and Eppley are positively correlated to NPGO.

Table 6-3: Correlation between NPP (average, max and min) anomalies values and the moving average values of multiple Climate Indices

Average		DMI	MEI	NAO	NPGO	PDO
NRS	VGPM	0.02	-0.10	0.04	0.30	-0.11
	Eppley	0.07	0.13	0.03	0.12	0.19
	CbPM	0.04	0.37	-0.14	-0.42	0.44
NCRS	VGPM	-0.20	-0.04	-0.08	0.42	-0.13
	Eppley	-0.30	0.09	-0.11	0.23	0.01
	CbPM	0.03	0.40	-0.22	-0.45	0.46
SCRS	VGPM	-0.20	0.17	0.12	0.38	0.06
	Eppley	-0.26	0.20	0.12	0.35	0.12
	CbPM	-0.05	0.37	-0.12	-0.36	0.35
SRS	VGPM	-0.17	0.20	-0.01	-0.09	0.11
	Eppley	-0.20	0.23	0.05	-0.08	0.16
	CbPM	0.26	0.24	-0.10	-0.47	0.37
Max		DMI	MEI	NAO	NPGO	PDO
NRS	VGPM	0.08	-0.20	-0.11	0.41	-0.27
	Eppley	0.06	-0.02	-0.14	0.28	-0.04
	CbPM	0.05	0.38	-0.16	-0.39	0.42
NCRS	VGPM	-0.29	-0.03	-0.24	0.41	-0.17
	Eppley	-0.35	0.05	-0.25	0.33	-0.10
	CbPM	0.07	0.34	-0.24	-0.46	0.41
SCRS	VGPM	-0.17	0.18	0.09	0.15	0.08
	Eppley	-0.21	0.18	0.12	0.16	0.09
	CbPM	0.08	0.32	-0.19	-0.44	0.34
SRS	VGPM	-0.12	0.22	-0.02	-0.27	0.17
	Eppley	-0.11	0.26	0.03	-0.29	0.21
	CbPM	0.30	0.11	-0.06	-0.51	0.21
Min		DMI	MEI	NAO	NPGO	PDO
NRS	VGPM	-0.11	-0.02	0.13	0.25	0.02
	Eppley	0.03	0.23	0.15	-0.09	0.36
	CbPM	0.00	0.37	-0.15	-0.40	0.44
NCRS	VGPM	-0.14	0.05	-0.04	0.39	-0.06
	Eppley	-0.11	0.29	-0.01	-0.04	0.22
	CbPM	-0.14	0.38	-0.24	-0.29	0.34
SCRS	VGPM	-0.25	0.12	0.10	0.41	-0.04
	Eppley	-0.29	0.08	0.08	0.40	-0.05
	CbPM	-0.36	0.14	0.04	-0.12	0.13
SRS	VGPM	-0.32	0.11	0.05	0.16	0.02
	Eppley	-0.36	0.15	0.10	0.16	0.08
	CbPM	-0.23	-0.06	-0.25	0.07	0.07

6.5 Discussion and Conclusion

Similar approaches to compare the performance of VGPM, Eppley and CbPM NPP models for regional applications have been reported in recent studies [319], [320]. An assessment of 36 NPP models, including VGPM, Eppley and CbPM, was undertaken to examine their ability to estimate the NPP trend, variability and mean value in the Bermuda Atlantic Time series Study (BATS) and the Hawaii Ocean Time series (HOT) datasets [269]. The study validated the argument that the model skill is not always improved by increased model complexity [266], [268]. Nevertheless, the mean NPP values at both sites were underestimated by most of the 36 models. For HOT, all three models have similar skills. However, at BATS, the CbPM model had the lowest skill among all the models, while VGPM and Eppley achieved much lower biases. The poor performance of CbPM was explained by its close relationship to MLD, which was affected by season and latitude [321]. In addition, the NPP is significantly enhanced by the presence of mesoscale eddies [322]. Both the variability of MLD and eddy activities result in interannual changes of nutrients necessary for phytoplankton growth [323]. This result can help explain the extreme low NPP of CbPM in Fig. 6-6. These abnormal NPP values may result from the increased MLD-caused substantially lowered $f(E)$ in (15), and altered value of PAR_{ML} in (12) and (13). As demonstrated in Table 6-2, VGPM and Eppley NPP at BATS are correlated to the NPGO but not correlated to MEI and PDO. By contrast, the CbPM NPP is negatively correlated to the NPGO but positively correlated to MEI and PDO. At HOT, the ENSO or PDO-related events impact the stratification and nutrient supply to alter the NPP. This may shed some light on the VGPM and Eppley NPP blooms in the NCRS during the strong El Niño 1997-1998 season. This indicates that VGPM and Eppley are more reliable than CbPM for the Red Sea NPP investigation. However, SST as a surface physical field fails to show a clear relationship with depth-integrated NPP

comparing to deeper physical fields, while both models substantially rely on the P_{opt}^B estimated with SST function. The ocean color models usually pay little attention to the contribution from the deep-layer related NPP, which explains the underestimation of the NPP in both HOT and BATS. Further research has examined the performance of satellite NPP models in coastal and pelagic regions across the globe, including the Mediterranean Sea and the Arabian Sea adjacent to the Red Sea [268]. Interestingly, this study concluded that the model skill evaluated by the root-mean square difference (RSMD) was lowest in the Mediterranean Sea (0.42 ± 0.06) and intermediate in the Arabian Sea (0.22 ± 0.09). The Eppley model achieved the best estimate (RSMD < 0.15) in the Arabian Sea. However, the different NPP trends between VGPM/Eppley and CbPM in SRS (Fig. 6-6) casts doubt on the ability of models using satellite-derived data to estimate the magnitude and the trends of NPP over multi-decadal or shorter time periods, which was also demonstrated at HOT and BATS [268], [269]. The NPP values estimated and agreed upon by all three models in the SCRS and SRS are exponentially higher than those in the NCRS and NRS. There are several possibilities for such differences: 1) The phytoplankton growth is promoted from the nutrient water obtained from GA exchange or eddies' upwelling near SCRS and SRS [275]; 2) dust deposition in this region could supply nutrients and prompt the phytoplankton growth, yet the presence of high atmospheric content of aerosol particles complicates atmospheric correction and limits the data availability [11]; 3) the sample points collected towards the south of the Red Sea, especially the in the SRS, are closer to the coastal areas. This may result in the uncertainty of remotely sensed ocean color data such as Chl-a and $Chl:C_{sat}$, because their ocean color signatures may possibly be averaged and mixed with other coastal regions.

It is also important to note that the performance of these three models is primarily dependent on the validity of input variables, derived from ocean color remote sensors (e.g. Chl-a,

BBP, SST and PAR), or even model simulations (MLD) (equation (15)). Additionally, it is also challenging to decide the parameters used in the NPP models, which require more regional in situ measurements. For example, the empirical parameters (c_1 and c_2) in (6) were calculated from thousands of field measurements, but not specifically for the Red Sea.

Beside carbon-based and chlorophyll-based production models, the phytoplankton absorption-based model or IOP-based production model, (known as inherent optical property), recently resulted in more PP studies on a global scale [250], [315], [316], [324]. It was noted that the absorption by phytoplankton pigments was a preferred parameter than pigment biomass for NPP retrievals [325]. This parameter was also regarded as better than SST to represent the photosynthetic rate of VGPM model in the Southern Sea [324]. As a good indicator of phytoplankton growth, KD490 can show short-term phytoplankton blooms and physical processes (anti-cyclonic and cyclonic eddies) in the Red Sea [326]. The absorption-based models using remotely sensed data could minimize the impacts of pigment packaging, colored dissolved organic matter (CDOM), and non-algal matter, in order to reach both lower bias and higher standard deviation evaluated by in situ datasets in the arctic ocean [327].

The rapid increase of SST was observed in all the regions of the Red Sea (Fig. 6-7), while its impact on NPP should be considered as one of the most crucial factors. As is illustrated in Fig. 6-4c, the most apparent disagreement between VGPM and Eppley lies in the response of the photosynthetic rate to the temperature, expressed by P_{opt}^B . The VGPM NPP shows a growth with increasing temperature until reaching a maximum at 20 °C, followed by a decrease at higher temperatures. This mechanism is based on the connection between nutrient limitation and warmer waters in the ocean [257], [282]. The NPP at BATS demonstrated an annual increase of 10.08 mg

C m⁻² day⁻¹ year⁻¹, with no significant increase of SST during 1988 to 2006, yet the HOT region had a similar increase of 10.23 mg C m⁻² day⁻¹ year⁻¹ but with noted SST increase of 0.06 °C year⁻¹. The decreased wind-forcing in the SCRS and SRS may lessen the MLD, which in turn limit the availability of nutrients in the euphotic zone [269]. The loss of nutrients, however, can be possibly compensated by the increasing dust deposition since 2014, particularly in the southern Red Sea. The frequent dust events covering the water surface also help lower the SST while blocking observations from ocean color satellites. Even though natural variations, such as a swing back to wetter phases of the Pacific Decadal Oscillation (PDO) and the El Niño/Southern Oscillation (ENSO) patterns, may temporarily relieve drought conditions and reduce the frequency of dust storms currently plaguing the Arabian Peninsula, long-term climate models indicate temperatures in the region will continue to rise and the observed drying trend will continue, leading to an overall increase in the number of significant regional dust events [328].

In conclusion, the three global NPP models used for deriving the satellite NPP products were evaluated in the Red Sea region. Models' intercomparison were performed using 8-day composite and monthly averages during the 1998–2018 period using different statistical methodologies. The estimated NPP using VGPM and Eppley significantly correlated well with the environmental and atmospheric variables allowing for accurate estimation of NPP as compared to CbPM, which performed poorly. This poor performance of the CbPM originates from the input variables that are not well parameterized for this region and need further enhancement using comprehensive local optical measurements. The models' intercomparison are further validated by the correlation maps presented.

Findings of this study could help the ocean color community and modelers make better choice among different PP models and associated satellite products for the Red Sea region, where chlorophyll concentrations are typically low. Moreover, this work elaborates on our previous findings in [11], [199] of possible dust impact on the marine PP and nutrient's supply affecting NPP.

Since the Red Sea is one of the warmest and saltiest ecosystems, it qualifies to be an ideal natural laboratory to study the physiological responses of phytoplankton community in such harsh conditions. The Red Sea could be a precursor to predict the behavior of the phytoplankton groups to nutrient variations, as well as to manifest the effects of global warming in other regions. Consequently, it requires further data at wider spatial and temporal scales and development of region specific NPP algorithms for future advances.

7 Sixth Study: Using Multi-indices Approach to Quantify Mangrove Changes over the Western Arabian Gulf along Saudi Arabia Coast

7.1 Introduction

Mangrove forests are present in the intertidal zone, located within small groups of trees and shrubs in the harsh interface between sea and land. They are distributed largely in the tropical and subtropical areas between 30°N and 30°S latitude. As a habitat to rich and biologically complex species, they are one of the most productive ecosystems in the world [329], providing considerable services to human communities with ecological and economic values to protect shoreline from storms, erosion, and sedimentation [330], as well as providing nutrients for algae blooms. The protective role of mangrove forests was also recognized during Asian Tsunami of 2004 and other natural disasters such as hurricanes [331], [332]. In addition, mangrove forests, acting as significant carbon sinks, play an important role in climate change [329]. However, mangroves are threatened due to both anthropogenic and natural stressors. One third of their forests has been lost in the past half century [333]. It is estimated that 35% of the mangrove forests were lost during 1980 to 2005 [334] in a much faster declining rate than coral reefs and inland tropical forests [335]. If no actions are taken to protect the mangrove ecosystem, 30%-40% of coastal wetlands and 100% of mangrove forest could lose their functionalities in the next 100 years with the present declining rate [336].

Mangrove forests cover around 152,000 km² in 123 countries and territories in the tropics and subtropics of the world [337], among which Middle East region has 624 km², about 0.4% of global coverage. Arabian Gulf, one of the most important inland sea at this region, is little known about its coverage and distribution of mangrove forests. The Arabian Gulf is a shallow basin of an average depth of 35m, extending approximately 24° - 30°N and 48° - 56°E [338]. Its coastlines, which is the most arid in the world, were formed in the past 3000 – 6000 years [339]. The water temperature vary from around 12°C - 35°C [340], and the surface temperature in intertidal zones can exceed 50°C in the summer [339]. The salinity in the Arabian Gulf is as high as 43 psu and may even reach 70-80 psu in tidal pools and lagoons. This is due to the high-latitude geographical location, high evaporation rates, as well as relative shallowness. In such an extreme environment, most of the marine species in the Arabian Gulf reach their tolerance limits [340]. Mangroves, however, are able to survive in this region because they tolerate the high salinity at early stages of development [341]. One type of mangroves, *Avicennia marina*, can be sparsely found at the southern shores, confined to sheltered coastal areas along the coastlines of Saudi Arabia, Arab Emirates and Qatar [339]. Despite the low volume, low diversity and intermittent occurrence of mangroves, the presence is of significant ecological importance in this region. Mangroves are among the only trees in the desert landscape, offering food for livestock and other wild animals. They support a variety of essential species of birds, fish, shrimps and turtles, contributing substantially to the coastal productivity [342]. It has been reported that Tarut Bay alone has lost a significant 55% mangrove forests (mostly in the south part) from 1972 till 2011. This is attributed to human and environmental pressures such as pollutants, land reclamation and urban encroachment. On the other hand a regional research of decadal changes of the Red Sea mangrove forest showed a slight increase of its coverage. Fortunately, the mangrove forests has been in a

recovery process with small increase by plantation activities by both government (i.e., the Ministry of Agriculture) and industry (Saudi-Aramco) in Saudi Arabia. As early as 1970s, vegetation indices had been used for quantitative measurement of vegetation conditions. High spatial resolution remote sensing imagery could generate various vegetation indices, such as Normalized Difference Vegetation Index (NDVI, NDVI2), Normalized Difference Red Edge index (NDRE, NDRE2), Green Normalized Difference Vegetation Index (GNDVI) and Chlorophyll Vegetation Index (CVI), which have been widely investigated to mangrove and other species, such as mangrove canopy chlorophyll concentration (, feedstock biomass production, and low and high density mangrove estimation.

Mangroves have very distinct spectral features in remote sensing data, especially in the spectral ranges corresponding to the visible red, near-infrared, and mid-infrared, making it easier to classify than other land cover types. The best combination of spectral bands to detect mangroves are Landsat 7 bands 3 (0.63–0.69 μm), 4 (0.77–0.90 μm), 5 (1.55–1.75 μm), and 7 (2.09–2.35 μm) [343]. Therefore, indices like the Normalized Difference Vegetation Index (NDVI) are useful in identification it has been employed for other applications. Recent advancement in computing and information technology, image-processing methodologies, as well as the availability of remote sensing data, have provided an opportunity to monitor mangroves at regional and global scales on a consistent and regular basis. Meanwhile, there has been an increase in high-performance cloud computing platforms, such as the NASA Earth Exchange (NEX), Amazon Web Service (AWS), and Google Earth Engine (GEE). The advantages of cloud computing include the parallel computing, offering nearly unlimited computer processing capabilities, as well as free access to a large volume of satellite remote sensing data stored in the remote cloud drives. This eliminates the need for large external hard disk storage and facilitates easy data access. For example, GEE

provides preprocessed Sentinel data (2014 - present), Landsat data (1982-present), as well as advanced classification machine learning algorithms accessible through JavaScript and Python programs [344]. One research project utilized GEE to analyze the changes of mangrove forests over 30 years in Thailand [345]. It is noteworthy that this Thailand mangrove study didn't use the Landsat 7 data after 2003 and had a missing scene in the year of 2012. This is because Landsat 7 Enhanced Thematic Mapper (ETM) sensor had a failure of the Scan Line Corrector (SLC) on 31 May 2003. Since that time all Landsat ETM data has wedge-shaped gaps on both sides of each scene, resulting in approximately 22% of data loss.

Mangrove forests mapping methods are usually based on a single-day imagery analysis, which can suffer from low or high tides. Such analysis can suffer by not taking the tide levels into consideration given that mangrove forests are periodically submerged by tides. This can impose a problem of over or under estimation in mangrove mapping when the images are observed during high-tide periods. Since mangroves grow along often-narrow extent along coastlines, detailed mangrove ecosystem characterization becomes difficult with moderate-resolution (30 m) satellite data and there is a need for high-resolution imagery to gain more accurate mapping results at different tide levels. A recent study proposed a new method to identify submerged mangrove forests via a submerged mangrove recognition index (SMRI) using high-resolution satellites' images, which considered different spectral signatures of mangroves under both low and high tide levels. However, due to naturally and/or human factors, mangrove communities along the Arabian Gulf coastlines covering more than 165 km² are predominantly separated from each other. This fragmentation brings massive cost to study mangrove at a regional scale with only using high resolution remote sensing images. For example, SA has a 700 km long coastline in WAG. This will cost around \$26,600 for getting entire coastline using WorldView 2 images with 8-bands for

one time period (calculated from price listed in www.landinfo.com: \$19/km² with 2 km minimum order width). The mangrove change detection study of two periods will cost double the price. Therefore, there is a need to improve mangrove detection methods through free accessible medium-resolution satellite imagery (such as Landsat 7/8). Here we employed high resolution images for selected regions for validation purposes.

We present a multi-indices based approach, using NDVI and SMRI, for long term mapping of mangrove forests in the WAG region along the Saudi Arabia coast. In this study, we evaluate the accuracy of three existing mangrove forests datasets and for the first time, incorporated SMRI as a new assessment for detecting submerged mangrove at different tide levels over the WAG region using Landsat medium-resolution remote sensing images.

7.2 Materials and Methods

7.2.1 Data

Three mangrove datasets were used in this research: 1) USGS Global Mangrove Forest Distribution of year 2000 [346]. This dataset was generated using Landsat satellite images of more than 1,000 scenes obtained from the USGS Earth Resources Observation and Science Center (EROS). Mangroves were classified using hybrid supervised and unsupervised digital image classification techniques. 2) World Atlas of Mangroves. This dataset shows the global distribution of mangroves, and was produced as a joint initiative of the Food and Agriculture Organization of the United Nations (FAO), the International Tropical Timber Organization (ITTO), International Society for Mangrove Ecosystems (ISME), UN Environment World Conservation Monitoring Centre (UNEP-WCMC) [337], United Nations Educational, Scientific and Cultural Organization's

Man and the Biosphere Programme (UNESCO-MAB), United Nations University Institute for Water, Environment and Health (UNU-INWEH), and The Nature Conservancy (TNC). 3) Global Distribution of Modelled Mangrove Biomass (2014) [347]. This dataset was developed by the Department of Zoology in University of Cambridge, with the support from The Nature Conservancy. It shows the global patterns of above-ground biomass of mangrove forests based on a review of 95 field studies on carbon storage and fluxes in mangroves world-wide.

Two kinds of remote sensing images are used here: 1) WorldView-2 image. WorldView-2 is a high-resolution satellite launched on October 8, 2009 from Vandenberg Air Force Base, CA. WorldView-2 collects 46-centimeter (cm) panchromatic and 1.85-meter (m) multispectral imagery. In this research, we obtained the image of four traditional bands (i.e. blue, green, red and NIR) over the Abu Ali Island during September, 2017 to study for the submerged mangrove detection. 2) Landsat 5, Landsat 7, and Landsat 8 Surface Reflectance Tier 1 dataset from the Landsat 5 TM, Landsat 7 ETM+ sensor and Landsat 8 OLI/TIRS sensors. These images contain 4 visible and near-infrared (VNIR) bands of 30m resolution for Landsat 7 (5 VNIR bands for Landsat 8), 2 short-wave infrared (SWIR) bands of 30m resolution processed to orthorectified surface reflectance, and one thermal infrared (TIR) band of resampled 30m resolution for Landsat 5/7 (2 thermal bands for Landsat 8) processed to orthorectified brightness temperature. The surface reflectance dataset was provided from GEE. They have been atmospherically corrected using The Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS), and include a per-pixel saturation mask and a cloud, shadow, water and snow mask produced using C Function of Mask (CFMASK). In this study, we utilized Landsat 5 image of 1985, Landsat 7 images of 2000, 2010 and 2018, and Landsat 8 images of 2018 for the aforementioned three mangrove datasets for inter comparison. Landsat 7 and 8 images were also used for detecting the mangrove changes between

2000, 2010, and 2018. Moreover, we obtained and processed Landsat 7 and Landsat 8 images of 2017 to quantify the submerged mangrove in Abu Ali Island based on tidal data. The tidal data was accessed from the harmonic model by WorldTides™ (<https://www.worldtides.info>) that uses a number of public and licensed sources for tidal predictions as well as land-based station observations from tide gauges and satellite observations when available for the maximum accuracy. Since tides are caused by the gravitational pull on water from the sun, moon, and other planets, hence the gravitational pulls' frequencies are well known, thus harmonic analysis models are employed here for future water levels prediction based on past observations.

7.2.2 Study region

Fig. 7-1 shows mangrove distribution for the years 2000, 2010 and 2014, respectively, using the three existing mangrove datasets over the WAG. The 2000 image from USGS Global Mangrove Forest Distribution is accessed through GEE searching tool, and 2010 image from World Atlas of Mangroves and 2014 image from Mangrove Forest Biomass are converted into GeoTIFF format files, then imported into GEE. Along the coast of Saudi Arabia, five regions are studied based on the mangroves' distribution: 1. Manifah, 2. Al-Khair, 3. Jubail, 4. North Tarout Bay, and 5. North Middle Tarout Bay, all marked by correspondent numbers in the Fig. 7-1. Fig. 7-1 shows obvious differences among the three datasets, for instance, mangroves in region 1 (Manifah) and region 2 (Al-Khair) can be found in 2000 (pointed at by the red arrow), but disappeared in 2010 and 2014. Mangroves of region 3 (Jubail) are observed in all three years, with the highest coverage in 2000 highlighted in black squared area, whereas in 2010 and 2014 the mangrove only be marked in the Gurmah Island (at location 3 in green color 2010 and red color 2014).

On the north side of region 4 (North Tarout Bay), both the 2010 (Fig. 7-1b) and 2014 (Fig. 7-1c) are marked with a mangrove distribution (pointed by a red arrow) near Ras Tanura, but not much appearing in the 2000 data (Fig. 7-1a). In addition, mangroves are distributed in region 5 (North Middle Tarout Bay) in the 2010 data (pointed by a red arrow in Fig. 7-1b) and 2014 (Fig. 7-1c), while they do not appear that much in 2000 (Fig. 7-1a). Therefore, it is clear that large discrepancies were identified among these three years datasets. This could be explained either due to a massive decline and disappearance of mangroves in 2000 in regions 1&2&3 after 2010 or a misclassification of the mangrove dataset by USGS accounting for other species as mangroves. Therefore, accurate assessment and validation work is highly needed to avoid misleading datasets, especially if it were to be used to build models for future mangrove change detection researches and for stakeholders and decision makers. In this study, we conducted a spectral analysis over the commonly recognized mangrove areas (in regions 3, 4 and 5), and from uncertain mangrove areas (region 3). The unique spectral signatures from mangrove habitats could help accurately decide on the consistency of distribution for mangrove habitats across the different data sets and at different locations.

Figure 7-1: Mangrove distribution in WAG for regions 1:Manifah, 2:Al-Khair, 3:Jubail, 4:North Tarout Bay, 5:North Middle Tarout Bay using (a) USGS Global Mangrove Forest Distribution of year 2000 (red color) (b) World Atlas of Mangroves of the year 2010 (blue color) (c) Mangrove Forest Biomass of the year 2014 (black color). The red arrows point to the mangroves, and black box highlights the massive mangrove coverage of USGS data.

7.2.3 Methodology

Classification methods

The workflow of generation and validation of mangrove classification model along with the procedures of classifying mangrove forests follow the workflow of the change detection analysis of coral reef habitat using Landsat data in the Red Sea (Hurghada, Egypt) [348]. The Landsat 7&8 images of the year 2018 are used to generate different mangrove detection models, including Supported Vector Machine (SVM), Decision Tree (DT), referred to as Classification and Regression Trees (CART) and Random Forest (RF). The results of these models are evaluated by the accuracy (generated from confusion matrices), and by comparing with high-resolution image from Google Earth. Then the most effective models are selected to classify the mangrove distribution for the areas of interest among the year of 2000, 2010, and 2018 using Landsat 7&8 images. It is noteworthy that Landsat 5 did not provide image after August 1st 2002 in these

regions. Alternatively, Landsat 7 images during the year 2010 were processed with GEE built-in mosaicking method to guarantee ideal results.

CART

CART, a supervised classification mining method, is used here to construct a decision binary tree structure through iterative analysis based on the training dataset that consists of features (i.e. spectral signatures) and target variables (i.e. mangrove or other classes) [349]. It has been widely used in land use analysis and change detection, wetlands and mangrove distribution classification [350], [351]. In this research, we used the maximum tree depth which controls the maximum number of allowed levels below the root node to construct the decision tree. Normally, the larger the maximum tree depth value, the more complex the decision tree and the higher the classification accuracy. Through multiple trials and the 10-fold cross validation, a maximum tree depth value of ten was selected for the CART classification.

SVM

The SVM machine learning algorithm, a well-adapted technique for solving non-linear, high dimensional space classifications, is used here as it showed a good performance in mangrove satellite sensing [352], [353]. It was found that SVM has better performance than maximum likelihood and artificial neural network classifiers using Landsat TM image [353]. Moreover, SVM outperforms discriminate analysis and decision-tree algorithms for airborne sensor data [354]. SVM uniqueness from other traditional classification approaches stems from its ability to create a hyperplane through n-dimensional spectral-space. This plane separates classes (mangroves versus

others) based on a user defined kernel function (linear in our case) and parameters that are optimized using machine-learning to maximize the margin from the closest point to the hyperplane.

RF

RF is a relatively new technique for mangrove species mapping, though it has been widely applied in landscape [355], [356] and plant species [357], [358] classification with different sensors in recent years. The RF algorithm is an ensemble algorithm for supervised classification based on CART. However, by combining the characteristics of CART together with further bootstrap aggregating, and random feature selecting, independent predictions can be established and therefore improve accuracies. For the RF algorithm, the tuning parameters mainly included “number of features”. This controls the size of a randomly selected subset of features at each split in the tree building process, which could have sensitive impact on classification [355]. The other tuning parameter also includes the maximum number of trees. In this research, the maximum level of trees used was five above which the accuracy did not change much.

Submerged Mangrove Recognition Index (SMRI)

Most previous change detection research of mangrove forests are based on remote sensing images captured at different dates, not considering the impacts of tide level changes. However, mangrove forests are distributed near the land–sea interface, such as shorelines and in elongated or fragmented patches, especially in the WAG. These mangroves periodically receive inundation of sea water, where the fluctuating water underneath the canopy dramatically changes the spectral signatures as observed using satellite images. Therefore, it is difficult to retrieve accurate mangrove information using the methods based on single-day remote sensing imagery comparison

of vegetation indices (i.e. NDVI). Recently, Xia proposed a submerged mangrove recognition index (SMRI) by using high-resolution GF-1 images in both low and high tides, to describe the unique spectral signature of submerged mangroves and to distinguish mangroves forests submerged by different tide levels. The detailed form of the SMRI index is based on a combination of NDVI and near-infrared bands, shown below:

$$SMRI = (NDVI_l - NDVI_h) \times \frac{NIR_l - NIR_h}{NIR_h} \quad [1]$$

$$NDVI_l = \frac{NIR_l - R_l}{NIR_l + R_l} \quad [2]$$

$$NDVI_h = \frac{NIR_h - R_h}{NIR_h + R_h} \quad [3]$$

where $NDVI_l$ and $NDVI_h$ are the NDVI values at low tide and high tide, respectively. NIR_l and NIR_h are the reflectance values of the near-infrared band at low and high tide, respectively. R_l and R_h are the reflectance values of the red band at low and high tide, respectively. In this research, we apply this index for detecting the submerged mangrove forests with Landsat medium-resolution imagery.

We also conducted studies to look at the effects of tide levels on the mangrove classification. WorldView-2 image was utilized to provide training data and validation for unsupervised classification cluster of mangrove in Abu Ali Island during the limited time period of September 2017. Landsat 7&8 images were used to implement the unsupervised classification method to explore the attributes of submerged mangroves for the same time period over the same region. All of the images were preprocessed, subset for coastal areas only and not including terrestrial vegetation and masked for marine habitats only and excluding water and land. We also applied the NDVI and SMRI, a new indicator to improve the submerged mangrove detection and to detect tidal impacts. It is noteworthy that all the Landsat and Worldview images are visualized

with false color configurations (R: near infrared band, G: red band, B: green band) to highlight the vegetation as red areas. Supervised classification models using three algorithms (CART, SVM and Random Forest) are implemented here to distinguish mangrove habitats from others.

7.3 Results and discussion

7.3.1 Comparison of existing mangrove datasets

Spectral analysis was conducted here to evaluate the data accuracy across different sources. Mangroves spectral signature is quite unique and has been correctly identified, used and compared with other sources to avoid misclassification with other marine habitats, namely salt marshes and macro algae. The left panel of Fig. 7-2 shows the spectral signature of end members from the mangrove habitat only identified by USGS Global Mangrove Forest Distribution dataset (red points in Fig.7-2a). They are displayed as Landsat 5 image of 1985 in Fig. 7-2c, the Landsat 7 images of 2000 in Fig. 7-2e and 2010 in Fig. 7-2g, and Landsat 8 image of 2018 in Fig. 7-2i. The right panel of Fig. 7-2 shows the spectral signature of samples from mangrove habitat agreed by all of three datasets (green points in Fig. 7-2b). They are displayed as the Landsat 5 image of 1985 in Fig. 7-2d, the Landsat 7 images of 2000 in Fig. 7-2f and 2010 in Fig. 7-2h, and Landsat 8 image of 2018 in Fig. 7-2j. It is noteworthy that the bands in Landsat 8 are renamed to have the same spectral range of Landsat 5 and Landsat 7. It is quite evident that the spectral distributions are coherent as shown in Figs. 7-2(d, f, h and j), with high value at band 4 and lower value at band 5 and band 7. However, Figs. 7-2(c, e, g and i) does not show the same pattern – band 5 value is always higher than the value of band 4 which should not be the case. From the above and based on the conducted spectral analysis using a wide range of endmembers and comparing with established research, we believe that USGS data overestimated mangrove habitats distribution. On

the other hand, the data obtained from Saudi Aramco shows the misclassified locations in the USGS dataset as saltmarsh habitats. The Landsat 5 data in 1985 was able to distinguish saltmarsh from mangroves, which is even more accurate for Landsat 7 & 8. This is because in Landsat 7 & 8 the values of each band show more distinctive behavior as compared to Landsat 5 images, where all bands show less distinction Figs. 7-2(d, f, h and j). Considering these differences and facts between these sensors, we opted to perform the change detection analysis on the mangroves habitats using Landsat 7&8 data.

Figure 7-2: Endmembers selection for spectral reflectance analysis using red and green points over (a) Jubail Conservation; (b) Tarout Bay. Red locations: classified as Mangrove forests according to USGS dataset only and Green locations: classified as Mangrove forests according to all three datasets with spectral profiles (c & d), (e & f), (g & h), (i & j) for 1985 Landsat 5, 2000 Landsat 7, 2010 Landsat 7, and 2018 Landsat 8 images, respectively.

7.3.2 Mangrove change detection

The supervised classification models used in this study (i.e. CART, SVM and RF) were built using the same training datasets from Landsat 7 (all samples from non-gap areas) and Landsat 8 images during 2018. Five different categories, namely: arid land, mangrove, tidal flat, saltmarshes and water body were identified using 30 sample observation points per category to ensure accuracy. Training datasets accuracy was assessed against new testing datasets through computing the confusion matrix for each model. In this work we looked at the “trainAccuracy” parameter that describes how well the classifier was able to correctly label resubstituted training data (i.e. data the classifier had already seen). However, to get a true validation accuracy, we showed our three classifiers a new ‘testing’ data and applied the classifiers to the new testing data to assess the “errorMatrix” for this withheld validation data. The accuracy values ranged from > 95% for CART and > 90% for others, being applied on both Landsat 7 & 8.

The mangrove forests distribution following the three models are shown using Landsat 7 & 8 in the Gurmah Island (GI) (Figs. 7-3 & 4(a, b and c), North Middle Tarout Bay (NMTB) (Figs. 7-3 & 4(e, f and g)), and North Tarout Bay (NTB) (Figs. 7-3 & 4(i, j and k) during 2018, respectively. High resolution true color images from Google Map were included for comparison (Figs. 7-3 & 4 (d, h and l). The resulting pixel coverage for mangrove forests based on three classifiers, after vegetation mask ($NDVI > 0.15$) was applied, is computed and presented for each location. The areas of the classified mangroves (in hectares) for Landsat 7 were: SVM (GI: 27.5, NMTB: 162, NTB: 159.3) > CART (GI: 25.7, NMTB: 140.6, NTB: 135.1) > Random Forest (GI: 24.6, NMTB: 97, NTB: 111.5) and for Landsat 8 were: SVM (GI: 38.9, NMTB: 180.6, NTB: 268.7) > CART (GI: 34.8, NMTB: 151.6, NTB: 190.2) > Random Forest (GI: 31.6, NMTB: 150.5, NTB: 183.8). It is clear that SVM classifier overestimated the distribution while RF underestimated it. The three models successfully showed similar mangrove distribution over the

different locations and using Landsat 7 & 8 datasets, yet we believe that CART showed the most accurate pixel coverage counting and best performance. Higher pixel coverage is expected from Landsat 8 images (Fig. 7-4) due to the absence of gaps exhibited in Landsat 7 data (Fig. 7-3). The variance in the pixel coverage following the three classifiers can be attributed to the sparse growth of mangrove habitats along coastlines, as seen from the high resolution true color composites, yet SVM failed to identify this sparsity and hence overestimated and RF did the opposite. Given the CART model higher performance and accuracy, it is now selected for the mangrove change detection analysis.

Figure 7-3: Supervised classification results of Landsat 7 image of 2018 for the mangrove forests (green area) and corresponding mangrove coverage (in hectares) using CART (a,e, i), SVM (b, f, j), RF (c, g, k), compared with high resolution true colour Google Map image (d, h, l), for GI(a-d), NMTB(e-h) and NTB(i-l)

Figure 7-4: Supervised classification results of Landsat 8 image of 2018 for the mangrove forests (green area) and corresponding mangrove coverage (in hectares) using CART (a, e, i), SVM (b, f, j), RF (c, g, k), compared with high resolution true colour Google Map image (d, h, l), for GI(a-d), NMTB(e-h) and NTB(i-l)

Change detection analysis is performed between 2000 and 2010 using the CART classifier based images for Landsat 7, after sub-setting our data to the previously mentioned five locations (Fig. 7-1) and masking terrestrial vegetation, land and water for classification purposes. Masking of terrestrial vegetation was crucial for the classification accuracy and to avoid overestimation errors by the classifiers. Landsat 7 is specifically selected against Landsat 8 to look at the change starting 2000 rather than 2013. Figs. 7-5 & 6 shows that regions 1 (Manifah) and 2 (Al-Khair) already with small mangroves fraction (0 and 2.3 hectares) in 2000 exhibits almost little to no change in 2010. It is noteworthy that an artificial island was built in region 1, for ship docking and tourists (Fig. 7-6, region 1). Alternatively, regions 3 (GI) and 5 (NMTB), with the larger mangrove

distribution (33.3 and 130.6 hectares) in 2000, showed an expected decline during 2010. This may be due to coastal developments and surrounding human activities.

The observed increase of 0.21 km² over the mangrove habits in the northern Tarout bay and Tarout Island from 2.25 km² to 2.46 km² during the period 2000-1010 matched the reported areal increase of 1.4 km² observed from 1999 (4 km²) to 2011 (5.4 km²) for the whole Tarout Bay. Moreover, the increase of 1.14 km² between 2010 (2.46 km²) and 2018 (3.6 km²) also agrees with the increasing trend of the Tarout bay mangrove habitats from 2011 to 2014. However, we believe that data SLC gaps, shown as empty clear stripes, also played a role in this observation. As for region 4 (NTB) the mangrove coverage increased from (94.4 hectares) in 2000 to (117.9 hectares) in 2010. It is highly likely that these classification results using gap-filled image by GEE mosaicking method contributed to this increase in the mangroves distribution that was validated with ground observations over some of the gap areas (Fig. 7-6, region 4). It is clear that mangrove biomass and distribution in NTB has unexpectedly increased from 94.4 to 117.9 to 190.2 hectares during 2000 (Fig. 7-5 region 4), 2010 (Fig. 7-6 region 4) and 2018 (Fig. 7-4i). Data filling may have contributed to better accuracy; however, tide levels also affect mangroves that is evident from their divergent spectral properties in high/low water levels. This will be discussed further in the next section.

Figure 7-5: Mangrove forest distribution using the CART classifier applied on Landsat 7 year 2000. Refer to Fig. 7-1 for regions.

Figure 7-6: Mangrove forest distribution using the CART classifier applied on Landsat 7 year 2010. Refer to Fig. 7-1 for regions.

7.3.3 Submerged mangrove detection

As mentioned above, tidal levels could have an impact on mangrove mapping and detection. SMRI was generated from low and high tides on the Abu Ali Island located in region 3 (Jubail), to use the unique spectral signature of submerged mangroves forest to distinguish them by different tide levels. The WorldView high resolution images of Abu Ali Island show mangrove forests in the south coast highlighted by the red square (Fig. 7-7a). Fig. 7-7b shows the sample points for dense high-stand mangroves in the south east corner (magenta points), tidal submerged mangrove in the middle (orange points), and tidal flats (red points). The mangroves total area, including tidal and non-tidal areas, was calculated using the K-means classification method applied on Fig. 7-7b and was found to be 19.28 hectares (see green area in Fig. 7-7c). To assess tidal impacts on mangrove distribution, the mean sea level (MSL) data was also used, mentioned above in the data section. False color composites for the region at low tides (MSL = -0.4m) and high tides (MSL = 0.5) are shown in Figs. 7-7(d & e) for Landsat 7 and Figs. 7-7(i & j) for Landsat 8, respectively. It is noteworthy that Landsat 7 SLC failure gaps did not intercede the areas of mangrove forests in the case of Abu Ali Island. Figs. 7-7(d & i) representing mangroves at low tides (marked as the red vegetation) from Landsat 7 & 8 exhibits larger distribution than the submerged mangroves that almost disappeared during the high tides (Figs. 7-7(e & j)). This indicates that change detection analysis of such area could be dramatically altered if images are not compared at the same water level. The NDVI images of low tides (Figs. 7-7f & 7k), and high tides (Figs. 7-7g & 7l) show that the NDVI index could be helpful to distinguish high-stand mangrove from others, but fails to discriminate the submerged mangroves and tidal flats in low tides, as well as submerged mangrove and land. While in the SMRI images (Figs. 7-7h & 7m), submerged mangroves could be seen as grey areas. The SMRI images indicate that: 1) for non-tidal regions such as land or high-stand mangrove, the SMRI value is close to 0; 2) for non-vegetation tidal flats regions, the SMRI value

could be very high above 1 (Fig. 7-7m), but also could be closer to submerged mangrove. One can use the spectral properties of submerged mangrove and tidal flats under high tides condition to separate them.

Figure 7-7: Worldview image of Abu Ali Island: (a) the mangrove forest in red square; (b) Sample points for tidal flats (red), high-stand mangroves (orange) and submerged mangrove (magenta); (c) Total mangrove area (green area). Landsat 7 and 8 images: (d, i) low tide; (e, j) high tide; (f, k) NDVI of low tide; (g, l) NDVI of high tide; (h, m) SMRI, respectively.

Figure 7-8 exhibits the ranges of NDVI and SMRI values of the samples for high-stand mangrove (Figs. 7-8a-c), submerged mangrove (Figs. 7-8d-e) and tidal flats (Figs. 7-8g-i) in Landsat 7&8 images displayed in Fig. 7-7. The NDVI values in low tides are higher than those in high tides in general. However, NDVI values of Landsat 8 images between tide levels are very close as seen in Fig. 7-8b. In the Fig. 7-8f, the SMRI values have very similar ranges (0.18 to 0.60 and 0.19 to 0.57) regardless of the different satellite images. This proves the robustness of SMRI as a submerged mangrove detection method. However, the ranges of SMRI values for Landsat 7

are overlapped between submerged mangroves and tidal flats (Fig. 7-8f and 8i). This could be solved by applying the divergence of high tide NDVI values for submerged mangrove (-0.18 to 0.09 in Fig. 7-8e) and tidal flats (-0.51 to -0.42) in Fig. 7-8h), which could be used to mask out tidal flats from SMRI-indicated mangrove areas.

Figure 7-8: Range of NDVI and SMRI values of the samples for high-stand mangrove (a-c), submerged mangrove (d-e) and tidal flats (g-i) for low tides and high tides of Landsat 7 and 8 images in Fig. 7-7.

Figure 7-9 shows the detection results for both high-stand mangrove as green areas using K-means unsupervised method, and submerged mangrove as yellow areas by choosing regions

with SMRI values (0.18 to 0.60 for Landsat 7, 0.19 to 0.57 for Landsat 8, then masking with high tide NDVI > -0.2). The areas of submerged mangroves are 8.25 and 10.67 hectares for Landsat 7 and Landsat 8 images, respectively. The classified mangrove areas of Figs. 7-9(b & d) cover most of the targeted mangrove areas shown in the background using the high resolution WorldView image. The summation of high-stand mangrove in high tide and submerged mangrove areas (19.2 hectares using Landsat 8, 18.42 hectares using Landsat 7) are very close to high resolution WorldView image result (19.28 hectares), indicating that this approach could provide an effective estimate and addresses the tidal impact on mangrove mapping.

Figure 7-9: (a) High-stand mangrove forests (green area) in high tide of Fig. 7-7e; SMRI indicated submerged mangrove forests (yellow area). (b) High-stand mangrove forests (green area) in low tide of Fig. 7-7d; same submerged mangrove forests as Fig. 7-9a. (d) High-stand mangrove forests (green area) and in high tide of Fig. 7-7j; SMRI indicated submerged mangrove forests (yellow area). (b) High-stand mangrove forests (green area) in low tide of Fig. 7-7i; same submerged mangrove forests as Fig. 7-9c. The text at the very right panel lists the mangrove area.

7.4 Conclusion

The spatial distribution and spatial-temporal changes of mangrove forests in Arabian Gulf along the Saudi Arabia during the period of 2000 to 2018 were explored using large data sets and spatial analysis. First, we used the medium resolution Landsat images to build a CART-based mangrove supervised classification model to obtain mangrove areas and distributions for 2000, 2010 and 2018. Second, with both Landsat and the high resolution Worldview images, the new SMRI method was applied in the area of Abu Ali Islands with the usage of K-means unsupervised method to identify and evaluate the biomass and distribution of submerged mangroves in the tidal area. This studies presents a unique approach of SMRI to detect mangroves with historical Landsat images that has historical record and can be used to address tidal impacts on mangrove mapping and areas estimation over different locations, which could achieve more accurate outcomes of mangrove detection within limited usage of costly high resolution remote sensing imagery.

8 Seventh Study: Assessment of Vegetation Changes and drying trends over the MENA Countries using Harmonic Analysis of the Enhanced Vegetation Index

8.1 Introduction

Studies have shown that global warming exacerbates dry weather. Climate in arid/semi-arid regions has also undergone significant changes making them increasingly drier over the past 100 years [360]–[362]. Temperature analysis of the main arid regions worldwide from 1900 to 1994 showed that they have experienced a warming trend [363]. By the end of this century, arid/semi-arid regions will increase in area by about 10% [364]. Meanwhile, different changes in arid areas might react differently to climate change, i.e., humid areas will become more humid and dry areas will become drier [365]–[369]

The MENA region is amongst the most arid/semi-arid areas globally, because of the lack of precipitation and prolonged drought events in the 1970s and 1980s [363]. MENA has a dry climate, scarce rainfall, lack of water resources, and extremely fragile ecological environment. It is sensitive to human activities and global climate change [370]–[372]. To obtain the spatial distribution of vegetation changes in the MENA region, EVI as a vegetation index can minimize

canopy background and atmospheric noise [373]. In this research, We aim to assess the predictive power of EVI for the ecosystems in this region in coherence with the prolonged observed drought conditions. The 2000-2017 MODIS EVI data with Harmonic analysis is to further model the changes of capital city area of five MENA countries (Tunisia, Egypt, Iraq, Saudi Arabia and Iran).

The region of Saudi Arabia (SA) is amongst the most arid/semi-arid areas globally, because of the lack of precipitation and high temperature [363]. SA is characterized by its dry climate, scarce rainfall, lack of water resources, and extremely fragile ecological environment, sensitive to human activities and global climate change [372]. To obtain the spatial distribution of vegetation changes in the SA region, vegetation indices such as Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI) can be used [373]. On the other hand, soil moisture is also considered to be a key variable to assess vegetation in drought conditions, with its wide range applications including wildfire and drought monitoring, climate forecasting and agriculture productivity [16]. Moreover, the Saudi vegetation conditions could also be impacted by certain climate events such as ENSO (El Niño-Southern Oscillation) for its global impact. Standardized sea temperature anomalies for various regions across Pacific Ocean could be used as indices to measure the severity of such ENSO events. These include Nino1+2 (90°W-80°W, 0°S-10°S), Nino3 (150°W-90°W, 5°S-5°N), Nino4 (160°E-150°W, 5°S-5°N), Nino3.4 and ONI (170°W-120°W, 5°S-5°N) and Trans-Niño Index (TNI) which measures the gradient in SST anomalies between the central and eastern equatorial Pacific (Nino 4 minus Nino 1+2). In this research, we aim to investigate vegetation changes in SA region with datasets from multiple satellite observations in synergy with modeling approach to study its drought conditions. Finally, we propose a possible teleconnection between SA's vegetation variation and ENSO events, which is worth further investigation.

8.2 Materials and Methods

8.2.1 Data

In this paper, we used two satellite-derived global soil moisture datasets generated by integrating the European Space Agency (ESA)'s Soil Moisture Ocean Salinity (SMOS) [374] and the National Aeronautics Space Agency (NASA)'s Soil Moisture Active Passive (SMAP) [375] in spatial/temporal resolution of 0.25 degree and 3 days, respectively. The vegetation health is closely connected with the soil properties such as soil moisture and salinity (Kim et al. 2014; Whitney et al. 2018). We used both datasets to investigate and explain the relationship between root zone soil moisture anomalies and precipitation as a function of land cover variability. Vegetation-type information was obtained from the ESA's global land cover data (GlobCover 2009), which includes 22 land cover classes defined by the Food and Agriculture Organization of the United Nations (UN) Land Cover Classification System (LCCS). The Climate Hazards Group Infrared Precipitation with Station (CHIRPS) (CHIRPS 2015) dataset is also used here to explore the spatial and temporal variability of precipitation at 0.5 degree spatial resolution. The vegetation index NDVI, which is obtained from Global Agricultural Monitoring System, is used to further explore the statistical relationship between ENSO and vegetation during the period from 1990 to 2013. Another vegetation dataset is the MOD13A1.006 Terra EVI Indices [376]. The Harmonic analysis is applied here over the EVI dataset to further model the changes of vegetation distribution over the area of SA from 2000 to 2019, as it is inspired by the study in the near region [58].

8.2.2 Methods

Harmonic analysis is a method involving the representation of functions or signals as a superposition of elementary waves. In this study, to estimate the variation of EVI, we build the

harmonic model with elements of a constant band (β_0), a linear term of slope (β_1) and harmonic terms of amplitudes (β_2 , β_3 , β_4 and β_5).

$$EVI(t) = \beta_0 + \beta_1 t + \beta_2 \cos(2\pi ft) + \beta_3 \sin(2\pi ft) + \beta_4 \cos(4\pi ft) + \beta_5 \sin(4\pi ft) \quad (1)$$

The term β_1 , associated with the linear part of EVI, represents the increasing/decreasing trend, whereas a constant band β_0 represents the extent of consistency of the time series. Moreover, f represents the fundamental frequency.

8.3 Results

8.3.1 Changing trends of EVI in the MENA Region

EVI trends and harmonic analysis for MENA area are presented in the Figure 8 1: a-e.

Figure 8-1: a) EVI changing trend among MENA countries, red indicates decrease, blue indicates increase, and green indicates no change. b-f) EVI trend (left), harmonic analysis (middle), regression analysis (right) for b) Tunis, Tunisia; c) Cairo, Egypt; d) Baghdad, Iraq; e) Riyadh, Saudi Arabia and f) Tehran, Iran.

Figure 8 1: a shows that regions among MENA area changes differently: regions such as Iraq and middle Saudi Arabia suffers drier climate, whereas dotted areas and part of Iran will be more humid. As seen in Figure 8 1: b, the EVI trend in the surrounding area of Tunis stays stable, but the southern region increase, except for a dotted red area. Harmonic model fits EVI data well (except for high records during 2004-2005), showing the same stable trend. In Figure 8 1: c, the Nile delta of Egypt trends slightly decrease (yellow), whereas the two wings of the delta shows obvious increase. Harmonic model fits the data perfect, showing the declining trend in Cairo region. Slightly decrease (yellow) also is observed along the river near Baghdad (Figure 8 1: d), but areas of southwest show an increase. Harmonic model shows the declining trend but misses some of the anomalous changes during 2014-2017. The Riyadh area (Figure 8 1: e) is an extremely dry region with low EVI value. The model shows the slow decrease trend in general. In Figure 8 1: f, the western part of Tehran area trends in very strong increase of vegetation. The model shows the overall stable trend and depicts the strong seasonal variations.

8.3.2 Vegetation Type Distribution in Saudi Arabia

Areas of different vegetation categories in SA are presented in the Table 8-1. Here we summarize the vegetation types into four main categories: cropland, mosaic vegetation, forest and sparse vegetation. Mosaic vegetation is the mixture of cropland and other vegetation such as grassland and shrubland. The area of forest in SA is only around 0.14% of the total area, whereas the sparse vegetation occupies more than 74%, which accounts for the majority of the vegetation area. The distribution of various vegetation categories could be found in Fig. 8-2a, where most of the vegetation habitats located in the southwestern mountain area, and some of the cropland field in the north and middle regions. Three regions marked as A, B and C, mainly representing cropland, sparse vegetation and mosaic vegetation, respectively, are selected to explore their changes.

Harmonic analysis for the whole Saudi Arabia with the EVI as the vegetation indicators are presented in Fig. 8-2b, with the same regions shown in Fig. 8-2a also selected. We could find that the different region within SA changes differently: regions such as coasts along northern Arabian Gulf and southern Red Sea show big area of decrease. Areas represents increase of EVI are mostly the agriculture region in the northern SA and areas near the cities. The majority region of Saudi Arabia shows no change since it is a permanent dessert. Fig. 8-2c shows vegetation changes: the increase of vegetation in the circled area near the cropland fields indicates new croplands was reclaimed after 2009 (Fig. 8-2c-A). Fig. 8-2c-B presents the overall decline trend of sparse vegetation in the mountain area. Both increase and decrease are also shown in the Fig. 8-2c-C, with most increasing region of mosaic vegetation, and decreasing region of sparse vegetation.

Table 8-1: Vegetation areas for each category in SA

	Vegetation type	Area (%)
Cropland	Post-flooding or irrigated croplands	0.94
	Rainfed croplands	10.15
Mosaic vegetation	Mosaic cropland (50-70%) / vegetation (20-50%)	8.81
	Mosaic vegetation (50-70%) / cropland (20-50%)	5.00
Forest	Open (15-40%) broadleaved deciduous forest (>5m)	0.05
	Mosaic forest-shrubland (50-70%) / grassland (20-50%)	0.09
	Close to Open (>15%) shrubland (<5m)	7.46
Sparse vegetation	Sparse (>15%) vegetation (woody, shrubs, grassland)	67.49
	Closed to open (>15%) vegetation (grassland, shrubland, woody vegetation) on regularly flooded or waterlogged soil - fresh, brackish or saline water	0.01
		0.01

Figure 8-2: a) Vegetation distribution of Saudi Arabia in 2009, b) EVI Trend of Saudi Arabia (in color Red: decrease, Blue: increase, Green: no change), c) the marked regions in a) and b)

In Fig. 8-3a, it is found that vegetation regions namely, (forest, cropland, mosaic and sparse), receive most precipitation in March, April and August. The surface/sub-surface soil moisture in cropland is most reactive to the impact of precipitation, which could be proven by the blooms in April – May, and August – September time windows. The lag correlation coefficients between SA's GIMMS NDVI standardized monthly anomalies and multiple ENSO indices are presented in Fig. 8-3b. For most indices (ONI, Nino 3, Nino4 and Nino 3.4), the value is lower than 0.2, indicating weak to no relationship. Comparably, the TNI index shows a growing trend

with more months till around 0.3 at lag of 11 months, which is different from the rest of ENSO indices.

Figure 8-3: a) Vegetation Monthly soil moisture and precipitation for the four categories of vegetation in SA, 2b) Lag correlation from 0-12 months for NDVI and ENSO indices over SA

8.4 Discussion

This research supports the view that some humid areas becomes more humid and dry areas become drier. Also, the regression analysis indicates that models in relatively humid regions (Tunis, Cairo and Tehran) matches better ($R\text{-square} > 0.5$) than the arid regions (Baghdad and Riyadh), since the arid regions are more influenced by anomalous records, i.e., Fig. 8-1e misses several higher record at 2004 and 2007. The harmonic analysis excelled in modeling the inter-annual variability of EVI index. Harmonic amplitudes β_2 and β_3 construct the seasonal changes within the year, whereas β_4 and β_5 more focus on the small scale within the season, i.e., an increase after the summer peak value represented in Fig. 8-1f. In general, the more harmonic components are used, the more details of variation will be denoted in the model. However, regardless

computational resources, introducing too many component could cause the overfitting problem, especially with some anomalous or missing records, i.e. high biases in modeling aerosol optical depth in desert area where summer records usually be absent.

According to the research, wild vegetation of SA is divided into five broad categories: 1. vegetation of the coastal plains and Sabkhas; 2. deserts and scarcely vegetated areas; 3. dwarf shrub-lands; 4. woodlands and xeromorphic shrub-lands of high altitude areas and 5. wadi Communities, this not including the cropland. Our study shows the reclamation's impact on the vegetation changes in the SA region. Additionally, El Niño events with negative/positive TNI, are classified as a "central Pacific El Niño " and "eastern Pacific El Niño", respectively. Therefore, Fig. 8-2 indicate the positive favor impact of eastern El Nino event to the vegetation growth in SA which needs further investigation. We also speculate that the cropland is more sensitive to the possible precipitation increases altered by ENSO events for it impact on soil moisture.

8.5 Conclusion

In this research, with the support from cloud-based platform to high scale of scientific data, the drying trend was assessed over the past 20 years for selected MENA areas using EVI. The EVI images exhibited varying spatial patterns of vegetation conditions with varying magnitudes in the different areas. Owed to the presence of some anomalous records in drier areas, the harmonic models showed a less correlated over Riyadh and Bagdad as compared to Cairo, Tunisia and Tehran. Generally, EVI tend to exhibit a level of uncertainty in sparsely vegetated lands due to the disturbance of blue band reflectance affected by aerosols. It is noteworthy to mention that the EVI time-series captured the largest inter-annual variability for the different locations. The EVI images

exhibited varying spatial patterns of vegetation conditions with varying magnitudes in the different areas. Overall, the vegetation in SA has a declining trend in most of their habitats, with the exception of regions with cropland reclamation. Most of the wild sparse vegetation areas (such as grassland and shrubland) suffers decreasing in the southwestern mountains. It is noteworthy to mention that the correlation between NDVI and TNI indicates a positive impact of eastern El Nino events to the growth of vegetation, which could affect through the precipitation increase in strength or frequencies. We found that soil moisture in relation to precipitation varies among different vegetation types, showing cropland is most sensitive to precipitation changes, which indicates that agriculture maybe also effected by the ENSO-related precipitation anomalies.

9 Other Anticipated Studies Related to the SDGs

9.1 SDG 3: Healthy lives and well-being

9.1.1 Monitoring Health Related Air Quality Indicators over the MENA Countries

Air pollution is reported as one of the most severe environmental problems in the Middle East and North Africa (MENA) region. Remotely sensed data from newly available TROPOMI - TROPOspheric Monitoring Instrument on board Sentinel-5 Precursor, shows an annual mean of high-resolution maps of selected air quality indicators (NO₂, CO, O₃, and UVAI) of the MENA countries for the first time. The correlation analysis among the aforementioned indicators show the coherency of the air pollutants in urban areas. This approach can improve the knowledge of air pollutant variability and intensity in the MENA region for decision makers to operate proper mitigation strategies.

Fig. 9-1 illustrates the application of using high-resolution products of TROPOMI for detecting the differences within the urban region – the example of three locations (central, south and north) of metropolitan Cairo area. The selected locations are all separating each other less than 25km, which is the spatial resolution of OMI product. Apparent differences between the locations are found except the O₃ products. The emerging SO₂ event of March 20th occurring in central location but not observed in the south and east locations. Such disagreements are also found in the

NO₂ values during April 3rd and UVAI values during March 5th. These values would otherwise turn out to be the same if the OMI data is used in the same assessment. The advantage of using TROPOMI products is therefore confirmed when compared with coarse resolution remotely sensed products.

Figure 9-1: Timeseries of air quality indicators (CO₂, SO₂, NO₂, O₃, and UVAI) over three locations within the urban Cairo from March 1 till April 30, 2019.

Fig. 9-2 demonstrates the correlation between the air pollutants over selected MENA countries. Strong positive correlation between CO and NO₂ is found in the urban areas: the Nile Delta region centered Cairo, the cities near the coast of the Gulf and Red Sea and Riyadh in Saudi Arabia (Fig. 9-5). This is due to the fact the vehicles and industries in the listed urban regions usually emits both pollutants simultaneously. The CO and UVAI is showing a weak relationship

in most regions except the negative correlation observed in the south of the Nile Delta close to Cairo. Meanwhile, the correlation map between UVAI and NO₂ also shows a generally weak relationship between them.

Figure 9-2: The correlation maps of the daily anomalies values for a) NO₂ and CO; b) CO and UVAI and c) NO₂ and UVAI, during the July 11th, 2018 till July 10th, 2019.

9.2 SDG 13: Climate change and its impacts

9.2.1 Dust Storm, Precipitation and El Niño

Atmospheric aerosol particles affect the formation of precipitation through influencing on microphysical properties of water and ice clouds. In early May of 2018, we observed the coincident of strong dust and rain events in the Nile Delta area. We also used Hybrid-Single Particle Lagrangian Inte-grated Trajectory (HYSPLIT) model, NMMB/BSC-dust model and NOAA-18 Cloud Height product to validate this same movement of dust and clouds that induced precipitation. In addition, Niño 3.4 index with historical rain and dust anomalous events during 1980-2017 were analyzed to re-veal the relationship between these events and global climate system. The results revealed an obvious matching in both intensity and movement for both dust and precipitation events in early May 2018. Extreme precipitation anomalies during 1990-1999 occurred in company with positive Niño indices and less dust events.

Aerosol optical depth (AOD) observations and analysis data during May 2018 were obtained from AERONET Cairo station. TRMM precipitation data for the Nile delta were studied for the same period. The combination of Integrated Multi-satellite Retrievals for GPM (IMERG) rain rate , MODIS Terra AOD and VIIRS SNPP True Color images were displayed for north Africa during May 3rd to 6th. In addition, the HYSPLIT air parcels trajectory analysis for Cairo station were compared with the movement of dust event (simulation from NMMB/BSC-Dust model) and precipitation induced cloud (NOAA-18 cloud height product). Furthermore, the normalized AOD and rain anomalies (Z-score calculated from MERRA-2 dataset) for this region were calculated and compared with Niño 3.4 index during 1980-2017.

The events of dust and precipitation in Nile Delta are presented in the Fig. 9-3a. The severe dust event ($AOD > 3$, coarse) reached Cairo on May 3rd and May 4th, with following events on

10th, 22th of the same month. Simultaneously, the precipitation also occurred in the same region on May 3rd, 4th, 6th, 10th and 23rd. On the right side of Fig. 9-3a, strong dust events were coincided with precipitation in the black squared region, with high AOD value. The path of the movement of cloud (middle Fig. 9-3b) and dust (right Fig. 9-3b) matches the output of HYSPLIT trajectory model. The relationship between climate change between dust and precipitation anomalies is shown in the Fig. 9-3c. It is worth noting that during the period of 1990 to 1999, the severe precipitation anomalies (Z-score > 3) coincided with positive Niño 3.4 index and negative dust AOD anomalies, indicating Nile Delta tends to have more rains during the El Niño years.

Figure 9-3: a). Aerosol records of AERONET Cairo station, and TRMM records of the same region (Left); MODIS TERRA AOD and IMERG Rain Rate in North Africa during May 3rd to 6th (right). b). 3-day HYSPLIT air parcels trajectory of for Nile Delta (left); Cloud movement of during May 1st-3rd (middle); Dust movement of NMMB/BSC model of same period (right). c). Niño 3.4 index, MERRA-2 Dust AOD and Rain Z-score during 1980 to 2017.

9.2.2 Impacts of Aerosols on the Sierra Nevada Glaciers in California

The snowpack in the Sierra Nevada mountain range is the primary source of water for California. Many studies have shown that the increase in aerosols could lead to a reduction of the snowpack in this region. This study focuses on evaluating changes in the snowpack during the winter and summer seasons from 2000 till 2016 and determining the relationship between aerosols and the retreat of glaciers in the Sierra Nevada. Utilizing the aerosol optical depth (AOD), Angstrom exponent, snow depth anomalies, snowfall, radiation fluxes, and albedo, the effect of aerosols on snowfall over the Sierra Nevada glaciers has been examined for this 17-year period. Overall, based on correlation analysis, a negative relationship exists between the AOD and the snowfall.

The Sierra Nevada mountain range is the largest in California, extending 400-miles north–south and 50-miles east–west, with a coverage of 24,370 square miles. The mountains began to form 200 million years ago, from the formation of granitic rocks. The climate in the Sierra Nevada is Mediterranean with wet, cool winters and dry, long summers. The main source of fresh water supplied to the state of California comes from the Sierra Nevada, with the snowmelt providing an average of 15 million acre-foot of water per year. Each year, 60% of California’s total annual precipitation falls on the Sierra Nevada mountain range as rain or snow, which is about 10–90 inches of rain. The rainfall and snowmelt from the Sierra Nevada travel hundreds of miles along the Sacramento-San Joaquin Delta, with 50% of water flow into the Delta originating from the Sierra Nevada. This study focuses on an area of the Sierra Nevada region shown in Fig. 9-4.

Figure 9-4: Base map showing the target area being studied

In order to reveal the aerosol and snow interaction in Sierra, we initially attempted to study factors such as snowfall and surface air temperature, which directly influence the snow coverage. From Fig. 9-5(a), a strong correlation (0.599) between the variations of snowfall and snow cover anomalies is evident. This suggests that snowfall is the critical contributing factor to the snow coverage in this area. In Fig. 9-5(b), snow depth during middle summer (July and August) equals to 0, meaning that snow cover in this region is mostly composed of winter and spring snowfall, which supports the previous result that the snowfall dominating the snow coverage in Sierra Nevada. It is logical that higher temperature accelerates the melting process of snow, which could be seen in the negative relationship (-0.265) between surface air temperature anomaly and snow depth. It is clearly shown that the pattern of “high snowfall & high snow cover, low temperature & high snow depth” during the period of 2010 to 2011, as well as “low snowfall & low snow cover, high temperature & low snow depth” during the period of 2012 to 2015. In this paper, we will

approach the impact of aerosols on snow coverage in this area by studying aerosols and the effect on the snowfall and temperature.

Figure 9-5: The variation of (a) Snowfall anomaly and snow cover anomaly; (b) Snow depth and surface air temperature anomaly; as well as parameter correlation coefficients in (a) and (b).

In Fig. 9-6, from the analysis of intra-annual AOD variations we conclude that the AOD values stay high during the period from March to August, and low during September to February. The plots of less snow period (September– November) and major snowfall period (December– February) show a negative relationship between AOD and snowfall anomalies (correlation of September = -0.193 , October = -0.052 , November = -0.332 , December = -0.379 , January = -0.078 , February = -0.205). We recognize the low correlation coefficient values, yet the negative behavior implies on the process of the snowfall that enhances aerosols absorption. On the other hand, during the spring and summer period (March–August), it shows a weak positive relationship between AOD and snowfall anomalies (correlation of March = 0.122 , April = 0.060), which indicates the high aerosol activity may improve the process of snowfall formation/precipitation. It also shows a negative relationship (correlation of May = -0.186 , June = -0.241) or no relationship

(July and August due to no snowfall record). It is clear that only one anomalously high snowfall event was recorded during June of 2011 and not during any other Junes. Therefore, it is evident that the period from June to August, according to the snowfall records, is not relevant to our analysis here due to the limited, if any, snowfall during these months. In general, the analysis of AOD and snowfall variations implies a negative relationship. It is noteworthy that the sources and types of aerosols during the year might not be alike. Different types of aerosols, regardless their intensities, could exert different influences on the snowfall precipitation.

Figure 9-6: Z-score for each month as variations of AOD and snowfall anomalies, as well as correlation coefficient in each month during 2000 to 2016.

From Fig. 9-7(a), the albedo diffusion of both NIR and visible bands increased after snowfall started around April 17, then decreased right after the occurrence of the AOD event at the afternoon of April 18. Albedo values peaked during the afternoon of April 19, then kept on decreasing after the snowfall ended on April 20. The sudden drop of the albedo values right after the AOD event indicates the deposition of aerosols that might cover the snow surface and hence contributes in decreasing the albedo values. Fig. 9-7(b) shows the increase in values of both

absorbed and incident longwave radiation, yet the absorbed is still higher than the increase of incident longwave radiation flux, confirming the decrease in the albedo values, since the surface absorbed more energy during aerosols' deposition conditions than the non-aerosol affected conditions. Both NLDAS MOS and NOAA models show a decreasing trend of surface skin temperature, while after the start of AOD event the values of the lower temperature for both models even simulated higher than the values before the snowfall as shown in Fig. 9-7(c). This abrupt change supports what is found in Fig. 9-7(b). The physical background for interpreting the effects of radiation flux on the snowpack melt, associated with aerosols deposition, is based on the increase of the absorbed energy that raised the average snowpack temperature leading to more melt.

In summary the deposited aerosols affected the albedo of snow surface to change the heat flux, increase the surface temperature, and then accelerate the melting process of snow cover. However, different kinds of aerosol deposition affect the melting process in distinct ways. The black carbon could function more effectively than other kinds such as sea salt or dust deposition. In order to explore the sources of the aerosols of this AOD event, we collected AOD data from the morning of April 15 to midnight of April 19, to track the entire life cycle of generation of the AOD event.

Figure 9-7: (a) Albedo NIR/Visible diffuse; (b) Surface absorbed longwave radiation/surface incident longwave radiation flux; (c) NLDAS MOS/NOAH surface temperature data during the period of April 15–20 of 2004.

The left side of each panel in Fig. 9-8 shows the aerosols transportation from eastern Asia, dust (mostly from northern China) and pollution (from both northern and southern cities of China) assembled together, moving over Japan then dispersed into the northern Pacific Ocean. Over time as shown in Fig. 9-8(g) (circled area), aerosols are observed over the Sierra which is confirmed by the low Angstrom exponent measurements obtained from the Fresno AERONET station, SDA retrievals showing fine and coarse mode fractions and the GSFC back trajectory as shown in Figs. 9-9(a)–9(c). It is evident that the dust originated from those events is moving southeastward over the Pacific Ocean shown in Figs. 9-8(a)–8(f). From all the above, it is reasonable to suggest that aerosols from eastern Asia are contributing to the aerosols' depositing over the Sierra. These

aerosols also passed over the cities along the California coast adding more pollutants from these regions which should also be considered. In summary, we can claim that the aerosols affecting the Sierra area are representing a mixing scenario between pollutants from both US and Asia cities with the dust from northern Asia as well as the sea salt from the ocean surface, through the processes of the atmospheric circulation and air-sea interactions. These mixing scenarios will be further investigated through a different research manuscript.

Figure 9-8: Aerosol AOD cross the Pacific Ocean during April 14–19 of 2004.

Figure 9-9: a) Angstrom Parameter, b) SDA Aerosol Optical Depth, c) Back-Trajectories analysis during April 18–19, 2015.

9.3 SDG 14: Marine habitats protection

9.3.1 Assessment to Oil Spill Response with modeling approach in the Tarut Bay, Saudi Arabia

Oil spills can cause catastrophic environmental damage that can harm sensitive marine and aquatic life in the Western Arabian Gulf (WAG). The sensitive coastal areas that should be protected immediately can be identified and highlighted using environmental sensitivity maps (ESM) to implement appropriate mitigation measures. The most vulnerable areas classified based on sensitivity indices so that stringent protective measures can be implemented in case of an oil spill, are Safaniyah, Khursaniyah-Jubail, the Tarut Bay and offshore Islands. Remote sensing observations and oil spill modelling were used to evaluate the impact of historical or possible oil spill event on these areas. This research investigated the impact probability of oil spill are

calculated through General NOAA Operational Modeling Environment/Automated Data Inquiry for Oil Spills (GNOME/ADIOS) model simulation.

In this case, the GNOME model used the 0.25 degree daily wind forecast data from the National Centers for Environmental Prediction (NCEP) Global Forecast System (NCEP, 2012), as well as 1/12 degree daily ocean current forecast data from the Hybrid Coordinate Ocean Model (HYCOM). Figure 9-10 shows the trajectory for a continuous oil spill simulation near the Tarut Bay, where the yellow dots are the best-guessed splots and red dots the uncertainty splots. The oil floated southeastward during January 21st and 22nd, until it reached Bahrain. On January 23rd, the floating oil starts to move northward, but some of the oil in the south is blocked by the shallow water to move further north. By the end of January 24th, most of the oil congregates near the eastern side of the Bay, with some of the oil moving into the Bay and reaching the beaches of the Tarut coast. The other processes, such as sedimentation and dissolution, do not remove a significant amount of the spilled-oil, because these processes require a longer time than the simulation period. The Figure 9-11 illustrates the speed of wind (left column) and ocean current (right column) variations during from January 21st to January 25th. The intense northwesterly wind (speed >10 m/s) drove the ocean currents in the Tarut Bay on January 21st to January 22nd, while the wind weakened at January 23rd, then changed to reverse direction on January 24th to January 25th. It shows the movement of the spilled oil is directed by the ocean current which is controlled by the wind activities. Therefore, the abrupt changing of meteorological conditions (such as wind speed and direction) will apparently impact the fate of spilled oil. Additionally, the Figure 9-10 also demonstrates some of the spilled-oil moves along with the currents because of the lower water level of ocean surface topography. Above all, the GNOME simulation of the oil

spill provides helpful insights to the scientists and decision makers to respond to oil spill incidents under different meteorological conditions.

Figure 9-10: The simulation of an oil spill near the Tarut Bay from 12 AM January 21, 2018 to 12 AM January 25, 2018 using GNOME.

Figure 9-11: Speed of wind (left column) and ocean current (right column) variations during from 12 AM January 21, 2018 to 12 AM January 25, 2018.

9.3.2 Long-term vegetation cover profiles of major offshore island nesting sites of sea turtles in the northern Arabian Gulf

Vegetation is an important ecological component of offshore islands in the Arabian Gulf (AG), which maintains long-term resilience of these islands. This is achieved by influencing sediment retention and moisture acquisition via condensation during periods of high humidity and by providing a variety of microhabitats for island fauna. The resilience of offshore islands' ecosystems in the Saudi waters is important because they host the largest number of nesting hawksbill and green turtles in the AG. This study defines the characteristics and the long-term trends in vegetation cover of the offshore islands used by sea turtles as nesting grounds in the northern AG. Landsat 7 and 8 satellite top-of-atmosphere reflectance images were used to calculate the Normalized Difference Vegetation Index (NDVI) from 1999 through 2018 to analyze the long-term vegetation profiles of the islands. Monthly rainfall data from five meteorological stations along the Eastern Province of Saudi Arabia and Oceanic Niño Index (ONI) are presented to provide a context of the long-term NDVI time series variability. The NDVI data for both islands are grouped into three periods, namely: 2001-2007 - high winter, low summer; 2008-2013 – low winter, low summer; 2014-2018 – irregular high/low winter, low summer. The long-term trend showed a slightly decreasing NDVI when compared in the context of the high NDVI measured for the two islands during the early 2000s, particularly during the winter time. An extended reduction in winter NDVI was recorded for six years from 2008 to 2013, which coincided with reduced rainfall in the region and prolonged La Niña. Five extreme dips in winter NDVI values coincided with strong (2000, 2008, and 2011) and moderate (2012 and 2018) La Niña events. Long-term vegetation profiles of the offshore islands seemed to be tightly coupled with long-term rainfall patterns.

Karan Is. ($27^{\circ}43'5.05''\text{N}$, $49^{\circ}49'28.91''\text{E}$) (dimensions: 2,024 m x 632 m; circumference: 5.3 km) and Jana Is. ($27^{\circ}22'6.85''\text{N}$, $49^{\circ}53'50.85''\text{E}$) (dimensions: 1,105 m x 300 m; circumference: 2.6 km) are the two largest islands located at the northwestern portion of the AG within the offshore territorial waters of Saudi Arabia at 65 km and 50 km from the main coastline, respectively (Fig. 9-12). Both islands are low and flat with wide sand beach platform, supported by two spines of underlying beach rock and are ~40 km away from each other. Both islands exhibit coral sand soils augmented by vegetation debris and bird guano and have no fresh water. Moreover, they both sit on the southern margin of a shallow reef flat and are characterized by extensively exposed beach rocks and storm berm and serve as major breeding areas for turtles and birds.

Figure 9-12: Satellite image base map showing the location of Karan Is. and Jana Is. (pointed by yellow arrows) in the Saudi waters of the AG. White circles represent the other four offshore islands in the Saudi waters. Left bottom inset is map of the whole AG.

An imputation algorithm using `imputeTS` package in R statistical software was used to replace the missing values in the NDVI time series. The imputation procedure yielded 33% and 35% of the missing monthly NDVI for Karan Is. and Jana Is., respectively (Fig. 9-13). The NDVI patterns showed a strong seasonal signal with higher NDVI during the winter months (December, January, February - DJF) and low NDVI during the rest of the year. The highest NDVI (0.468) was recorded on Jana Is. in February 2007 followed on the same island in January 2014 (0.452). The same periods also registered high NDVI values on Karan Is. but values were relatively lower than at Jana Is. The NDVI time series for both islands can be grouped into three periods, namely: 2001-2007 — high winter, low summer; 2008-2013 — low winter, low summer; 2014-2018 — irregular high/low winter, low summer. From 2001-2007, the mean NDVI for winter months (DJF) were 0.198 for Karan Is. and 0.224 for Jana Is. while during the rest of the year (March-November) it was 0.08 for Karan Is. and 0.082 for Jana Is. The winter mean NDVI from 2008-2013 decreased (0.098 for Karan Is. and 0.144 for Jana Is.) while for the rest of the year, it also decreased and remained low (0.06 for Karan Is. and 0.07 for Jana Is.). During the period 2014-2018, the winter mean NDVI slightly increased (0.158 for Karan Is. and 0.178 for Jana Is.) but remained lower than the 2001-2007 period. The mean NDVI for the rest of the months in 2014-2018 were still low at 0.071 and 0.082 for Karan Is. and Jana Is., respectively.

Using the time series analysis in R statistical software, the components of the NDVI time series were decomposed into the seasonal, trend, and irregular components. Figure 9-13 also shows the trend component of the NDVI time series for Karan Is. and Jana Is. The trend components clearly showed the reduction of NDVI for both islands from 2008-2013 and a subsequent irregular NDVI increase in the succeeding recent years. The reduction was more pronounced on Karan Is.

during that period. There were five sharp dips in the winter NDVI of the two islands, particularly in 2000, 2008, 2011, 2012, and 2018.

Figure 9-13: Observed and imputed monthly NDVI values for Karan Is. (top) and Jana Is. (bottom) from January 1999 to December 2018, as well as the trend components of NDVI time series of Karan Is. (top) and Jana Is. (bottom) from January 1999 to December 2018. The seasonal and irregular components were removed from the time series.

Seasonal fluctuations of NDVI indicate the role of winter (December to March) rainfall dynamics that tend to promote the growth of plants and thereby increase the NDVI during these months. Rainfall during the winter months is the main source of freshwater for the plants because rainfall is essentially confined to this period and zero precipitation falls during the summer months. It is identified the drivers of rainfall events during the winter months as being: (1) cyclones from the Mediterranean Sea, (2) thermal convection cells, (3) the formation of new cyclonic depressions in front of the Zagros Mountains above Iraq and eastern Iran, and (4) currents from equatorial areas in Sudan and Ethiopia. The mean of the observed total rainfall data among the five meteorological stations along the Eastern Province of Saudi Arabia (Dhahran, Dammam, Al-Ahsa, Qaysumah, Hafr al-Batin) from January 1991 to December 2017 (Fig. 9-14) showed the seasonal high winter month rains lowering to bare toward summer (data source: General Authority for Statistics-KSA).

Figure 9-14: Bar plot shows the mean of monthly rainfall data from five meteorological stations along Saudi Arabia's Eastern Province from January 1991 to December 2017 (Qaysumah, Hafr Al-Batin, Dhahran, Dammam, Al-Ahsa) (Data Source: General Authority for Statistics-Saudi Arabia Annual Yearbook, General Authority for Meteorology and Environmental Protection, NB: no rainfall data available for 2003 and 2018-2019).

In Fig. 9-15, over the past 20 years based on the Oceanic Niño Index (ONI), three strong La Niña events were recorded, namely, 1999-2000, 2007-2008, and 2010-2011 (pointed by red arrows), two moderate La Niña in 2011-2012, 2017-2018, and weak La Niña in 2000-2001, 2005-2006, 2008-2009, and 2016-2017. The NDVI values were adjusted (times 10) for better presentation. Both strong and weak La Niña events coincided with sharp dips in winter NDVI values on Karan Is. and Jana Is. in 2000, 2008, 2011, 2012, and 2018. For the weak La Niña years, NDVI values burst occasionally after high precipitation events, such as in November 2000 and 2013 (pointed by black arrows). The 6-year low NDVI from 2008 to 2013 also coincided with a series of strong, moderate, and weak La Niña, which was briefly interrupted by a strong El Niño in 2009-2010. It is worth noting that since 2015, the NDVI values stayed in low values, regardless of a strong El Niño occurring during 2015-2016, until the rejuvenation by the end of 2018. This may due to the impact of recent accelerated warming in the MENA region (years indicated by blue line). Teleconnections of regional and global events such as the ENSO and IOD indices are known to influence the variability in the meteorological rainfall patterns in the region. Athar (2015) showed that rainfall records at the weather stations at northern Saudi Arabia (Al-Jouf, Wejh, Riyadh old, Yenbo and Jiddah) have rainfall amounts better correlated with the IOD and ENSO indices (i.e., higher ENSO means higher rainfall while La Niña periods mean lower rainfall). Abid et al. (2016) also reported that there is a statistically significant correlation between the Niño3.4 index and rainfall in the northeastern region of the Arabian Peninsula, which means that El Niño increases and La Niña decreases the rainfall in the region.

Figure 9-15: Bar plot shows the Oceanic Niño Index (ONI), normalized rainfall monthly anomalies, scaled (times 10) NDVI monthly anomalies for Jana Is. and Kara Is. for the period received most rainfall (November to February) for each year (e.g., November 1999 - February 2000) from 1999 until 2018 (Data source: NOAA National Weather Service, Climate Prediction Center, https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php).

9.3.3 The review of EO applications in monitoring *Posidonia oceanica* as the major the Mediterranean seagrass habitats

The EO provides seagrass datasets at regional/global scale, which can support resource management, strengthen decision-making, and facilitate tracking of progress towards global conservation targets set by multilateral environmental agreements, including: 1) the Aichi Biodiversity Targets of the United Nations' (UN's) Strategic Plan for Biodiversity 2011–2020; 2) the Ramsar Convention; 3) the Sustainable Development Goals (SDG) of the UN's 2030 Agenda for Sustainable Development—particularly Goal 14: “Conserve and sustainably use the oceans, seas and marine resources for sustainable development” of the UN SDG 2030.

In addition, seagrass habitats, such as *Posidonia oceanica*, are protected at the regional/continental scales through legislation. For example, *P. oceanica* species is protected by legislation under the EU Habitat Directive (92/43/CEE), the Bern (Annex II, Strictly Protected Flora Species) and the Barcelona (dedicated Action Plan under the “Protocol concerning Specially Protected Areas and Biological Diversity in the Mediterranean”) Conventions as well as other legislations at a national level. Furthermore, according to the Marine Strategy Framework Directive (MSFD; 2008/56/EC), *P. oceanica* is selected as a representative species of the angiosperm quality elements for the Mediterranean marine environment and a ‘Good Environmental Status’ shall be achieved by all Member States regarding the angiosperm habitats.

Posidonia Oceanica detection with satellite images comprises one of the most popular methods to detect, map and monitor seagrass ecosystems over large areas. Spectral imagery obtained from sensors on board satellites is preferable in data collection due to its time- and cost-effectiveness over any other surveying methods. Stable revisits to the same locations by the satellites can be used to monitor and characterize the *P. oceanica* change detection analysis. Moreover, recent advances of image-processing and classification algorithms with improved computational power have opened the new era of new quantitative and machine-learning techniques to achieve state-of-art results in terms of cost, effectiveness, independence, scale and accuracy [378].

Several studies have utilized satellite imagery to monitor and study the distribution of *P. oceanica* in the Mediterranean seagrass ecosystems [379]–[389]. The most common satellite imagery for the seagrass mapping are Landsat, IKONOS, Quickbird, WorldView-2 and Sentinel-2, as well as MIVIS, KOMPSAT-2 and PlanetScope CubeSat. The meadows of *P. oceanica* habitats to occupy depths of up to 20 m were investigated with the SPOT5 imagery in the Laganas

Bay of Zakynthos Island, Greece with an accuracy between 73% to 96% (Pasqualini et al., 2005). Fornes et al. (2006) used an IKONOS image to map *P. oceanica* habitats up to 15 m of depth in the Balearic Islands, SW Mallorca, Spain with an accuracy of 92%. The usage of multispectral and high-resolution Quickbird imagery was processed to map *P. oceanica* habitats in the middle Tyrrhenian Sea, Italy (Borfecchia et al., 2013). The artificial neural network (ANN) algorithm was implemented to achieve an overall accuracy of 84%. The *P. oceanica* beds that ranges with a depth between 0 to 10m, were studied by Matta et al. (2014) using MIVIS, KOMPSAT-2 and RapidEye imagery to map its distribution in the Gulf of Oristano, Italy with an overall accuracy of 84%. Recently, a team from German Aerospace Center (DLR) have published numerous studies that utilized multiple sources of satellite imagery (CubeSat, Sentinel-2, RapidEye) to map the *P. oceanica* seagrass habitats in the Greece part of Aegean Sea and Ionian Sea [385]–[389]. A variety of machine learning algorithms such as Support Vector Machine (SVM), Random Forest, Maximum Likelihood, Classification And Regression Trees (CART) were selected and evaluated to monitor the seagrass changes and the accuracy was ranged between 68.1% to 99.5%. The differences between medium – resolution satellite images (Sentinel-2 and Landsat-8 OLI) and high-resolution images (MIVIS and WorldView-2) in terms of spatial accuracy to map *P. oceanica* habitats were also evaluated in the Marine Protected Areas of Capo Rizzuto, Southern Ionian Sea, Italy [382]. The results showed high resolution satellite and airborne images are more accurate and thus more effective than medium resolution images in obtaining mapping products, mapping elements to local spatial scales, and estimating parameters such as habitat coverage, extension, produced biomass. While the Sentinel-2 and Landsat-8 OLI imagery are still valid for mapping on a regional scale. In addition, Borfecchia et al., (2019) also demonstrated the improvement of Landsat-8 OLI through introduction of new coastal band to produce more reliable distribution

maps of *P. oceanica* leaf area index (LAI) and seabed substrates in the middle Tyrrhenian coast, Italy. Besides, multiple satellite derived products, including sea surface temperature (SST), significant wave height (SWH), sea level anomalies (SLA) and other meteorological data are used to investigate recent large scale environmental changes in the Mediterranean Sea and their potential impacts on *P. oceanica* (Stramska and Aniskiewicz, 2019). The aforementioned studies were local Mediterranean region and more advances of satellite remote sensing technology for *P. oceanica* monitoring are expected since their publication. Table 9-1 lists all the discussed studies in the article which relied on satellite imagery data to implement *P. oceanica* detection.

The Fig. 9-16 shows the distribution map of *P. oceanica* along the Mediterranean coast of Egypt. It demonstrates higher concentration of *P. oceanica* in the western coast (Matrouh and Alexandria) than that of eastern coast (Port Said). This may be due to the natural environment or anthropic pressure, but limited studies have been undertaken. Besides, no conservation program to preserve *P. oceanica* and coastal habitat in Egypt is implemented so far. Establishment of protection sites for this population in Egypt is a must. .

Figure 9-16: Bar The distribution of *Posidonia Oceanica* along the Mediterranean coast of Egypt. Source: <https://www.emodnet-seabedhabitats.eu/>

Table 9-1: List of *Posidonia Oceanica* detection approaches based on satellite imagery data

Author	Location	Satellite Data	Method	Accuracy
Pasqualini et al., 2005	Zakynthos Island, Greece	SPOT 5	PCA, Supervised Classifier	73% to 96%
Fornes et al., 2006	Balearic Islands, SW Mallorca, Spain	IKONOS Imager	Supervised Classifier	92%
Borfecchia et al., 2013	Middle Tyrrhenian Sea, Italy	Quickbird	ANN	84%
Matta et al., 2014	Gulf of Oristano, Italy	MIVIS, KOMPSAT-2, RapidEye	Vegetation Maps	84%
Traganos et al., 2017	Thermaikos Gulf, Greece	PlanetScope CubeSat	SVM	68.1%
Traganos and Reinartz, 2018a	Thermaikos Gulf, Greece	RapidEye	Random Forest	73.5% to 82%
Traganos and Reinartz, 2018b	Thermaikos Gulf, Greece	Sentinel-2	Maximum Likelihood, SVM, Random Forest	86%
Traganos and Reinartz, 2018c	Thermaikos Gulf, Greece	Sentinel-2	Semi-analytical inversion method, SVM	95.3% and 99.5%
Traganos et al., 2018	Ionian Sea and Greek part of the Aegean Sea	Sentinel-2	CART, SVM, Random Forest	72%
Dattola et al., 2018	Marine Protected Areas of Capo Rizzuto, Southern Ionian Sea, Italy	Sentinel 2, Landsat 8 OLI, MIVIS, WorldView-2	N/A	N/A
Borfecchia et al., 2019	Middle Tyrrhenian Sea, Italy	Landsat 8 OLI	Leaf area index (LAI) Modelling	N/A

10 Conclusion

The 2030 Agenda for Sustainable Development emphasizes that the implementation of policies and the decision-making process should be based on scientific evidence. Continuous, timely data relevant to SDGs needs to be collected and analyzed to generate reliable, high-quality information to assist UN member states in making informed policies and decisions.

This dissertation presents case studies highlighting the use of EO Data to evaluate 14 indicators in four SDGs, focusing on challenges in aspects of data, methodological models, and the decision-making process. Below is a summary of the four SDGs addressed in the dissertation.

(1) For SDG 6, the case study employ multiple approaches including harmonic, time series and correlational analysis to assess and evaluate the indicators SDG 6.4.1(water-use efficiency) , SDG 6.4.2 (water stress levels) and SDG 6.6.1 (changes of water-related ecosystem) in the Nile watershed countries. The results show the changing trend of multiple hydrological variables and their interactions, as well as spatial and temporal water recharge pattern in the Nile watershed. The study calls for rigorous implementation of water resource management (SDG 6.5.1) and transboundary cooperation (SDG 6.5.2).

(2) For SDG 11, this dissertation firstly puts forward a method to calculate indicator SDG 11.a.1 (urban and regional development plans), using a contemporary deep-learning classifier - Fully Convolution Neural Networks (FCNN) was trained on top of the cloud platform to classify the percentage of impervious surface areas in the selected cities in the Nile basin. Clear urban expansions are observed in the developed regions while the classifier is limited to identify

slums/rural areas and their changes (SDG 11.1.1), therefore it suggests more specialized financial and technical support to the least developed countries to improve the slums monitoring to have sustainable, resilient and resource efficient buildings (SDG 11.c.1). Secondly, this dissertation makes use of the Random Decision Forest (RDF) model to convert satellite-based AOD and other meteorological parameters to predict PM10 (SDG 11.6.2). It also shows annual population weighted and geographic mean PM2.5 of the entire Egypt during 1998 to 2016. These cases provide new methods to evaluate SDG 11 indicators at the global and regional scale.

(2) For SDG 14, the dissertation presents case studies that comprehensively evaluate the eutrophication (aka. algal blooms) (SDG 14.1.1) in the waters of the Red Sea using a wide range of oceanographical and meteorological datasets, including Chl-a concentrations, sea surface temperature (SST), sea surface height (SSH), mixed layer depth (MLD), ocean current velocity and aerosol optical depth (AOD) obtained from different sensors and models. The study initially detects an anomalously high algal bloom event and proposes statistical methods for evaluating the typical marine ecosystems in the Red Sea waters. The following research investigates various factors that normally regulate nutrients supply in the Red Sea. It also finds the ocean color data has quality issue of temporal inconsistencies due to the inclusion of different sensors and the study addresses those issues in our analysis with a valid interpretation of these complex relationships.

(5) For SDG 15, this dissertation takes proportion of Middle East and North African (MENA) region for terrestrial and coastal biodiversity as research objects. The harmonic analysis model is used for comparison with observation data to reveal changing trends of vegetation and forests within the MENA region (SDG 15.1.1 forest monitoring). For the Saudi Arabia region, the soil moisture products, vegetation and precipitation-based products are assessed to monitor and

predict the distribution of different vegetation types (SDG 15.2.1 sustainable forest management). This dissertation also find out the misclassification of mangrove forest from the USGS dataset in this region. Therefore, the study provides a new method related to evaluating SDG 15.5.1 (Red List Index), to identify and analyze the endangered mangrove forests distribution via a submerged mangrove recognition index (SMRI) and Normalized Difference Vegetation Index (NDVI) in the Abu Ali Island, Saudi Arabia's Jubail Conservation as indicated by SDG 15.1.2 (proportion of protected areas). Additionally, the dissertation also summarizes the other SDG researches the author anticipated, ranging from air pollutants, dust storms and precipitation, El Niño, oil spill modeling and marine habitat protections.

The case studies mentioned in the dissertation in terms of EO supporting SDGs have been summarized in the Table 10.1:

Table 10-1: List of Cases on EO Data for SDGs

Indicator	Name of Case	EO and Model Data	Method	Decision Support
SDG 3.9.1	Assessing Air Pollution Factors in the MENA Countries	MODIS, TROPOMI, AERONET	Deep Neural Network	Provide data support for the air pollution management at the MENA countries
SDG 6.5.2	Assessing Water Resources in the Nile Watershed Countries	FLDAS, GRACE, CHIRPS	Harmonic Analysis, Correlative Analysis	Reveal the groundwater recharge patterns for effective water resources management in the Nile Basin Countries
SDG 11.a.1	Monitoring Urban Impervious Surface in the Nile Watershed Countries	NLCD, Landsat 8	Fully Convolution Neural Network	Decision support is provided for the comprehensive evaluation of sustainable urban development at the Nile Basin Countries
SDG 11.6.2	Monitoring Air Quality in the Greater Delta Region in Egypt	AERONET, MERRA-2, MODIS	Random Decision Forest	Provide new methods to estimate and Control PM ₁₀ in Cairo Region
SDG 13.3.1	Intercomparison Between Net Primary Productivity Models in the Red Sea	VGPM, Eppley, CBPM, ENSO, GlobColour	Multi-linear Regression, Correlative Analysis	Provide model advices to study the ocean primary production in response to climate variation in the Red Sea
SDG 13.3.1	Studying the Impacts of Aerosols on the Sierra Nevada Glacier in California	GLDAS, Landsat	Time Series Analysis, HYSPLIT	Provide case study of dust deposition altering

				surface albedo and its impact on temperature
SDG 13.3.1	Monitoring Dust and Rainfall Interactions in the Egypt	MODIS, NMMB/BSC, AERONET, NOAA-18	HYSPLIT	Provide case study of dust's impact on altering precipitation
SDG 14.1.1	Investigating An Algal Blooms Event in the Red Sea	MODIS, OC-CCI, GHR SST, HYCOM	Time Series Analysis, Correlative Analysis	Provide case study of irregular algal blooms in the oligotrophic waters
SDG 14.1.1	Studying Factors Regulating Phytoplankton Growth in the Red Sea	MODIS, OC-CCI, GHR SST, CALIOP	Time Series Analysis, Correlative Analysis	Provide decision support for fishery and resources management advices in the Red Sea
SDG 14.5.1	Monitoring Vegetation Changes in Sea Turtle Nesting Islands	MODIS, Landsat 8	NDVI, ENSO, Time Series Analysis	Provide protection advices to the sea turtle nesting islands
SDG 14.5.1	Oil Spill Modelling in the Western Gulf Region	HYCOM, NCEP	GNOME Model	Provide simulation cases study of oil spills and mitigation advices
SDG 15.5.1	Monitoring Mangrove Changes in the Western Gulf Region	Landsat 5,7,8, WorldView 2	CART, NDVI, SMRI	Provide data and model advices for effective mangrove protection in the western Gulf area
SDG 15.1.1	Studying Land Cover Changes in the MENA Region	MODIS	EVI, Harmonic Analysis	Provide methods and data toward sustainable land management in the MENA countries

The world must achieve the SDGs, which is extremely challenging in reality within next 10 years. We still face many challenges in leveraging EO Data to support SDGs. The cases presented in this report aim to improve scientific methods and explore new and innovative technologies to support sustainable development. By relying on EO Data and artificial intelligence (AI) technology and analytical tools, as well as with the cloud data storage and computing platforms, the researchers are benefited to collect and analyze data more efficiently, make up for the data gaps in current SDG indicator evaluations, increase the spatiotemporal resolution and accuracy of data, and provide new ways to evaluate and monitor more indicators. In conclusion, the studies in this dissertation successfully address some key environmental issues with its goal of finding rigorous, reliable, scientific, and user-friendly methodologies to facilitate AI-driven and cloud computing-integrated investigations to support the implementation of SDG by 2030.

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