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Fishing from Space: Mackerel fishing in Icelandic waters and correlation with satellite variables

Kristín Ágústsdóttir

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Department of
Physical Geography and Ecosystems Science
Lund University
Sölvegatan 12
S-223 62 Lund
Sweden

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Kristín Ágústsdóttir

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Supervisor:

Jonathan Seaquist

Department of Physical Geography and Ecosystems Science

Lund University

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Abstract

As concentrations of measured CO_2 in the atmosphere reach a record high it is important to attempt all possible efforts to reduce the emissions of greenhouse gases (GHG) in all aspects of industry. The fishing sector contributes 15% of total GHG emission in Iceland, with the majority originating from fishing vessels using fossil fuel. The relationship between catching locations of Atlantic Mackerel (*Scomber scombrus*) in Icelandic waters and satellite remote sensing variables was explored. The aim was to provide information for possible fisheries forecasting, which could facilitate reduced energy consumption in Icelandic fishing vessels. The hypothesis was that satellite variables were a valuable source of information for determining viable fishing grounds in Icelandic waters.

The variables explored were sea surface temperature (SST), chlorophyll (CHL), photosynthetically available radiation (PAR), water leaving radiance (L443) and down welling diffusion attenuation coefficient (kd490). The spatial resolution was about 4.6 km and temporal resolution 1 day. Effects of decreased spatial and temporal resolution were also explored.

Binomial generalized additive models were created to identify the possible relationship with fishing locations represented as absence or presence of mackerel catches. Seven day PAR was the strongest single variable, explaining 47% of deviance, with the spatial variables latitude and longitude incorporated. The most successful multiple variable models included one or seven day averages of PAR and SST and seven day averages of L443, explaining 48% of deviance. Decreasing temporal resolution to 7 days improves the predictive ability of all variables. Decreasing spatial resolution to 3*3 cells does not decrease or increase the predictability to any extent.

In order to estimate the usefulness of global data sets in local situations, a correlation of observed and remotely sensed CHL in Icelandic waters was estimated. Results on a minor sample size revealed a strong significant correlation, suggesting that global datasets were useful in local situations around Iceland.

The satellite variables explored significantly contribute to a model explaining the absence and presences locations for mackerel fishing in Icelandic waters. Mackerel catches were most successful in a temperature range of 7.5°-13°C where there were high amounts of incoming visible solar radiation and intermediate concentration of phytoplankton. Clear waters due to little absorption as well as turbulent water with high scattering also had effects. This suggested that mackerel caught in Icelandic waters was more dependent on visual foraging than previously considered.

Keywords: Physical Geography and Ecosystem Analysis, Sea Surface Temperature, Water Leaving Radiance, Photosynthetically Available Radiation, Downwelling diffuse attenuation coefficient, Chlorophyll, Atlantic Mackerel, Scomber scombrus, Icelandic waters, Satellite variables, Remote sensing

Ágrip [Abstract in Icelandic]

Styrkur CO_2 í andrúmslofti mældist í fyrsta sinn yfir 400 ppm í maí 2013. Með Kyotobókuninni frá 1997 hafa þjóðir heimsins hafa skuldbundið sig til að draga úr losun gróðurhúsalofttegunda. Ísland er þar á meðal. Sjávarútvegurinn leggur til um 15 % af heildarlosun gróðurhúsalofttegunda á Íslandi. Meiri hlutinn kemur til vegna brennslu jarðefnaeldsneytis skipaflotans. Ein af tíu lykilaðgerðum Umhverfis- og auðlindaráðuneytisins til að draga úr losun gróðurhúsalofttegunda er að leita leiða til að draga úr útblæstri íslenska fiskiskipaflotans.

Tengsl milli veiðistaða makríls (*Scomber scombrus*) á Íslandsmiðum og fjarkönnunarganga frá gervitunglum var könnuð. Markmiðið var að afla upplýsinga fyrir mögulegar fiskiveiðispár, sem geta stuðlað að minni orkunotkun fiskiskipa. Tilgátan var sú að fjarkönnunargögn úr gervitunglum séu uppspretta gagnlegra upplýsinga til að ákvarða vænlegar fiskislóðir á Íslandsmiðum.

Fimm gervitunglabreyturnar voru kannaðar: yfirborðshiti sjávar (SST), magn blaðgrænu (CHL), styrkur ljóstillífunargeislunar (PAR), full staðlaður geislunarljómi endurkastaðs ljóss frá vatni (L443) og stuðull fyrir niðurstreymi dreifðrar geislunar í vatni (kd490). Svæðisupplausn gervitunglabreytanna var um 4.6 km og tímaupplausn 1 dagur. Áhrif þess að minnka bæði svæðis –og tímaupplausn voru einnig könnuð.

Tengsl gervitunglabreyta og veiðistaða makríls voru könnuð með tvíkostadreifðu GAM-líkani (Generalized Additive Model). Háða breytan var veiðistaðsetningar sem voru skilgreindar sem veiddur makríll eða enginn veiddur makríll. Óháðar breytur voru gervitunglabreyturnar með mismunandi svæðis – og tímaupplausn. Sjö daga meðaltal ljóstillífunargeislunar var sú einstaka breyta sem skýrði best makrílveiðar. Það módel með fleiri en einni óháðri breytu sem skýrð best makrílveiðar var módel með eins eða sjö daga meðaltal fyrir ljóstillífunargeislun og yfirborðssjávarhita og sjö daga meðaltal fyrir full staðlaðan geislunarljóma endurkastaðs ljóss frá vatni. Minni svæðisupplausn hafði ekki mikil áhrif á hæfileika gervitunglabreytanna til að skýra makrílveiðar en minni tímaupplausn frá einum degi til sjö daga bætti hæfileika flestra breytanna.

Gervitunglabreyturnar sem voru notaðar komu úr stórum gagnasöfnum sem eru unnin fyrir heiminn í heild sinni. Til að meta hversu árangursrík slík gagnasöfn eru við staðbundnar aðstæður eins og á Íslandsmiðum voru tengsl milli blaðgrænu sem mæld er í sjó á Íslandsmiðum og magn blaðgrænu sem mæld er með gervitunglum á sömu stöðum borin saman. Niðurstöður, sem byggðu á litlu úrtaki, sýndu sterka marktæka fylgni.

Gervitunglabreyturnar bættu marktækt módel til að skýra staðsetningu makrílveiðistaða. Makrílveiðar voru árangursríkastar við yfirborðshita sjávar frá 7,5°C – 13°C þar sem styrkur sólarljóss var mikill og þar sem magn blaðgrænu var í meðallagi. Tærari sjór og einnig sjór þar sem mikið endurkast á sér stað hefur líka áhrif. Þessar niðurstöður gefa til kynna að makríll sem veiddur er á Íslandsmiðum sé meira háður sjón við fæðuöflun en hingað til hefur verið álitið. Flestar heimildir segja að makríllinn afli fæðunnar fyrst og fremst með því að sía hana.

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Abbreviations

SST – Sea Surface Temperature

CHL - Cholorphyll

PAR – Photosynthetically Available Radiation

GAM – Generalized Additive Model

L443 – Fully normalized water leaving radiance at wavelength 443 nm

kd490 - Down welling diffuse attenuation coefficient at wavelength 490 nm

EEZ – Exclusive Economic Zone

AIC – Akaike Information Criterion

ESA – European Space Agency

NASA - National Aeronautics and Space Administration

1 Introduction

1.1 Motivation and overall aim

The measured concentration of CO_2 in the atmosphere at Mauna Loa, Hawaii exceeded 400 ppm for the first time on the 9th of May 2013 (Kunzig 2013). Following the Kyoto protocol international agreement in 1997, nations around the world have striven to decrease the amount of emitted greenhouse gases (GHG), including Iceland. According to an Action plan on climate change*,* by the Ministry for the Environment and Natural Resources in Iceland, one of the ten key actions for reducing GHG emissions in Iceland is to reduce fossil fuel energy usage by fishing vessels (Ministry for the Environment 2010).

Fisheries have been the most important export sector in Iceland for more than a century. Its proportion in total exports exceeded 95% in the 1940's and is currently close to 42% (Arnason and Agnarsson 2005; Statistics Iceland 2013). The fishing fleet is also a large contributor to GHG emissions. In 2009 15% of the total emission in Iceland came from fisheries (with heavy industry included). The majority of the emission originates from fishing vessels, but fishmeal factories have also contributed in a large way. The current aim is to reduce the emission by the fisheries sector by 27% in 2020 (Ministry for the Environment and Natural Resources 2012). The main focus of the Ministry for the Environment and Natural Resources is to attempt to substitute fossil fuels with biofuels. Other schemas are also being explored, such as various technologies to reduce energy consumption. These are mostly related to redesigning fish gear, which are intensive energy consumers. Innovative ideas and development of novel procedures include the invention of using low frequency sounds (Björnsson 2012) or light beams to gather fish (Innovation Center Iceland 2012).

This study aims to provide information which can be used to reduce energy consumption in Icelandic fishing vessels by investigating how satellite remotely sensed variables can be used to forecast potential fishing grounds for Atlantic Mackerel in Icelandic waters.

On short term basis, correlative information between satellite variables and location of catches can be quite valuable and will support those fishermen that are already using satellite data onboard their vessels. On a longer term basis the knowledge can serve as an input into the development of fish finding tools specifically designed for Icelandic waters. Either way the knowledge is likely to encourage more energy efficient fishing methods and contribute to lowering the carbon footprint of the industry.

Remote sensing has the ability to provide data with high spatial and temporal resolution and has the potential to be a valuable source of data in fisheries management and forecasting around the world. It has been suggested that remote sensing will revolutionize fisheries management and forecasting in the years to come with improved understanding of the relationship between various fish species and different ecosystem aspects (Stuart *et al.* 2011).

Remote sensing has not been used systematically in Icelandic fisheries management. Studies are mainly carried out with research vessels and point measurements of the various aspects of the ecosystem. Such methods are both limited in time and space. As marine ecosystems are vast and vary both temporally and spatially, it is evident that such methods are not efficient in providing frequent information on the status of the ecosystems in near-real time (Klemas 2010; Stuart *et al.* 2011). Only a few studies have been carried out in Icelandic waters using remote sensing. Remotely sensed variables and *in situ* observations have been investigated (Jonason *et al.* 2009; Gudmundsson *et al.* 2009; Zhai *et al.* 2012). One attempt has been made to forecast possible fishing grounds for capelin

(*Mallotus villosus*) in north Icelandic waters (Sánchez 2003) and Einarsson (2011) used satellite data as a model input to predict spawning migration pattern of the capelin stock.

Previous studies on fisheries forecasting with satellite data have shown that satellite data can be used successfully to predict viable fishing areas for many different species and substantially increase catches (Solanki *et al.* 2003; Zagaglia *et al.* 2004; Klemas 2010; Stuart *et al.* 2011; Chassott *et al.* 2011).

The theoretical ground gained in studies on the relationship between fishing locations and satellite variables has contributed to development of commercial tools and service for fisheries, which are now widely used in professional fisheries around the world to provide near -real time information at different resolutions (Chassott *et al.* 2011; Stuart *et al.* 2011; Saitho *et al.* 2011). These tools are now commonly used in larger Icelandic pelagic fisheries vessels.

This study aims at providing information for fisheries forecasting in Icelandic waters. Successful forecasting will clearly reduce energy and time spent in searching for fish and may provide an initiative that will lead to economic gain in fisheries around the world. Previous studies have mainly focused on large fishing areas and used coarse resolution satellite data, averaged over weeks, months and seasons. Thus there is a need to test finer scale spatial and temporal resolution, on the exact date of fishing and extraction of single cell value for every location of caught mackerel (spatial resolution limited to single cell size of satellite data). To my knowledge this is the first study using such fine temporal and spatial scale.

1.2 Objectives

The main objective of the study is to identify relationships between actual fishing locations of Atlantic Mackerel in Icelandic waters from 2007 to 2012 and variables derived from remote sensing.

The hypothesis is that remotely sensed variables are a valuable source of information for determining viable fishing grounds in Icelandic waters.

H_1= There is a relationship between catches of Atlantic Mackerel and various remotely sensed environmental variables

H_0 = There is no relationship between fishing locations and remotely sensed variables.

Additionally the following questions are addressed:

1. Which remotely sensed variable or combinations of variables are most successful in predicting catch locations of mackerel?
2. How does decreased temporal resolution influence the relationship?
3. How does decreased spatial resolution influence the relationship?
4. How can the relationship between catch locations and remotely sensed variables be explained?
5. Is there a correlation between observed environmental variables around Iceland and remotely sensed variables, with focus on chlorophyll?
6. How has the pattern of mackerel fishing in Icelandic waters changed spatially and temporally from 2007 to 2012?

2 Background

2.1 The species - Atlantic Mackerel

The Atlantic Mackerel (*Scomber scombrus*) is a pelagic fish, typically found in large schools in the uppermost layers of the open ocean. It is a superb swimmer and as it has no swim belly to control its buoyancy so it needs to swim continuously to avoid sinking (Utne *et al.* 2012).

The Atlantic Mackerel is found in two separated stocks on the in the NE and the NW Atlantic. The mackerel found in the Icelandic waters is considered to belong to the NE-stock (Astthorsson *et al.* 2012).

The NE Atlantic stock is large and the spawning stock has been increasing. The spawning stock biomass is estimated every year by the International Council for the Exploration of the Sea (ICES). Since 1981, the stock has been estimated to vary between 2 and 2.5 million tones. However in 2009 it expanded rapidly to approximately 3.1 million tons while in 2011 it was estimated to be about 2.9 million tons (ICES 2009, ICES 2011, Nøttested and Huse 2012).

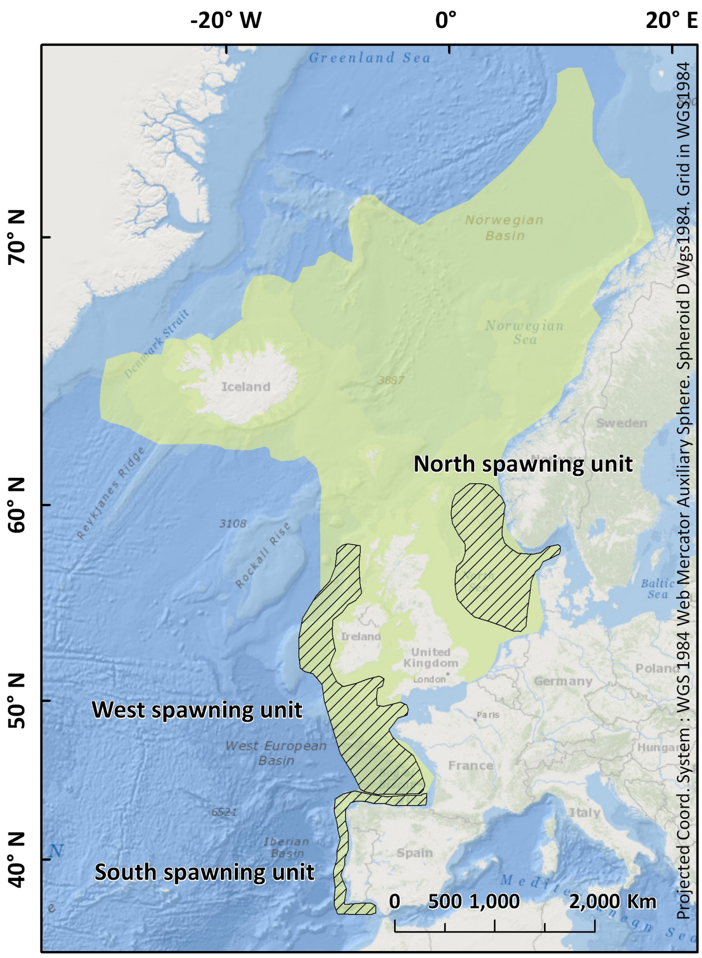

Figure 1 Recent distribution of the NE Atlantic Mackerel stock. Green filled area is the recent distribution and hatched areas are the three spawning areas. Redrawn from Astthorsson *et al.* (2007) and Working group on mackerel fishing (2012). Modified according to mackerel fishing locations in the fisheries logbook from the Directorate of Fisheries (unpublished data). Base map: ESRI 2012.

The distribution of the NE stock extends over a wide area, from NW Africa north to the Barents Ocean and from Norway in East to Jan Mayen in the west (Astthorsson *et al.* 2012). In recent years its distribution has extended westwards through the Icelandic EEZ and in 2011 small catches were reported for the first time in the Greenlandic EEZ (The Norwegian Ministry of Costal Affairs 2012). The spawning stock is divided into three units; south, west and north. The south unit spawns off the east coast of Spain and Portugal. The west unit spawns in Bay of Biscay and west of Britain. The north unit spawns in the North Sea and in northern Skagerrak (Astthorsson *et al.* 2012) (Figure 1).

The mackerel is a voracious and opportunistic feeder and mainly feeds on zooplankton, in particular *Calanus finmarchicus,* but also eats larvae, fish and invertebrates smaller than themselves (Olaso *et al.* 2005; Langøy *et al.* 2012, Utne *et al.* 2012). Mackerel is considered to be primarily a passive filtering feeder (Astthorsson *et al.* 2010), swimming with the mouth open and filtering smaller pelagic organism. But it is also known to visually select the prey (Olaso *et al.* 2005). It is a constant eater, feeding both day and night (Conway *et al.* 1999).

Increased water temperature is considered to be the main reason of the periodic occurrence of mackerel in Icelandic waters. The Atlantic Mackerel prefers waters above 8°C and during the summer months it stays in the warmer surface layers, while during the colder periods of the year it moves to greater depths where the ocean is warmer (Utne *et al.* 2012; Valdimarsson *et al.* 2012). A study on the distribution of mackerel and other pelagic species in the Norwegian Sea shows that the presence of mackerel is positively correlated with temperature. It prefers the warm Atlantic water mass and is likely to avoid the colder water masses from the Arctic, even though there is a high availability of zooplankton for it in to feed on in these colder water masses (Langøy *et al.* 2012).

From 2006 onward, mackerel has been caught in the Icelandic EEZ during its summer feeding migration from May/June to September/October. A study on summer feeding migration in the North Sea revealed that all schools are found in the top 100 m of the ocean layers, and that the majority are found in the top 40 meters. Interestingly the study revealed that the direction of migration was not random, but dominated by east-west directions movements (Godø *et al.* 2004).

2.2 Mackerel in Icelandic Waters

Several fish species have changed their ranges in Iceland waters during the last 15 years (Asthorsson *et al.* 2012). Species traditionally found further south have moved northwards and northern species have shifted even further north. These changes in the ecosystem are explained by warming of 1-2°C in the waters south and west of Iceland during this time period (Valdimarsson *et al.* 2012). The expansion of the Atlantic Mackerel northward into Icelandic waters comprises one of the more interesting examples of this type of range expansion. This species has traditionally been classified as a vagrant in the Icelandic area, although its presence has increased periodically during the 20th century, as a response to warmer marine climate and positive phases of AMO - the Atlantic Multidecadal Oscillation (Astthorsson *et al.* 2012).

Factors other than SST which are considered to have contributed to the changes in distribution of the Atlantic Mackerel include increased size of the stock, changes in the size and age of the stock structure, the size of other competing stocks and changes in concentration and distribution of zooplankton (ICES 2011; Astthorsson *et al.* 2012; Utne *et al.* 2012).

In short, the distribution and abundance of mackerel in Icelandic waters increased gradually during the first years of the 21st century. Since 2006 it has been found in larger quantities than before leading to direct commercial fishing of the species by Icelandic fishing vessels within the Exclusive Economic Zone (Astthorsson *et al.* 2012). The total catch of the Icelandic fishing fleet increased from 1741 tons in 2006 to 146 thousand tons in 2012, and the fishing period expanded (Table 1).

Table 1 Tons of mackerel caught in Iceland from 2006 to 2012 and the catching period (months).

Year	2006	2007	2008	2009	2010	2011	2012
Total catch in tons	1,741	31,835	109,855	112,510	118,489	156,802	145,802
Period of fishing	Jul.-Sept.	Jul.-Sept.	Jun.-Sept.	May-Sept.	Mai.-Okt.	Jun.-Sept.	Jun.-Okt.

2.3 Study area – in time and space

The study area is defined by the fishing locations of mackerel from 2007 to 2012 registered in the fisheries logbook database of the Icelandic Directorate of Fisheries (unpublished data). It extends from about 60° to 73°N and 33°W to 2°E (Figure 2). The time period is defined by the first year of substantial commercial mackerel catches in July 2007 to October 2012. During these years mackerel was caught from May/June/July to September/October each year.

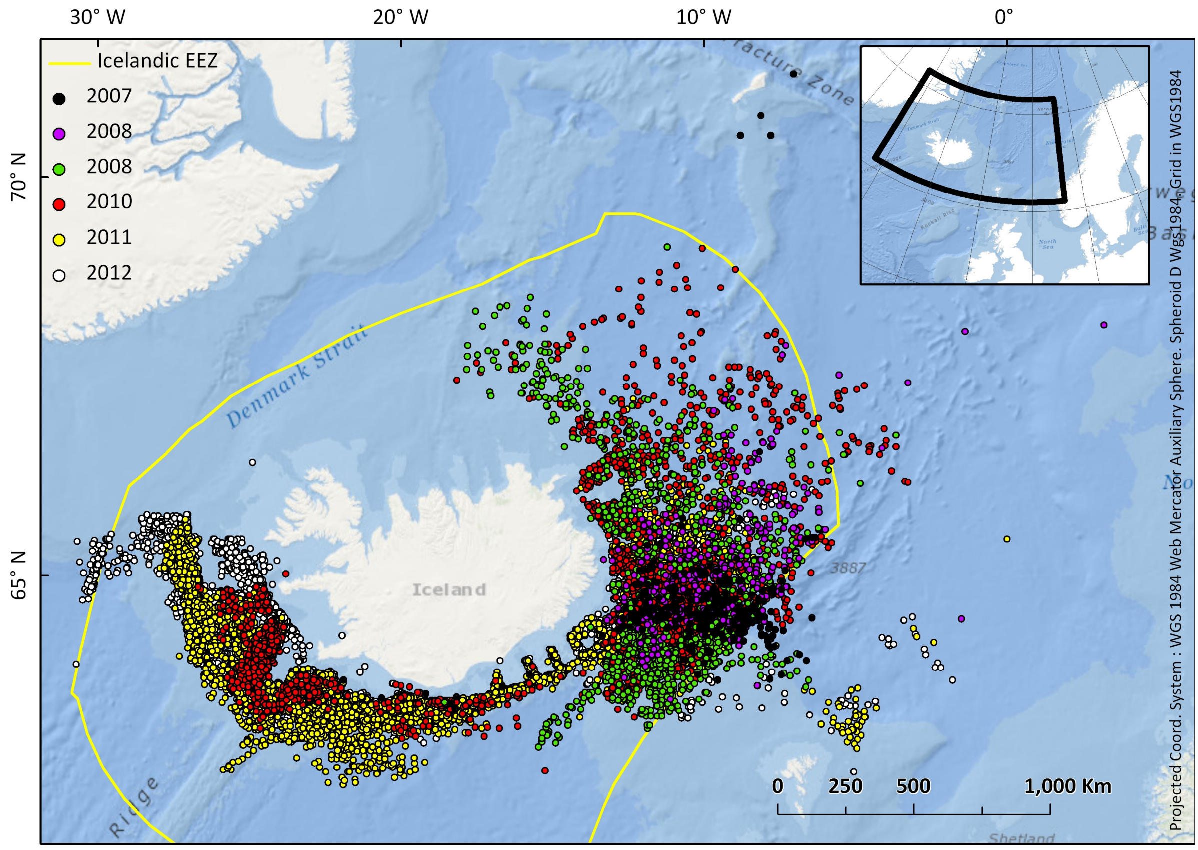

Figure 2 The study area is defined by the mackerel catches in 2007-2012. Fishing locations are identified with a different color for each year. The line represents the Icelandic Exclusive Economic Zone (EEZ). Base map: ESRI 2012.

Icelandic waters are characterized by a frontal zone where two primary water masses with very different origins and characteristics meet. The cold Arctic Polar water masses flow southward from the north to meet warmer northward flowing North Atlantic water masses of the Gulf Stream (Figure 3 and Figure 4). Most other water masses in the area are a mixture of these two (Palsson *et al.* 2012; Valdimarsson *et al.* 2012).

As a result of the great hydrodynamic variability in this area, the environmental conditions are highly variable. The areas north and east of Iceland differ from the areas in the south and west of Iceland, both in terms of biology and physical properties of the ocean. In the south and west, where the warmer and saltier Atlantic Ocean is dominant, the mean annual primary production is generally higher and the temperature ranges from 6-11 °C. The northern and eastern areas are characterized by fluctuation in the influence of warm Atlantic and cold Arctic water masses with temperature ranges from 0-1 °C, causing large interannual variations in the fauna and physical properties. Primary production is generally lower in this area (Gudmundsson 1998; Gislason 2009).

The frontal areas to the southeast and northwest of Iceland experience the highest primary production in Icelandic waters. The overall means range from 4.3 to 9.2 mg C m^3 h^1 for different regions. When conditions are favorable, phytoplankton spring bloom starts in March/April and peaks in May. The regions to the north and east experience a single, well-defined peak of spring bloom, while the south and west regions have frequently observed sequences of peaks (Gudmundsson 1998).

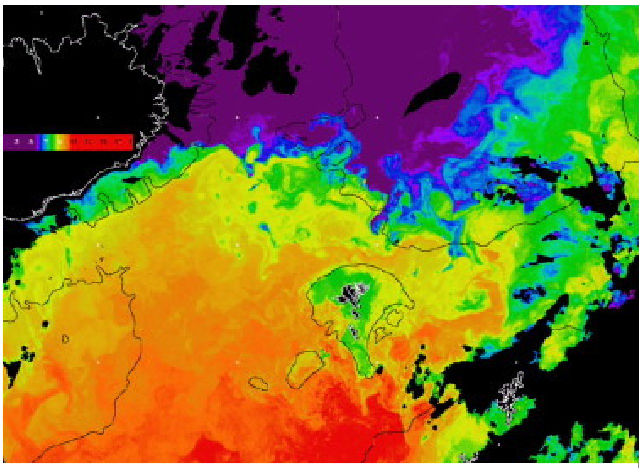

Figure 3 Satellite image of SST vividly expresses the meeting of two water masses, the cold blue and purple from the north and the warmer red and yellow from the south (Klemas 2010). With permission no. 3144380837828.

Zooplankton abundances are on an average higher south of Iceland than to the north, but it varies between years. The most abundant species of zooplankton is *Calanus finmarchicus*, which is a preferred food by mackerel (Astthorsson *et al.* 2010; Gislason *et al.* 2009; Gislason and Silva 2012; Palsson *et al.* 2012).

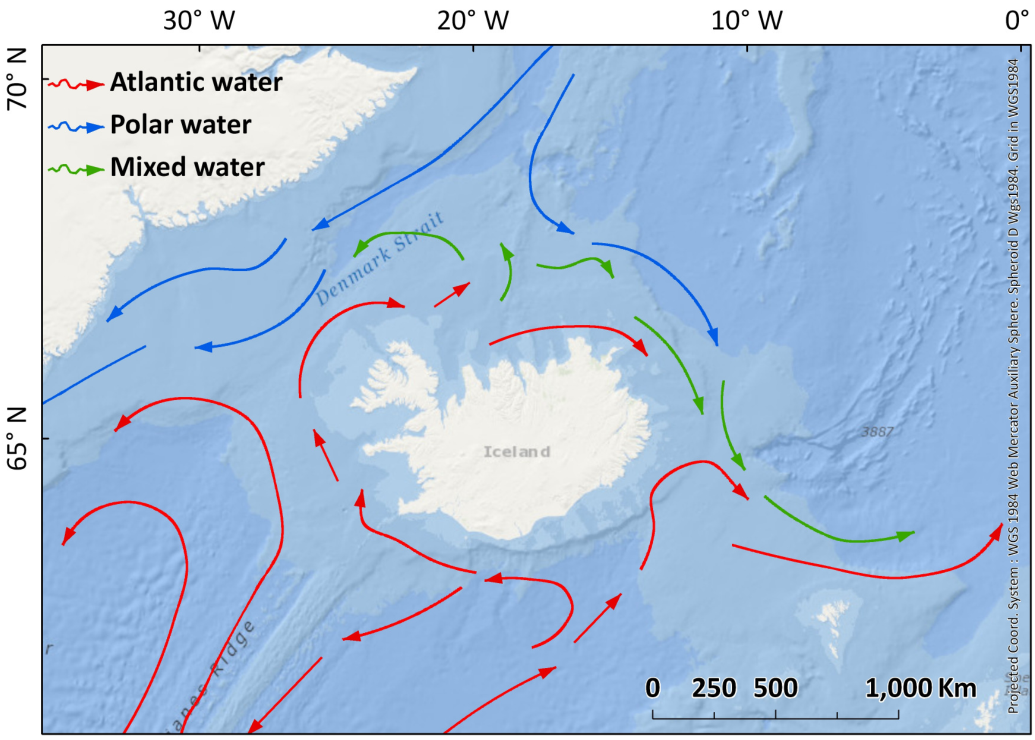

Figure 4 Ocean currents around Iceland. (Based on Valdimarsson and Malmberg 1999 and Valdimarsson *et al.* 2012).

As mentioned previously, oceanic ecosystems vary in time and space, both on long term and short term basis. Hátún *et al.* (2005; 2009) discusses the effects of the dynamics of the Subpolar Gyre on ecosystems in the North Atlantic. Presence of weak or strong Subpolar Gyre has prominent effect on the fauna in the N-Atlantic Ocean as it affects exchanges of subarctic and subtropical water masses in the north-eastern North Atlantic Ocean (Figure 5). It influences salinity (Hátún *et al* 2005), phytoplankton productivity (Hátún *et al.* 2009) and spawning distribution of the pelagic species blue whiting (Hátún *et al.* 2009; Brickman *et al.* 2009; Payne *et al.* 2012). A period with a weak Subpolar Gyre has been ongoing since late 1990's.

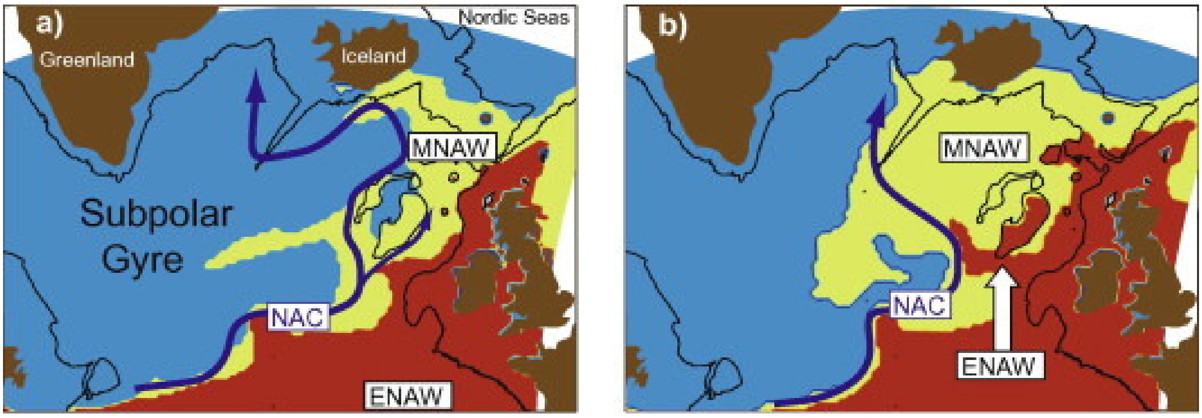

Figure 5 Simulated annual average temperature of water masses in the North Atlantic during a) strong Subpolar Gyre and cold period (1993) and b) weak Subpolar Gyre and warm period (1998). Red represents SST > 9°C, blue SST< 7°C and green SST between 7-9°C. Blue arrows indicate currents associated with Subpolar Gyre and the white arrow represents movement of relatively warm and saline water of subtropical origin (Hátún *et al.* 2009) With perm.nr. 3144420069728.

2.4 Fishing from space – fisheries forecasting

The characteristics of a good fisherman are ability to read (sense) the environmental signs of probable fishing areas. Fishermen can detect different shades or colors of the ocean, heat differences and identify productive areas, for example by watching bird behaviour. Similar environmental properties are detected by satellite sensors and have proved to be helpful in supporting fishing vessels to find fish (Klemas 2010; Chassot *et al.* 2011; Stuart *et al.* 2011)

Satellite remote sensing variables have been used in fisheries research, management and forecasting since the early days of remote sensing. The first sensor specifically designed to detect oceanic properties, namely productivity of the ocean (ocean color or chlorophyll-a) was NASA´s Coastal Zone Color Scanner (CZCS) onboard NIMBUS-7, launched in 1978. It was successfully in service for 18 years (Wilson 2010). Today the number of sensors detecting different properties of the oceans has expanded. For example the sensors detecting ocean color are currently about 10 with different properties and resolution (IOCCG 2013). The best known sensors are probably NASA's MODIS onboard Aqua and the recently retired ESA's MERIS onboard ENVISAT. Since the first sensor was launched 35 years ago, the development of methods, algorithms and products of sensors has advanced (Wilson 2010). Free access to satellite data and free software to work with satellite data in the recent years has encouraged the use of satellite data in many aspects of fisheries research.

Fisheries forecasting based on remote sensing has been successfully carried out for decades in an attempt to save fuel and time. Diverse methods have been used to link fishing locations and satellite variables. Some studies focus on frontal zones and specific phenomenon in satellite imagery, such as eddies and currents (Solanki *et al.* 2003; Zainuddin *et al.* 2006). Others look more at actual values of certain predefined parameters such as chlorophyll-a and sea surface temperature (Radlinski *et al.* 2013). Some studies focus on hind casting while others strive for the more difficult task; to foresee the future (Solanki *et al.* 2003; Zagaglia *et al.* 2004; Chassott *et al.* 2011). Solanki *et al.* (2003) used ocean color and SST to define potential fishing zones in the Arabic Ocean. Then, actual fishing was carried out to validate the forecast. The results suggest a substantial increase in fishing catch per effort in these zones. The method was improved by incorporating surface winds into the forecast (Solanki *et al.* 2005; 2010). Zagaglia *et al.* (2004) compared actual catches of Yellow Fin tuna (*Thunnus albacares*) in the tropical Atlantic Ocean northeast of Brazil to sea surface temperature, chlorophyll, sea surface height anomaly and others variables. They conclude that sea surface temperature and chlorophyll are significant factors in controlling tuna abundance. Zainuddin *et al.* (2004) used sea surface temperature, chlorophyll and sea surface height anomalies to locate tuna fish schools and Wall *et al.* (2009) found that chlorophyll and water clarity associated with bait significantly influenced successful recreational catches of King Mackerel west of Florida.

Studies such as those mentioned above have contributed to development of governmental and commercial tools and service for fisheries which are now widely used in professional fisheries (Chassott *et al.* 2011). An example of a commercially developed tool which is used on Icelandic pelagic fishing vessels is CATSAT, which is a worldwide satellite service especially designed for professional pelagic fishing, "*providing near real time oceanographic and marine meteorological information"* (Saitoh *et al.* 2011; Catsat 2013). It provides information on sea surface temperature, chlorophyll and sea level anomalies from satellite data at resolutions of 2 to 25 km as well as information derived from models with a coarse resolution of 25 km. The temporal resolution of the satellite variables varies from 2 days to 7 days (Catsat 2013). Opinions vary amongst fishermen in Iceland on the applicability of such tools for aiding fish finding as well as which variables are most successful. While some think it is a very successful tool, others are doubtful. Variables like thermocline, which is derived from models, and sea level anomalies, sea surface temperature and chlorophyll concentrations derived from satellite data, are mentioned as successful (personal comments based on discussion with Icelandic fishermen onboard pelagic vessels in the period January to May 2013).

2.5 Correlation of observed and satellite sensed CHL values in Icelandic waters

The satellite variables used in this study come from global data sets which have been merged from different sensors and validated with *in situ* observations from around the world, but not specifically with observation data collected by the Icelandic Marine Research Institute (Globcolor 2007; Hu *et al.* 2010). To get an idea of how representative the satellite variables are on the local scale in Icelandic waters, a minor validation check is carried out for one of variables: chlorophyll.

The validation procedure for CHL in different oceanic waters is commonly split into two categories: Case 1 and Case 2 waters. Case 1 waters are considered waters where the color and optical properties of the ocean are determined primarily by phytoplankton and dissolved organic matter. These situations are commonly found in open waters. Case 2 waters are all other waters where the color and optical properties are influenced primarily by minerals, bubbles and dissolved organic matter. These are commonly referred to as more turbid waters and coastal waters (Mobley *et al.* 2004; ESA 2011).

A strong correlation (r^2>0.49) is found between observed chlorophyll concentrations and satellite sensed chlorophyll-a concentrations calculated assuming open waters (Case 1). Regional and seasonal divergence is known, especially in high latitude areas and in areas defined as Case 2 waters. The correlation between Case 2 waters and satellite sensed chlorophyll is lower than for Case 1 waters, or from r^2 =0.11 to r^2 <0.35 (Globcolor 2007). This is mainly due to the presence of dissolved or suspended materials in the water column of the more turbid waters. Such materials can be wrongly interpreted as chlorophyll in chlorophyll algorithms used (Mobley *et al.* 2004; Gudmundsson *et al.* 2009).

Gudmundsson *et al.* (2009) suggest that the waters around Iceland may in general be characterized as Case 2 waters. Lee and Hu (2006) mapped the global distribution of Case 1 waters to find there is a seasonal variation in the distribution. The waters around Iceland are on the borders of Case 1 and Case 2 waters. During spring and summer the areas south and east of Iceland are classified as Case 1, while in autumn and winter they are mostly Case 2 waters. Thus, it is interesting to know how chlorophyll from the Globcolor dataset correlates with observed satellite chlorophyll in this area. A study by Gudmundsson *et al.* (2009) revealed a fairly weak correlation (20% deviance explained) between *in situ* measurements of chlorophyll in Icelandic waters and multiannual averages of 8 day composites of SeaWiFS satellite sensed chlorophyll-a in the period 1998-2005. Seasonal variations in the strength of the correlation were quite apparent. Adding temporal and spatial patterns to the regression model for chlorophyll improved the model and resulted in 49% of the deviance explained in the fitted data.

3 Data and methods

3.1 Flowchart for data and methods

The main features of data acquisition, manipulation, modelling and the methods and software used are described in Figure 6. A more detailed description of each part is presented in the following sections.

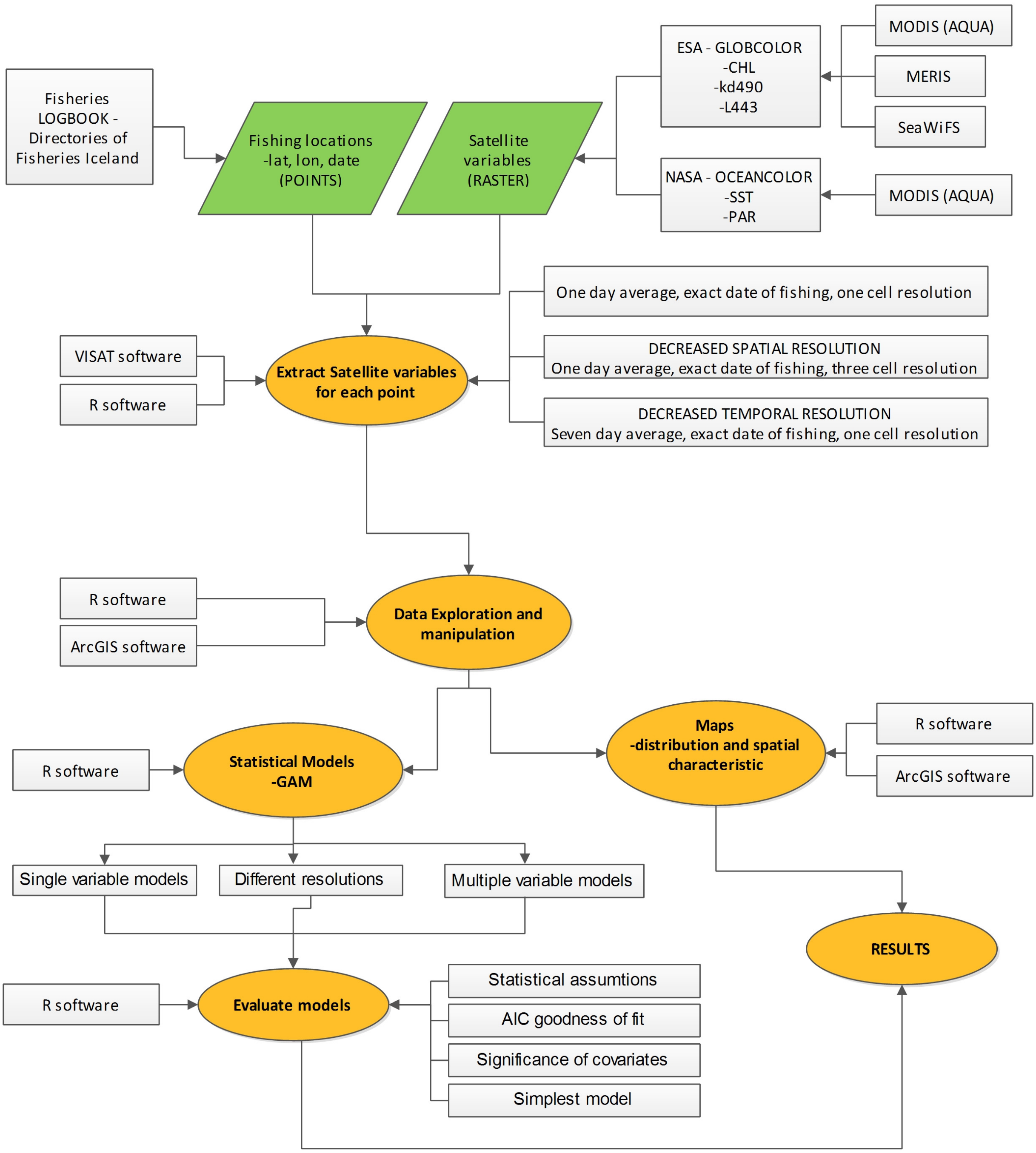

Figure 6 Flowchart of data acquisition and methods.

3.2 Satellite variables

3.2.1 Data

The remotely sensed environmental variables used were provided by the Ocean Biology Processing Group (OBPG) at the NASA Goddard Space Flight Center, Greenbelt, MD, USA (OBPG, 2013) and ACRI-ST GlobColour service, supported by EU FP7 MyOcean & ESA GlobColour Projects, using ESA ENVISAT MERIS data, NASA MODIS and SeaWiFS data (Globcolor 2013).

The variables selected for analysis are:

- Daily average Surface Chlorophyll-a measured in mg/m^3 per day (CHL)
- Sea Surface Temperature measured in °C per day (SST)
- Photosynthetically Available Radiation, measured in Einsteins m^2 day^{-1} (PAR)
- Fully normalized water leaving radiance at wavelength 443 nm, measured in mW/cm²/µm/sr per day (L443)
- Down-welling diffuse attenuation coefficient at wavelength 490 nm in m^{-1} per day (kd490)

The products "colored dissolved and detrital organic materials" (CDM) from the Globcolor dataset and "Sea Surface Salinity" and "Sea Surface Wind Speed" from NASA's Aquarius were also scrutinized but are not reported.

All variables are level 3 products which are spatially and temporarily combined from higher resolution products. Globcolor data is combined from three different sensors. An overview of the sensors, source, unit of measurement and abbreviation of the satellite variables are listed in Table 2. All variables have 1 day temporal resolution and 4.6 km spatial resolution (Globcolor 2007, OBPG 2013).

Time range for the satellite variables is defined by the time range of the fishing locations of mackerel, from May/June to September/October for the years 2007 to 2012.

Table 2 Overview of the abbreviation, unit of measurement, sensors and source of the satellite variables. All variables have 1 day temporal resolution and 4.6 km spatial resolution

Variable	Abbre-viation	Unit	Sensor	Source (www.)
Sea Surface Temperature	SST	°C	Modis /Aqua	oceancolor.gsfc.nasa.gov
Photosynthetically Available Radiation	PAR	Einsteins m^{-2} day^{-1}	Modis /Aqua	oceancolor.gsfc.nasa.gov
Surface Chlorophyll-a	CHL	mg m^{-3} day^{-1}	Merged Modis&Meris &SeaWiFS	globcolor.info
Downwelling diffuse attenuation coefficient at wl 490	kd490	m^{-1}	Merged Modis&Meris &SeaWiFS	globcolor.info
Fully normalized water leaving radiance	L443	mW/cm²/µm/sr	Merged Modis&Meris &SeaWiFS	globcolor.info

These variables provide basic information on the biology, physics and optics of the ocean and are considered to help identify attractive areas for fish aggregation. Some are considered to have direct influence on the distribution of mackerel, for example SST. Other variables do not have as obvious direct influence on the distribution, but can be considered proxies for causal factors, for example PAR which controls photosynthesis and growth of phytoplankton, the variable kd490 which can be used as proxy for water transparency and L443 as a proxy for water clarity or turbidity. Other variables of interest are for example sea level anomalies, calculated ocean fronts, and fluorescence, but these are excluded due to lack of time.

Some of the variables are correlated and even partially derived from the same spectral products of the satellite sensors. For example L443 is sometimes used as an input in the algorithms for CHL for the three different sensors constituting the Globcolor dataset (ESA 2011) and kd490 is computed from CHL (Globcolor 2010).

3.2.1.1 Chlorophyll-a

Chlorophyll-a is the photosynthetic pigment of phytoplankton. Phytoplankton plays a key role in ocean ecosystems as they are the first link in the food web. Their distribution is related to many environmental factors such as nutrients and carbon dioxide. Knowledge of the distribution of high and low concentrations of chlorophyll gives valuable information on the ecosystems of the oceans. Satellite sensors detect the spectral signature of chlorophyll-a. Light entering the ocean is absorbed and scattered depending on the contents, such as organic matter and other particles. Pure water scatters sunlight in blue wavelengths, causing the ocean to appear blue. Chlorophyll-a absorbs the blue and red radiation, but strongly reflects in the green. In the presence of chlorophyll-a, water turns from the unproductive blue to more productive green (Klemas 2010; Stuart *et al.* 2011).

Chlorophyll-a is thus a direct indicator of primary production in the ocean but is also used indirectly as a proxy for water mass boundaries and to identify upwelling areas (Chassott *et al.* 2011).

3.2.1.2 Sea Surface Temperature

Sea surface temperature is detected by thermal infrared sensors in long wave bands at about 11 to 12 μm or the shortwave bands at 3.9-4.0 μm (Savtchenko *et al.* 2004). Measuring SST has been successful since the early days of remote sensing. The thermal radiance measured over the oceans primarily reflects changes in the actual SST as the ocean is considered to behave almost as a black body. After atmospheric corrections, SST is considered fairly accurately determined by a degree of -/+ 0.5°C (Savtchenko *et al.* 2004; Chassott *et al.* 2011; Klemas 2010).

Sea surface temperature is directly linked to locations of fish species which often have their own preferred temperature and many are very sensitive to temperature. Temperature can directly or indirectly affect many different stages of fish's lifecycle, from spawning time to feeding activity and growth rates (Studholme *et al.* 1999, Stuart *et al.* 2011). It influences distribution and aggregation of fish, migration and behaviour of fish schools. Furthermore, thermal changes (e.g. eddies and fronts) are particularly linked with high concentrations of food for fish, caused either by better thermal conditions or increased food availability e.g. in upwelling areas where rising cold water transports nutrients to the surface enabling phytoplankton to grow (Klemas 2010; Chaossott *et al.* 2011).

3.2.1.3 Photosynthetically available radiation

PAR indicates the amount of solar light or energy in the spectral range of 400-700 nm, reaching the surface of the ocean which is useful to organisms in the photosynthesis process and expressed in Einsteins m^{-2} day^{-1} (Frouin *et al.* 2003). The unit Einstein measures light energy concentration, defined as one mole (amount of substance) of photons, or wave of particles, regardless of their frequency (Encyclopædia Britannica, 2013). High and low PAR controls the growth of phytoplankton and defines the depth of the euphotic zone, or the topmost sunlit zone in the oceans where almost all primary productivity occurs. Low PAR values can suggest turbid and less clear waters and high values clearer and warmer surface layers, which is preferred by some fish species (Sanches *et al.* 2008).

3.2.1.4 Fully normalized water leaving radiance at wavelength 443 nm

Fully normalized water leaving radiances at 443 nm (blue wavelength), can be used as a proxy for water clarity or turbidity. The parameter measures the radiance backscattered out of the water to the top of the atmosphere, and has been corrected for different atmospheric phenomenon such as viewing and sun geometry, time and atmospheric conditions and is thus normalized (Gordon 2005; Wall *et al.* 2009; Globcolor 2010). The values of water leaving radiance are somewhat confusing, as both high and low values can suggest low light availability (Hu *et al.* 2003).

Low water leaving radiance indicates less clear waters due to high absorption (Hu *et al.* 2003). As mentioned earlier, pure water scatters sunlight at blue wavelengths, causing the ocean to appear blue. Increased phytoplankton growth and increased amounts of certain color dissolved organic matters results in a decreased water-leaving radiance at a wavelength of 443 nm. As more of the light is absorbed in the water column, the less light exits and the lower the values of the water leaving radiance become (Hu *et al.* 2003; Gordon 2005; Wall *et al.* 2009; Salisbury *et al.* n.d.). Some fish species, especially visual predators like tuna, are more commonly found in clear waters for foraging (Wall *et al.* 2009).

High water leaving radiance indicates less clear waters due to high scattering in the water column (Hu *et al.* 2003). Suspended materials of both organic and inorganic origin can act as mirrors redirecting the incoming sunlight and reduce the light penetration in the water column. Turbidity can be induced for example by strong wind mixing (Hu *et al.* 2003). Turbidity due to scattering of light can have both negative and positive effect on visual feeding of fish by either decreasing or increasing the contrast between the prey and the background. Increased turbidity in the water column can also act as shelter from predators. The effects of light scattering in the water column on the behaviour of fish species is complex and dependant on the size of prey, color of the prey and the size of fish species involved (Utne-Palm 2002). Waters with values of around 2-2.5 mW/cm²/µm/sr for L443 are considered turbid (Royal Belgian Institute of Natural Sciences, 2013)

3.2.1.5 Down- welling diffuse attenuation coefficient at wavelength 490 nm

The kd490 down welling diffuse attenuation coefficient at wavelength 490 nm is used to quantify the penetration in the water column of the light in the blue-green spectrum. Attenuation is the total loss of light because of both scattering and absorption in the water column. Like L443, it can be used as a proxy for water transparency or turbidity (Globcolor 2010; Kumari *et al.* 2009). A large coefficient means that the light is quickly attenuated and thus the water is less transparent or more turbid. Turbidity can be an indicator of eddies and other upwelling phenomenon indicating areas of increased productivity and high abundance of prey fish. On the other hand increased transparency to a certain depth and less turbid waters are important factors in locating tuna aggregation (Kumari *et al.* 2009). In waters with high coefficient photosynthesis and growth of primary producers can be limited (Kelble *et al.* 2005).

3.2.2 Extraction Method

Satellite variables were extracted from the exact latitude and longitude of the fishing locations with the *Pixel extraction* tool in the VISAT Beam software (Brookman Consult and contributors 2001-2010). Three different methods were used for extraction (Figure 7):

1. Extraction of cell value including the actual point location on the actual date of fishing. This resulted in a variable value with temporal resolution of one day and spatial resolution of ≈21 km^2. This extraction method focused on keeping temporal and spatial resolution as fine as the dataset offered: one day and one cell.
2. Extraction of the mean of the one neighboring cell in all directions from the cell including the actual fishing location on the actual date of fishing. This resulted in a variable value with temporal resolution of one day and spatial resolution of ≈190 $km^{2.}$
   This extraction method explored the effects of decreased spatial resolution. Decreasing the resolution to a matrix of 3*3 cells was the smallest decrease possible when ensuring that the actual cell of interest (the fishing location cell) was in the middle of the merged area with equal number of cells to all sides. Decreasing the resolution to a 5*5 matrix would result in spatial resolution of ≈529km^2
3. Extraction of single cell values including the actual point location for seven days before the actual date of fishing. Then the mean value for the seven days was calculated. This resulted in a variable value with temporal resolution of one week and spatial resolution of ≈21 km^2.
   This extraction method explored the effects of decreased temporal resolution. Previous studies suggest that the relationship between temperature, primary production and other properties of the ocean need to be sustained for some time to attract forage fish (Kumari *et al.* 2009; Wall *et al.* 2009). A time lag of seven days was chosen based on a study in the Arabian Sea which suggests that a minimum time delay for phytoplankton patch to mature to viable forage ground for tuna fish is 5-7 days (Kumari *et al.* 2009).

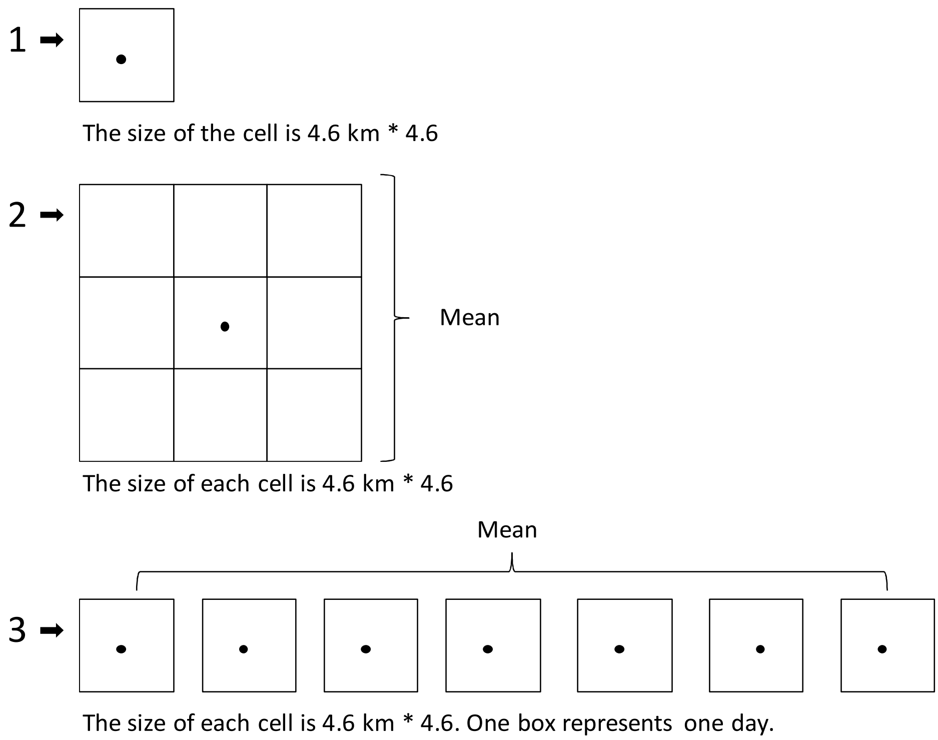

Figure 7 The three different methods used for extraction. The black dot represents a fishing location.

3.3 Mackerel fishing locations

Fishing locations of mackerel originate from fisheries logbook maintained by the Directorate of Fisheries (unpublished data) but were provided by the Marine Research Institute in Reykjavík. Vessels in Iceland mostly use pelagic trawlers for mackerel fishing (ICES 2011). All recorded locations where mackerel catch was >0 were extracted from the *pelagic trawl* dataset in the fisheries logbook for the years 2007 to 2012. These locations were considered to represent the presence of mackerel. A total of 15388 locations were extracted, and in most of the catches (79%), mackerel was the majority (>50%) of the total catches, but Norwegian spring spawning herring dominated the by-catch. In 50% of all catching locations mackerel was the only species caught, but that varied within the study period.

Locations for representing absence of mackerel were also extracted from the *pelagic trawl* dataset by selecting all recorded locations where mackerel catch was zero within the same time period and study area as the presence locations. The study area was defined with the Arc GIS (ESRI 1999-2010) *minimum convex polygon tool*, where the smallest possible polygon was draw to include all presence locations of mackerel catches in the period 2007-2012 (Figure 8 and Figure 9). A total of 2659 absence locations were extracted. Mostly locations of Norwegian-spring spawning herring fishing (79%), but that varied within the study period.

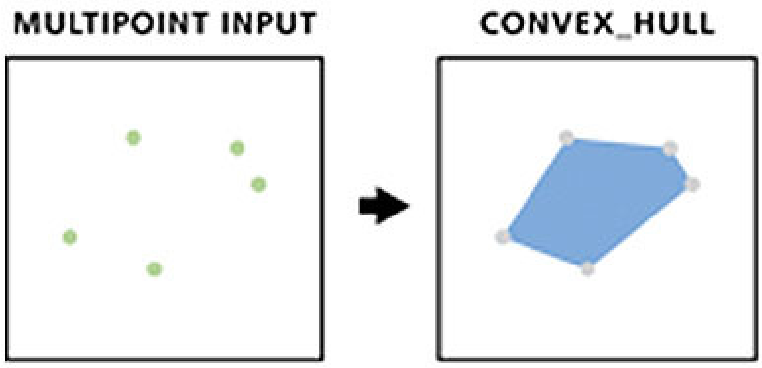

Figure 8 The study area was defined by specifying a minimum bounding polygon enclosing all catching locations recorded in the fisheries logbook where mackerel is >0. (Figure from ESRI 1999-2011).

During the process of satellite data extraction and merging, the number of points decreased substantially, for example due to clouds and atmospheric distortions of different kinds. When all satellite variables and fishing locations had been merged, only 264 absence points for the period 2008-2012 and 2348 presence points remained for the same period. Only 18 points remained for the year 2007 and thus it was excluded from the data set used for modeling.

To limit bias in the model the number of presence and absence locations was kept equal. The final number of absence locations were fewer than presences and thus defines the size of the data set for modeling. Presence locations were randomly sampled for each year to match the number of the absences for the corresponding year. The total number of locations of absences and presences for the model design and testing was 528 (Figure 10), 38 for 2008, 152 for 2009, 68 for 2010, 148 for 2011 and 122 for 2012.

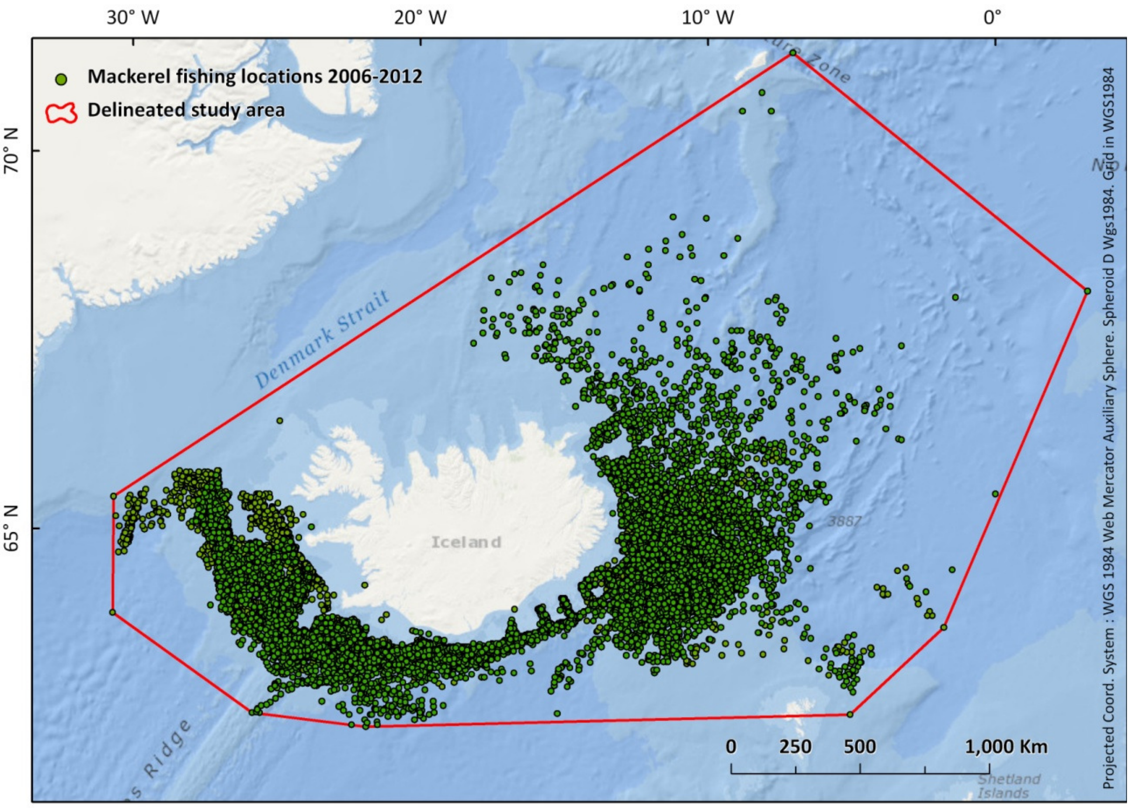

Figure 9 Delineation of the study area is defined by a minimum convex polygon around all presence location points in the period 2007-2012 (n=15388). Base map: ESRI 2012.

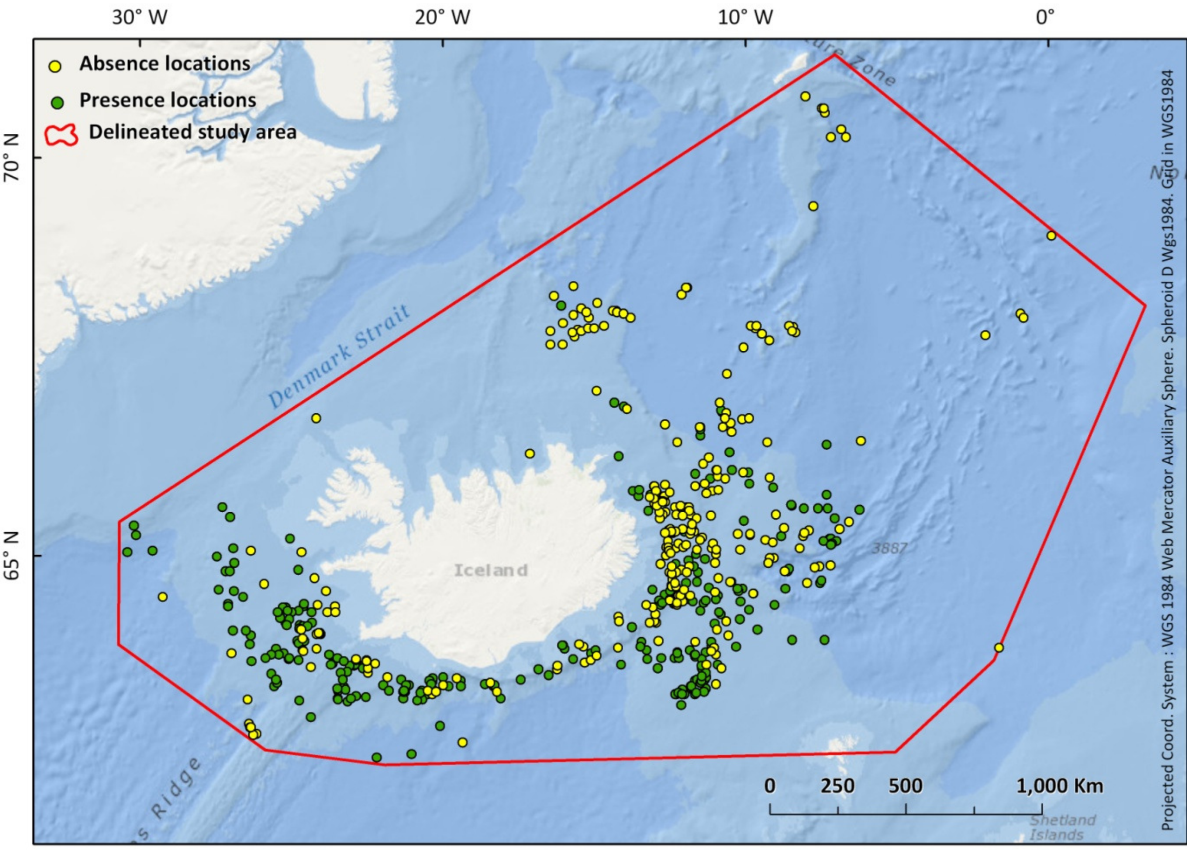

Figure 10 Distribution of absence and presence location as used in the final modeling (n=528). Base map: ESRI 2012

3.4 Methods to explore and test main characteristics of fishing locations and satellite data

Violating the assumptions underlying statistical techniques in regression modeling can increase the possibility of type I or type II errors. Type I errors involve rejecting the null hypothesis when it is true, thus wrongly concluding that a relationship exists. Type II errors involve not rejecting the null hypothesis when it should be accepted. For example autocorrelation can increase the possibility of type I errors and collinearity amongst explanatory variables can increase the possibility of type II errors (Zuur *et al.* 2010, Field *et al.* 2012).

Detailed data exploration is important for extracting the main characteristics of the data and to avoid violating statistical assumptions. The main characteristics of the satellite variables and the dependent variable absence - presence of mackerel location, were explored, tested and visualized in ESRI ArcGIS (ESRI 1999-2011) and the R program and associated packages (Davison and Hinkley 1997; Wood 2000; Venables and Ripley, 2002; Wood 2003; Wood 2004; Pebesma and Bivand 2005; Plummer *et al.* 2006; Wood 2006; Bivand *et al.* 2008; Depayan 2008; R Development Core Team 2011; Wood 2011; Bates and Maechler 2012; Canty and Ripley 2012; Bivand 2013; Bivand and Lewin-Koh 2013; Bivand *et al.* 2013; Girdoux 2013; Pinheiro *et al.* 2013, R Development Core Team 2013; Rowlingson et al. 2013). The focus was on graphical tools, but some statistical tests were also performed. An overview of the various methods used is provided in Table 3.

Outliers can have a dominant effect on model performance. Possible outliers were searched for with Cleveland dot plots and box plots. Collinearity of variables was investigated with conditional box plots, scatter plots, and correlation coefficients. Conditional box plots were used to look for temporal patterns and variograms were drawn to explore the spatial autocorrelation (Table 3).

Significant differences in satellite variables values between the groups absence and presence were tested. Histograms were used to explore normality prior to statistical tests. The data is not distributed according to previously described distributions in statistics, such as normal distributions, thus the non-parametric Wilcoxon’s rank sum test is performed (Table 3). Non-parametric tests test significant differences between medians, but not between means as parametric tests do. Wilcoxon´s rank sum test can be viewed as a non-parametric alternative to the parametric t-test (Field *et al.* 2012).

Significant differences in satellite variable values between years and months for both absences and presences were tested with the Kruskal-Wallis test, which is a non-parametric alternative to the ANOVA F-test.

Significance of the correlation between different satellite variables was tested with the non-parametric Spearman’s rho rank correlation test (Table 3).

Transformation of data was avoided, as the statistical model used (Generalized Additive Model, see section 3.5.1) can deal with untransformed and non-linear data (Zuur *et al.* 2010). Different opinions exist upon the process of transforming data prior to statistical modeling (Field *et al.* 2012). Zuur *et al.* (2010) argue that transformation of the data can lead to difficult interpretation and different conclusions than those reached using untransformed data, and thus suggest avoiding transformation when possible.

Spatial characteristics of the point pattern of the fishing locations were expressed with a standard deviation ellipse created with the *Directional distribution* tool in ArcGIS. The ellipse was created with one standard deviation for all mackerel fishing locations for each year. Tons of caught mackerel are used as a weight field when ellipses are created. The ellipse summarizes the spatial characteristics such as directional and central tendency and the dispersion of the point patterns (ESRI 1999-2011).

The geographical mean center of the mackerel catches for each year was defined by using the *Mean Center* tool in ArcGIS. A geographical center was created with weighted effects, where tons of caught mackerel were used as an input to emphasize the bulk of catches of mackerel and without weight effects to emphasize the actual location, regardless of how much was caught at each location.

Table 3 Overview of data exploration methods, both graphical methods and statistical tests.

Data exploration	Graphical tools and other tools	Statistical test
Outliers	Cleveland dotplots Boxplots	
Collinearity	Scatterplot Correlation coefficient	
Independance	Variograms Conditional boxplots	
Normality	Histograms Conditional boxplots	
Significant relationships		Spearman's rho correlation test Wilcoxon rank-sum test
Significant differences between values of satellite varibles (years and months)		Kruskal -Wallis test
Geographical Mean Center	Mean center	
Central tendency	Standard deviation ellipse	
Directional tendency	Standard deviation ellipse	
Dispersion of points	Standard deviation ellipse	

3.5 Modeling the relationship between mackerel locations and satellite variables

3.5.1 Statistical models

The statistical model used to identify possible relationships between fishing locations and various satellite variables was a Generalized Additive Model (GAM), which is one type of general regression method commonly applied in studies on species distribution (Guisian *et al.* 2006). It can be thought of as an extension of linear modeling. But instead of linear predictor, the functions of the covariates are smoothed, based on the data itself, which improves the ability to deal with non-linear relationships (Guisian *et al.* 2006; Marra and Wood 2011).

A generalized additive model is is a semi- parametrical approach to model the relationship between a response variable and explanatory variables (Guisian *et al.* 2002). Splines are used to describe the relationship and can be applied in a different way to each individual explanatory variable and even linear relationships can be included, resulting in a very flexible model (Wood 2006). The splines are based on certain predefined smoothing classes or even specific user defined smoothing classes. It is semi-parametrical in the sense that the probability distribution of the response variable must be defined, but the relationships are non-parametrical (Guisian *et al.* 2002; Wood 2006). It was developed by Hastie and Tibshirani (1986) and is popular in ecology research and fisheries research, and has proved to be useful when modeling species distribution (Pearce and Ferrier 2000; Guisian *et al.* 2002; Lobo *et al.* 2010; Palialexis *et al.* 2011).

GAM's are often described as a data-driven model approach, as the data input to the model defines the relationship, rather than assuming a predefined parametrical relationship. Due to this empirical nature, GAM's can first and foremost be seen as models to model the realized distribution of species rather than the potential distribution of species. It can therefore be difficult to compare a model for the same species in different areas, or even for same species in the same area but in different times (Guisian *et al.* 2002; Lobo *et al.* 2010).

GAM's have their limitation like other models. As the name suggests it is an additive model and thus assumes that all covariates are independent of other covariates in the model. Any interaction between covariates must by manually defined and incorporated into the model. Another important issue is the selection of appropriate level and basis of smoothing for each predictor (Guisian *et al.* 2002; Wood 2006).

3.5.2 Absence – Presence data

In this study a binomial regression was applied, where the dependent variable was represented as the absence and presence of mackerel catches. Presence can be interpreted in a straightforward manner, as it is mostly certain that the species is present in the location at the time of recording. Absence on the other hand is more uncertain and can be difficult to interpret. Absence can represent either that the species is absent due to lack of favorable conditions or that the favorable conditions are actually there, but other restrictive factors affect the species distribution (Lobo *et al.* 2010). An example of such restrictive factors can be interactions to other species or that the size of the favorable area recording absence is too small. Finally absence can also simply be poorly recorded presence. Another important factor of absence data is its proper distribution and the extent of the study area, as this is what determines the final result of the model. If distance between absence and presence points is large the absence points may not be very informative, resulting in misinterpretations (Lobo *et al.* 2010).

3.5.3 Applying a model to the data

Generalized additive models with binomial distribution and logit link functions were fitted to catch (presence) /no catch (absence) data to determine which variable, or set of variables, best described the pattern of catch/no catch of mackerel in the study area. The R package *mgcv* developed by Simon Wood was used for the analysis (Wood 2000; Wood 2003; Wood 2004; Wood 2006; R Development Core Team 2011; Wood 2011). The degree of smoothing was based on the data itself and the restricted maximum likelihood method (REML) as recommended by Marra and Wood (2011). The smoothing class for all variables was based on thin plate regression splines, which according to Marra and Wood (2011) tends to perform well overall and result in low mean square error compared to other smoothing bases. Thin plate splines refers to a specific form in geometric design for modeling purposes and are considered appropriate when working with two dimensional data in GAM's, such as latitude and longitude (Wood 2003; Wood 2006).

Spatial autocorrelation was evident in explanatory variables. In an attempt to account for the spatial aspect, the location of each observation in latitude and longitude was incorporated into the model as a single smoother.

3.5.4 Sample size

A total of 528 absence and presence locations are used to fit and test the models. According to a study by Pearce and Ferrier (2000) a sample size of 250 or greater is needed to maximize predictive accuracy of generalized additive models. Wisz *et al.* 2008 tested the performance of various species distribution models with various sample sizes to find that generalized additive models were quite sensitive to smaller sample sizes (n =30 and n= 50) but performed well compared to other species distribution models with a sample size of 100.

3.5.5 Selecting explanatory variables

Both *backward* and *forward* selection of variables was performed to determine the most successful model for explaining variance in the catch/no catch of mackerel. For backward selection the smoothing base was set to thin plate regression with shrinkage for all variables and so-called double penalty approach. A penalty was added to each smoother, allowing it to be thrown out of the model by optimization of the smoothing parameter selection criterion, which in this case was restricted maximum likelihood (REML) (Wood 2006). This method has proven to perform better in including important variables than the classical backward stepwise selection of removing variables one by one, based on their significance level, which sometimes eliminates influential predictors (Marra and Wood 2011). Stepwise forward selection was performed by first modeling each variable separately and then adding the variables one by one to explore and find the best models. This was performed based on:

i) Akaike Information Criterion value (AIC), which is a measure of the goodness of the fit of a model (lower value preferred). It accounts for model complexity and is thus a good tool to compare models of different complexities (Field *et al.* 2012).
ii) Significant effects of each predictor (lower p-value preferred).
iii) Model fit, or the deviance explained by the model (higher percentage preferred).The deviance explained is the proportion of the null deviance (likelihood without any parameter) explained by the model.

The *best* single variable was selected and other *high-scoring* variables in these terms were added on to improve the fit of the model.

3.5.6 Model selection

Various parameters were used to select the best models. Validation plots were used to visually interpret and determine how well the models performed and related to underlying statistical assumptions. Pair-wise scatterplots and correlation coefficients were used to assess collinearity in explanatory variables. Histograms were used to determine the distribution of residuals (Table 4).

Model residuals were tested for spatial autocorrelation using Moran's I test in the *pgirmess* package in R (Giraudoux, 2013). The Moran's I spatial autocorrelation coefficient was computed on distance classes based on the spatial coordinates of the fishing locations and possible correlation at each lag tested for significance ($p<0.05$). Values of the coefficient range from -1 to +1. A full negative spatial autocorrelation, indicating dispersion in the data has a value (-1), a random pattern, or absence of spatial autocorrelation has a value of 0 and perfect positive autocorrelation a value of +1 (Bourgeron *et al.* 2001).

Temporal autocorrelation of model residuals was tested using the Autocorrelation Function (ACF) in the package *stats* in R (R Development Core Team (2011). The autocorrelation was estimated at different lags which are plotted in units of time. A confidence limit of 95% was estimated and all values extending outside the limits were considered correlations that significantly differed from zero (Table 4) (Zuur *et al.* 2009).

Table 4 Overview of parameters and methods used to select model variables and validate models.

Parameter	Methods	Preference
Validating models		
Residuals normality	Histograms	Normal distribution
Residuals autocorrelation	Autocorrelation function	Sign. autocorr. not present ($p<0.05$)
Residuals spatial - autocorrelation	Morans I test	Sign. autocorr. not present ($p<0.05$)
Selecting variables and best models		
Successful variables	p-values of smoothers	lowest preferred
Best model(fit)	Deviance explained by model	highest preferred
Best model (fit and complexity)	Akaike's information criterion	lowest preferred

Final models were selected based on avoidance of collinearity in covariates and fulfillment of other statistical assumptions. Deviance explained by the model, AIC of the model and significant effects of the smoothers of variables were considered (Table 4) (Johnson and Omland 2004; Wood 2006; Zuur *et al.* 2009). The simplest models were favored.

3.5.7 Model evaluation

Prior to model design the data set was split up into a training data set (75%), used to design the models and search for relationships, and test data set (25%), used to estimate the efficiency of the model fit. Commonly used partitioning of training and test data sets is 70% - 30% (Dobbin and Simon, 2011; Rodriguez-Castaneda *et al.* , 2012) and 75% -25% (Crisci *et al.* 2012). A suggested rule of thumb says that the proportional split of data set into testing and training should be $1/(1+\sqrt{p-1})$, where p is the number of predictors. A data set with more than 10 predictors should be split to 75% - 25% (Franklin 2009). Prior to model design it was not clear how many predictors would be included in the final models. As they could likely reach 10, a partitioning of 75%-25% was considered appropriate.

The predicted values of a binomial model with 1 and 0 as dependent variables are always between 0 and 1, but are never 0 or 1 (Zuur *et al.* 2009). A threshold probability for estimating the efficiency was arbitrarily set to 0.5, which is commonly used (Manel *et al.* 2001). This means that all values above 0.5 in the models were regarded as presence and all values below 0.5 were regarded as absence.

Cohen´s Kappa coefficient was used to estimate the model performance. It provides a simple and effective statistic to evaluate the performance of species distribution models based on absence-presence, compared to many other evaluation methods (Manel *el al.* 2001). The Kappa coefficient is based on the idea that any random model can by a chance generate acceptable results. It measures if correctly predicted absences and presences are higher than expected by chance alone (Liu *et al.* 2011). The coefficient takes values from -1 to 1, where 0 represents a random chance. Landis and Koch (1977) introduced arbitrary divisions of the strength of agreement for Kappa values to use as benchmarks in comparison discussions: <0.00 = *Poor*, 0.00-0.21 = *Slight*, 0.21-0.40 = *Fair*, 0.41-0.60 = *Moderate,* 0.61-0.80 = *Substantial* and 0.81-1.00 = *Almost perfect.*

3.6 Correlation of observed and satellite sensed CHL values

Only one year of observations was available for validation during the time of this thesis project work - period. Kristinn Guðmundsson and Hafsteinn G. Guðfinnsson at the Marine Research Institute in Reykjavík (unpublished data) kindly provided observation points from surveys in 2006 in the area around Iceland, extending from 62°N to 71°N and 0° to 35°W. A total of 456 observation points for chlorophyll observations were available for the period from 14th of May to the 2nd of August 2006, with most of the samples sampled in July (Figure 11). Chlorophyll was systematically sampled at two depths; 0-5 meters and 5-15 meters. Hundred and thirty nine observations were available for the depth of 0-5 meters and 317 observations for the depth of 5-15 meters.

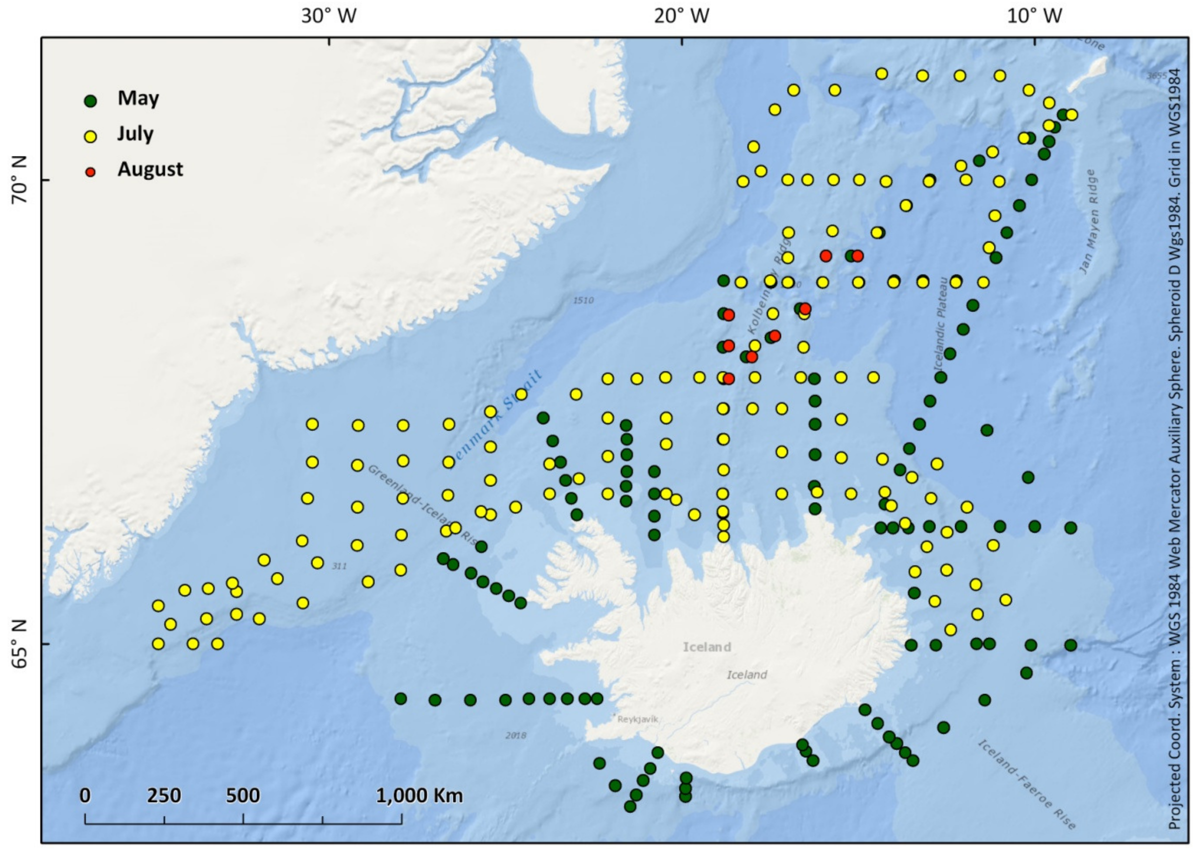

Figure 11 Spatial and temporal distribution of sampling locations of CHL at two different depths. Different sampling months are identified with different colors. Base map: ESRI 2012.

Satellite CHL values were extracted from the Globcolor dataset according to the dates and locations of in situ observations. Their correlation was analyzed and tested for significance using the non-parametric Spearman's rho correlation coefficient, as histograms reveal non-normal distribution. An overview of the data acquisition and manipulation as well as the methods and software used are shown in Figure 12.

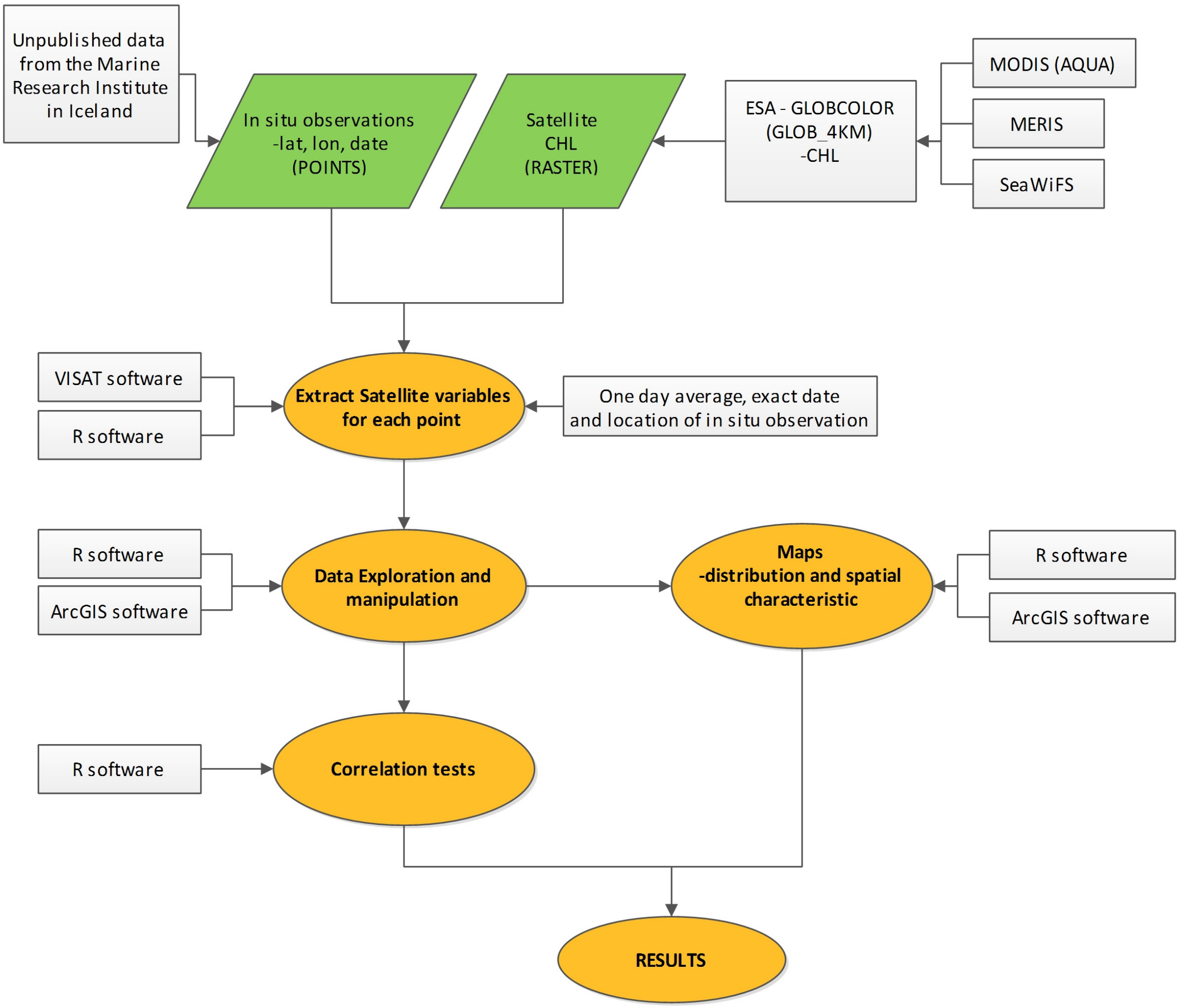

Figure 12 Flowchart of data acquisition and methods used to correlate observed and satellite sensed CHL.

4 Results

4.1 The spatial and temporal pattern of mackerel catches from 2007-2012

Mackerel catches in Icelandic waters have moved westward from 2007 to 2012. Changes in the spatial pattern from 2007 to 2012 are vividly shown in Figure 13. In 2007, mackerel were caught in a few

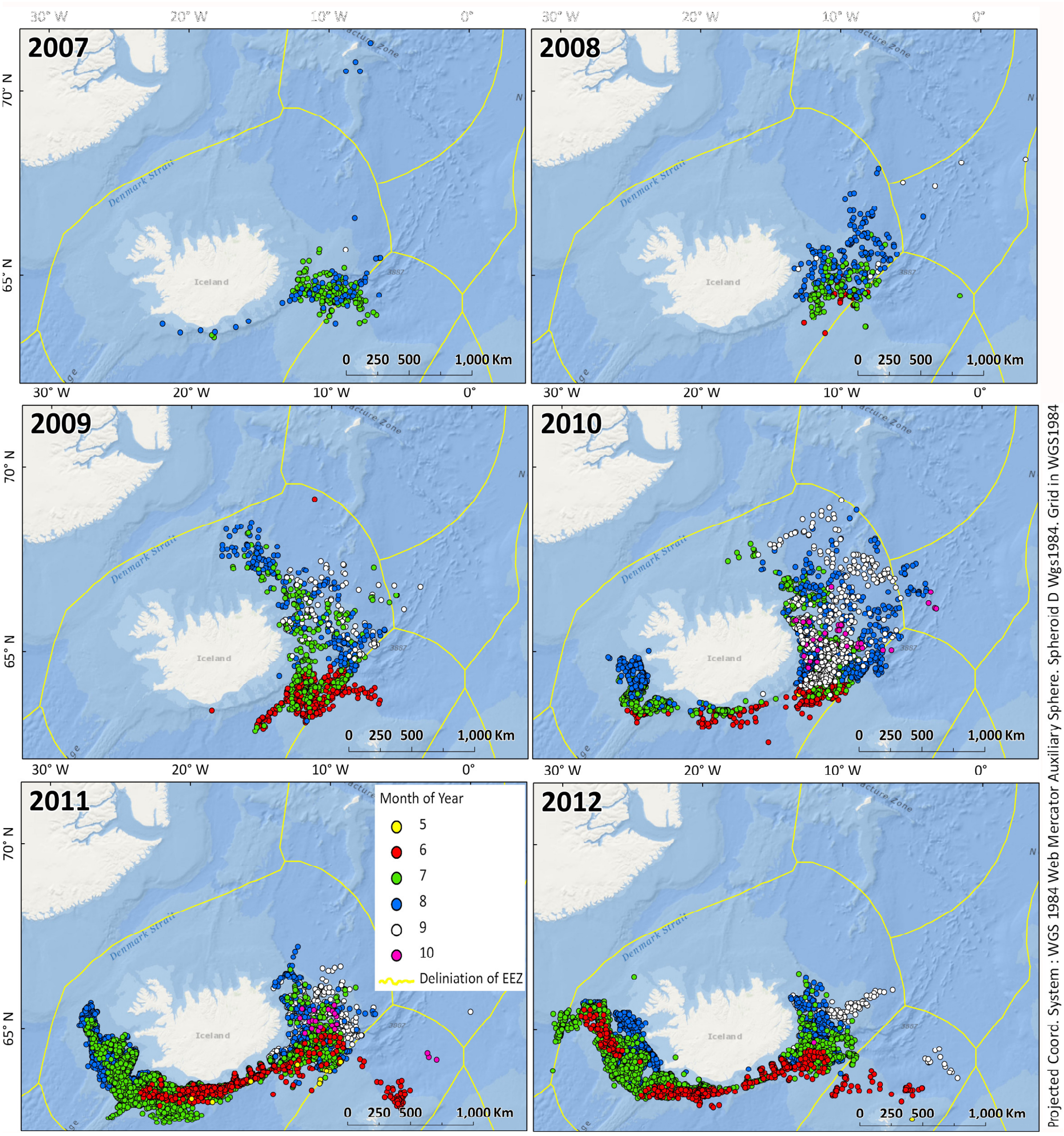

Figure 13 Spatial and temporal pattern of mackerel fishing locations in Icelandic waters 2007-2012. Base map: ESRI 2012.

locations clustered east of Iceland for the months July, August and September. The pattern in 2008 was similar, but with a little northward expansion and an extended period. Fishing started in June and more locations were recorded in September compared to the year before. In 2009, mackerel fishing started as early as May and the locations continued to be mainly in the east, but with more expansion to areas NE and NW of Iceland. A marked change in the pattern was evident in 2010, when mackerel was caught all along the south coast and in areas west of Iceland. The fishing period also extended to

October that year. The distribution patterns in 2011 and 2012 showed the continuing westward movement and in 2012 mackerel was caught in the waters of Greenland (Figure 13).

Spatial characteristics of the fishing locations also revealed that fishing locations moved westwards and furthermore extended over wider areas. The standard deviation ellipses summarize the spatial characteristics of the pattern each year (Figure 14). They were based on weighted locations, where amount of mackerel caught gives weight to each location. The ellipses reflect the directional and central tendency each year and how the catches are dispersed over the study area. Changes from year to year are evident.

The bulk of catches of mackerel fishing are still located to the east of Iceland. The calculated mean center for mackerel fishing locations further emphasized the pattern of westward movement during the period 2007-2012, with the exception of 2008, when it moved slightly northwards (Figure 14). A comparison of the mean center, where each location got the same weight regardless of the amount of mackerel caught, to weighted mean center, where the amount of caught mackerel had an impact on the location, revealed that the bulk of catches remained more to the east.

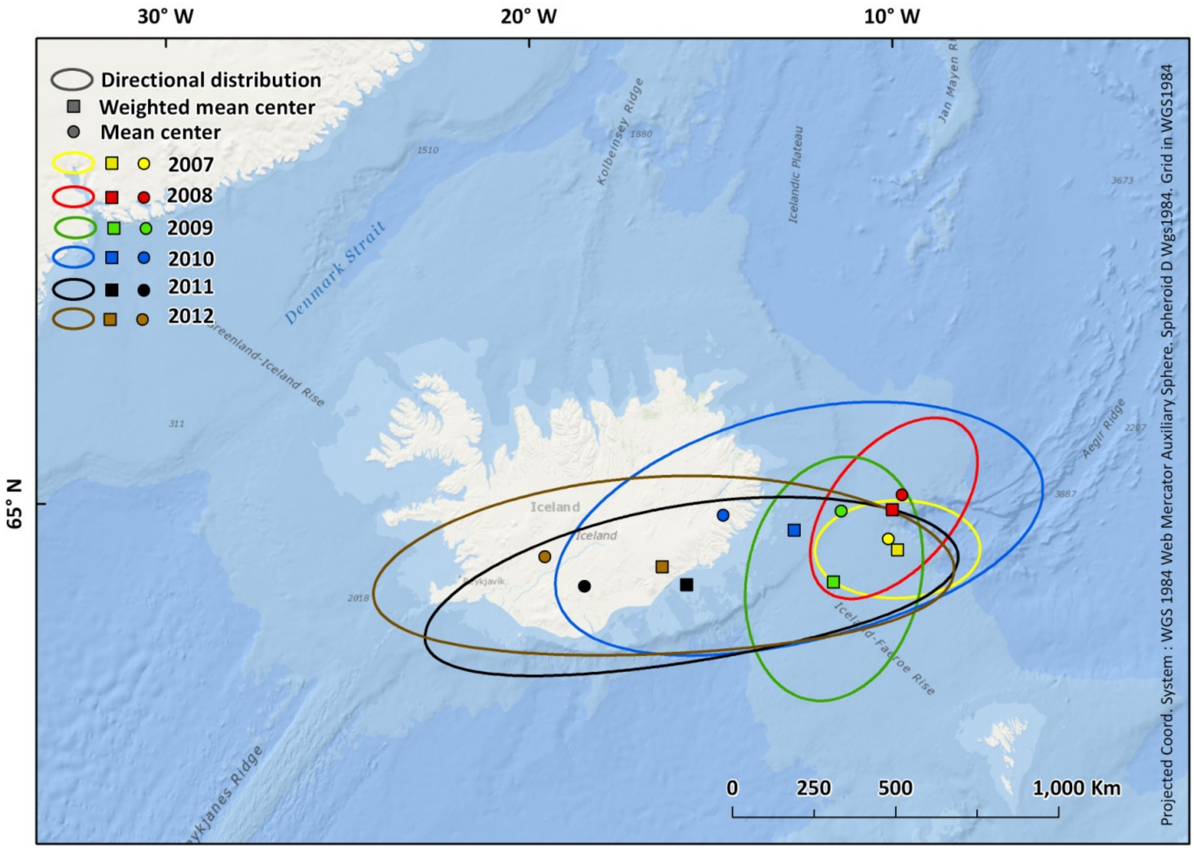

Figure 14 Spatial characteristics of the fishing locations of mackerel in Icelandic waters from 2007 to 2012. Two mean centers are displayed for each year. Weighted mean center, represented with squares and un-weighted mean center, represented with circles. Base map: ESRI 2012.

Size of mackerel catches had on average decreased and mackerel changed from being a bycatch species to the main species caught during the period 2007-2012. During the first years the catches of mackerel were on an average larger and the mackerel was most often caught with other species. In 2011 and 2012 there was a marked change in the fishing behaviour as the catches got smaller on averge and mackerel became the main species caught. An overview of the main characteristics of the changing fishing pattern by years and by months is shown in Figure 15. The boxes contain 50% of the observations, between the 25% and the 75% quartiles. The black line in the middle represents the median. The distance of the lines extending out of the box represent the lowest and highest 25% of the values. Outliers are not included in the plots, thus excluding a few very large catches in 2011 and 2012. The width of the boxes is proportional to the sample size. The sample sizes are largest for 2011 and 2012, but smallest for 2007 and 2008. The indents around the median are called notches and if they do not overlap notches of other boxes it is strong evidence that the medians differ.

Largest catches of mackerel during the period 2007-2012 are on average in June (Figure 15, top left).

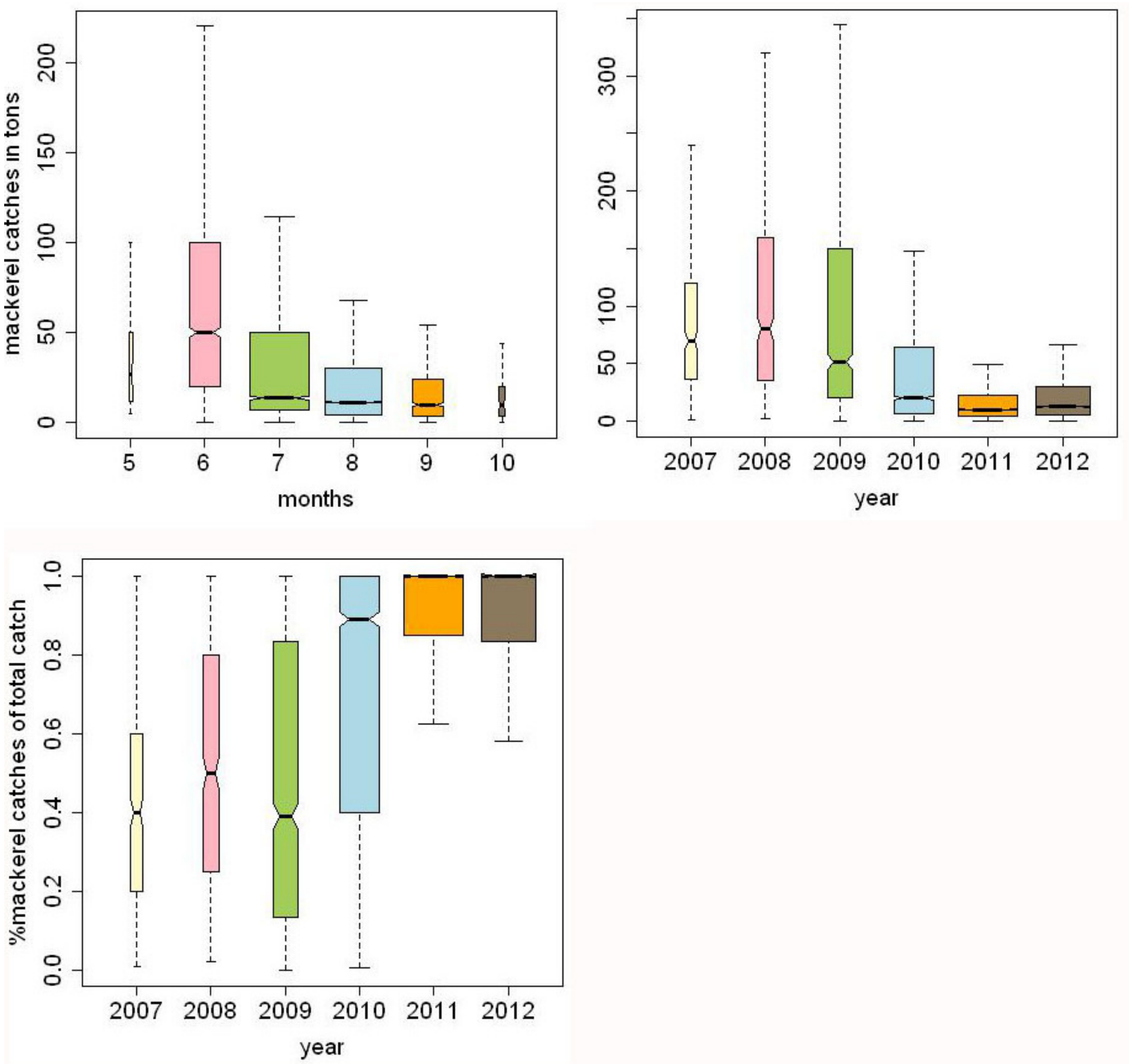

Figure 15 Temporal differences in the catching pattern of mackerel by months for all the years (top left). By year (top right) and the proportion of mackerel in total catch at each location each year (bottom left).

4.2 Fishing locations and satellite variables

4.2.1 Visualizing the relationship

Visual estimation of the relationship between satellite remote sensing variables and fishing locations was somewhat confusing. The ban on mackerel fishing within the isoline of 200 m depth influenced the distribution pattern (Figure 16, Figure 17 and Figure 18) (Icelandic regulation no. 504/2010, no. 233/2011 and no. 329/2012). Comparison of mackerel fishing locations and spatial distribution of SST indicated that mackerel avoided the colder water masses below about 7°C (Figure 16).

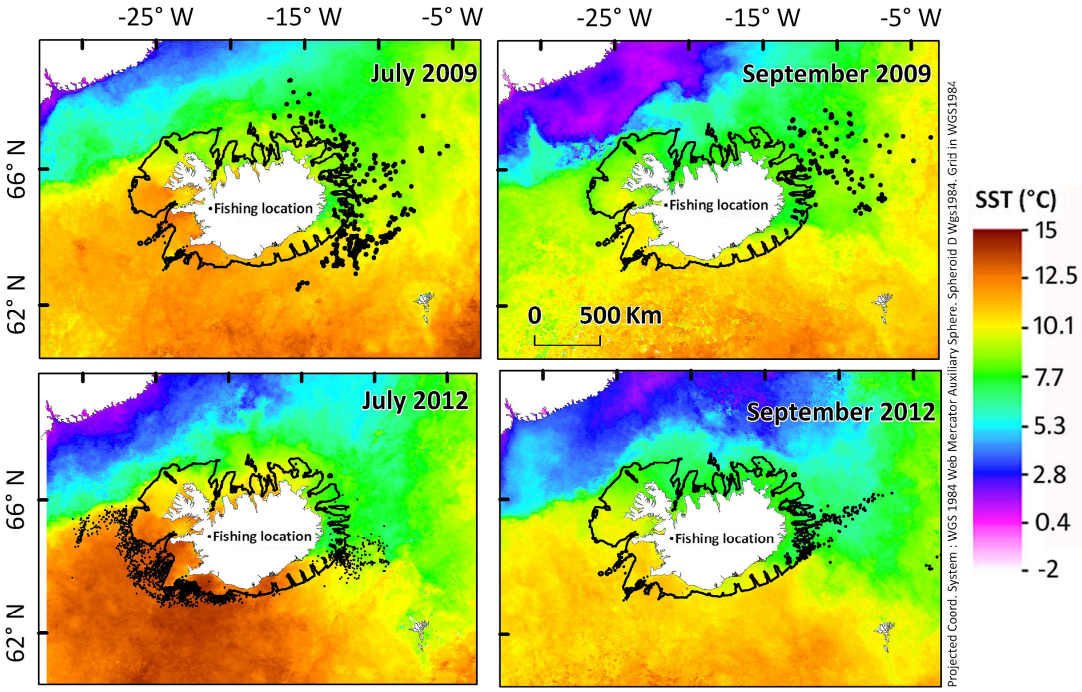

Figure 16 SST and fishing locations in July and September in 2009 and 2012, which were arbitrarily chosen for display in this report. The black line represents the isoline for 200 m depth.

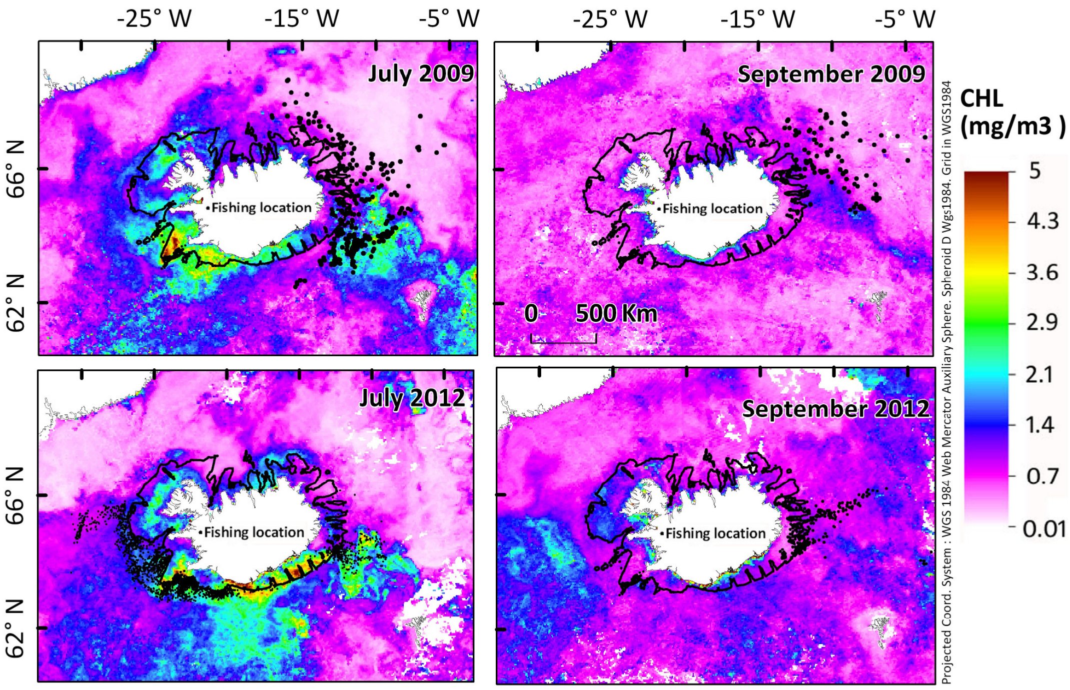

Figure 17 CHL and fishing locations in July and September in 2009 and 2012. The black line represents the isoline for 200 m depth.

Comparison of fishing locations and CHL concentrations suggests that mackerel was caught in intermediate concentrations of CHL, or around 1-3 (mg/m^3) (Figure 17). No specific pattern was obvious when fishing locations were visually compared to the values of PAR (Figure 18), L443 (not shown) and kd490 (not shown).

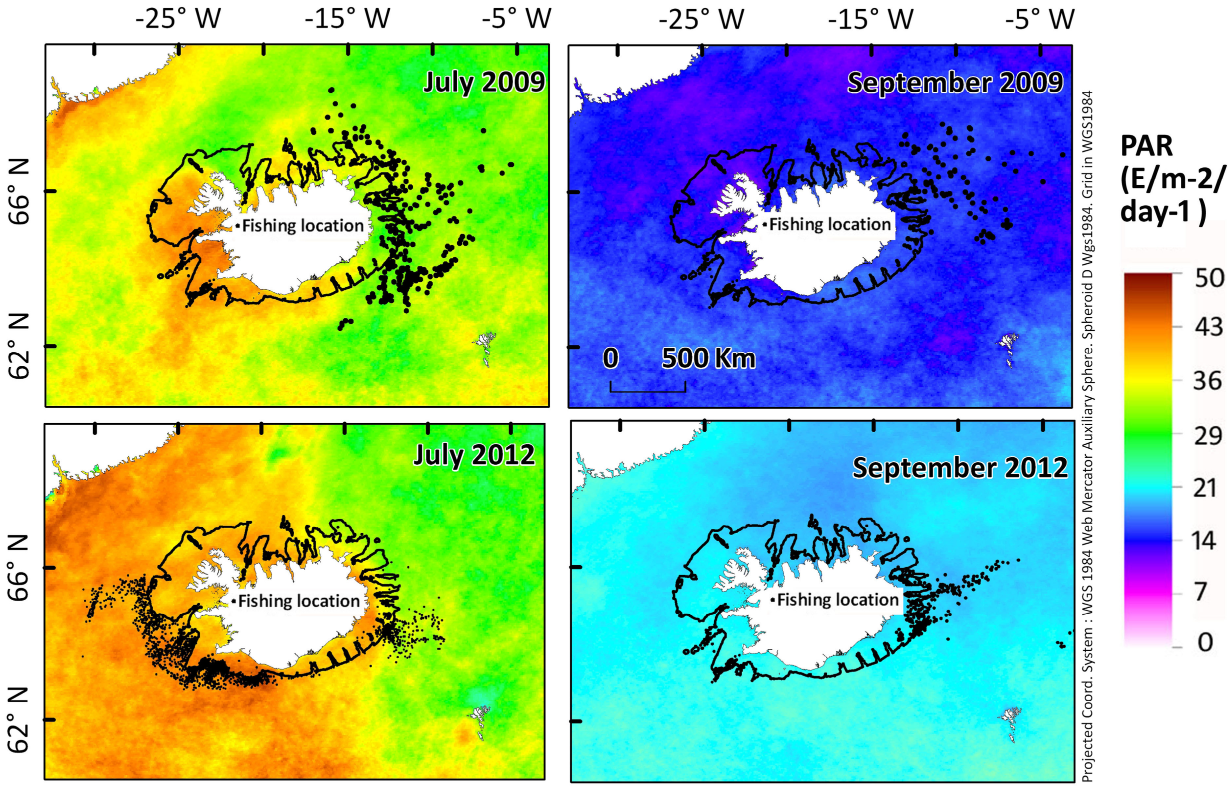

Figure 18 PAR and fishing locations in July and September in 2009 and 2012. The black line represents the isoline for 200 m depth.

4.2.2 Statistically describing and testing the relationship

The spread of the values of the satellite data differed between absence and presence locations. Large differences in values of PAR and SST for absences and presences are evident in Figure 19. As the notches of the box plots for absences and presences for both L443 and kd490 do not overlap, there is evidence that their medians differ. The values of absence and presence values of CHL are more similar than the other variables explored.

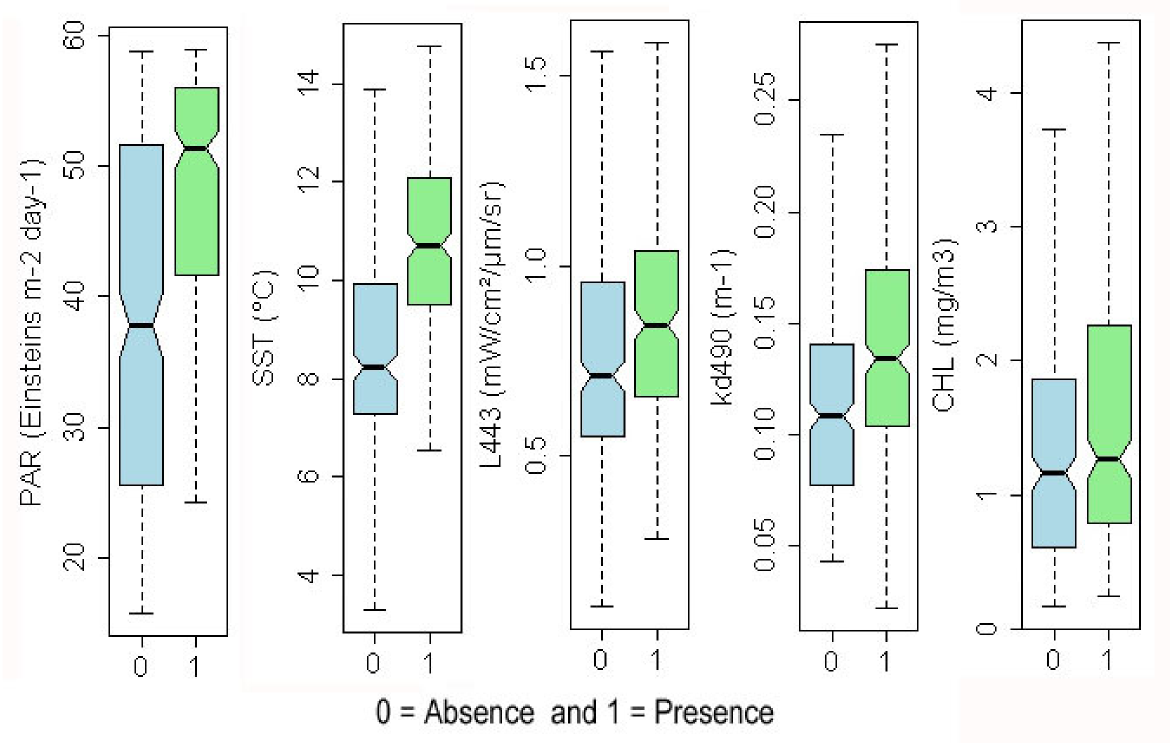

Figure 19 Differences in satellite parameter values for absences and presences for CHL, L443, kd490, SST, PAR.

Significant differences are present between the groups absence and presence for all five satellite variables: CHL ($p=0.02$), L443 ($p<0.001$), kd490 ($p<0.001$), SST ($p<0.001$) and PAR ($p<0.001$).

Monthly temporal differences were evident in the values of the satellite variables for both absences and presences and the differences were similar for the two groups (Figure 20). The largest differences were seen in PAR, which was highest in June and July and lowest in September. SST and L443 had the highest values in July, but values for CHL and kd490 were highest in June.

Significant differences ($p<0.05$) were found in absence values between the different months for all five variables. Significant differences ($p<0.05$) are also found in presence values between the different months for all five variables.

Annual temporal differences are also evident in the values of the satellite variables for both absences and presences, but with patterns not as obvious as those found in the monthly differences (Figure 21). A trend is apparent towards warmer SST at the majority of the mackerel catching locations from 2008 to 2012, but the trend is not as apparent in the absence locations. Other variables show irregular differences between years.

Significant differences ($p<0.05$) are found in absence values between the different years for all variables except SST ($p=0.161$). Significant differences ($p<0.05$) are also found in presence values between the different years for all variables except CHL ($p=0.056$).

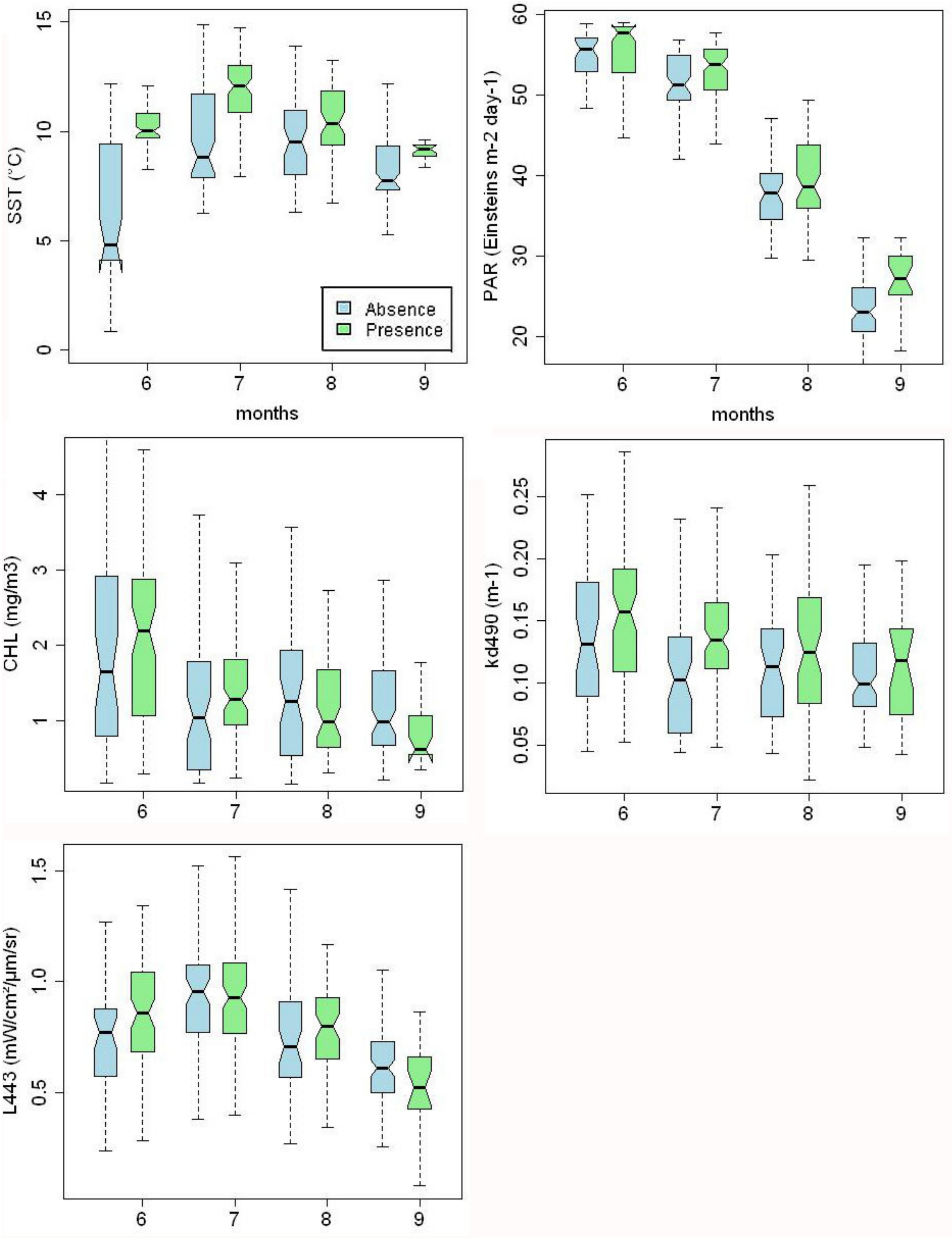

Figure 20 Monthly temporal differences in satellite variables values for both absences and presences for 2008 to 2012.

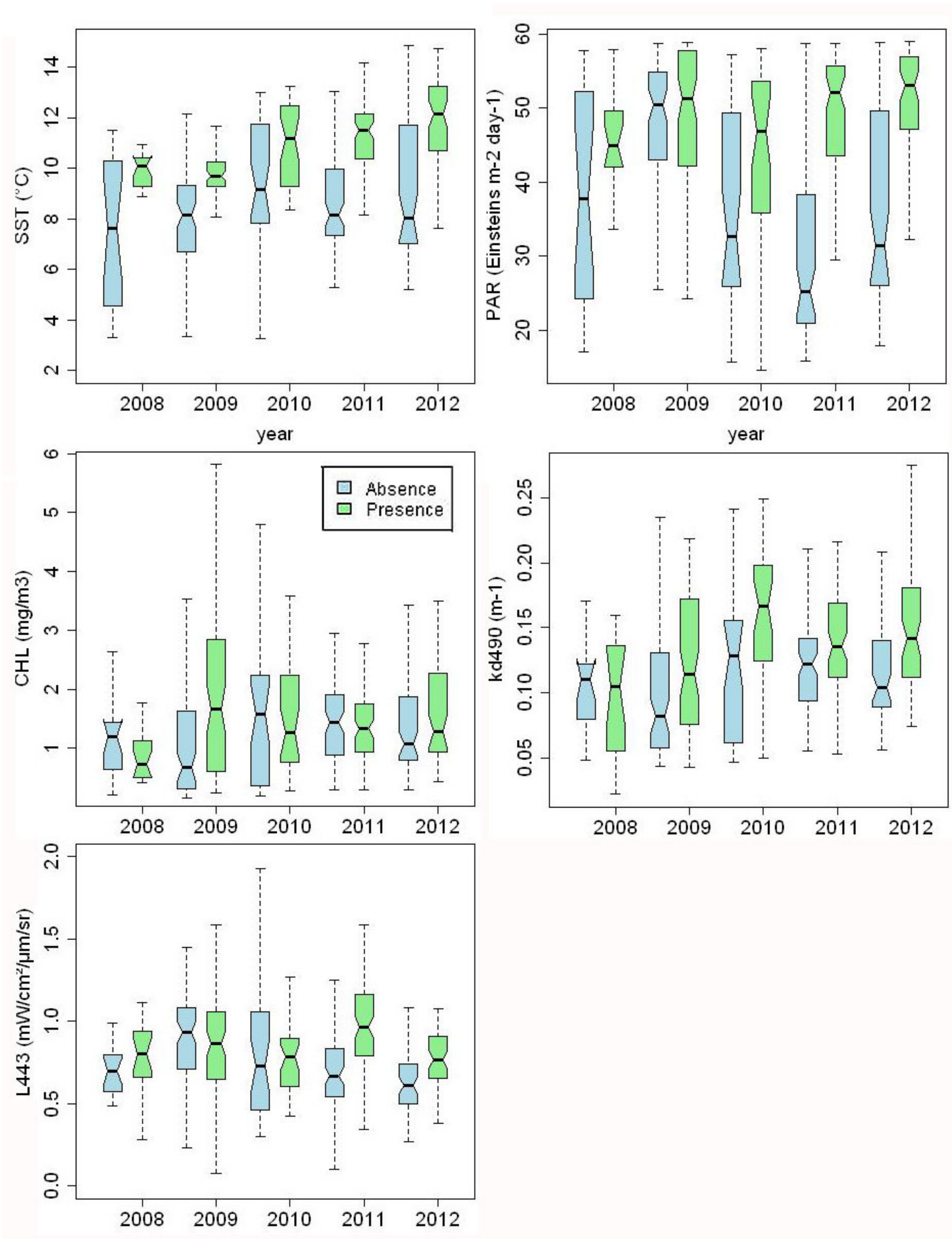

Figure 21 Annual temporal differences in satellite variables values for both absences and presences for 2008 to 2012.

4.2.3 Modeling the relationships

4.2.3.1 Single satellite variable models

SST was the most important single variable indicated by the first model results, explaining about 24% of the deviance in presence and absence of mackerel at fishing locations. Deviance explained by other individual variables ranged from 2.2% for L443 to 4.7% for CHL and 13% for PAR for single cell and single day. The spatial variables latitude and longitude explained more deviance (30.8%) than any single environmental variable. Latitude alone explained 18% of the deviance and longitude 8.4%.

The first models were not successful as residuals were not normally distributed and autocorrelation was evident in the residuals of models with all the different single variables: CHL, SST, PAR, CDM, kd490 and L443. A Moran's I test revealed a significant spatial autocorrelation ($p<0.05$) at the shorter distances for all variables (Figure 22a).

Single variable models improved considerably by adding a smoothing term with the spatial variables latitude, longitude. Spatial autocorrelation was eliminated (Figure 22b) and the distribution of residuals improved. Fit of the models, or deviance explained also increased.

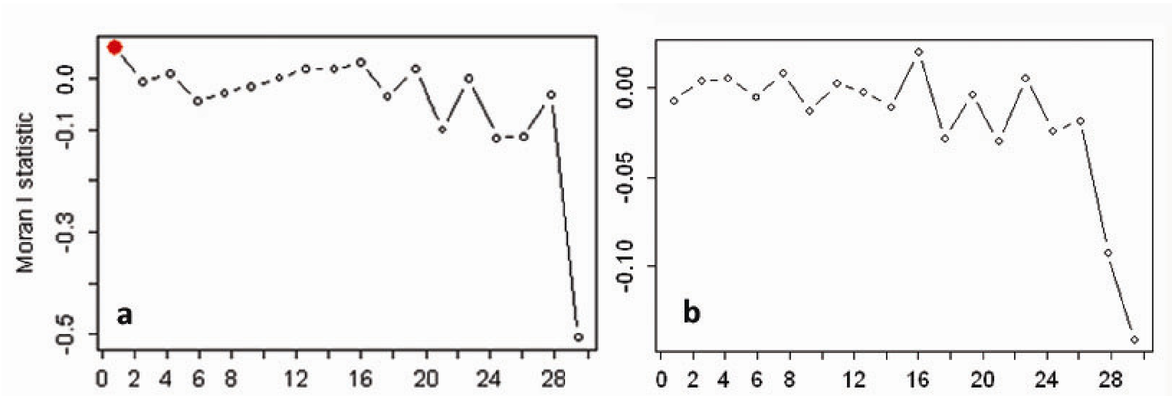

Figure 22 Results of a Moran's I test on the spatial autocorrelation of the residuals in two models for SST. X-axis represents different distance classes/lags of two degrees. Red (filled) dot represents a significant spatial autocorrelation ($p<0.05$). To left: Spatial autocorrelation was evident at the shortest distances. To right: Including the spatial variables latitude and longitude in the model removed spatial autocorrelation (note difference in Y-axis). Similar results were obtained for all other single variable models.

CHL became the most successful single environmental variable in terms of model fit, when latitude and longitude were incorporated into the models, explaining 39% of the deviance. Considering both model fit and complexity of the models, both PAR and SST had a slightly lower AIC value than the CHL model, so they were considered successful as well (Table 5).

Decreasing spatial resolution to 3 cells did not improve the models. The proportion of deviance explained by each variable did not or increase nor decrease to a large extent. CHL still explained the most deviance and the model improved in terms of the AIC value (Table 5).

Decreased temporal resolution improved the deviance explained for all single variables models. PAR became the most successful variable with an increased deviance explained from 36% to 47%. kd490 increased from 32% to 43% deviance explained, L443 increased from 33% to 45% deviance explained and SST increases from 34% to 44% deviance explained. CHL only increased from 41% to 42% deviance explained (Table 5).

The most successful model, when models for all the different spatial and temporal resolutions were compared, was the 7 day average PAR model, explaining about 47% of deviance. Seven day SST explained 44% of the deviance in the dependent variable (Table 5).

The smoothers of the variables were significant for all the models, except the kd490 model for one day, one cell and the kd490 model with one day and decreased spatial resolution to three cells (Table 5).

Table 5 Models with single satellite variables for different spatial and temporal resolutions. All models include the spatial variable latitude and longitude. The most successful model for each resolution variation is highlighted.

Single satellite variables	Deviance Explained %	AIC	Smooth terms P-value
One day - one cell			
SST	35	397	0.001
PAR	36	393	0.000
CHL	39	385	0.000
kd490	32	416	not sign.
L443	33	404	0.000
One day - three cells			
SST-3 cells	34	399	0.000
PAR-3 cells	36	393	0.000
CHL-3 cells	41	378	0.000
kd490-3 cells	32	416	not sign.
L443-3 cells	35	403	0.000
Seven days - one cell			
SST-7 days	44	344	0.001
PAR-7 days	47	335	0.000
CHL-7 days	42	371	0.000
kd490-7 days	43	360	0.001
L443-7 days	45	345	0.000

The shapes of the smoothers, defined by the models, depicted the relationship between absence and presence of mackerel catches and the satellite environmental variables (Figure 23).

Better light conditions increased the probability of catching mackerel. The probability of catching mackerel rapidly increased with PAR between 10 and 30 $E/m^{-2}/day^{-1}$. With PAR above 30 $E/m^{-2}/day^{-1}$ the probability remained high (Figure 23).

Mackerel was more likely caught in clearer waters where there was less absorption, but also in more turbid waters due to high scattering. The probability of catching mackerel increased rapidly from 0.5-1 $mW/cm^2/\mu m/sr$ and with L443 above 1 the probability remained high, but the confidence level widened as there were fewer values (Figure 23).

The probability of catching mackerel also rapidly increased as SST increased from 4-8°C where it peaks. At temperatures higher than 9-10°C the likelihood of catching mackerel decreased again, although it still remained quite high, or $p=0.6$ at 14°C (Figure 23).

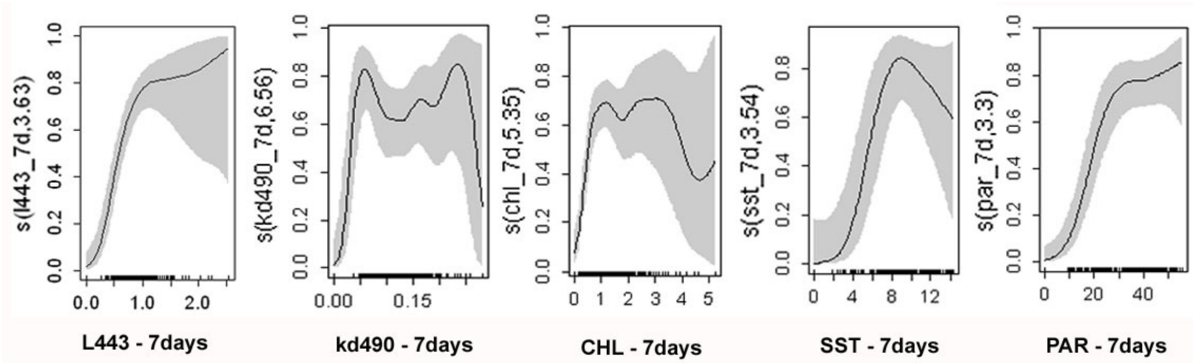

Figure 23 Shapes of the non-linear relationships (smoothing functions) between dependent variable and the five explanatory variables in single variable models. Y-axis represents the probability of catch (1) or no catch (0). The number in brackets is the estimated degrees of freedom for the smooth curves. Bars at the bottom show distribution of covariate values. Shaded areas represent the 95% confidence limit, which widens where there are fewer values of covariates.

According to the smoother for kd490, it was most likely to catch mackerel at 0.05 and 0.25 m^{-1} and the probability decreased rapidly with values above 0.25 m^{-1}. Note that the rapid decrease is based on only one value (Figure 23).

Intermediate concentrations of CHL increased the probability of catching mackerel. As concentration of CHL increased from 0 to 1 mg/m^3, the probability of successful mackerel fishing increased. With concentration above 1 mg/m^3 the probability remained steady with $p \approx 0.7$. CHL concentrations above 3.5 mg/m^3 resulted in decreased probability (Figure 23). Note that the highest probability value for CHL ($p \approx 0.7$) was somewhat lower than the highest probability values for other variables ($p \approx 0.8$-0.9).

4.2.3.2 Multiple satellite variables model

The most successful multiple variable models included the one or seven day variables SST, PAR and L443 for seven day mean with 48% of deviance explained. A comparison of models created with both backward and forward selection reveals that these are the best models in terms of the highest deviance explained, strong significant effects, lowest AIC value and no collinear variables. Other similarly successful models include variations of seven day SST and PAR values along with either seven day CHL or seven day CHL and seven day L443 (Table 6). All the models include the spatial variables latitude and longitude. Residuals are fairly normally distributed and temporal and spatial autocorrelation was not present in residuals of the most successful models.

A model including all the single day, single cell variables: SST, PAR, CHL, L443 and kd490 proved to be the most successful model according to an automatic backward selection of variables with a penalty. But because kd490 and CHL were highly correlated (ρ^2=0.84) with strong significance ($p<$ 0.001), one of them was excluded to avoid collinearity. This resulted in a much worse model, no matter which variable was excluded (Table 6).

The smoothing functions of the multiple variable model with single-day PAR, SST and seven day average of L443 suggested similar breakpoints in probability as the single variable models (Figure 23 and Figure 24). The model indicated that the probability of catching mackerel increased rapidly as L443 increased from about 0.25 mW/cm²/µm/sr to 0.75 mW/cm²/µm/sr and remained high with values above 1. The probability of catching mackerel in waters with SST from 2°C to 6 °C was low, but increased rapidly between 6°C and 8°C. It peaked at about 8° to 9°C where the probability started to decrease again but still remained high with p>0.5. As the PAR value gets higher, the probability of catching mackerel increased steadily (Figure 24). The smoothing function for PAR looks basically linear, but a model where PAR was included as a linear parameter resulted in a worse model.

Table 6 Models with multiple satellite variables for different spatial and temporal resolutions. The most successful models are highlighted.

Multiple environmental variables models (significance in brackets)	Dev. Expl. %	AIC
One day - one cell		
SST (***)+PAR (***)+ kd490 (***)+CHL (***) + L443 (n.s.)	51	306
SST (***)+PAR (***)+CHL (***) + L443 (n.s.)	44	348
SST (***)+PAR (***)+kd490 (n.s.) + L443 (n.s.)	31	389
SST (***)+PAR (***)	36	376
One day - three cells		
SST (***)+PAR (***)+ L443 (*)	37	338
SST (***)+PAR (***)	36	378
PAR (***) +SST (***)+CHL (***)	46	340
Seven days - one cell		
SST (***)+PAR (***)	46	325
SST (***) +L443 (***)	45	336
PAR (***) +L443 (***)	47	328
SST (***)+PAR (***)+ L443 (*)	48	321
SST (***)+PAR (***)+ CHL (n.s.)	46	325
Mixed spatial and temporal resolution		
1d PAR (***) +1d SST (***)+7d CHL (***)	43	341
1d PAR (***) +1d SST (***)+7d L443 (***)	48	321
1d PAR (***) +7d L443 (***)	47	333
1d SST (***) +7d L443 (***)	46	335
1d PAR (***) +1d SST (***)+3c CHL (***)	46	338

*Signif. codes: 0 '***' 0.001 '**' 0.01 '*' n.s.=not significant*

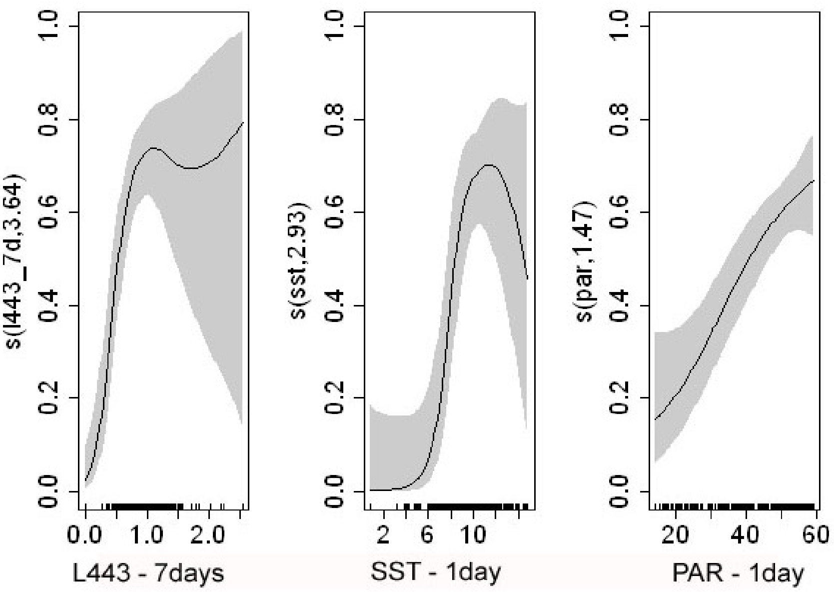

Figure 24 Shapes of the non-linear relationships (smoothing functions) between catching locations and the three explanatory variables included in the one of the most successful models with multiple satellite variables: A seven day average of L443 and a daily average of SST and PAR.

4.2.3.3 Model evaluation

Fitting the *highest scoring* models to the test data set was successful. Results supported the suggestions of models that the probability of catching mackerel rapidly increases with SST in the range 7.5 °C to 8.5 °C. With values of L443 above 0.05 the probability of a catch was higher. Increased PAR values steadily increased the probability of a catch (Figure 25).

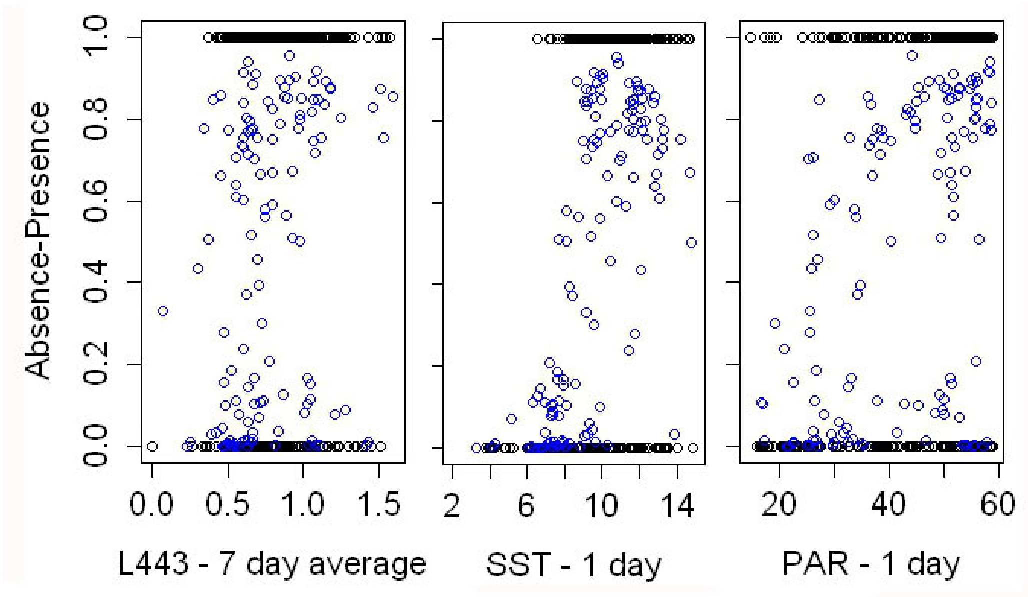

Figure 25 Predicted values from a test data set (blue circles) for the three variables L443 – 7 day average and one day average of SST and PAR and the actual values of presence and absence of mackerel catches (black circles).

The predictive ability of some of the most successful models was good. The predictive capabilities of the models are summarized in Table 7. All models predicted presence better than absence. The model with seven day average value of SST predicted absences most successfully and the 1 day average SST and PAR with seven day average L443 model best predicted presences, but only with 1% more success than the 7 day average PAR and 7 day average SST models did. According to the Kappa coefficient, the 7 day SST model was most successful and the only model with a *Substantial* strength of agreement according to the Landis and Koch divisions. The other models tested had a *Moderate* strength of agreement.

Table 7 Predictive success of some of the most successful models. Overall accuracy for absence and presence predictions is shown and the Kappa coefficient value along with the strength of agreement division class.

Model	Absence	Presence	Total	Kappa	Strength of agreement*
1day CHL	72%	83%	77%	0.53	*Moderate*
7day PAR	68%	91%	77%	0.55	*Moderate*
7day SST	75%	91%	81%	0.62	*Substantial*
1daySST + 1day PAR + 7day L443	72%	92%	80%	0.60	*Moderate*

** divisons by Landis and Koch (1977)*

4.3 Correlation of observed and satellite sensed CHL values

Extraction success was not high for the observed values. Only 20 values were extracted (14.3%) for the shallower depth interval of observations of 0-5 m and only 43 values (13.5%) for the observations from 5-15 meter depth. Distribution of the observations for the two different depth intervals and the extraction success for the two depths are shown in Figure 26 and Figure 27.

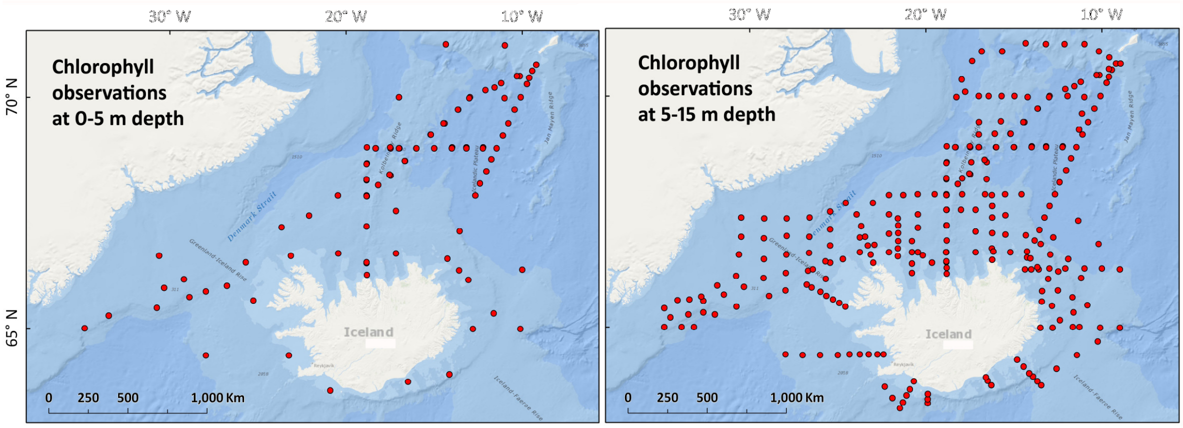

Figure 26 Chlorophyll observations locations in 2006 at depth 0-5 m (left) and 5-15 m depth (right). Base map: ESRI 2012.

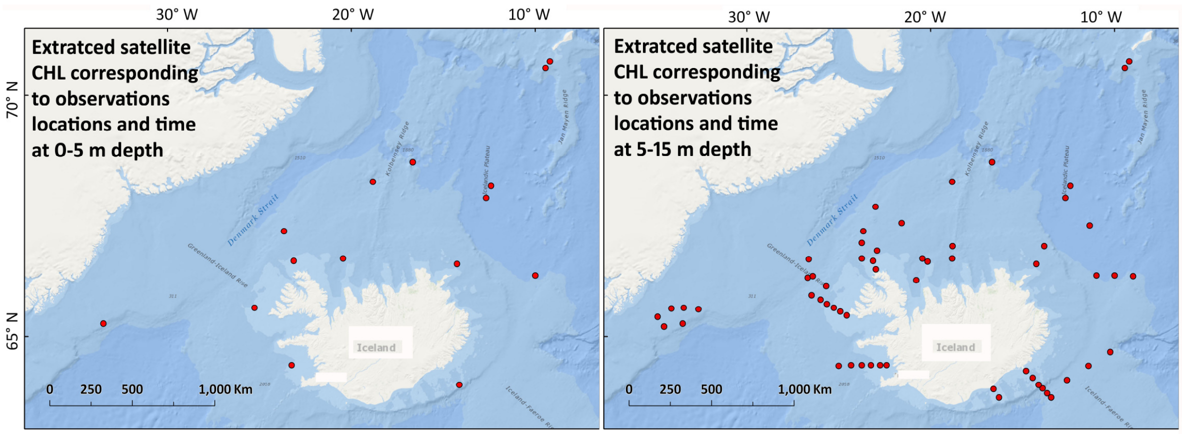

Figure 27 Extraction success for chlorophyll observations at the depths, 0-5 m and 5-15 m. Base map: ESRI 2012.

Highly significant relationships ($p<0.001$) between observed and satellite CHL was revealed by Spearmans's rho test. The correlation coefficient was $\rho=0.92$ ($\rho^2=0.85$) for observed CHL in the topmost layer and surface CHL detected by satellite. For CHL observed at 5-15 m the correlation coefficient was a bit lower, or $\rho=0.81$ ($\rho^2=0.66$) (Figure 28).

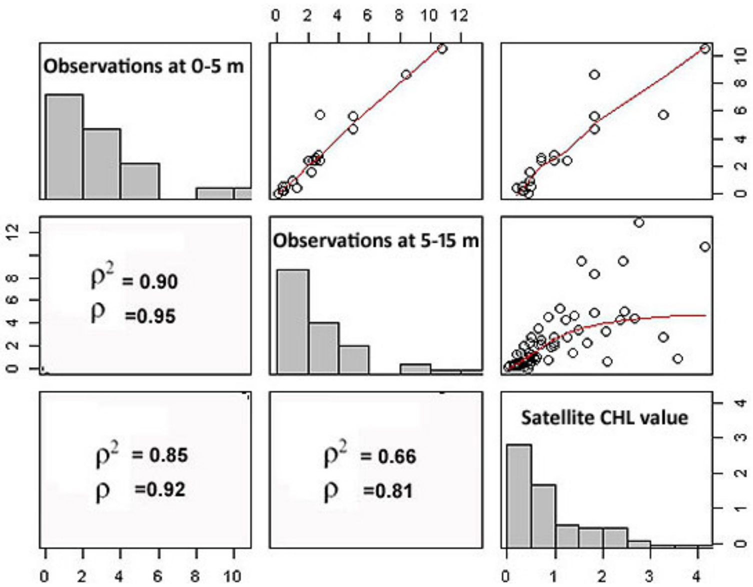

Figure 28 Scatter plot and a Spearmans's rho shows a strong relationship between observed and satellite remotely sensed chlorophyll values.

5 Discussion

This study demonstrates that there is a relationship between catches of Atlantic Mackerel and remotely sensed environmental variables, thus the hypothesis is supported. The preceding results suggest that there is a significant difference between the satellite variable values between the groups delimiting absence and presence of mackerel at fishing locations. The remotely sensed variables CHL, SST, PAR and L443 significantly contribute to models which can partially explain absences and presences of mackerel catch in Icelandic waters. Decreased temporal resolution from one day to seven days increases the ability of satellite variables to explain locations of absences and presences. The shapes of the non-linear relationships of explanatory and dependent variables suggest that increased light (PAR), SST in the range from 8° to 13°C and waters with intermediate concentration of CHL are conditions where the probability of catching mackerel increases. Increased water clarity due to less absorption and also decreased water clarity, or increased turbidity, due to scattering in the water column seems to increase the probability of catching mackerel. Furthermore a strong significant correlation between *in situ* observed and satellite sensed CHL gives confidence in the use of global satellite data sets in local situations around Iceland. In this chapter the results are discussed in the context of previous findings, from the point of view and as to whether they make sense given what is known about the biology and ecology of the Atlantic Mackerel and other pelagic fish.

5.1 The most successful explanatory variables summarized

The satellite variable CHL is the most successful single explanatory variable for variables with one day temporal resolution and both one and three cell spatial resolution, when the spatial components latitude and longitude have been incorporated. Other important variables are PAR and SST. For seven day resolution, PAR becomes the most successful single explanatory variable. The most successful models with multiple covariates are models with either one day or seven day average values of PAR and SST and seven day average values of L443. The most successful model in predicting absences and presences in the test data set was 7 day SST, with a slightly better ability to predict absences than the one day average PAR and SST with a seven day L443 model.

5.2 Satisfactory models

The deviance explained by the more successful models ranges from 39% to about 48%, when the spatial variables latitude and longitude are included. According to Smith *et al.* (2013) such values are considered satisfactory. Models with similar values of deviance explained, have been used to map and predict potential habitat of various fish species. For example for anchovies in the Mediterranean Sea, models with 24% to 42 % of deviance explained were used (Giannoulaki *et al.* 2012).

5.3 Modeled relationships in an ecological perspective

The modeled relationships are sensible from an ecological perspective and are in line with previous studies.

5.3.1 Sea surface temperature

With SST between 6°C to 8°C the probability of catching mackerel increases. It peaks at 8°C to 9°C were it starts to decrease again, but still the probability remains high with $p > 0.6$, but the confidence areas become wider at higher temperatures. More sample points in the higher temperature range are needed to define the upper limit sufficiently. The NE Atlantic Mackerel is known to be sensitive to temperature changes. Studies suggest that its migration is temperature driven (Overholz *et al.* 2011) and it prefers waters with SST around 8°C or higher (Utne *et al.* 2012). Studies on the NW Atlantic Mackerel suggest that it is intolerant of water temperatures less than 5-6°C and greater than 15-16°C both in terms of physiological and behavioral responses and timing of migration and spawning (Overholz 1991).

5.3.2 Light conditions – the photosynthetically available radiation

The probability of catching mackerel increases with increased amount of visible solar light reaching the ocean surface. This might suggest that the mackerel prefers the warmer sunlit surface layers and/or that the increased PAR increases the visibility in the water, improving foraging conditions. PAR has previously been used as a parameter in defining catching areas of visual predators like the European Squid (*Loligo vulgaris)* (Sanches *et al.* 2008) and fish habitat for adult anchovies (Giannoulaki *et al.* 2012). Solar illumination affects schooling behaviour of some pelagic fish, like anchovy and round herring (Agenbag *et al.* 2003), and Horse Mackerel (*Trachurus trecae*) around Angola show a difference in behaviour and distribution by day and night. During day the mackerel schools close to surface, but during night it disperses down to deeper layers (Velho *et al.* 2010).

5.3.3 Clearer waters due to less absorption– the water leaving radiance

Clearer water due to less absorption in the water column increases the probability of catching mackerel. This suggests that mackerel is more likely to be found in less productive waters, where there is less chlorophyll and other absorbing materials. L443 at 0.5 to 1.0 mW/cm²/μm/sr leads to more successful catches, which echoes the finding of Wall *et al.* (2009) who conclude that intermediate water clarity as defined by L443 in the range 0.7-1.0 mW/cm²/μm/sr leads to more successful recreational catches of King Mackerel and vice versa, decreased water clarity leads to reduced catching success. Other studies also conclude that some fish species, especially visual predators like tuna, are more commonly found in clear waters for foraging (Wall *et al.* 2009).

5.3.4 More turbid waters due to scattering– the water leaving radiance

Less clear water due to increased scattering in the water column also increases the probability of catching mackerel. With L443 above 1.0 mW/cm²/μm/sr the probability of catching mackerel is high. This suggests that the increased scattering attracts mackerel. The reason might be that the scattering has positive effects on the visual feeding conditions for mackerel by increasing the contrast between the pray and the background. The reason might also be that the increased scattering provides a shelter for mackerel from their predators (Utne-Palm 2002).

5.3.5 Transparent water – the down welling diffuse attenuation coefficient

kd490 is the least successful variable in explaining catches of mackerel. It is not significant at resolution of one day and one cell and not with decreased spatial resolution to three cells. Furthermore it does not contribute to the most successful multicovariate models. It becomes significant when temporal resolution is decreased to 7 days. However, the smoothing function for seven day kd490 further emphasizes the importance of transparent waters for successful mackerel catches. The probability of catching mackerel is high in the range of 0.05 m^{-1} to 0.25 m^{-1}. These results are not necessarily in opposition to the results suggested by the water leaving radiance curve, as the attenuation coefficient evaluates the water transparency based on both the absorptions and scattering. Kumari *et al.* (2009) suggests that increased transparency is an important factor when locating tuna aggregation areas.

5.3.6 Primary production – chlorophyll concentrations

CHL, indicating primary production, is a successful single variable and contributes to one of the more successful multi-covariate models. The probability of catching mackerel increases rapidly as CHL concentrations increase from 0 to 1 mg/m^3. The probability remains high until the concentrations reach above ≈ 3.5 mg/m^3 when it rapidly drops. This rapid decline at higher concentrations might further underline the importance of clear, transparent water to mackerel. Higher primary production contributes to increased absorption in the water column and leads to less clear waters.

5.3.7 Time lags– decreased temporal resolution

Decreased temporal resolution improves the predictability of all the single satellite variables. This reflects the findings of Kumari *et al.* (2009) which suggest that relationships between many fish species and primary production are often obscured by time-lags and spatial dislocation. They found that a minimum time delay for phytoplankton patch to mature to viable forage ground for all the dominant species of tuna in the Arabian Sea is 5-7 days. It also reflects the typical patchiness of the ocean ecosystems and the importance of a certain preferred situation in primary production, temperature and other properties of the ocean to be sustained for some time to attract forage fish (Wall *et al.* 2009; Klaoudatos *et al.* 2010; Klemas 2010).

5.4 Temporal patterns

Both significant annual and temporal differences are evident in satellite variable values, within the groups absence and presence. The largest monthly differences are seen in PAR, which is highest in June and July and lowest in September. SST and L443 have the highest values in July but values for CHL and kd490 are highest in June. This suggests that the oceans at fishing locations are warmest and clearest in July. The higher CHL in June causes less transparent water with higher kd490. The pattern of PAR echoes the sun path at higher northern latitudes with the longest days and shortest nights in June.

Patterns in annual differences are more difficult to interpret, but such differences are in agreement with previous findings of large interannual variation in fauna and physical properties of the ocean around Iceland (Gudmundsson 1998, Gislason 2009).

5.5 Best models

Best model is a vague term and dependent on the purpose being searched in any given case. The focus in this study is not to find the *absolute best model,* but to identify variables that can successfully predict viable fishing locations. Furthermore, statistical models like the once introduced here, are always just an approximation of the possible underlying processes (Kindt and Coe 2005).

The best model according to AIC and deviance explained includes the variables seven or one day PAR and SST and seven day L443. From the perspective of parsimony, it can be argued that this more complex model with three satellite variables does not add much to the deviance explained by the simpler seven day PAR model. According to the predicative success of the models, the seven day SST is the most successful model in predicting correct values of absence and presence. But the predictive ability of the models must be viewed with caution as it is based on an arbitrarily set threshold of 0.5. This threshold is widely used in ecology but has been criticized for its arbitrary nature and for having no ecological bases (Liu *et al.* 2005). A selection of other thresholds will affect the results. No significance tests are available for these threshold methods of evaluating the model performance (Manel *et al.* 2001).

Selecting the best model is thus somewhat arbitrary. All the most successful models should be considered and tested further to estimate their predictive capability in finding viable mackerel fishing grounds. Simpler models normally have more advantages, both practically and computationally, thus it is wise to start further exploration on the more simple models.

5.6 Most successful conditions for catching mackerel – a visual predator?

This study suggests that mackerel catches are most successful in a temperature range of 7.5°C to about 13°C where there are high amounts of incoming visible solar radiation and intermediate concentration of phytoplankton. Clear and transparent waters due to less absorption and decreased clarity due to increased scattering also have an effect. This might indicate that mackerel caught in Icelandic waters is somewhat dependent on visual foraging during its migration. Literature on the NE Atlantic Mackerel suggests it is primarily a passive filtering feeder but also known to be a particulate visual predator (Olaso *et al.* 2005; Astthorsson *et al.* 2010). Studies on the NW stock imply that filtering mostly occurs when and where small plankton is plentiful, particularly in summer. But during spring and autumn the mackerel is mostly a visual feeder, while other studies suggest that visual feeding occurs throughout the season (Studholme *et al.* 1999).

5.7 Global dataset useful in local situations around Iceland

Strong significant correlation of observed CHL in Icelandic waters and satellite remotely sensed CHL gives confidence in the usefulness of the global data sets from Globcolor for analysis of local situations in the waters around Iceland. Both surface chlorophyll observations and sub-surface chlorophyll observations reveal strong significant correlation with that of surface satellite sensed CHL.

The correlation is much stronger than in previous study in Icelandic waters based on satellite values on a larger temporal scale of multiannual averages of 8 day composites (Gudmundsson *et al.* 2009). It is also stronger than results from a validation process for the Globcolor dataset in Case 2 waters and more in accordance with correlations found in the Globcolor validation process for case 1 waters (Globcolor 2007). Thus it might be an indicator that the Icelandic waters should be considered Case 1 waters (less turbid), at least during summer, as suggested in a study by Lee and Hu (2006), where the waters south of Iceland were classified as Case 1 waters during summer. The strong correlation must be taken with caution, as it is based on very few samples from only one year which are sampled systematically. Further research is needed with larger dataset of observed values for a longer time period.

5.8 Unexpected results

The results presented are in many aspects somewhat surprising. It was not expected that decreased temporal resolution would improve the predictability of covariates. The indifferent effects of decreased spatial resolution were also surprising. The evidents suggesting that mackerel might be more of a visual predator when foraging in Icelandic waters than previously considered was interesting. Furthermore it was interesting that only intermediate concentrations of CHL, but not higher concentrations of CHL, seem to attract mackerel. Finally the strong significant correlation between *in situ* observed and satellite sensed CHL was not expected.

5.9 Limitations

The models presented here only tell a part of the story. They are derived from a relationship between fishing locations and satellite variables where the original data set of fishing locations is highly subset to fit data sampled by satellites on cloudless days and when/where atmospheric distortions are not an issue. Thus it is only tells a story of mackerel fishing under these certain conditions. It should be kept in mind when deriving assumptions from such models that the relationships under cloudy conditions are still unknown.

The fishing locations are most likely biased due to various reasons and lacking in coverage. The locations are based on occurrences records of fish as logged by fishermen, in non-systematic manner and must be treated with reservations as such. The definition of a fishing location is vague. As a haul can extend over a few kilometers, the exact fishing location is only a point location. The strain of quota on mackerel fishing is likely to have effect on the pattern of fishing location in time and space. Furthermore many vessels already have satellite remote sensing systems onboard which might affect the relationship detected. In addition, no records of actual mackerel absences are available in the log book. Absences as used here are based on “lack of presence”, rather than clear absence and thus add an important source of uncertainty to the model design. Finally fishing is a human activity. There are no attempts to capture variables explaining this factor in the model.

Inaccurate assumptions on relationships in regression models can be caused by violating underlying statistical assumptions in regression modeling, leading to either type I or type II error. In this study autocorrelation was overcome in the modeling process by incorporate a smoothing parameter for latitude and longitude of the fishing locations, thus reducing the possibility of type 1 error. As a result of high correlation between kd490 and CHL the best scoring model was rejected to reduce the possibility of type II error. But even though these variables cannot be included together in a statistical model it is important to be aware that they can still be important in explaining the distribution of mackerel. Correlation between other variables is not high and thus the possibility of type II error is reduced.

5.10 Suggested improvements

Improvement of the predictability of models for mackerel fishing locations can possibly be achieved by including more systematically spatially and temporarily structured samples of absences and presences and by scrutinizing the relationships of other possible explanatory remotely sensed variables. Temperature and primary production fronts have been proven to attract forage fish (Zainuddin *et al.* 2008; Wall *et al.* 2009; Klemas 2010). Other interesting variables are for example sea level anomaly (Giannulaki *et al.* 2012) and fluorescence which can possibly help to identify different phytoplankton functional types (Nair *et al.* 2008). Furthermore, accounting for the temporal patterns which are evident in the satellite variables explored, might result in improved models.

6 Conclusion

This study demonstrates that remote sensing variables can be significantly successful in defining absence and presence of mackerel at fishing locations in Icelandic waters, thus the null hypothesis is rejected. The results provide valuable information to develop methods to predict viable fishing grounds of mackerel in Icelandic waters. Successfully predicted fishing grounds contribute to reduced energy consumption of fishing vessels and lower carbon footprint of the industry, as well as increasing economic gain.

Products from satellite remote sensing are commonly based on algorithms which are developed and validated on global scale and not necessarily successful in local situations. Validation of CHL observations in Icelandic waters and satellite remotely sensed CHL in this study gives confidence in the usefulness of the global data sets in analysis of local situations in Icelandic waters.

Models are only just an approximation of the possible and often very complex underlying processes. The objective of this study was not to find the one true model to predict fishing locations of mackerel, but to explore and identify if and what satellite variables can be useful to define viable fishing grounds. PAR, SST, CHL and L443 all contribute to explain the locations of absence and presence of mackerel catching in Icelandic waters. The results and shapes of the modeled relationships are sensible from an ecological perspective and in compliance with previous studies on mackerel and other pelagic fish. Interestingly increased temporal resolution does not improve the predictability of the covariates and effects of decreased spatial resolution are somewhat unclear.

It is concluded that mackerel catches in Icelandic waters are most successful in a temperature range of 7.5°C to about 13°C where there are large amounts of incoming visible solar radiation and intermediate concentration of phytoplankton. Clear and transparent waters due to absorption and increased scattering in the water column seem to be important factors too. This suggests that mackerel caught in Icelandic waters is possibly more dependent on visual foraging than previously considered.

Remote sensing provides large data sets in near-real time with high temporal resolution and large spatial coverage which are not feasibly obtained in any other manner for fisheries research and forecasting. But like in other fields of remote sensing studies, there are problems with clouds, atmospheric distortion and seasonal availability at high latitudes. Furthermore algorithms used to create the products are constantly being scrutinized in an attempt for possible improvements.

References

Agenbag, J. J., Richardson, A. J., Demarcq, H., Fréon, P., Weeks, S. and Shillington, F. A., 2003. Estimating environmental preferences of South African pelagic fish species using catch size- and remote sensing data, *Progress in Oceanography,* 59: 275-300.

Arnason, R and Agnarsson, S., 2005. Sjávarútvegur sem grunnatvinnuvegur á Íslandi. [Fishing as main industry in Iceland]. *Fjármálatíðindi* [Financial News] 52: 14-35 [In: Icelandic]

Astthorsson, O. S., Valdimarsson, H., Gudmundsdottir, A., & Oskarsson, G. J.,2012. Climate-related variations in the occurrence and distribution of mackerel (*Scomber scombrus*) in Icelandic waters. *ICES Journal of Marine Science*, 69, 1289-1297

Astthorsson, O.S., Sigurdsson, Þ., Sveinbjörnsson, S., 2010. Makríll á Íslandsmiðum [Mackerel in Icelandic waters]. Þættir úr vistfræði sjávar 2009. [*Environmental conditions in Icelandic waters 2009*]. Hafrannsóknir 152: 26-31. [*Marine Research*]. [In: Icelandic].

Bivand, R. and Lewin-Koh, N., 2013. maptools: Tools for reading and handling spatial objects. R package version 0.8-23. http://CRAN.R-project.org/package=maptools

Bivand, R.S., Pebesma, E.J. and Gomez-Rubio, V., 2008. *Applied spatial data analysis with R.* Springer, NY.

Bivand,R., Altman, M., Anselin, L. AssunÃ§Ã£o,R., Berke, O., Bernat, A., Blanchet,A., Blankmeyer, E., Carvalho, M., Christensen, B., Yongwan Chun, Dormann, C, Dray, S., Halbersma, R., Krainski,E., Legendre, P., Lewin-Koh,N., Hongfei Li, Jielai Ma, Millo, G., Mueller, W., Ono, H., Peres-Neto, P., Piras, G., Reder, M., Tiefelsdorf, M. and Danlin Yu. ,2013. spdep: Spatial dependence: weighting schemes, statistics and models. R package version 0.5-56. http://CRAN.R-project.org/package=spdep

Bivand,R., Tim, K. and Rowlingson, B., 2013. rgdal: Bindings for the Geospatial Data Abstraction Library. R package version 0.8-5. http://CRAN.R-project.org/package=rgdal

Björnsson,B., 2012. Lágtíðnihljóðmerki til fiskveiða [Low frequency sounds in fishing]. Hafrannsóknastofnun Íslands . [Icelandic Marine Research Institute]. http://www.hafro.is/undir.php?ID=19&nanar=1REF=3&fID=15108 [In: Icelandic].

Bourgeron P.S, Fortin, M-J., Humphries, H.C., 2001. Elements of Spatial Data Analysis Ecological Assessments. In: Jensen, M.E and Bourgeron, P.S., (eds.), *A Guidebook for Integrated Ecological Assessments* (Editors). Springer Verlag, New York, Inc 187-199.

Brickman, D., Hátún, H., Payne, M. R. and Jacobsen, J. A., 2009. The North Atlantic subpolar gyre regulates the spawning distribution of blue whiting (Micromesistius poutassou), *Canadian Journal of Fisheries and Aquatic Sciences,* 66: 759-770.

Brookman Consult and contributors,2001-2010. BEAM VISAT SOFTWARE, VERSION 4.10.4. http://www.brockmann-consult.de/cms/web/beam/ 15-01-2013

Canty, A. and Ripley, B.,2012. boot: Bootstrap R (S-Plus) Functions. R package version 1.3-7.

Catsat 2013. Catsat. Worldwide satellite service to help fishing. http://www.catsat.com/ 25-03-2013

Chassot, E., Bonhommeau, S., Reygondeau, G., Nieto, K., Polovina, J. J., Huret, M., Dulvy, N. K. and Demarcq, H., 2011: Satellite remote sensing for an ecosystem approach to fisheries management, *ICES Journal of Marine Science,* 68: 651-666.

Conway, D. V. P., Coombs, S. H., Lindley, J. A. and Llewellyn, C. A., 1999. Diet of mackerel Scomber scombrus larvae at the shelf-edge to the south-west of the British Isles and the incidence of piscivory and coprophagy, Vie et Milieu 49: 213-220.

Crisci, C., Ghattas, B. and Perera*,* G., 2012. A review of supervised machine learning algorithms and their applications to ecological data, *Ecological Modelling,* 240: 113-122.

Davison, A. C. & Hinkley, D. V. ,1997. *Bootstrap Methods and heir Applications.* Cambridge University Press, Cambridge

Dobbin, K.K. and Simon, R.M., 2011. Optimally splitting cases for training and testing high dimensional classifiers. *BMC Medical Genomics* 4:31-39.

Douglas Bates and Martin Maechler (2012). Matrix: Sparse and Dense Matrix Classes and Methods. R package version 1.0-5. http://CRAN.R-project.org/package=Matrix

Einarsson, B, 2011. *An Interacting Particle Model and Dynamic Energy Budget Theory: Analysis and Applications.* PhD diss. Faculty of Physical Sciences. University of Iceland, Reykjavík, Iceland.

Encyclopædia Britannica, Inc., 2013. Photosynthesis: Energy efficiency of photosynthesis. http://global.britannica.com/EBchecked/topic/181347/einstein 2013-05-21

ESA – European Space Agency, 2011. *MERIS Product Handbook Issue 3.0*, 1 August 2011 https://earth.esa.int/handbooks/meris/ 28-04-2013.

ESRI, 1999-2012. Esri help. Mininum Convex Polygon Tool

ESRI, 2012. Ocean basemap http://www.arcgis.com/home/item.html?id=6348e67824504fc9a62976434bf0d8d5 2013-01-28

Field, A., Miles, J., Field, Z., 2012. *Discovering statistics using R*. Sage, London.

Franklin, J., 2009. *Mapping Species Distribution. Spatial Inference and Prediction.* Cambridge University Press, New York.

Frouin, R., Franz, B.A. and Werdell, P.J., 2003. The SeaWiFS PAR product. In: Hooker, S.B. and Firestone, E.R.,(eds.), *Algorithm Updates for the Fourth SeaWiFS Data Reprocessing.* NA- SA/TM 2003-206892: 46-50.

Giannoulaki, M., Iglesias, M., Tugores, M. P., Bonanno, A., Patti, B., De Felice, A., Leonori, I., Bigot, J. L., TiČIna, V., Pyrounaki, M. M., Tsagarakis, K., Machias, A., Somarakis, S., Schismenou, E., Quinci, E., Basilone, G., Cuttitta, A., Campanella, F., Miquel, J., Oñate, D., Roos, D. and Valavanis, V., 2013: Characterizing the potential habitat of European anchovy Engraulis encrasicolusin the Mediterranean Sea, at different life stages, *Fisheries Oceanography,* 22: 69-89.

Giraudoux, P.,2013. pgirmess: Data analysis in ecology. R package version 1.5.7. http://CRAN.R-project.org/package=pgirmess

Gislason, A. and Silva, T., 2012. Abundance, composition, and development of zooplankton in the Subarctic Iceland Sea in 2006, 2007, and 2008, *ICES Journal of Marine Science,* 69: 1263-1276.

Gislason, A., Petursdottir, H., Astthorsson, O. S., Gudmundsson, K., and Valdimarsson, H.,2009. Inter-annual variability in abundance and community structure of zooplankton south and north of Iceland in relation to environmental conditions in spring 1990-2007. *Journal of Plankton Research, 31*, 541-551.

Globcolor, 2013 GLOB_4KM dataset. ACRI-ST GlobColour service, supported by EU FP7 MyOcean & ESA GlobColour Projects, using ESA ENVISAT MERIS data, NASA MODIS and SeaWiFS data http://www.globcolour.info/data_access_full_prod_set.html 2013-01-12

GlobColour , 2007 : Full Validation Report ACRI-ST/LOV, UoP, NIVA, BC, DLR, ICESS consortium ESA DUE GlobColour Global Ocean Colour for Carbon Cycle Research. An EO based service supporting global ocean carbon cycle research. http://due.esrin.esa.int/prjs/Results/131-176-149-30_200831993920.pdf 29-04-2013

GlobColour ,2010 : Product User Guide An EO based service supporting global ocean carbon cycle research. http://www.globcolour.info/CDR_Docs/GlobCOLOUR_PUG.pdf, 29-12-2012

Godø, O., Hjellvik, V., Iversen, S., Slotte, A., Tenningen, E. and Torkelsen, T., 2004. Behaviour of mackerel schools during summer feeding migration in the Norwegian Sea, as observed from fishing vessel sonars, *ICES Journal of Marine Science,* 61: 1093-1099.

Gordon, H. R., 2005. Normalized water-leaving radiance: revisiting the influence of surface roughness, *Applied optics,* 44: 241-248.

Gudmundsson, K., 1998. Long-term variation in phytoplankton productivity during spring in Icelandic waters. – ICES Journal of Marine Science, 55: 635–643.

Guðmundsson, K., Heath, M.R., and Clarke, E.D., 2009. Average seasonal changes in chlorophyll a in Icelandic waters, *ICES Journal of Marine Science,* 66.

Guisan, A., Edwards, T.C.Jr. and Hastie T., 2002: Generalized linear and generalized additive models in studies of species distributions: setting the scene, *Ecological Modelling,* 157: 89-100

Guisan, A., Lehmann, A., Ferrier, S., Austin, M., Overton, J. M. C., Aspinall, R. and Hastie, T., 2006. Making better biogeographical predictions of species' distributions, *Journal of Applied Ecology,* 43: 386-392.

Hastie, T.and Tibshirani, R.,1986. Generalized Additive Models, *Statistical Science*, 1: 297-318.

Hátún, H., Payne, M. R., Beaugrand, G., Reid, P. C., Sandø, A. B., Drange, H., Hansen, B., Jacobsen, J. A. and Bloch, D., 2009. Large bio-geographical shifts in the north-eastern Atlantic Ocean: From the subpolar gyre, via plankton, to blue whiting and pilot whales, *Progress in Oceanography,* 80: 149-162.

Hátún, H., Sando, A. B., Drange, H., Hansen, B. and Valdimarsson, H., 2005. Influence of the Atlantic subpolar gyre on the thermohaline circulation, *Science,* 309: 1841-1844.

Hu, C., Lin,I-I. Chun-Chin, L., 2010. Introduction to SeaWiFS/MODIS chlorophyll data products and data analysis tools. Appendix A.2. In: Liu, Kone-Kee, Atkinson, L., Quiñones, R. and McManus, L.T. (eds.), *Carbon and Nutrient Fluxes in Continental Margins: A Global Synthesis (Global Change - The IGBP Series)*, Springer,Berlin.

Hu, C., Hackett, K.E., Callahan, M. K, Andréfouët,S. Wheaton, J.L., Porter, J.L. and Muller-Karger, F.E., 2003. The 2002 ocean color anomaly in the Florida Bight: A cause of local coral reef decline? Geophysical Research Letters, 30: 1151

Icelandic Directorate of Fisheries [Fiskistofa], 2012. Makríll, 2006 – 2012. Afli íslenskra skipa eftir löndunarmánuðum og veiðisvæðum. [Mackerel 2006-2012. Catches of Icelandic vessels by landing months and fishing areas.]. http://www.fiskistofa.is/media/aflatolur/makrill_fra_2006_vefskjal.pdf 15-01-2013 [In: Icelandic]

Icelandic regulation no. 504/2010. Reglugerð um breytingu á reglugerð nr. 285/2010 um stjórn makrílveiða íslenskra skipa árið 2010, með síðari breytingum. [Regulation on changes on regulation no. 285/2010 on management of mackerel fishing of Icelandic vessels in 2010 as subsequently amended].

Icelandic regulation no. 233/2011. Reglugerð um stjórn makrílveiða íslenskra fiskiskipa árið 2011, [Regulation on management of mackerel fishing of Icelandic fishing vessels in 2011].

Icelandic regulation no. 392/2012. Reglugerð um stjórn makrílveiða íslenskra fiskiskipa árið 2012, [Regulation on management of mackerel fishing of Icelandic fishing vessels in 2012].

ICES - International Council for the Exploration of the Sea, 2011. Report of the Working Group on Widely Distributed Stocks (WGWIDE). ICES Document CM 2011/ACOM: 15

ICES - International Council for the Exploration of the Sea,, 2009. Report of the Working Group on Widely Distributes Stocks (WGWIDE), 2-8 September 2009, ICES CM 2009/ACOM 12. Copenhagen, Denmark.

Innovation Center Iceland [Nýsköpunarmiðstöð Íslands], 2012. Ljósvarpa [Light trawl]. http://www.ru.is/media/skjol-td/Nyskopunarmidstod-Islands.pdf [In: Icelandic].

IOCCG-International Ocean-Color Coordinating Group , 2013. Ocean Color Sensors. http://www.ioccg.org/sensors_ioccg.html . 23-03-2013.

Johnson, J. B. and Omland, K. S., 2004. Model selection in ecology and evolution, *Trends in Ecology and Evolution,* 19: 101-108.

Jonasson, J. P., Gunnarsson, B. and Marteinsdottir, G., 2009. Abundance and growth of larval and early juvenile cod (Gadus morhua) in relation to variable environmental conditions west of Iceland, *Deep Sea Research Part II: Topical Studies in Oceanography,* 56: 1992-2000.

Kelble, C.R.,Ortner, T.B., Boyer, G L. and Hitchcook, J.N. ,2005. Attenuation of Photosynthetically Available Radiation (PAR) in Florida Bay: Potential for Light Limitation of Primary Producers, *Estuaries,* 28: 560-571.

Kindt, R. and Coe R., 2005. *Tree diversity analysis. A manual and software for common statistical methods for ecological and biodiversity studies.* Nairobi: World Agroforestry

Klaoudatos, D., Kapiris, C., Conides, A., Papaconstantinou,C. and Glykokokkalos, S., 2010. Assessment of demersal distribution between two fishing areas in North and Central Greece, *International Aquatic Research,* 2: 176-154.

Klemas, V., 2010. Fisheries Applications of Remote Sensing: An Overview, *Fisheries Research.* doi:10.1016/j.fishres.2012.02.02

Kumari, B., Raman, M. and Mali, K., 2009. Locating tuna forage ground through satellite remote sensing, *International Journal of Remote Sensing,* 30: 5977-5988.

Kunzig, R., 2013. Climate Milestone. Earth's CO2 Level Passes 400 ppm - Published May 9, 2013 http://news.nationalgeographic.com/news/energy/2013/05/130510-earth-co2-milestone-400-ppm/

Landis, J.R. and Koch, G.G., 1977. The Measurement of Observer Agreement for Categorial Data, *Biometrics,* 33: 159-174.

Langøy, H., Nøttestad, L., Skaret, G., Broms, C. and Fernö, A., 2012. Overlap in distribution and diets of Atlantic Mackerel (Scomber scombrus), Norwegian spring-spawning herring (Clupea harengus) and blue whiting (Micromesistius poutassou) in the Norwegian Sea during late summer, *Marine Biology Research,* 8: 442-460.

Lee, Z. and Hu. C., 2006. Global distribution of Case-1 waters: An analysis from SeaWiFS measurements, *Remote Sensing of Environment,* 101: 270-276.

Liu, C., Berry, P. M., Dawson, T. P. and Pearson, R. G., 2005. Selecting thresholds of occurrence in the prediction of species distributions. *Ecography* 28: 385-393.

Liu, C., White, M. and Newell, G., 2011. Measuring and comparing the accuracy of species distribution models with presence-absence data, *Ecography,* 34: 232-243.

Lobo, J. M., Jiménez-Valverde, A. and Hortal, J., 2010. The uncertain nature of absences and their importance in species distribution modelling, *Ecography,* 33: 103-114.

Manel, S., Williams, H.C. and Ormerod, S.J., 2001. Evaluating presence–absence models in ecology: the need to account for prevalence, *Journal of Applied Ecology,* 38: 921-931

Marra, G. and Wood, S. N., 2011. Practical variable selection for generalized additive models, *Computational Statistics & Data Analysis,* 55: 2372-2387.

Ministry for the Environment [Umhverfisráðuneytið], 2010. Aðgerðir í loftslagsmálum [Action plan on climate change]. Umhverfisráðuneytið [Ministry for the Environment.] [In: Icelandic].

Ministry for the Environment and Natural Resources [Umhverfis- og auðlindaráðuneytið], 2012. Aðgerðir í loftslagsmálum Skýrsla samstarfshóps til umhverfisráðherra 2012 [Action plan on climate change. Progress report to Minister of the Environment 2012].

http://www.umhverfisraduneyti.is/media/PDF_skrar/Adgerdaaaetlun-i-loftslagsmalum.pdf [In: Icelandic].

Mobley, C. D., Stramski, D., Bissett, W. P. and Boss, E. ,2004. Optical modeling of ocean waters: Is the Case 1–Case 2 classification still useful? *Oceanography*, 17(2), 60–67.

Nair, A., Sathyendranath, S., Platt, T., Morales, J., Stuart, V., Forget, M.-H., Devred, E. and Bouman, H., 2008: Remote sensing of phytoplankton functional types, *Remote Sensing of Environment,* 112: 3366-3375.

Nøttested, G. and Huse, G., 2012. *Consolidate historical data to provide spatially explicit estimates of stocks sizes, structure, biomass and diet of herring, blue whiting and mackerel in the N. Atlantic***.** Project European Basin-scale Analysis, Synthesis and Integration. Seventh framework programme theme 6 Environment

OBPG - Ocean Biology Processing Group, 2013. MODIS. Level 3 mapped products. The NASA Goddard Space Flight Center,Greenbelt, MD, USA. http://oceandata.sci.gsfc.nasa.gov/MODISA/Mapped/ 2013-01-12

Olaso T., Gutierrez J.L., Villamor B., Carrera P, Valdes L. and Abaunza P.,2005. Seasonal changes in the north-eastern Atlantic Mackerel diet (Scomber scombrus) in the north of Spain (ICES Division VIIIc). *Journal of the Marine Biological Association of the United Kingdom* 85:415-418.

Overholtz, W. J., Armstrong, R. S., Mountain, D. G., and Tercerio, M.,1991. *Factors influencing spring distribution, availability and recreational catch of Atlantic Mackerel* (*Scomber scombrus*) in *the Middle Atlantic and Southern New England regions*. NOAA Technical Memorandum NMFS-F/NEC-85.

Overholtz, W. J., Hare, J. A. and Keith, C. M., 2011. Impacts of Interannual Environmental Forcing and Climate Change on the Distribution of Atlantic Mackerel on the U.S. Northeast Continental Shelf, *Marine and Coastal Fisheries,* 3: 219-232.

Palialexis, A., Georgakarakos, S., Karakassis, I., Lika, K. and Valavanis, V. D., 2011. Prediction of marine species distribution from presence–absence acoustic data: comparing the fitting efficiency and the predictive capacity of conventional and novel distribution models, *Hydrobiologia,* 670: 241-266.

Palsson, O. K., Gislason, A., Guthfinnsson, H. G., Gunnarsson, B., Olafsdottir, S. R., Petursdottir, H., Sveinbjornsson, S., Thorisson, K. and Valdimarsson, H., 2012. Ecosystem structure in the Iceland Sea and recent changes to the capelin (Mallotus villosus) population, *ICES Journal of Marine Science,* 69: 1242-1254.

Payne, M. R., Egan, A., Fässler, S. M. M., Hátún, H., Holst, J. C., Jacobsen, J. A., Slotte, A. and Loeng, H., 2012: The rise and fall of the NE Atlantic blue whiting (*Micromesistius poutassou*), *Marine Biology Research,* 8: 475-487.

Pearce. J and Ferrier, S., 2000. An evaluation of alternative algorithms for fitting species distribution models using logistic regression, *Ecological Modeling,* 128: 127-147.

Pebesma, E.J. and Bivand, R.S., 2005. Classes and methods for spatial data in R. *New* 5, http://cran.r-project.org/doc/Rnews/.

Pinheiro, J. Bates, D., DebRoy, S., Sarkar, D. and the R Development Core Team, 2013. nlme: Linear and Nonlinear Mixed Effects Models. R package version 3.1-108.

Plummer,M., Best, N., Cowles, K. and Vines, K., 2006. CODA: Convergence Diagnosis and Output Analysis for MCMC, *R News*, 6:7-11

R Core Team , 2013. foreign: Read Data Stored by Minitab, S, SAS, SPSS, Stata, Systat, dBase, R package version 0.8-52. http://CRAN.R-project.org/package=foreign

R Development Core Team ,2011. R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. ISBN 3-900051-07-0, URL http://www.R-project.org/.

Radlinski, M. K., Sundermeyer, M. A., Bisagni, J. J. and Cadrin, S. X., 2013. Spatial and temporal distribution of Atlantic Mackerel (*Scomber scombrus*) along the northeast coast of the United States, 1985-1999, *ICES Journal of Marine Science*. doi:10.1093/icesjms/fst029

Rodriguez-Castaneda, G., Hof, A.R., Jansson, R. and Harding, L.E., 2012. Predicting the fate of biodiversity using species' distribution models: enhancing model comparability and repeatability, *PLoS One,* 7: e44402.

Rowlingson, B., Diggle, P. adapted, packaged for R by Roger Bivand, pcp functions by Giovanni Petris and goodness of fit by Stephen Eglen ,2013 . splancs: Spatial and Space-Time Point Pattern Analysis. R package version 2.01-32. http://CRAN.R-project.org/package=splancs

Royal Belgian Institute 2013. Turbid water extension ot the standard SeaWiFS and MODIS atmospheric correction. http://www2.mumm.ac.be/remsem/software/description.php 2013-05-24

Saitoh, S. I., Mugo, R., Radiarta, I. N., Asaga, S., Takahashi, F., Hirawake, T., Ishikawa, Y., Awaji, T., In, T. and Shima, S., 2011. Some operational uses of satellite remote sensing and marine GIS for sustainable fisheries and aquaculture, *ICES Journal of Marine Science,* 68: 687-695.

Salisbury, J.E., Campbell, J.W., Meeker, L.D. and Vörösmarty, C.,no date. Covariance between ocean color and riverine discharge reveals the areal extent and nature of fluvial influence in coastal waters Bio-optical Oceanography Group, Ocean Process Analysis Laboratory, Institute for the Study of Earth, Oceans, and Space, at the University of New Hampshire http://ccg.sr.unh.edu/pdf/Fluvial-index_EOS.pdf 2013-04-10

Sánchez, E. E. L., 2003. Remote sensing and geographic information system for pelagic fising ground forecasting in North Icelandic Waters . Final Project. Fisheries Training Programme, The United Nations University, Reykjavík, Iceland.

Sanchez, P., Demestre, M., Recasens, L., Maynou, F. and Martin, P., 2008. Combining GIS and GAMs to identify potential habitats of squid Loligo vulgaris in the Northwestern Mediterranean, *Hydrobiologia,* 612: 91-98.

Sarkar, Deepayan, 2008. *Lattice: Multivariate Data Visualization with R.* Springer, New York.

Savtchenko, A., Ouzounov, D., Ahmad, S., Acker, J., Leptoukh, G., Koziana, J. and Nickless, D., 2004. Terra and Aqua MODIS products available from NASA GES DAAC, *Advances in Space Research,* 34: 710-714.

Smith, J. M., Macleod, C. D., Valavanis, V., Hastie, L., Valinassab, T., Bailey, N., Santos, M. B. and Pierce, G. J., 2013. Habitat and distribution of post-recruit life stages of the squid Loligo forbesii, *Deep Sea Research Part II: Topical Studies in Oceanography*. , [Accepted manuscript] http://dx.doi.org/10.1016/j.dsr2.2013.03.039

Solanki, H. U., Dwivedi, R. M., Nayak, S. R., Somvanshi, V. S., Gulati, D. K. and Pattnayak, S. K., 2003. Fishery forecast using OCM chlorophyll concentration and AVHRR SST: validation results off Gujarat coast, India, *International Journal of Remote Sensing,* 24: 3691-3699.

Solanki, H. U., Prakash, P., Dwivedi, R. M., Nayak, S., Kulkarni, A. and Somvamshi, V. S., 2010. Synergistic application of oceanographic variables from multi-satellite sensors for forecasting potential fishing zones: methodology and validation results, *International Journal of Remote Sensing,* 31: 775-789.

Statistics Iceland [Hagstofa Íslands] 2013. Útflutningur eftir vinnslugreinum mars 2012-2013 [Export classified by sectors in March 2012-2013] Gagnagrunnur Hagstofu Íslands. [Statistics Iceland Database. http://www.hagstofa.is/?PageID=2601&src=/temp/Dialog/varval.asp?ma=UTA02201%26ti=%DAtflutningur+eftir+vinnslugreinum+mars+2012%2D2013%26path=../Database/utanrikisverslun/Utflu

tningur/%26lang=3%26units=Fob%20ver%F0%20%ED%20millj%F3num%20kr%F3na 2013-04-15 [In: Icelandic]

Stuart, V., Platt, T. and Sathyendranath, S., 2011. The future of fisheries science in management: a remote-sensing perspective, *ICES Journal of Marine Science,* 68: 644-650.

Studholme A.L, Packer, D.B., Berrien P.L, Johnson, D.L, Zetlin C.A and Morse W.W., 1999. Essential fish habitat source document: Atlantic Mackerel, Scomber scombrus, life history and habitat characteristics, *NOAA Tech Memo NMFS NE,* 141: 35.

The Norwegian Ministry of Fisheries and Coastal Affairs ,2012. Atlantic mackerel (*Scomber scombrus*). http://www.fisheries.no/ecosystems-and-stocks/marine_stocks/fish_stocks/atlantic_mackerel/ 16-04-2013

Utne, K. R., Huse, G., Ottersen, G., Holst, J. C., Zabavnikov, V., Jacobsen, J. A., Óskarsson, G. J. and Nøttestad, L.,2012. Horizontal distribution and overlap of planktivorous fish stocks in the Norwegian Sea during summers 1995–2006, *Marine Biology Research,* 8: 420-441.

Utne-Palm, A. C., 2002. Visual feeding of fish in a turbid environment: Physical and behavioural aspects, *Marine and Freshwater Behaviour and Physiology,* 35: 111-128.

Valdimarsson, H. Malmberg, S.A., 1999. Near-surface circulation in Icelandic waters derived from satellite tracked drifters, *Rit fiskideildar*, 16: 23-39.

Valdimarsson, H., Astthorsson, O. S. and Palsson, J., 2012. Hydrographic variability in Icelandic waters during recent decades and related changes in distribution of some fish species, *ICES Journal of Marine Science,* 69: 816-825.

Velho,V., Barros, F P., and Axelsen, B.E., 2010. Day–night differences in Cunene horse mackerel (*Trachurus trecae*) acoustic relative densities off Angola. – *ICES Journal of Marine Science*, 67: 1004–1009.

Venables, W. N. & Ripley, B. D., 2002. *Modern Applied Statistics with S.* Fourth Edition. Springer, New York.

Wall, C. C., Muller-Karger, F. E. and Roffer, M. A., 2009. Linkages between environmental conditions and recreational king mackerel (Scomberomorus cavalla) catch off west-central Florida, *Fisheries Oceanography,* 18: 185-199.

Wall, C. C., Muller-Karger, F. E., Roffer, M. A., Hu, Chuanmin., Yao, Wengsheng and Luther, M. E., 2008. Satellite remote sensing of surface oceanic fronts in coastal waters off west–central Florida, *Remote Sensing of Environment,* 112: 2963-2976.

Working group on mackerel fishing [Vinnuhópur um makrílveiðar] 2012. Vinnuhópur um makrílveiðar. Greinargerð unnin fyrir sjávarútvegs-og landbúnaðarráðherra. [Working group on mackerel fishing. A report prepared for the Minister of Fisheries and Agriculture]. http://www.atvinnuvegaraduneyti.is/media/Skyrslur/Makrilskyrsla-2012.pdf 2013-01-25

Wilson, C., 2010. The rocky road from research to operations for satellite ocean-colour data in fishery management, *ICES Journal of Marine Science,* 68: 677-686.

Wisz, M. S., Hijmans, R. J., Li, J., Peterson, A. T., Graham, C. H. and Guisan, A., 2008. Effects of sample size on the performance of species distribution models, *Diversity and Distributions,* 14: 763-773.

Wood, S., 2006. *Generalized Additive Models. An Introduction with R*. Chapman&Hall/CRC, London.

Wood, S.N. (2000) Modelling and smoothing parameter estimation with multiple quadratic penalties. *Journal of the Royal Statistical Society (B)* 62:413-428.

Wood, S.N. ,2004. Stable and efficient multiple smoothing parameter estimation for generalized additive models. *Journal of the American Statistical Association,* 99:673-686.

Wood, S.N., 2003. Thin-plate regression splines. *Journal of the Royal Statistical Society (B),*65:95-114.

Wood, S.N., 2011. Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B),* 73:3-36

Zagaglia, C. R., Lorenzzetti, J. A. and Stech, J. L., 2004. Remote sensing data and longline catches of yellowfin tuna (Thunnus albacares) in the equatorial Atlantic, *Remote Sensing of Environment,* 93: 267-281.

Zainuddin, M., Saitoh, K. and Saitoh, S.-I., 2008. Albacore (*Thunnus alalunga*) fishing ground in relation to oceanographic conditions in the western North Pacific Ocean using remotely sensed satellite data, *Fisheries Oceanography,* 17: 61-73.

Zhai,L., Gudmundsson, K., Miller, P., Peng, W., Guðfinnsson, H., Debes, H., Hátún, H., White, G. N., Hernández Walls, R., Sathyendranath, S. and Platt, T., 2012. Phytoplankton phenology and production around Iceland and Faroes, *Continental Shelf Research,* 37: 15-25.

Zuur, A. F., Ieno, E. N. and Elphick, C. S., 2010. A protocol for data exploration to avoid common statistical problems, *Methods in Ecology and Evolution,* 1: 3-14.

Zuur, A.F., Ieno, E.N., Walker, N.J., Saveliev, A.A and Smith, G.M., 2009. *Mixed Effects Models and Extensions in Ecology with R.* Springer, London

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