

**Statistical Modeling of the Red Sea Chlorophyll  
Concentration and Application to the ERSEM  
Ecological Model**

Thesis by  
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# Chapter 1

## Introduction and Motivation

### 1.1 Phytoplankton and the Red Sea Biology: Importance, Impact, Large-Scale Features, and Applications

#### 1.1.1 The Importance of Phytoplankton

Phytoplankton are unicellular, free-floating, photosynthetic algae that live in the upper layers of bodies of water (ocean, lakes, rivers or ponds). There exists a wide diversity of phytoplankton species. To this date, about 5000 of them have been identified [Tett and Barton, 1995]. Phytoplankton are also highly variable in sizes, ranging from 0.2m for cyanobacteria to 200m for the largest species of diatom [Pal, 2014]. In the oceans, phytoplankton live in the surface layer where there is enough sunlight for photosynthesis.

Phytoplankton plays a fundamental role for the ocean ecology. It is the basis of the marine food web and traps most of the energy used by pelagic ecosystems [Pal, 2014]. Zooplankton graze phytoplankton which are then consumed by higher trophic levels. It has been estimated that nearly 98% of the ocean primary productivity comes

from phytoplankton [Pal, 2014]. Phytoplankton are also responsible for maintaining the dissolved oxygen level necessary for other species to survive. However, high phytoplankton concentration also impact their environment by creating dead zones when they die and are decomposed by bacteria, consuming all the available oxygen [Pal, 2014]. Due to the rapid growth of phytoplankton, it responds very well to changes in its environment, making it a key parameter to monitor water quality [Wu et al., 2014].

Phytoplankton place at the bottom of the marine food chain makes it is an important factor for fisheries. Productive fishing zones like the regions in the Arabian seas, Californian coast, north-west African coast and Chilean coast are explained by the upwelling of cold nutrient rich water favourable to phytoplankton growth. On the other hand, the El-Nino phenomenon creates less favourable conditions for phytoplankton in the Eastern Pacific, resulting in a dramatic reduction of fish catches of fisheries in the western coast of South America [Robinson, 2010]. Remotely-sensed chlorophyll data have been routinely used since the last decade to help fisheries predict the timing of phytoplankton blooms [Robinson, 2010]

Phytoplankton also plays the role of a biological CO<sub>2</sub> pump and strongly impact the Earth climate. During photosynthesis, phytoplankton captures carbon and releases oxygen. A part of this organic material stays in the food web, either transmitted to higher trophic level, or degraded by bacteria. Another part, however, sinks to the bottom of the ocean and sediments. It is estimated that phytoplankton accounts for 48% of Earth carbon fixation [Pal, 2014].

### 1.1.2 Red Sea Large-Scale Phytoplankton Dynamics

Typical tropical seas (TTS), like the Red Sea, are characterized by a highly stratified structure, where warm nutrient-depleted surface water is separated from the cold nutrient-rich deep water by a steep gradient of temperature zone called pycnocline. The pycnocline acts as barrier that limits the upward nutrients flow [Mann and Lazier, 2006]. As a result, TTS are oligotrophic and have low chlorophyll concentrations. Until recently, marine biologists have thought that tropical and subtropical seas have therefore a very low productivity. However, recent investigations have contested this idea and shown that different upwelling mechanisms exist that bring new nutrients to the surface water [Mann and Lazier, 2006].

Despite being an oligotrophic and challenging environments for marine life, the Red Sea presents a surprisingly rich and diverse ecosystem [Raitsos et al., 2011], and an very developed coral reef system [Racault et al., 2015]. The source of nutrient for sustaining such a developed ecosystem is not well understood yet, but the interaction with the open sea through the mesoscale eddies is believed to play an important role [Raitsos et al., 2013].

Remotely-sensed data show an important seasonality of the Red Sea chlorophyll concentration, that has been linked to winter deep mixing, and the inversion of the wind direction in the southern Red Sea that enhances the intrusion of nutrient rich Gulf of Aden water [Raitsos et al., 2013]. Despite this strong seasonality, there is a large interannual variability caused by the unpredictable occurrence of large phytoplanktonic blooms. Diverse causes have been hypothesized for these blooms such as wind-induced mixing, eddies or dust storms carrying nutrients [Raitsos et al., 2013].

Although the Red Sea environment is relatively preserved, it is pressured by human activities. An abrupt increase of temperature has occurred in the last decade

that threatens the fragile coral reef system [Raitsos 2011]. Moreover, the increasing urbanization and fishing activity contribute to the fragilization of this unique ecosystem [Acker et al., 2008].

Because of the lack of in-situ data, the large-scale phytoplankton dynamics of the Red Sea remain largely unknown [Raitsos et al., 2013, Triantafyllou et al., 2014]. However, in recent studies, remotely-sensed data and computer simulations have been used to improve our knowledge of the biology of this region. The Red Sea is deficient in the major nutrients [Weikert, 1987], and the only significant input of water comes from the Gulf of Aden. This explains a general increase of chlorophyll concentration from north to south [Raitsos et al., 2013]. The lowest concentration is found in the northern central Red Sea. The Red Sea also displays a distinct seasonality, with a peak in concentration during the winter. A weak summer peak is also observed around July, everywhere except in the northernmost region [Raitsos et al., 2013]. Despite this regularity, a strong interannual variability is observed, with blooms that can reach mesotrophic concentration levels [Raitsos et al., 2013]. According to [Triantafyllou et al., 2014], the variations in the Red Sea ecology are mainly driven by circulation. In the rest of this section, we explore some of the mechanisms that have been linked to the major features of chlorophyll concentration.

The exchange of water with the nutrient-rich Gulf of Aden is a major driving mechanism for the whole Red Sea [Triantafyllou et al., 2014]. It is the most important source of nutrient. The maximum chlorophyll concentration observed in the southern Red Sea during winter is attributed to wind-driven water intrusion [Raitsos et al., 2013]. In Summer, this exchange of water is believed to be the only significant source of nutrients for the whole Red Sea. The influence of the water intrusion weakens as the latitude increases, explaining the low concentration in the northern half of the Red Sea [Raitsos et al., 2013].



Deep convection also plays an important role in allowing nutrient-rich deep water to mix with water of the euphotic zone. The vertical mixing is the most vigorous in the northern extremity of the Red Sea during the winter. This explains its higher chlorophyll concentration compared to the north-central Red Sea, a region of weak mixing [Raitsos et al., 2013]. The northern Red Sea mixing is believed to be driven by wind [Raitsos et al., 2013].

The Red Sea circulation is strongly influenced by mesoscale eddies [Yao et al., 2014, Zhan et al., 2014] that could impact primary production [Zhai and Bower, 2013]. In particular, the anti-cyclonic eddy in the central Red Sea is believed to control the June concentration peak and the summer productivity of this region, by transporting nutrients and/or phytoplankton from the adjacent coral reefs [Raitsos et al., 2013]. In the northern Red Sea, a cold-core eddy plays a role in enhancing the vertical mixing in that region [Raitsos et al., 2013].

Aerial depositions of dust could also be an important input of nutrient for the Red Sea, but it has been largely left unexplored [Triantafyllou et al., 2014]. [Raitsos et al., 2013] noticed for example that sand storms in the Red Sea most frequently happen in June and July, which coincides with the summer chlorophyll peak. Finally, climate mode indices have been shown to be strongly correlated with air-sea heat exchanges in the Red Sea [Abualnaja et al., 2015], and might therefore influence its biology.

## 1.2 Remotely-Sensed Chlorophyll Data: Relevance and Challenges for the Red Sea

### 1.2.1 Measuring Chlorophyll Concentration

Chlorophyll is a molecule present in algae, phytoplankton and plants that is critical for photosynthesis. Chlorophyll is a poor absorber of green light, and is responsible for the coloration of plants. When phytoplankton are present in high concentrations, the water also takes a detectable green coloration (it can also take a red or blue coloration depending on the type of phytoplankton dominating) [Robinson, 2010]. This offers a way to estimate the chlorophyll concentration of the water.

However, in-situ measurements of chlorophyll are expensive and have limited temporal and spatial coverage [Robinson, 2010]. In-situ measurement of chlorophyll concentration can be gathered through scientific cruises, buoy stations or gliders (unmanned submarines). These methods are expensive to deploy and therefore the coverage is limited. Political issues, like in the Red Sea, is also a barrier to in-situ measurements.

Satellite measurements of chlorophyll provide excellent proxies for phytoplankton concentrations with a good temporal and spatial coverage [Robinson, 2010]. The SeaWiFS, MODIS and MERIS missions have provided an uninterrupted coverage of the world since 1997. High-resolution maps of daily chlorophyll concentration are freely accessible to the scientific community. Despite some limitations, like missing data due to cloud coverage and sunglint, or problematic values in coastal areas, remotely-sensed chlorophyll concentration are used intensively by the scientific community. In regions, like in the Red Sea, where little in-situ measurements are available [Raitsos et al., 2013], it is often the most important data source.

### 1.2.2 Limitation of Remotely-Sensed Chlorophyll Data

The performance of remotely-sensed chlorophyll data products such as MODIS and SeaWiFS in the Red Sea is comparable with that of the rest of the world for case I waters (open sea) [Brewin et al., 2013]. However, the data present a huge amount of missing values because of persistent clouds, sun-glint and sensor saturation [Racault et al., 2015]. This problem is particularly acute during the summer in the southern Red Sea where the data coverage is 0% [Racault et al., 2015].

Chlorophyll concentration estimation in optically complex case II waters is a recurrent problem in this data that particularly affects the southern Red Sea. In this region, the remotely sensed chlorophyll data could be overestimated [Raitsos et al., 2013]. However, all high values are not necessarily bad, as highly productive coral reefs are also present in this region [Raitsos et al., 2013]. However, these values have not been validated yet, due to the lack of in situ data [Raitsos et al., 2013].

One solution to missing and bad values is to use a data filling algorithm, of which one of the most popular is DINEOF. It is an EOF based data filling approach introduced by [Beckers and Rixen, 2003]. It has been used for multivariate reconstruction of SST fields using chlorophyll data in [Alvera-Azcarate et al., 2007]. In [Sirjacobs et al., 2011], it has been employed to fill chlorophyll data with 70% of missing values. [Taylor et al., 2013] has compared DINEOF with other EOF-based reconstruction algorithms, showing that the former is the best method for data filling. DINEOF has been employed in several other chlorophyll studies [Miles and He, 2010, Waite and Mueter, 2013].

The OC-CCI is a new chlorophyll data product that considerably increases the Red Sea coverage. It merges the data from sensors SeaWiFS, MODIS and MERIS. Overall, it achieves a 75-80% coverage in the entire Red Sea basin against 50-65% for

a single sensor [Racault et al., 2015]. This is mostly due to the use of the POLYMER algorithm [Steinmetz et al., 2011] that allows to exploit MERIS data collected during hazy conditions. However, this new dataset has not been fully explored to revisit the assumptions made on the large-scale Red Sea phytoplankton productivity.

## **1.3 Modeling Chlorophyll: Data-Driven and Physics-Driven Approaches and Applications**

### **1.3.1 Why Modeling Chlorophyll?**

Models can be useful to identify causes behind the chlorophyll patterns we observe in the Red Sea. Many hypotheses have been made about the drivers of chlorophyll concentration in this region, but some of them have not been yet investigated through models. The role played by the exchange of water with the Gulf of Aden and winter overturning in the northern Red Sea have been successfully modeled a 3D coupled ecological model [Triantafyllou et al., 2014]. However, the interaction between the open sea and coral reefs and the role of sand storms has not been investigated. Models, can also be helpful in discovering new dynamics affecting the chlorophyll concentration. In particular, the interaction between the productivity level of the different regions of the Red Sea has not been studied yet.

Model predictions for chlorophyll concentration also have practical applications. Phytoplankton blooms can be harmful to humans and marine life and are closely monitored in many regions of the world [Pettersson and Pozdniakov, 2013]. In the Red Sea, where tourism and aquaculture are developing it is likely to become a concern too. Phytoplankton is also directly, and indirectly through zooplankton, the cause of microfouling that affects desalination plants. In 2008-2009, a red tide

forced desalination plants along the Gulf of Oman and the Persian Gulf to close [Richlen et al., 2010].

### 1.3.2 Data-Driven Approaches

On the other hand, data-driven statistical models are relatively easier to apply. They are relevant when the phenomenon producing the data is very complex or poorly known. They have been applied to predict chlorophyll concentration, mostly in small regions that have complex dynamics (see ??). Some statistical models, such as linear regression, GAM or tree regression have the advantage of being easy to interpret, and can be used to understand the dynamics driving the chlorophyll concentration.

#### Machine Learning Algorithms

Machine learning algorithms, in particular Artificial Neural Networks have been very popular for forecasting regional chlorophyll concentration in regions with very complex dynamics. In such regions, deterministic ecological models are usually too complicated to use and less efficient than data-driven approaches. Neural networks have been widely used for forecasting chlorophyll concentration in fresh as well as in coastal water systems. In [Jeong et al., 2006], temporal recurrent recursive neural network have been used and found superior to traditional time-series model for daily forecasts of chlorophyll concentration. [Wang and Yang, 2013] also used recurrent neural networks for daily chlorophyll forecasting in Lake Taihu, China. [Mulia et al., 2013] combined Neural Network and genetic algorithm for nowcasting and forecasting of the chlorophyll concentration up to 14 days ahead, in the tidal dominated coast of Singapore. Finally, [Lee et al., 2003] used neural networks for the forecasting of algal bloom with one and two weeks lags in the coastal waters of Hong-Kong.

## Geostatistics

Phenomena such as propagation and diffusion play a key role in the chlorophyll spatial concentration, but are difficult to represent without spatial modeling. There is also a difference in the chlorophyll patterns of different regions of the Red Sea, in particular between the nutrient rich southern Red Sea and the oligotrophic northern Red Sea, and between the open ocean and the coastal waters [Raitsos et al., 2013]. There is however no clear cut division between regions with different pattern, making it difficult to divide the Red Sea into regions. Finally we can expect the different regions of the Red Sea to interact. A model is therefore needed to account for the spatial and temporal interaction of the chlorophyll.

Classical geostatistics is the most widely used spatial statistical model. It models spatial data as the realization of a two-dimensional Gaussian process, of which one can estimate the parameters. Geostatistics can be easily extended to spatio-temporal datasets. Many flexible ways of constructing space-time covariance functions for these models have been proposed recently. Space-time geostatistics has been applied to many environmental studies, but not to chlorophyll data yet.

The theory of space-time geostatistics is closely related to that of spatial statistics. In fact, the time dimension is an additional dimension. However, the time and space interactions derive from physical interaction, and must be taken into account in the definition of the covariance function [Gneiting and Guttorp, 2010]. Some space-time can actually be derived from a physical formulation, such as the frozen fields [Gneiting and Guttorp, 2010], or SDEs [Brown et al., 2000, North et al., 2011].

Despite their theoretical interest, physically-derived space-time covariance functions have been little used [Gneiting and Guttorp, 2010]. More popular, are covariance functions built from simple building blocks. One of the most simple types are sep-

arable covariance functions, that are the product of a spatial covariance function and temporal covariance function. They are computationally efficient, but are enable to represent space-time interactions [Cressie and Huang, 1999, Stein, 2005], making them of limited use for modeling physical systems. The Cressie, Huang spectral characterization theorem of space-time covariance functions has opened the door to wider ways of constructing them. For example, [Gneiting, 2002] presented a simple criterion that allows their construction from a very large class of models.

Space-time geostatistical models have been use in a variety of applications. [Hohn et al., 1993] used it for forecast the outbreaks of an invasive specie. They have been used in meteorology to model temperature fields [Handcock and Wallis, 1994, North et al., 2011] or wind [Cressie and Huang, 1999, Gneiting, 2002], and in environmental studies for ground-level ozone concentration. [Gneiting et al., 2007, Gneiting and Guttorp, 2010] present recent more details on the theory of space-time geostatistics and its applications.

### 1.3.3 Deterministic Models

Ecological ordinary differential equation (ODE) deterministic models are a popular way to model marine ecology. Such models can be as simple as the nutrient-phytoplankton-zooplankton (NPZ) model that only has three variables representing two trophic levels, or as complex as the European regional seas ecosystem model (ERSEM) that has dozens of variables and represents many ecological, biological and chemical interactions. Such a model has been coupled to the MITgcm circulation model used to simulate the Red Sea ecology [Triantafyllou et al., 2014]. However the complexity of these models makes them difficult to parametrize correctly if not enough data is available, which is usually the case [Anderson, 2005].

## Ecological Models

### Data Assimilation

Data assimilation schemes are used to improve the simulations of ecological dynamics models by correcting their predictions with observations. The most common use of data assimilation is to improve the forecast of an ecological model, by providing it with an estimated initial state. Such prediction capabilities are deployed in operational expert systems, for example to study the impact of human activities on the ecosystem of the Gulf of Pagasitikos [Korres et al., 2012]. The deployment of such a forecasting system in the Red Sea is currently under study [Triantafyllou et al., 2014]. Hindcasting, the estimation of unobserved variables, is another application of assimilation scheme. [Ciavatta et al., 2011] showed that they could improve the seasonal and annual hindcast of non assimilated biogeochemical properties in a shelf area (Western English Channel). Finally, data assimilation can be used for reanalysis, to provide estimates of past years biogeochemical variables [Fontana et al., 2013].

In the marine ecology modeling community, two assimilation schemes have been widely used: the Ensemble Kalman filters (EnKF) and the Singular Evolutive Extended Kalman filter (SEIK). The Stochastic EnKF, a Monte-Carlo approximation of the Kalman Filter, has been used in [Ciavatta et al., 2011, Ciavatta et al., 2014]. However, it suffers from sampling errors when the ensemble size is smaller than the number of observations, as is usually the case when assimilating remotely-sensed data. The Singular Evolutive Interpolated Kalman filter (SEIK) is a deterministic version of the EnKF that do not suffer from sampling problems, as it projects the propagated error in a low-dimensional subspace. SEIK has been used by [Triantafyllou et al., 2013, Korres et al., 2012]. SEEK is a reduced order version of the Extended Kalman filter (EK), that is intractable in high-dimensions. Like SEIK, it projects the error co-



variance in a low dimensional space. SEEK has a long history in data assimilation for marine ecology models and is still used in recent studies [Fontana et al., 2013, Korres et al., 2012, Butenschon and Zavatarelli, 2012]. [Korres et al., 2012] shows that SEIK and SEEK are both comparably robust methods for highly non linear systems.

Current assimilation schemes are however affected by problems that have been addressed in the past years. First, biogeochemical variable are usually positive concentration, whereas Kalman filters expect Gaussian variables, and log-transformation can fail at solving this issue [Ciavatta et al., 2011]. However, [Fontana et al., 2013] has successfully introduced Gaussian anamorphosis transformations to solve this issue. Second, ecological blooms are intermittent and highly nonlinear, conditions that are challenging for assimilation schemes [Triantafyllou et al., 2013, Korres et al., 2012]. Third, SEIK and SEEK both project the error covariance in a subspace, resulting in an underestimation of the estimation error. [Butenschon and Zavatarelli, 2012] studied different ways to propagate the error covariance in order to alleviate this issue. Finally, the model error statistics are required by Kalman-derived filters, but are difficult to estimate. [Triantafyllou et al., 2013] proposes to use the  $H_\infty$  method with SEIK in order remove this requirement.

## 1.4 Thesis Objectives





# Chapter 2

## Research Plan

### 2.1 Task 1: Dataset Building and Exploration

#### 2.1.1 Motivation

#### 2.1.2 Open Questions

#### 2.1.3 Method

#### 2.1.4 Expected Outcomes

#### 2.1.5 Accomplished Work and Preliminary Results

### 2.2 Task 2: Forecasting Chlorophyll Concentration in Regional Aggregates

#### 2.2.1 Motivation

#### 2.2.2 Open Questions

#### 2.2.3 Method

#### 2.2.4 Expected Outcomes

#### 2.2.5 Accomplished Work and Preliminary Results

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# APPENDICES

## A Appendix A Title

Detailed experimental procedures, data tables, computer programs, etc. may be placed in appendices. This may be particularly appropriate if the dissertation or thesis includes several published papers.



## B Appendix B Title

Your content goes here.



## C Papers Submitted and Under Preparation

- Author 1 Name, Author 2 Name, and Author 3 Name, “Article Title”, *Submitted to Conference/Journal Name*, further attributes.
- Author 1 Name, Author 2 Name, and Author 3 Name, “Article Title”, *Submitted to Conference/Journal Name*, Mon. Year.