Karenia brevis Hot Spots in the West Florida Shelf and their Associated Socio-economic Implications

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*KARENIA BREVIS* HOT SPOTS IN THE WEST FLORIDA SHELF AND THEIR ASSOCIATED SOCIO-ECONOMIC IMPLICATIONS

By

Diana A. Moanga

A THESIS

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*KARENIA BREVIS* HOT SPOTS IN THE WEST FLORIDA SHELF AND THEIR ASSOCIATED SOCIO-ECONOMIC IMPLICATIONS

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Harmful algal blooms are almost an annual occurrence on the West Florida Shelf. They are caused by the toxic dinoflagellate *Karenia brevis* (*K. brevis*). Intense bloom events result in significant environmental, economic, and human-health impacts associated with the release of potent natural toxins, known as brevotoxins. If inhaled or ingested they can produce substantial adverse health effects. In order to mitigate and minimize the vast array of impacts associated with *K. brevis* blooms, an overarching interdisciplinary framework is needed.

A critical factor in understanding *K. brevis* dynamics requires mapping and monitoring bloom development and transport, and identifying areas of localized bloom maxima, also referred to as bloom hot spots. To date, no studies have identified the spatial location and extent of clusters of statistically significant hot spots in Florida coastal waters. Few existing studies provide any confidence level when identifying areas characterized as hot spots. The goals of this research was to accurately identify *K. brevis* hot spot areas during different bloom periods, and explore potential correlations between school absenteeism rates and the distance from toxic bloom hot spots. Additionally, a coastal vulnerability index was developed in an attempt to assess the likelihood that some regions will experience greater health impacts from aerosolized brevotoxin exposure,
compared to others. This was done through the use of Geographic Information System (GIS). The GIS Hot Spot Analysis function identified areas of significant clusters of *K. brevis*, while spatial interpolation methods illustrated a visual display of the extent and intensity of recurring coastal blooms. The results of the study revealed that hot spot areas are often identified around 27° 30′0″ N, and 27°0′0″N. Distance from hot spots has proved to be a relatively small factor influencing school absenteeism levels (multiple r-squared = 0.188), and coastal vulnerability was found to be unevenly distributed. Some regions characterized by higher population numbers and predominantly populated by individuals (65 and older) are more susceptible to experience a greater numbers of cases manifesting adverse health effects resulting from inhalation of brevotoxin contaminated aerosols.
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Chapter 1: Introduction - Background and problem statement

Coastal areas are not only the most desirable residential locations, but also some of the most vulnerable ones. The frequent occurrences of harmful algal blooms in coastal waters pose a significant threat not only to aquatic biota, but also to humans. Dinoflagellates, important marine primary producers and grazers, also represent the major causative agents of harmful algal blooms (HAB), producing various natural toxins (Wang et al., 2008). Bloom events, also called red tides, have been documented in the Gulf of Mexico since early 1500’s (Van Dolah et al., 2009). One of the first written accounts of this phenomenon was recorded by Spanish explorer Cabeza de Vaca, who reported fish-kills along with a visible discoloration of the water occurring in an area which is now Tampa Bay (Van Dolah et al., 2009). Other historical documents date back to 1844, and describe the effects of red tides along the West Florida Shelf (Steidinger et al., 1998). Almost a century later, in 1948, the cause of massive fish kills was attributed to the toxins released by the single-celled photosynthetic organism, Karenia brevis (Davis G. Hansen and Moestrup comb. nov.) (Daugbjerg et al., 2000). Multiple Karenia species other than K. brevis exist, but have not yet been described (Heil and Steidnger, 2009). At least five species have been documented in the Gulf of Mexico, while several unknown similar species still remain unnamed (Steidinger et al., 2008). K. brevis, formally known as Gymnodinium breve, and Ptychodiscus brevis represents the dominant species of dinoflagellate prevalent in the phytoplankton communities of the Western Florida Shelf (Steidinger, 1993; Vargo, 2009).
Throughout recent decades, toxic algal blooms have increased in frequency, and expanded their geographic distribution throughout various regions of the world (Wang et al., 2008; Gannon et al., 2009). The Mediterranean Sea (Barale et al., 2008), the Arabian Gulf (Shuhaibar and Riffat, 2008), the East China Sea (Wang et al., 2009; Wu et al., 2013) the coast of California (Das et al., 2010; Frolov et al., 2013), and the coast of Alabama (Liefer et al., 2009) are all regions where red tides have been observed, documented and analyzed. On the West Florida Shelf, toxic dinoflagellate blooms represent a nearly annual phenomenon (Hoagland et al., 2009; Kirkpatrick et al., 2010; Heil et al., 2014). The recurring episodic perturbations that arise when *K. brevis* becomes dominant in coastal waters have widespread implications on marine ecosystems, public health, fisheries, and coastal economies (Backer, 2009; Fleming et al., 2009; Nierenberg et al., 2011; Hoagland et al., 2014; Anderson et al., 2015).

Within the south-eastern part of the United States, the west coast of Florida is often considered the epi-center of harmful algal blooms, experiencing more frequent events than other regions (Hoagland et al., 2014). However, high densities of toxic dinoflagellate have also been recorded along the eastern Florida coast (Hitchcock et al., 2014), and in the Florida Keys and around the Florida Panhandle (Wolny et al., 2015). The reason behind the recent rise in recorded blooms is twofold. First, improvements in monitoring systems facilitate the increase in frequency of reported events (Anderson et al., 2015). Second, a variety of factors act synergistically, and contribute to the development of extensive and prolonged blooms. Some studies suggest that climate change effects coupled with an alteration in nutrient dynamics (due to anthropogenic activities) are the triggering factors responsible for bloom initiation (Dixon and Steidinger 2002;
Gannon et al., 2009; Anderson et al., 2015). Other studies propose that the interaction between upwelling, favorable wind patterns, offshore advection forces, and *K. brevis* vertical migration patterns explain seasonal bloom development (Strumpf et al., 2008).

Substantial research has been dedicated to identify the biological characteristics of *K. brevis* and investigate the interplay between bloom nutrient physiology and other organisms within a constantly changing environment (Steidinger and Haddad, 1981; Tester and Steidinger, 1997; Walsh et al., 2006; Van Dolah et al., 2009; Vargo, 2009). The sequential development of blooms of various severities has been thoroughly studied for the past 60 years (Van Dolah et al., 2009; Heil et al., 2014). However, due to the highly complex interactions between members of the microbial community and their surrounding environment, the factors influencing the various stages of bloom development (initiation, growth, maintenance and termination) are not yet fully understood (Das et al., 2010; Heil et al., 2014). Consequently, the mechanistic processes that lead to the sporadic occurrence of *K. brevis*, its migration along the coastline, and the accumulation of high concentrations in coastal regions, require further investigation (Heil et al., 2014).

Technological advances have substantially enhanced existing knowledge of *K. brevis* blooms. Even though monitoring toxic blooms is complicated by a variety of factors, satellite ocean color imagery has been used for monitoring purposes (Stumpf et al., 2003; Frolov et al., 2013). The size and duration of the blooms, the remoteness of offshore initiation zone, the extensive area covered by the toxic dinoflagellate and the presence of multiple *Karenia* species, encumber successful monitoring of incipient
phases of bloom formation (Heil and Steidinger, 2009). However, remote sensing techniques have been used to facilitate identification of incipient bloom phases, through the early detection of chlorophyll anomalies (Tomlinson et al., 2009). Studies using Geographic Information Systems (GIS) have been conducted in various regions of the world. Yet, relatively little GIS analysis has been applied to study *K. brevis* occurrences on the West Florida Shelf.

### 1.1 Significance of study

To date, socio-economic implications of *K. brevis* blooms are often tied to an array of health risks associated with the ingestion or inhalation of brevotoxins (Kirkpatrick et al., 2004), loss to fishing revenue (Backer et al., 2009), a decrease in tourism during the duration of the bloom (Backer et al., 2009; Hoagland et al., 2014), or even a drop in real estate prices (Larkin and Adams, 2013). No studies have yet to analyze the possible relationship between red tide and recorded school absenteeism rates. The proposed research not only reveals insight into localized bloom maxima (hot spot areas), but also uses the tools provided by GIS software in the process of strategically partitioning, overlaying and analyzing existing information and identifying coastal areas of high vulnerability.

The use of GIS computing capabilities allows for the study of environmental issues in coupled human-natural systems by simultaneously incorporating and analyzing biological, physical, social, and economic data. Within this study, GIS maps are designed to provide a visual display of *K. brevis* occurrences, and to facilitate the understanding and conceptualization of the complex spatial relationships found in the natural world.
Spatially overlaying and statistically analyzing the existing cell count data (within specific periods of time) could reveal valuable insight with respect to bloom formation, persistence, and termination. Further, linking this understanding with documented socio-economic and health impacts could provide the necessary underlying foundation to advance existing knowledge of the multiple parts of this complex natural phenomenon. Identifying highly vulnerable areas could minimize the adverse socio-economic and ecological impacts associated with abundant *K. brevis* development in coastal waters. Armed with this knowledge, resource managers could focus mitigation efforts towards the most vulnerable areas. Additionally, informing and educating the general public about the existence of bloom hot spots could minimize exposure through avoidance of vulnerable coastal regions adjacent to offshore hot spots. Therefore, knowledge of the *K. brevis* hot spot locations could have widespread implications influencing people’s decisions, aiding public health officials and natural resource managers, as well as potentially also impacting coastal businesses.

In the following sections, a synopsis of the existing hypotheses regarding bloom formation and dynamics is presented. Associated ecological, economic and human health impacts are also described. The proposed research adopts an interdisciplinary framework for interpreting spatial data, with highly relevant applications for health care resource allocation, emergency preparedness and harmful algal bloom mitigation procedures.
Chapter 2: Literature review

As the frequency of bloom events intensified, the resources dedicated to studying these unusual biologic events also increased within the past 50 years. Currently, considerable knowledge exists on the nutrient requirements, preferences and uptake capabilities of *K. brevis* (Heil at al., 2014). Recent developments in cellular and molecular biology, particularly the use of population genetic markers, have revealed a high genetic diversity in *K. brevis*, which were long assumed to consist of clonal populations (Van Dolah et al., 2009). However, the mechanisms fueling bloom initiation and termination remain poorly understood, yet are critical for the prediction, management and mitigation of resulting impacts (Van Dolah et al., 2009). The difficulty of studying this biological phenomenon is in part due to the complex forces acting offshore, partially due to the physiological versatility of the organism, and partly due to the large temporal and spatial variability of the blooms (Heil at al., 2014). To date, there is no single hypothesis accounting for their development, evolution, and dynamics (Steidinger and Haddad, 1981; Walsh et al., 2006; Vargo, 2009). Multiple potential mechanisms fueling *K. brevis* development will be further reviewed.

2.1 Bloom initiation and dynamics

Historically, it has been thought that life cycles along with local physical conditions are the primary drivers for *K. brevis* proliferation (Steidinger and Haddad, 1981). Other early investigations of bloom initiation were linked to river runoff, human-induced pollution, and other sources of nutrient enrichment (Steidinger and Haddad, 1981). Terrestrial runoff was thought to be one of the main causes of bloom
formation (Vargo, 2009). Other potential factors that facilitate the growth of the toxic dinoflagellate are associated with: upwellings, mixing of dissolved organic matter, changes in water masses caused by weather disturbance, reductions in grazing or selective feeding, and increased runoff due to heavy rains (Gunter et al., 1948; Steidinger and Haddad, 1981; Vargo, 2009).

There is an apparent paradox between the offshore nutrient-poor environment in which *K. brevis* is thought to originate and its subsequent growth, and proliferation through the marine ecosystem (Bronk et al., 2014). Blooms are believed to originate offshore, in the oligotrophic waters of the Florida shelf. Transported by winds and currents, they accumulate in eutrophic coastal bays and inlets (Dixon et al., 2014). An initiation zone was initially identified as the area between 18 to 74 km offshore (Steidinger and Haddad, 1981). However, this zone was found to vary from year to year due to changes in water chemistry, ocean currents, and ecological processes.

2.2 Hypothesis behind the mechanisms fueling bloom initiation

The chemical environment characteristic of the West Florida Shelf is N-limited, and additional N inputs have been hypothesized as potential triggering factors fueling bloom initiation (Mulholland et al., 2014). N$_2$-fixation is recognized as one of the principal nutrient sources. Initial studies performed by Gunther et al., (1948) have emphasized the importance of studying *K. brevis* in relation to other organisms. Walsh and Steidinger (2001) linked the occurrence of nitrogen-fixing filamentous cyanobacteria, *Trichodesmium spp.* and *K. brevis*. They hypothesized that the nitrogen fixed by *Trichodesmium spp.* represents a source of nitrogen that supports the persistence of *K. brevis* (Vargo, 2009).
In accordance with this hypothesis, Walsh et al., (2006) proposed a full sequence of physical and ecological events leading to the origination of high *K. brevis* concentrations. Initially, phosphorous-rich nutrient supplies in conjunction with the deposition of iron-rich Saharan dust particles are thought to create the necessary conditions for the development of *Trichodesmium* blooms. These blooms assure the required nitrogen supply in the otherwise nitrogen-depleted marine environment of the West Florida Shelf. The vertical migration of diazotrophs (nitrogen-fixing bacteria and archaea) and other toxic dinoflagellates, abundant nitrogen and phosphorous sources, supplemented by decaying fish matter, are all elements believed to contribute to the growth of a *K. brevis* (Walsh et al., 2006). Future projections estimate an increased rate of cyanobacterial N\textsubscript{2}-fixation due to climate change. More precisely, higher temperatures and pCO\textsubscript{2} are thought to encourage N\textsubscript{2}-fixation (Mulholland et al., 2014).

Yet another pathway leading to extensive blooms is proposed by Stumpf et al., (2008). In the 2008 study, a modelling framework was created using satellite chlorophyll concentrations, wind measurements, sea surface temperatures, nutrient data, and recorded *K. brevis* cell concentrations. The results of the model showed that frontal boundaries (generated by wind patterns, ocean currents and bathymetric characteristics of the coastal area) transport *K. brevis* cells into coastal surface waters. In these regions the dinoflagellates become progressively more nutrient-depleted. Chemotactic behavior (the movement of an organism in response to a chemical stimulus) is then responsible for their downward migration towards nutrient-rich bottom water layers. It is assumed that, as the numbers of dinoflagellates flourish replenished by the fresh nutrient supply, the cross-
shelf flow advects the dinoflagellates and concentrates large numbers in coastal regions (Strumpf et al., 2008).

2.3 Rainfall patterns and the occurrence of *K. brevis* blooms

The correlation between rainfall patterns, river runoff and extreme weather events (hurricanes) has also been studied throughout the past five decades. Feinstein (1956) found no linear relationship between these variables. Several years later, Finucane (1964) came to the conclusion that high numbers of *K. brevis* usually occurred between fall and winter during the 4 year period studied. The recorded blooms were preceded by periods of high rainfall and river discharge (Vargo, 2009). Even though a conclusive direct linkage between periods of high rainfall and *K. brevis* occurrences still requires further research, Rouneffell and Nelson (1964) highlighted that rainfall should be considered as one of the factors favoring *K. brevis* outbreaks (Vargo, 2009).

During the early 1970’s, Martin (1971) postulated that rainfall could be a variable which would increase the number of bloom occurrences by transporting organic matter into coastal regions. It was assumed that an increase in precipitation levels would enhance the volume of river flow, carrying iron, tannic and humic acids into nearshore waters (Vargo, 2009). However, no conclusive relationship between the occurrences of these trace metals and high toxic dinoflagellate cell counts was fund.

The relationship between elevated precipitation levels and bloom development may not be easily identifiable. The possibility of a time lag between periods of high rainfall and bloom initiation has been proposed by Dixon and Steidinger (2002). This time difference may hinder the discovery of a direct, causative relationship.
2.4 The importance of nutrient sources

Significant literature has been devoted for exploring potential nutrient reservoirs, particularly nitrogen (N) and phosphorous (P), and recycling mechanisms that support the initiation and development of *K. brevis*. Potential nutrient reservoirs have been identified as: atmospheric deposition, terrestrial runoff, estuarine and benthic fluxes, N-fixation, remineralized nutrients from the decay of diatoms and fish populations, N regeneration from zooplankton excretion and sediment N remineralization through benthic fluxes (Vargo, 2009; Heil et al., 2014; Dixon et al., 2014; Bronk et al., 2014; Killberg-Thoreson et al., 2014; Kirkpatrick et al., 2014). Anthropogenic nutrients sources have been linked to land runoffs, fertilize use, industrial effluents, and submerged groundwater discharges (Kirkpatrick et al., 2014; Hoagland et al., 2014). However, the toxic dinoflagellates exhibits a wide range of nutrient strategies, and hence, direct links between *K. brevis* blooms and terrestrial contributions of nutrients have not yet been proven (Dixon et al., 2014).

The role of estuaries and ground water as potential nutrient reservoirs was explored by Odum et al., (1955). His research showed conflicting results. The conclusions suggested that Tampa Bay and Peace River estuary provide sufficient nutrients to support a growing *K. brevis* population, while Caloosahatchee River and the identified ground water sources exhibit lower nutrient levels compared to the surrounding coastal waters (Vargo, 2009).

Yet another hypothesis proposed by Wilson (1959) postulates that *K. brevis* growth is supported by a variety of chelators and trace metals (Vargo, 2009). Similarly,
Pasteur and Abbot (1970) theorized that gibberellic acid, a terrestrial plant hormone, contributes to the development of blooms by breaking down the matter of macroalgae and plant remnants (Vargo, 2009).

Investigating other biological and ecological factors potentially influencing bloom initiation and dynamics, Vargo et al., (2004) evaluated a variety of nutrient sources prevalent in near-shore areas. Among the most predominant sources were zooplankton excretion and fish decay. Atmospheric deposition and benthic fluxes were found to be minor contributing factors to required nutrients (Vargo, 2009). Estuarine fluxes also represented a significant source of nutrients, however their spatial areal extent was limited.

The physiological characteristics of *K. brevis* were also studied. The rates of nutrient uptake of *K. brevis* have been studied by Bronk et al. (2014), and the results showed that the toxic dinoflagellate displays average nutrient-uptake capabilities compared to other phytoplankton species. Therefore, other factors must account for *K. brevis* ability to become the dominant species found in coastal waters (Bronk et al. 2014).

Among the variety of both natural and anthropogenic nutrient reservoirs, not one source has been identified as a dominant contributor to bloom development (Dixon et al., 2014; Heil et al., 2014). Field evidence suggests that a combination of nutrient sources is responsible for the development of significantly high *K. brevis* cell accumulations (Heil et al., 2014). The toxic dinoflagellate uses both organic (urea and amino acids such as alanine and glutamate) and inorganic forms (nitrate and ammonia) of nutrients, and hence, does not necessarily rely on a particular source (Tester and Steidinger 1997;
Killberg-Thoreson et al., 2014; Bronk et al., 2014; Kirkpatrick et al., 2014; Killberg-Thoreson et al., 2014). Consequently, one potential underlying reason behind the relatively frequent development and persistence of *K. brevis* blooms may be the dinoflagellate’s capability of adapting to a physically and chemically dynamic environment (Heil et al., 2014). Research has shown that *K. brevis* has the ability to thrive in a wide range of temperatures, salinity regimes, and irradiance levels (Vargo, 2009). Field and laboratory studies have determined the optimum temperature values to range between 22 and 28 degrees C. (Vargo, 2009). A minimum salinity tolerance was found at 24 ppm, while maximum levels are considered to be around 45 ppm (Vargo, 2009; Heil et al., 2014).

Furthermore, a number of studies have concluded that the complex interplay between nutrient sources, light, temperature, salinity, areas of upwelling, as well as other physical parameters create the necessary conditions required for *K. brevis* to originate and become dominant in coastal waters (Steidinger and Haddad, 1981; Vargo, 2009). Marine communities are influenced by a balance between bottom-up nutrient availability and top-down grazing (Walsh and O’Neil, 2014). It is hypothesized that high nutrient conditions not only promote the development of toxic algal blooms, but also suppress grazing by enhancing the production of toxin grazing deterrents (Anderson et al., 2015). This positive feedback is thought to intensify the negative impacts associated with high concentrations of toxic dinoflagellates (Anderson et al., 2015).
2.5 Physical forces influencing bloom dispersion

In addition to the physiological characteristics of *K. brevis*, it is thought that specific areas may exhibit the necessary conditions necessary for bloom formation. Large concentrations of toxic dinoflagellates have been primarily recorded in coastal areas. Dilution and mixing processes acting further offshore are thought to disrupt the integrity of the water mass and create unfavorable conditions for the persistence of *K. brevis* in high concentrations (Steidinger and Haddad, 1981). Therefore, it is believed that physical forces (high wind, current interaction) act as dispersion mechanisms (Steidinger and Haddad, 1981). For instance, the Gulf Stream can transport *K. brevis* as far north as North Carolina (Wolny et al., 2015). The Loop Current, a major force driving circulation on the west Florida shelf, was assumed to be responsible for the suspension of the dinoflagellate’s benthic resting stage (Tester and Steidinger, 1997). Additionally, salinity and thermal fronts act as both barriers and transport mechanisms (Vargo, 2009). Other hypotheses assume that bloom initiation occurs offshore, yet is transported shoreward by movements of the Loop Current or spinoff eddies (Tester and Steidinger, 1997).

Some of the most intense and prolonged blooms have been thoroughly described in detail in the literature (Vargo et al., 2004; Gannon et al., 2009; Hitchcock et al., 2014). According to Gannon et al., (2009), the year 2007 had the fewest days of red tide conditions (11%), while 2005 had the most (95%). Weisberg et al., (2014) describes the 2007 bloom as being ‘cut short’ by the Loop Current and transported to the east Florida coast and further north.
Specific years, such as 1998 and 2010, have not been characterized by extensive _K. brevis_ offshore concentrations. The year 2010 was an atypical period, since it displayed extremely low concentrations of _K. brevis_ (Weisberg et al., 2014). One potential explanation is given by the interaction of oceanographic forces with the underlying shelf ecology (Weisberg et al., 2014). For example the absence of a bloom in 2010 was linked with the presence of a strong Loop Current. It is hypothesized that not all upwelling events have the same consequences (Weisberg et al., 2014). It is thought that the upwelling of deep nutrient-rich waters caused by the Loop Current and eddy interaction with the shelf slope, suppresses the development of a _K. brevis_ by facilitating anomalous high nutrient fluxes across the shelf break. These fluxes are thought to create the necessary conditions for the growth of other phytoplankton species (Weisberg et al., 2014).

The overarching theme of these hypotheses highlights the fact that there is not one single factor responsible for the formation of _K. brevis_ blooms, rather it is the synergistic effects of favorable environmental conditions, physical oceanographic forces, and potential anthropogenic nutrient enrichment of coastal waters.

As previously mentioned, it is extremely difficult to distinguish the driving mechanisms of this natural phenomenon since these drivers span a vast continuum of spatial and temporal scales. These processes range from: molecular mechanisms within the dinoflagellate cell that respond to environmental cues, to oceanographic and even atmospheric processes that determine local environmental conditions (Van Dolah et al., 2009).
Chapter 3: Florida red tide impacts

Background levels of *K. brevis* have been documented year round and are estimated around 1000 cells/l or less (Tester and Steidinger, 1997). A bloom is considered to originate due to a combination of growth and concentration processes (Vargo, 2009). Bloom conditions are defined in cases when *K. brevis* reaches a density of over $10^5$ cells/liter (Stumpf et al., 2008; Gannon et al., 2009).

The physical manifestations of toxic algal blooms include water discoloration, fish kills, manatee mortalities, noxious odors, beach closures, and human respiratory impairments (Hoagland et al., 2014). Monitored levels above 5000 cells/l require shellfish closures and fishing restrictions (FWC, 2015). For concentrations between 1000 and 10 000 cells/l, possible negative effects, such as respiratory irritation, may occur (FWC, 2015). Therefore, the vast array of consequences associated with red tides heavily impact coastal communities.

A large number of studies have been dedicated to analyzing and quantifying the ecological, economic and social (health related) impacts associated with the Florida red tide (FRT) phenomenon. Each aspect will be further discussed, providing a broad overview of the multifaceted consequences resulting from *K. brevis* blooms.

3.1 Ecological impacts

The effects of monospecific dinoflagellate blooms cascade through the food web, negatively impacting marine fauna and causing significant changes in the marine ecosystem (Landsberg et al., 2009; Seubert and Caron, 2011). Primary production has been recorded 2-3 times higher than background rates during non-bloom periods (Vargo
et al., 2004). In addition to this, the disturbance caused by extensive blooms may result in a change in fish community structure, the development of hypoxia conditions (due to an increase in oxygen demand of *K. brevis*), and could also lead to a substantial decrease in species richness across all habitats (Gannon et al., 2009).

Ocean circulation also plays an important role in moderating the overall range of ecological impacts. Advected inshore currents and areas of upwelling transport *K. brevis* toxins, affecting both plankton and nekton communities (Gray, 2014). Benthic species are exposed either in areas of bloom origination, or in coastal waters where the toxic dinoflagellates move further onshore (Weisberg et al., 2009; Walsh et al., 2011).

The wide-ranging adverse effects are due to the potent neurotoxins, known as brevotoxins (PbTx) released by *K. brevis*. These neurotoxins primarily affect vertebrate neuromotor systems by altering sodium-potassium channels, potentially leading to death (Kirkpatrick et al., 2004). Brevotoxins are also known to persist in the food web for long periods of time (over a year) following red tide events (Gannon et al., 2009). Experimental studies revealed that brevotoxins found in dinoflagellates were also found in zooplankton grazers, and in juvenile fish (Landsberg et al., 2009). Acute neurological symptoms are responsible for widespread fish kills, as well as morbidity and mortality in marine mammals, and sea birds (Gannon et al., 2009; Fleming et al., 2009).

Even low concentrations of toxins can become bio-accumulated and biomagnified in filter feeders, adversely impacting upper levels of the food web (Steidinger and Haddad, 1981; Landsberg et al., 2009). Numerous ecological adverse impacts associated with the presence of high levels of brevotoxins have been documented over time. During
the four year time period from 2003 through 2007, 96% of local recorded fish kills were during red tide events (Gannon et al., 2009). Studies suggest that as a consequence of intense bloom periods, up to 100 tons of fish are killed (Kirkpatrick et al., 2004). Following the extended 2005 bloom, sea turtle strandings in southwest Florida significantly increased compared to the average numbers recorded over the past decade (Landsberg et al., 2009). Bottlenose dolphins and manatee mortalities have also been linked to the ingestion of the lethal toxin (Landsberg et al., 2009). It has been documented that inhalation exposure to marine aerosol containing brevetoxins causes respiratory symptoms (Cheng et al., 2005). This significantly affects not only humans, but also marine mammals. In 1996, 149 manatees were found dead as a consequence of a severe bloom (Flewelling et al., 2005). When analyzing the cause of death, lung pathology indicated that brevetoxins had been inhaled (Flewelling et al., 2005).

Among the large number of organisms negatively impacted by *K. brevis*, shellfish are less likely to experience mortality from exposure to the toxic dinoflagellates. Nevertheless, they act as vectors for the transport of brevotoxins to higher trophic levels. Toxins become accumulated in their tissue and passed on throughout the food web, long after an original bloom has dissipated (Landsberg at al., 2009; Gray, 2014). Filter-feeder organisms, such as bivalves, accumulate the toxins in their system, and when consumed by humans are the cause of acute neurotoxic shellfish poisoning (NSP) (Steidinger et al., 1998; Naar et al., 2004; Walsh et al., 2006; Landsberg at al., 2009; Wolny et al., 2015). Laboratory experiments reveal that the residence time of brevotoxins in the tissue of the filter feeders may be species-specific. Hard clams and eastern oysters retain the compounds for periods of time between 2 and 8 weeks, while Pacific oysters rapidly
diminish their tissue brevotoxin concentration within 24 hours, reaching levels close to those safe for human consumption (Landsberg et al., 2009).

### 3.2 Economic impacts

Intense bloom periods are associated with a number of direct and indirect effects on coastal communities. The economic burden of extensive *K. brevis* blooms is multifaceted. Quantifying the magnitude of the economic impact is relatively difficult due to the vast array of indirect, unreported and hidden costs (Kirkpatrick et al., 2004). The public health sector, the tourism and recreational sectors, seafood industry, as well as commercial and artisanal fisheries all suffer significant losses (Anderson, 2000; Backer, 2009). Furthermore, during bloom periods there is an increased demand on health care providers (Kirkpatrick et al., 2006; Fleming et al., 2009). Negative economic impacts are often linked to medical costs associated with cases of irritation respiratory response, and NSP (Kirkpatrick et al., 2004). A significant 40% increase in the total number of gastrointestinal emergency room admission during bloom periods was recorded compared to non-bloom periods (Kirkpatrick et al., 2010).

One component of the total economic impact, the estimated costs of illness, has been estimated by Hoagland et al., (2009). Their results have shown that the approximate marginal costs of respiratory illnesses in Sarasota County varies between $0.5 and $4 million depending on bloom severity (Hoagland et al., 2009). A more recent study, Hoagland et al., (2014), analyzed the relationship between the number of emergency room visits and associated red tide periods. Their results suggested that older cohorts (>55 years) are mostly affected by both respiratory and digestive illnesses resulting from
brevotoxin exposure. The annual estimated costs of illness were found to vary between $60,000 and $700,000, with the potential of exceeding $1.0 million in the case of prolonged and severe blooms (Hoagland et al., 2014). Future projections that use a discount rate of 3%, approximate the capitalized costs of illnesses due to red tide events to vary between $2 and $24 million (Hoagland et al., 2014). Similar to the findings of Hoagland et al., (2014), research done by Meyer et al., (2014) concluded that brevotoxins can cost the Florida economy $26 million dollars each year a bloom is present.

In addition to this, closure of shellfish beds results in significant economic losses. Fishing and aquaculture activities are also highly affected for long periods of time (Backer, 2009). General lack of knowledge regarding the causes and consequences of toxic blooms yield additional economic losses. Misplaced concerns among Southwest Florida residents regarding consumption of seafood during bloom periods negatively impacts coastal business (Backer, 2009). The costs related to the disposal of fish kills that float ashore represents an additional financial stress on the already impacted coastal economy (Kirkpatrick et al., 2004).

3.3 Human health impacts

Illnesses of various severities have been often linked to the existence of an offshore toxic bloom (Hoagland et al., 2041). The potent natural toxins released by the dinoflagellates can reach the nervous system of humans and animals causing significant damage. Brevotoxins are depolarizing substances which open the voltage gated sodium ion channels in cell membranes. This in turn, facilitates uncontrolled sodium flux into the cell and leads to the disruption of respiratory and cardiac function (Kirkpatrick et al.,
Potential remedies for the adverse effects could be atropine (drug that regulates the activity of glands regulated by the parasympathetic nervous system), brevenal (a natural inhibitor of brevotoxins) and tetrodoxin (Kirkpatrick et al., 2004; Gold et al., 2013). Tetrodotoxin inhibits the firing of action potentials in nerves by binding to the voltage-gated sodium channels in nerve cell membranes and blocking the passage of sodium ions (Lee and Rubern, 2008).

The health impacts associated with harmful algal blooms materialize in various forms. The two most common routes of exposure are through the ingestion of contaminated shellfish and seafood, causing neurotoxic shellfish poisoning, or through the inhalation of aerosolized brevotoxins, leading to a number of adverse upper and lower respiratory symptoms. These symptoms are more intensely expressed in persons suffering from asthma (Cheng et al., 2005; Fleming et al., 2011; Kirkpatrick et al., 2014).

3.3.1 Neurotoxic shellfish poisoning (NSP)

The digestive illnesses caused by the ingestion of brevotoxins manifests as a gastroenteritis with neurologic symptoms. The recorded adverse symptoms become apparent within minutes and up to three hours after the consumption of contaminated seafood. Abdominal pains, nausea and diarrhea, as well as a number of neurologic symptoms such as headaches, dilated pupils, incoordination, and dizziness are all frequently reported consequences (Kirkpatrick et al., 2004). The adverse effects are milder compared to other forms of marine toxin poisoning such as paralytic shellfish poisoning, and ciguatera fish poisoning (Kirkpatrick et al., 2004). In extreme cases, NSP
could cause bradycardia (abnormally slow heart action), convulsions, and the subsequent need for respiratory support (Kirkpatrick et al., 2004).

Even though shellfish harvesting is stopped when *K. brevis* cell counts reach 5000 cells/l, there still are numerous cases of patients diagnosed with NSP. This could be a result of consumption of illegally harvested seafood, whole finfish consumption, or swallowing of contaminated seawater (Hoagland et al., 2014). One of the first reported cases of NSP was recorded in North Carolina, and was associated with the consumption of cooked and raw oysters that were contaminated with brevotoxins (Kirkpatrick et al., 2004).

### 3.3.2 Respiratory illnesses

Historically, accounts of acute respiratory and eye irritation have been associated with periods of exposure to aerosolized brevotoxins. The first adverse health effects were reported in 1947. Woodcock (1948), documented the reports of individuals complaining from respiratory irritation during a severe red tide period (Kirkpatrick et al., 2014). In 1972, symptoms such as eye and respiratory irritation were described by a number of individuals. The extent of these adverse health effects was associated with the amount of time the individuals have spent on the beach. During the same time and general location, persons who were not exposed to the breaking surf, did not report any symptoms (Kirkpatrick et al., 2004).

In later studies, seawater containing brevotoxin particles was sprayed into the nose and throat of volunteers. The volunteers started coughing and experiencing a burning sensation, describing similar symptoms to those manifested on the beach.
(Kirkpatrick et al., 2014). During a research cruise conducted in 1999, two scientists experienced symptoms such as burning of eyes and respiratory irritation while sampling. They also exhibited difficulty breathing and a decrease in pulmonary function (Kirkpatrick et al., 2004).

Brevotoxins can also concentrate in water droplets, and become aerosols through wave action (Backer, 2009). Laboratory experiments conducted by Pierce et al., (1990) simulated the red tide aerosol formation. This was achieved by bubbling air though cultures of lysed *K. brevis* cells. The result of this experiment documented an increase of 5 to 50 times in toxin enrichment found in seawater compared to initial levels (Kirkpatrick et al., 2014). In addition to this, the collection and analysis of marine aerosols during toxic bloom periods, reveals the same aerosolized toxins as those found in seawater, and similar to those resulting from *K. brevis* culture experiments (Kirkpatrick et al., 2014).

Inhalation of marine aerosol containing brevotoxins causes a vast array of respiratory symptoms including: involuntary coughing and sneezing, rhinorrhea bronchoconstriction, watery eyes, dizziness, a burning sensation in the throat and nose, nasal congestion, tunnel vision, skin rashes, tightness of chest, shortness of breath, and difficulty breathing (Kirkpatrick et al. 2004; Cheng et al., 2005; Kirkpatrick et al., 2014). In addition to this, susceptible individuals may suffer from asthma attacks (Cheng et al., 2005; Fleming et al., 2009). Fleming et al., (2011) discovered that the inhalation of brevotoxin contaminated aerosols could significantly exacerbate asthma and other respiratory condition. Therefore, exposure to aerosolized brevotoxins has been documented to have significant health impacts, which may vary in severity depending on
the individual’s medical conditions. Research has shown that even low levels of neurotoxin concentration can cause significant distress such as burning of the eyes, nose and throat (Kirkpatrick et al., 2004). Furthermore, it has been hypothesized that the effects of aerosolized brevotoxin contamination could be chronic and not acute, resulting in chronic neurointoxication, hemolytic anemia, and immunologic compromise (Kirkpatrick et al., 2004).

Potential relief from some of the adverse effects produced by the inhalation of contaminated aerosols is manifested when entering an air-conditioned area, or leaving the region of high brevotoxin concentration. The use of particle filter masks may also diminish the severity of the respiratory symptoms experienced (Kirkpatrick et al., 2004).

Recent research identified alternative routes for human exposure to brevotoxins. Kirkpatrick et al., (2010) described the range of exposure possibilities to brevotoxin contamination. Their research demonstrated that other than digestive and respiratory illnesses, aerosolized brevotoxins could be the potential causative agent for a number of gastrointestinal diseases. Brevotoxins inhaled from aerosols are rapidly absorbed in the bloodstream and can reach the brain, leading to gastrointestinal illnesses through the same neurologic pathways as NSP (Kirkpatrick et al., 2010). A compilation of hospital records from 2001 to 2006, revealed that the number hospital emergency admission for gastrointestinal illnesses significantly increased during the 2001 bloom period, compared to 2002, when there was no offshore bloom recorded.

It is widely recognized that the health-risks associated with either ingestion or inhalation of brevotoxins poses a significant threat to the inhabitant of coastal regions
In the previous sections, the proposed causative agents leading to bloom formation have been reviewed. The wide range of ecological and socioeconomic impacts have also been summarized. Throughout this study, we propose that identifying recurring areas of bloom hot spots can provide guidance in allocating exiting resources in areas that are the most vulnerable to the impacts of *K. brevis* blooms. Although significant efforts have been dedicated towards studying the biological characteristics, and subsequent impacts of red tide events, to date, *K. brevis* hot spot areas have not been identified on the West Florida Shelf.
Chapter 4: Existing definitions of harmful algal bloom hot spots

Existing literature defines ‘hot spots’ as: either areas of high algal biomass, localized zones of chlorophyll a anomalies, or locations where blooms most frequently occur (Barale et al., 2008; Wang and Wu, 2009; Wu et al., 2013). To our knowledge, a quantitative definition of *K. brevis* hot spots is lacking. Furthermore, few existing studies provide any confidence level when identifying areas characterized as hot spots. Wang and Wu (2009) conducted a study of risk assessment based on bloom hot spots in the East China Sea. The authors used the tools provided by GIS modules to develop a temporal and spatial analysis. Mapping the density of coastal blooms, and conducting a time series analysis highlighted the areas in which blooms most frequently occur. The frequency of occurrence of toxic dinoflagellates was mapped by Kernel Density estimation. Hot spot locations were determined under the assumption that regions with high densities represent hot spots. A nearest neighbor analysis was conducted in the attempt to understand the spatial pattern of bloom occurrences. Their results produced a visual illustration of the coastal area classified by risk levels, or likelihood to suffer from the effects of toxic blooms. Risk assessment was defined as a product of toxicity and exposure (Wang and Wu, 2009). However, this study did not provide any confidence level assessing the accuracy of the hot spot identification methodology.

An array of studies, summarized in Table 1 (Appendix A), identified and explored the presence and development of harmful algal blooms at various spatial scales, in different parts of the world. However, no studies have used the Hot-Spot Analysis tool provided by GIS (Statistical Analyst toolset) to identify clusters of statistically significant hot spots recorded at a small, regional scale. To address this gap in knowledge, this study
will analyze the time progression of *K. brevis* cell counts off the West Florida Shelf, while mapping major *K. brevis* hotspots. This information will be further used to assess potential social implications, and incorporated in the design of a vulnerability index. Since vulnerability is not evenly distributed, some coastal areas will experience higher negative consequences resulting from brevotoxin exposure, compared to others. Similarly, some individuals will be more prone than others to manifest adverse symptoms during an active red tide. The newly created vulnerability index is a metric which is proposed to indicate the likelihood that a large, and susceptible population will be exposed to brevotoxins.

4.1 GIS Hot-Spot Analysis: An overview

Traditionally, the Hot Spot Analysis statistical function (part of the GIS Spatial Analyst extension) has been used in the process of monitoring and identifying social-spatial patterns. For instance, it was initially used to locate areas with high crime incidents, or areas where a particular disease originated, and monitor its spreading pattern. Consequently, hot spot areas have been defined as concentrations of incidents within a limited geographical area that appear over time (ICPSR, 2014). This definition can also be applied to biological incidents such as harmful algal blooms. Areas and clusters of intense biological activity, often referred to as ‘hot spots’ can be identified using multiple methods. However, up until present this term has been applied solely in a descriptive, qualitative form.

The Hot Spot Analysis function has unexplored ecological applications. It can successfully be employed to locate statistically significant zones where toxic algal
blooms are recorded. We define hot spots as regions in which high values of *K. brevis* cell counts have been measured. Cold spots are defined as statistically significant clusters of low values. GIS analysis is used to test whether or not the apparent clusters are statistically significant and worth further investigation. The results of this GIS function gives specific z-scores and p-values. A high negative z-score signals the presence of a cold spot, while a high positive z-score indicates the existence of a hot spot. The higher the z-value, either positive or negative, the stronger or more intense the hot spot or cold spot. The p-value is the probability that the hot spot, cold spot, or the observed spatial pattern is random. A p-value below 0.01 signals that a less than 1% probability that the hot spot occurred randomly. Therefore, the area identified as a hot spot is statistically significant.

The GIS-based Hot Spot Analysis is needed in order to explore whether *K. brevis* clusters spatially. The analysis assumes, as a null hypothesis, that the toxic dinoflagellate is distributed randomly within coastal waters. The identification of either areas of hot spots or cold spots disproves the null hypothesis, showing that *K. brevis* blooms do not occur arbitrarily, but exhibit an identifiable spatial pattern, which may have a number of external causative agents.

The identification of these agents can provide key knowledge which could significantly enhance existing monitoring procedures and improve current mitigation strategies. Consequently, if a hot spot (monitored locations with high cell count values) is identified, then further investigation may be directed towards analyzing the specific characteristics of that particular area. A number of variables may converge in that region and provide the perfect medium for bloom accumulation and development. On the other
hand, if a cold spot is identified (monitored locations with low cell count values) then either the factors that support bloom development are largely absent (a lack of nutrient supply), or oceanographic currents lead to bloom dispersal, and subsequent termination.

4.2 Objectives

This study will significantly enhance the existing body of knowledge in three ways. First, a newly created methodology for identifying areas of statistically significant hot spots distinguishes itself from existing definitions of harmful algal bloom hot spots. Second, this study will contribute to the current understanding of *K. brevis* impacts though it’s pursued avenues of research. Exploring the potential relationship between school absenteeism rates recorded during active bloom periods could shed light on the unseen and unquantified social impacts of coastal toxic blooms. Third, coastal areas will be classified based on their susceptibility to suffer from a significant number of adverse health effects resulting from aerosolized brevotoxin exposure.

The temporal progression of *K. brevis* blooms are illustrated for the time periods selected between 2001 and 2013. This period was chosen with the goal of having a time frame broad enough to cover multiple bloom periods, yet limited enough to ensure accuracy of the methods of analysis used. Cell counts and their associated spatial-temporal patterns shall be displayed through thematic maps created with the use of ArcGIS. A new methodology for identification of *K. brevis* hot spots is proposed.

Due to the health impacts associated with harmful algal blooms, it is of interest to explore the potential social implications associated with high *K. brevis* concentrations along the shoreline. The direct impacts of red tides on coastal communities have been
already identified (Bauer et al., 2009; Fleming et al., 2009; Hoagland et al., 2009; Hoagland et al., 2014; Kirkpatrick et al., 2014). However, potential indirect effects, such as the association of a long-lasting *K. brevis* bloom with variations in schools absenteeism rates, have not yet been explored.

First to be addressed, is the hypothesis that *K. brevis* distribution is random, and does not display any identifiable spatial or temporal pattern. This can be tested though the used of GIS Hot Spot Analysis (Getis Ord-Gi*) function, which identifies statistically significant clusters of low, or high *K. brevis* cell counts.

The second hypothesis analyzed within this study proposes that hot spot areas do not correlate with school absenteeism. The validity of this statement will be tested. The alternative hypothesis is that either bloom intensity, the location of hot spot areas, or both, influence the percentage of school absenteeism in Sarasota County. Consequently, we explore if during periods when *K. brevis* cell counts reached peak levels, the number of students not attending school peaked as well. This hypothesis also implies that the location of the schools, with respect to the distance from the coast, is an important variable influencing absenteeism levels. Assessing the health risks associated with inhalation of brevotoxins, the distance from the shoreline has been documented as an important variable influencing the severity of the symptoms recorded. In this case, the null hypothesis proposes that distance from shore is not a variable influencing school absenteeism levels. Further analysis will reveal whether or not this relationship can be proven or dismissed.
Lastly, an objective of this study is to develop a vulnerability index, a measure of the exposure of a population to a specific hazard, in this case *K. brevis* toxicity. In assessing vulnerability of coastal areas several assumptions are made. It is assumed that areas closer to shore are potentially more vulnerable than those further inland. For this reason, the index will be calculated primarily for regions located within 1 km from the shoreline. It is also assumed that communities located in the proximity of identified hot spots will be more prone to suffer from the health effects associated with the release and spread of brevotoxins. Densely populated areas are believed to be much more vulnerable compared to other coastal regions that exhibit lower population numbers. In addition to this, based on recent findings (Hoagland et al., 2014) it is though that the older population is more likely to report adverse symptoms during red tide periods. Based on these three assumptions, a new vulnerability index is created. This metric could be used to enhance current mitigation strategies, facilitate preparedness procedures, and minimize health-related costs.
Chapter 5: Methods

This section is divided into three main parts. The first part explains a new methodology for identifying areas of bloom maxima, also referred to as hot spots. The second part applies this method to explore the unseen social implications of $K. \ brevis$ blooms. Examining any potential correlations between school absenteeism and proximity to bloom hot spots presents a new approach for predicting some of the social implications of toxic algal blooms. The third part of the study, incorporates the information on the location and extent of bloom hot spots in the process of developing a coastal vulnerability index. This newly designed metric can substantially improve existing outreach and educational programs, as well as aid the effective allocation of financial and medical resources during red tide periods.

I. Bloom hot spot identification: A new approach

Historically, Tampa Bay and Charlotte Harbor are known as epicenters for $K. \ brevis$ blooms (Weisberg et al., 2014). The area of interest for this study extends from Clearwater, Florida, in the northern part, to Naples, Florida, in the southern part. Regions of high $K. \ brevis$ concentrations are often found in coastal areas, close to large population centers. Consequently, the negative impacts resulting from coastal blooms affect a large number of individuals. Figure 1 and Figure 2 provide a representation of the geographical extent of the study area, along with an illustration of southwest Florida’s mostly populated regions. This is important knowledge in the process of assessing coastal vulnerability and will be further analyzed in Section III of the Methods chapter.
Figure 1: Representation of study area as an interpolated surface displaying estimated population density. Data on population numbers was taken from 2010 Census.
Figure 2: Contour of densely populated regions identified within the study area
The original *K. brevis* data was obtained from Mote Marine Laboratory. The dataset consisted of 2,092,657 individual entries recorded in an Excel spreadsheet. *K. brevis* cell counts (cells/liter) were measured from samples taken at various locations and depths. The spreadsheet also contained information such as: latitude-longitude coordinates, date, time, and location by county. The information was monitored starting in 1980, through 2013. The *K. brevis* recordings were taken along the West Florida Shelf, at various distances from the shoreline, with decreasing number of measurements taken with increasing distance from the coastline. The minimum levels of *K. brevis* recorded were 0 cells/l, while maximum levels reached 358,000,000 (December 1994).

It is widely recognized that blooms can persist for extended periods of time, and that high concentrations of *K. brevis* are temporally and spatially variable (Stumpf et al., 2008). Existing literature emphasizes that red tide events represent an almost annual occurrence on the West Florida Shelf (Hoagland et al., 2009; Kirkpatrick et al., 2010; Heil et al., 2014). For this reason, the available *K. brevis* cell count data was graphed as a time series progression. The yearly graphs are displayed in Appendix B. The time frame chosen for the purposes of this analysis incorporates blooms monitored from 2001 to 2013. Within this timeframe, individual years were identified by placing a filter on the date column. This allowed for one to easily choose particular years, specific count ranges, or specific sampling locations, within the large dataset. Bloom periods were selected from the attribute table using the ArcGIS Select by Attribute function. The incipient bloom phases along with the termination phase were identified visually based on the time series graphs created. The *K. brevis* data for the following periods was selected: August 2001 – April 2002; January - November 2003; January – March 2004; January –
December 2005; July – December 2006; September – December 2011 and January – April 2013. Bloom hot spots were identified for each of the time periods and displayed in Appendix C.

5.1 *Karenia brevis* data analysis

The *K. brevis* spreadsheet data were added to ArcMap, displayed, and projected. The geographic coordinate system used was GCS_North_American_1983_HARN and the projected coordinate system used was Albers Conical Equal Area [Florida Geographic Data Library]. The spatial extent of the blooms is visualized through the use of GIS interpolation techniques.

Interpolation is a procedure used to predict values at locations in which sample points are lacking. This method is based on the principle of spatial autocorrelation or spatial dependence, which measures the degree of dependence/correlation between near and distant features (Childs, 2004). There are two categories of interpolation techniques: deterministic, (such as Inverse distance weight-IDW) and geostatistical (such as Kriging). Both methods are used in the attempt to design accurate illustrations of *K. brevis* blooms. A brief description of these methods is provided below.

5.2 Deterministic interpolation technique - IDW

The IDW technique creates a continuous surface based on the information given at a number of locations (such as sampling points or monitoring stations). It estimates the cell values in a raster from a set of sample points that have been weighted. The further a sample point is from a cell, the less weight is attributed to that point. This technique is based on Tobler’s first law of geography, which assumes that points that are closer
together are more similar than points that are further apart. The formula used for interpolation is presented below. The function interpolates the unknown point values using the weighted average of the known values in the sample points (Sárközy, 1998):

$$ F^*_0 (x_0) = \sum_{i=1}^{n} \lambda_{i0} \cdot F(x_i) $$

where $F^*_0 (x_0)$ is the interpolated value in the place $x_0$, $F(x_i)$ is the value of the measurement in the sample point $x_i$, $i=1...n$ and the numbers $\lambda_{i0}$ are the weights (Sárközy, 1998).

However, this method has limitations. The IDW method may not be fully accurate for the following reasons. The lack, or scarcity of sampling points within certain regions of the study area may lead to the development of inaccurate estimations of bloom surfaces. More precisely, through the IDW interpolation method, the sample points are weighted such that the influence of one point relative to another declines with distance from the newly created point. Therefore, the quality of the interpolation can decrease if the distribution of sample data points is uneven (Documentation QGIS 2.2). For example, if there is an insufficiency of *K. brevis* monitoring locations in a particular area, the surface created will represent a very rough estimation of the potential values found in the area. In addition to this, potential outliers could significantly influence the characteristics of the continuous surfaces. For instance, if a monitoring station has erroneously recorded remarkably high cell counts compared to its surrounding stations, then this will skew the representation of the interpolated surface. Two possible explanations could account for this spike in cell count values at a particular location. Oceanographic processes may have
accumulated extremely high toxic dinoflagellate concentrations in a relatively constricted spatial extent. Alternatively, the high discrepancy in count values observed may be caused by a sampling error or misreporting of data.

5.3 Geo-statistical interpolation technique (Kriging)

Yet another technique used, kriging, is a powerful statistical interpolation method that assumes that the distance and/or direction between sample points reflects a spatial correlation explaining variations in the surface (Childs, 2004). It uses statistical models that allow a variety of output surfaces including predictions, prediction standard errors and quantile (ESRI, 2015).

The kriging formula is very similar to the IDW formula, however in the IDW, the weight $\lambda_i$ depends solely on the distance to the prediction location. One of the characteristics of the kriging method is that the weights are based not only on the distance between the measured points and the prediction location, but also on the overall spatial arrangement of the points (ESRI, 2012). The formula is:

$$\hat{Z}(s_0) = \sum_{i=1}^{n} \lambda_i Z(s_i)$$

where $Z(s_i)$ represents the recorded value at the $i^{th}$ location, $\lambda_i$ is an unknown weight for the measured value at the $i^{th}$ location, and $s_0$ is the prediction location (ESRI, 2012).

Both interpolation methods present limitations. The errors associated with the bloom prediction surface generated though kriging method may not represent a fully
reliable model. For this reason, the GIS Hot Spot Analysis function is used in the process of identifying the location and extent of area of significantly high \textit{K. brevis} concentrations. The benefits of using this function and its specific properties are described below.

5. 4 GIS Hot Spot Analysis (Getis-Ord, Gi*)

The Hot Spot Analysis method is the chosen method to identify areas of localized bloom maxima because it determines whether or not weighted features are dispersed or clustered by looking at each feature within the context of its neighbors. The null hypothesis assumes that the recorded \textit{K. brevis} cell counts are dispersed randomly throughout the shallow waters of the Florida shelf. However, as with many natural phenomena, this may not be the case. Trends, patterns, and clusters in spatial distributions of the dinoflagellate may disprove the null hypothesis. The Hot Spot Analysis GIS function explores the spatial distribution of the data features. If clustered areas are identified, then they are further categorized as hot spots, or cold spots depending on the value of the cell count recorded in those locations.

This statistical function, described below, accurately identifies areas of bloom hotspots by calculating the recorded count of a monitoring location in conjunction with the counts recorded in neighboring locations. Therefore, a point is determined to be a hot spot, only if it is surrounded by points which also have high cell count values. If this is not the case, then the particular monitoring location is not seen as a \textit{K. brevis} hot spot. Consequently, potential outliers (erroneous data entries, or inaccurate measurements) with very high cell/l values found in the data are not considered hot spots. For example, a
monitoring location (a point feature) with a high value is interesting, but may not be a statistically significant hot spot. To be a statistically significant hot spot a feature will have a high value, while at the same time be surrounded by other features with high values as well (ESRI, 2012). This significantly improves the reliability of determining the spatial extent of recurring bloom maxima.

The $G_i^*$ statistics is a z-score, the spatial function is given as:

$$G_i^* = \frac{\sum_{j=1}^{n} w_{i,j} x_j - \bar{X} \sum_{j=1}^{n} w_{i,j}}{\sqrt{n \sum_{j=1}^{n} w_{i,j}^2 - \left( \sum_{j=1}^{n} w_{i,j} \right)^2}}$$

where $x_j$ is the attribute value for the feature $j$, $w_{i,j}$ is the spatial weight between feature $i$ and $j$, $n$ is equal to the total number of features. $X$ and $S$ are defined as:

$$\bar{X} = \frac{\sum_{j=1}^{n} x_j}{n}$$

$$S = \sqrt{\frac{\sum_{j=1}^{n} x_j^2}{n} - \left( \bar{X} \right)^2}$$

5.5 Methodology for identifying areas of *K. brevis* hot spots

In order to acquire a better understanding of the spatial extend of offshore toxic blooms, and to recognize statistically significant hot spot areas, the GIS Hot Spot Analysis function was employed. The following steps were designed in order to successfully identify bloom hot spots.
The first step in the process is creating interpolated surfaces using the *K. brevis* data reported during the bloom periods selected. The time frames which were characterized by abnormally high numbers of *K. brevis* were identified based on the cell count peaks illustrated in Appendix B. Bloom surfaces were designed through the use of both IDW and Kriging interpolation techniques. IDW technique does not display its associated level of accuracy, while kriging does so by computing prediction error statistics.

Ordinary kriging is performed through the use of the ArcGIS Geostatistical wizard. The data field utilized for creating the predicted model is the *K. brevis* Count field. The accuracy of the interpolation method can be assessed through the prediction errors statistics associated with each interpolated surface. Each of the kriging processes gives the estimated prediction kriging standard errors (ESRI, 2012). The root-mean-squared standardized error should be close to 1 if the prediction standard errors are valid (ESRI, 2012). In this case, the best prediction model had a multiple R-squared standardized value of 0.87345. This is far from a perfect prediction, yet still represents a fairly good estimation of the spatial extent and intensity of the toxic blooms. As an example, the map presented in Figure 3 illustrates the prediction surface generated through the kriging method for the 2011 bloom. Other kriging surfaces displayed very high error values either due to the data properties, or due to the number of data points available. In these cases, the bloom surfaces resulting from the IDW interpolation technique were used for further processing and analysis.

In the process of displaying the spatial extent of various blooms using the IDW technique, the cell counts (Count field) are used as a weight field. A maximum cell size
of 200 was used. Additionally, for better accuracy of the resulting interpolation surface, the processing extent and raster analysis were limited and masked to the study area. The study area encompasses solely aquatic environments immediately following the coastline and ranging from inshore bays, inlets and estuaries, to offshore coastal waters. Furthermore, the estimated *K. brevis* bloom surface was manually classified within the following intervals based on the recorded cell counts: 5000-10,000; 10,000-100,000; 100,000 - 1,000,000; 1,000,000 - 10,000,000; 10,000,000 - 25,000,000; 25,000,000 - 50,000,000; 50,000,000 - 75,000,000; 75,000,000 - 100,000,000; and 100,000,000 - max value.

The second step in the process is converting the interpolated surfaces to raster format. The newly created raster layers are reclassified using the Spatial Analyst Reclass function. The reclassification is done based on the previously defined cell count ranges (5000-1000; 1000-10,000 etc.). A high reclassification value is representative of areas with high cell concentrations, while a low reclassification value symbolizes an area with low accumulation of the toxic dinoflagellates.

The third step of the process is the conversion of the reclassified raster layer into a vector data layer, by using the Raster to Polygon function. The resulting polygon will be subdivided in differently ranked regions characterized by estimated *K. brevis* cell counts. The highest ranked regions are also the ones exhibiting the highest *K. brevis* count. The polygon is further color coded. Intense red colors are associated with areas of high *K. brevis* biomass, while areas represented in blue shades illustrate regions of relatively low bloom concentrations. This step was applied for all years analyzed. Figures 3 and 4 provide a visual illustration of this step for only one bloom period recorded in 2011.
Figure 3: Predicted *K. brevis* bloom surface displaying regions of high (red) and low (blue) *K. brevis* cell counts. Data collected during late 2011 bloom. Sampling locations classified according to the probability of representing a bloom hot spot or cold spot
Figure 4: Bloom surface for late 2011 bloom converted into polygons. Each region is classified based on its associated cell count and sampling locations identified as hot spots.
The fourth step is classifying sampling locations based on their possibility of being a hot spot or a cold spot. This is done through the use of Hot Spot Analysis (Getis-Ord, Gi*). A new layer is created with the *K. brevis* sampling locations classified as either hot spots or cold spots, along with the associated confidence level of this prediction. Some points will be classified as neither a hot spot nor a cold spot, and they will be recognized as not statistically significant values. The result of the GIS Hot Spot Analysis gives z-scores and p-values. Points that fulfill the following conditions: they have a p-value less than 0.01, and they have a z-score greater than 0, are selected and exported as a new shapefile. A positive z-score signals the existence of a hot spot, while a negative z-score indicates the presence of a cold spot. A p-value less than 0.01 symbolizes that there is less than 1% chance that the particular point identified as hot spots is falsely classified as one. Therefore, different p values are associated with various confidence levels (p < 0.10, confidence of 90%; p < 0.05 confidence of 95%; p < 0.01, confidence 99%). The maps represented in Figures 5 and 6 show the visual display of this step, depicting potential bloom hot spot locations identified for the period June – December 2006. Figure 5 illustrates the sampling locations that have statistically significant high cell counts, highlighting clusters of *K. brevis*. Figure 5 focuses solely on clusters of high *K. brevis* values. While Figure 6 exemplifies the final result of the hot spot identification methodology for the 2006 bloom.

In the existing literature, the initiation zone was identified near Ft. Myers, around 120 km south of Sarasota Bay. The area of bloom dispersion and termination was located in the southern region, around the Caloosahatchee river mouth (Hitchcock et al., 2014). This area is also identified as a cold spot as illustrated in in Figure 5.
Figure 5: Geographic location of sampling points for the 2006 bloom classified based on the statistical results of the Hot Spot Analysis ArcGIS function. Coastal population densities mark regions characterized by high population numbers and located close to *K. brevis* hot spots.
Figure 6: Sampling locations which could potentially be bloom hot spots as determined by Hot Spot Analysis function. Population data recorded in 2012 and provided by ESRI.
In the process of identifying patches of high concentration of *K. brevis*, the interpolation method IDW is used. Since the Hot Spot Analysis GIS function creates a point layer, it is of interest to use the information given to display a surface. An estimation of the bloom hot spot spatial extent is created though interpolation (IDW) using only the cell count values recorded in the sampling locations classified as hot spots with an associated confidence level of 99%. Not all the existing sampling locations are interpolated. The result displays a raster surface divided in different areas, with various cell count ranges. The raster is further converted into a polygon though the use of Raster to Polygon function. The highest cell count class is selected and identified as a hot spot surface. The result of this step is depicted in Figure 8.

The sequence of steps previously described represents the novel approach in the process of hot spot identification, ensuring a higher level of accuracy. The flowchart presented below summarizes the methodology.

![Identifying K. brevis hot spots](image)

Figure 7: Schematic representation of the sequence of GIS tools used in the process of identifying bloom hot spot areas
Figure 8: Identified *K. brevis* hot spot area characteristic of June – December 2006 bloom. Hot spot surface created through interpolation of sampling locations identified as hot spots.
The maps illustrated in Appendix C show *K. brevis* surfaces and identified hot spots areas for each of the seven bloom periods analyzed from 2001 to 2013. As previously states, the bloom periods were identified based on the graphs displayed in Appendix B.

**II. School absenteeism in Sarasota County and *Karenia brevis* hot spots**

School absenteeism data consists of the weekly percentage of students absent recorded in each of the 46 schools in Sarasota County. Absenteeism rates were reported on a weekly basis, starting March 1st 2004 through May 3rd 2004, and from January 2nd 2006 through June 1st. Three schools, namely Sarasota Sun AC, Student Lenders, and Phoenix Academy had an overall 100 % student absenteeism across all weeks, and were eliminated from the data entries for the 2004 dataset. Wings Academy, GC Vocational Institute, and SCTI also had 100 % values and were taken out of the 2006 dataset. The 100 % values are thought to represent either a lack of data, or inaccurate data entries.

The locations of the schools are plotted through the use of GIS data display function (Display XY) from the Excel table. Figure 9 illustrates the locations of the 46 Sarasota schools along with the regional population density. It is observed that almost all the schools are located in highly populated areas of Sarasota County.
Figure 9: Sarasota school locations and population density per square mile. Population data obtained from ESRI.
In the process of exploring the available data, weekly absenteeism levels are plotted. Color-coded graduated symbols are used to denote the level of students absent. Figure 10 depicts the weekly absenteeism levels (percent students absent) for weeks 22 (starting January 2nd) through week 29 (starting February 20th). A close look at Figure 10 reveals that some schools are characterized by overall higher levels of absenteeism compared to others.

There are a number of factors that may influence the variation in absenteeism levels. Demographic, as well as economic variables play a role in determining school attendance levels. In an effort to control for this factor, instead of using absolute absenteeism values, the deviation from the mean is calculated for each school. The average absenteeism rates are calculated for each school. A change over time (from January 2006, through May 2006) in absenteeism rates compared to the average is calculated by computing the standard deviation for each school. If the standard deviation is positive, then higher levels of absenteeism occur during that particular week. If the standard deviation is a negative number, then the school experienced lower levels of absenteeism compared to the average. Plotting the change in absenteeism levels throughout time could potentially reveal periods when school attendance rates fluctuated as a result of external forces. The following sections will focus on exploring whether or not the distance from the coastline, or the distance from the identified *K. brevis* hot spot areas are a factor influencing fluctuations in school attendance levels.
Figure 10: Weekly absenteeism rates (January-June 2006) for all schools
5.6 Distance from coastline and school absenteeism

It is of interest to analyze the geographic location of schools relative to the coastline. Figure 11 displayed below illustrates the frequency distribution of the schools according to their distance from the coast.

Figure 11: Frequency distribution of the number of schools with respect to the distance from the nearest shoreline. It is apparent that the majority of schools lie in close proximity to the coastline.

Based in the information given by the frequency distribution graph, schools were divided into three categories. Those close to shore, with a distance from the coastline of less than 1200 m (15 schools fall within this category), schools further away from shore, located between 1200 and 5000 m, and educational institutions positioned beyond 5000 m from the shoreline. This was done in order to test whether or not the location of the school with respect to the distance from the shoreline influences absenteeism rates during active bloom periods.
In the process of testing if distance from the coastline played a factor in moderating school absenteeism levels, the Euclidian distance from the coastline was calculated for each school. This was achieved through the use of the GIS Spatial Join function. This function computes the closest distance between two spatially overplayed layers. The two layers used were the school location point layer, and the polygon shapefile of the Florida coastline contour. This shapefile was obtained from merging a newly created rectangular shapefile with the Florida county shapefile downloaded from GIS Maps and Surveys Shapefile library (http://www.swfwmd.state.fl.us/data/gis/layer_library/category/cartographic).

This is done with the help of the ArcGIS Union function part of the Geoprocessing Toolset. After the new layer was created, only the contours of the coastal regions were selected in order to obtain a highly detailed imprint of the Florida coastline.

After identifying the location of each school with respect to the coastline, the GIS Spatial Statistics function Ordinary Least Square regression was used. The Ordinary Least Squares (OLS) linear regression generates predictions, or models the relationship between a dependent variable in terms of a set of explanatory variables (ESRI, 2012). The outcome of this analysis will be presented in the Results section of this paper.

In order to obtain a better understanding of the overall absenteeism values, a number of two dimensional graphs were created. Figures 12-14, illustrate the change in absenteeism levels for the school semester beginning January through the end of May 2006. While designing the graphs, the schools are divided based on their location with respect to the coastline.
Figure 12: Standard deviation of weekly student absenteeism levels per school. Positive standard deviation indicates an increase in absenteeism rates compared to the average levels, while negative standard deviation indicate lower absenteeism rates.

Figure 13: Standard deviation of weekly absenteeism per school, for schools located between 1200 and 5000 m from the coastline.
5.7 Distance from bloom hot spots and school absenteeism

The assumption that high offshore accumulations of *K. brevis* biomass may have contributed to the peak in absenteeism levels is further explored. The origination of an offshore bloom could have impacted school attendance rates through either respiratory or digestive illnesses associated with brevotoxin exposure, or by encouraging families to keep their children at home due to the fear of aerosolized exposure. This would be particularly relevant for learning facilities located in close proximity to the coastline. In order to further analyze this assumption, two distinct approaches are used.

In the first approach, the time progression of *K. brevis* cell counts is plotted along with school absenteeism levels recorded within the same time period. Absenteeism levels are displayed as the weekly change in attendance rates. The result is presented in the graph displayed in Figure 15. The graph illustrates the potential of a time lag between the early
spike in cell counts and the subsequent spike in absenteeism rates. The existence of a time lag between the moment a bloom is observed offshore up to the moment when the first human health impacts are recorded has been described in the literature. Hoagland et al., (2009), using a comprehensive data set from 2001 to 2006, found that a local measure of *K. brevis* cell counts lagged by a week would explain the variation in numbers of emergency department visits. However, within the current study, the possible existence of a time lag represents a visual assumption which was not statistically demonstrated.

Figure 15: *K. brevis* cell counts over the time frame (January through June 2006) symbolized thought the blue line and change in percent student absent (orange line). Weeks are represented on the bottom axis and labeled with roman numbers. In order to facilitate the clear display of data, the first week (January 2 through January 6) for which school absenteeism is provided is labeled as 1, while the last week May 22 through May 26) is labeled as 20

The second approach examines any potential correlations between average absenteeism rates and distance from bloom hot spots. The offshore regions of *K. brevis*
hot spots are identified based on the results of the Hot Spot Analysis. The Euclidian distance from each school to the hot spot region is calculated through ArcGIS Spatial Join function. Some schools are closer to regions of intense $K. \ brevis$ activity, while other educational institutions are further away. In order to test whether or not the distance from the identified area of bloom hot spot influences school attendance rates, the GIS Spatial Statistics Ordinarily Least Square Regression function is used. The regression results will be further discussed in the Results section.

III. Coastal vulnerability

The third step is to locate highly populated areas, as well as identify areas which have a predominantly older population. This is based on the assumption that densely populated areas are more likely to have a larger number of individuals exposed to aerosolized brevotoxins during bloom periods. Additionally, it is believed that an older population is at greater risk of experiencing negative consequences associated with inhalation of brevotoxins. The recent study conducted by Hoagland et al., (2014) has shown that older individuals (ages $\geq 55$) are more susceptible to suffer from adverse health effects when exposed to brevotoxin contaminated aerosols. The research examined the health effects resulting from Florida red tides using a broad field of health data encompassing 6 counties. Their findings suggested that adverse health effects were predominantly expressed in the responses of patients ages 55 and older. This was confirmed by both the recorded number of emergency department visits, and by the information provided by inpatient hospital reports.
Lastly, throughout this study, an assessment of coastal vulnerability is done by analyzing information regarding the location of *K. brevis* hot spots along with information on the demographic characteristics of coastal regions located in close proximity to these offshore hot spot areas.

### 5.8 Developing a vulnerability index

Population data was downloaded from US Census Bureau. The Florida shapefile is divided in numerous census tracts which are characterized by their population numbers, and their age groups. Census Tracts are small, subdivisions of a county that are updated by local participants prior to each decennial census as part of the Census Bureau's Participant Statistical Areas Program (US Census Bureau, 2010). Figure 16 illustrates the frequency distribution of the census tracts and their associated population numbers. The frequency distribution reveals that the majority of population per tract is less than 2000 inhabitants per block tract.

![Frequency distribution of population numbers per census tract](image)

Figure 16: Total population numbers per tract group
Figure 17: Frequency distribution of census tracts with population ages 65 and above

Figure 17 displays the frequency distribution of the census tracts categorized by the number of individuals of ages 65 and above. As previously stated, existing studies (Hoagland et al., 2014) reveal that individuals of ages 55 and over are the ones particularly susceptible to experience adverse health effects resulted from inhalation of brevotoxin contaminated aerosols. The available data downloaded from the US Census Bureau did not have ages 55 and over as one of the age groups recorded. For this reason, population of ages 65 and over was used to identify the proportion of individuals thought to have higher vulnerability to brevotoxins. Analyzing the graph illustrated in Figure 17 shows that there are relatively few community subdivisions (tract groups) which are predominantly inhabited by an older population.

The distance between identified bloom hot spots and coastal community subdivisions is calculated thought the use of the ArcGIS Near function. The minimum, maximum, and average distances are identified. The coastal communities will be characterized by not only their respective population numbers and their age groups, but
also by their distance from *K. brevis* hot spots. Figure 18 shows a frequency distribution of census tracts according to their distance from *Karenia brevis* hot spot areas.

![Frequency distribution of census tracts and their associated distance from hot spot areas](image)

Figure 18: Frequency distribution of census tracts divided by their shortest distance to *Karenia brevis* hot spot areas

5.9 Defining vulnerability and creating a ranking system

The following rankings describe the characteristics based on which the vulnerability index was developed.

- Vulnerability 1 (considered most vulnerable): areas with population > 2000 and distance from hot spots < 1000 m and population ages 65 and over > 1000 m.
- Vulnerability 2: population > 2000 and distance from hot spots < 1000 m.
- Vulnerability 3: population > 1500 and distance from hot spots < 1000 m and population ages 65 and over > 1000.
- Vulnerability 4: population > 1500 and distance from hot spots < 1000 m.
· Vulnerability 5: population > 1000 and distance from hot spots < 1000 m and population ages 65 and over > 500.

· Vulnerability 6 (considered least vulnerable): areas with population > 500 and distance from hot spots < 1000 m.

Using this ranking system for assessing vulnerability, highly vulnerable areas were identified. The variables incorporating in the ranking system are further summarized in the Table displayed in Figure 19.

<table>
<thead>
<tr>
<th>Vulnerability Ranking</th>
<th>Population numbers</th>
<th>Distance from hot spot (m)</th>
<th>Population age (65 and up)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>&gt; 2000</td>
<td>&lt; 1000</td>
<td>&gt; 1000</td>
</tr>
<tr>
<td>2</td>
<td>&gt; 2000</td>
<td>&lt; 1000</td>
<td>-</td>
</tr>
<tr>
<td>3</td>
<td>&gt; 1500</td>
<td>&lt; 1000</td>
<td>&gt; 1000</td>
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<tr>
<td>4</td>
<td>&gt; 1500</td>
<td>&lt; 1000</td>
<td>-</td>
</tr>
<tr>
<td>5</td>
<td>&gt; 1000</td>
<td>&lt; 1000</td>
<td>&gt; 500</td>
</tr>
<tr>
<td>6</td>
<td>&gt; 500</td>
<td>&lt; 1000</td>
<td>-</td>
</tr>
</tbody>
</table>

Figure 19: Vulnerability rankings and their associated variables (population numbers, distance from hot spot areas, and population age)
Chapter 6: Results

The previous section described a new approach that could potentially be used for identifying coastal *K. brevis* hot spot regions. Throughout this study, bloom hot spots are areas of statistically significant sampling locations which are characterized by high *K. brevis* cell counts, and are also surrounded by sampling locations with a large number of toxic dinoflagellate cells. In order to have a broad overview of the geographic location of hot spot areas throughout time (2001-2013), individual yearly hot spot surfaces are aggregated using the ArcGIS Union function. The result is displayed in Figure 20. The newly created layer covers the entire time period analyzed, and is referred to as Spatial Hot Spot Extent. A closer look at Figure 20 shows that some coastal regions are often in close proximity of *K. brevis* hot spots (27°30’0” N, and extending approximately 27°0’0”N), while other coastal areas are not adjacent to offshore regions of intense bloom activity.

The map presented in Figure 21 illustrates the area of recurring *K. brevis* hot spots. This area is identified around Sarasota city. During the years 2003, 2004, 2005 and 2006, bloom hot spots were located approximately around the same geographic region, in the coastal waters surrounding Sarasota.

The information on the location of *K. brevis* hot spot areas can be applied in a number of ways and will be further discussed in the next sections. One of the applications developed throughout this study examined the potential correlation between school absenteeism and distance from *K. brevis* hot spots. Yet another use of this information will be applied in creating an assessment of coastal vulnerability.
Figure 20: Identified areas of *K. brevis* hot spots identified from 2001 to 2013 along with population numbers. Data provided by the US Census Bureau.
Figure 21: Spatial hot spot extent identified throughout the time period (2003-2006)
6.1 School absenteeism

Figure 22 illustrates potential areas of high accumulations of *K. brevis* with respect to the geographic location of educational institutions. Numerous factors can influence school absenteeism levels. A strong correlation between areas of bloom maxima and the percent of students absent (recorded in schools located close to the shoreline), is hard to identify. Regression analysis was used in the attempt to analyze whether distance from bloom hot spots explains the variation in absenteeism rates recorded. The dependent variable was the change with time in average absenteeism levels, while the independent variable was the distance from the identified area of bloom *K. brevis* hot spot.

Distance from the coastline has proved to not be significantly correlated with school absenteeism rates. However, when the distance from the area of identified *K. brevis* hot spot was computed for the schools located less the 1200 m from the coastline, the regression analysis revealed that the relationship between absenteeism levels (displayed as percent change compared to average) and distance from the closest hot spot region was statistically significant (p < 0.05). The calculated value for the multiple R-squared was 0.188, implying that approximately 18% of the observed variation in school absenteeism rates can be explained by their relative distance to the identified area of bloom maxima.
Figure 22: Average absenteeism rates reported from January through the end of May 2006, along with potential offshore harmful algal bloom hot spots. The representation of the bloom extent is masked by a defined study area.
6.2 Coastal vulnerability

Figure 23 illustrates coastal areas classified by their estimated vulnerability to suffer from the negative effects associated with brevotoxin exposure. The vulnerability is calculated based on their total population numbers per census tract, their age group, and their distance from identified hot spot areas.

It is readily observable that vulnerability is disproportionally distributed geographically. Even though distance from the identified bloom hot spot represents one of the main variables incorporated in the vulnerability assessment, a closer look at Figure 23 shows that census tracts located in close proximity to *K. brevis* hot spots do not necessarily rank high in vulnerability. This is explained by the relatively low population numbers characteristics of those areas.

Figure 23 provides an example of a method of classification which can be further applied throughout the entire west Florida coastline. This ranking system provides a basic understanding of the spatial location of highly vulnerable areas and signals regions where large numbers of susceptible individuals can suffer from brevotoxin related illnesses.
Figure 23: Coastal areas partitioned by census tract and characterized by their vulnerability index. (a rank of 1 represents high vulnerability, a rank of 6 represents relatively low vulnerability)
Chapter 7: Discussion

Multiple studies have examined the biology of *K. brevis*, its effect on the marine food web, its development in relation to potential nutrient sources, and its associated human health-related impacts. There is an increasing need to view coastal areas as complex adaptive systems (Newton et al., 2012). A holistic approach needs to be adopted when analyzing dynamic biologic systems and the complexity of their impacts. Within this contextual framework, GIS modules can be used to display and analyze dynamic ecologic, demographic, and social data. Knowledge on the spatial extent and location of bloom hot spots is essential, especially, since *K. brevis* is not randomly distributed through the waters of the West Florida Shelf. Analyzing the spatial, and temporal patterns in the distribution of the toxic dinoflagellate reveals vital knowledge of the geographic location and extent of high concentrations of algae cells. This newfound information could effectively become incorporated in resource allocation strategies and mitigation procedures. Additionally, information on the location of bloom hot spots could become incorporated in outreach and educational programs designed to inform citizens and visitors about the importance of protective measures during active red tide periods. Wearing protection masks when an individual is located in close proximity to hot spots, could minimize the adverse health effects resulted from the inhalation of aerosolized brevotoxins. The following subsections will discuss the results of the hot spot analysis, its benefits, possible uses, and potential avenues for improvement.

Unlike previous work, which identified hot spot areas as either: areas of high algal biomass (Shuhaibar and Riffat, 2008), localized zones of chlorophyll a anomalies (Barale et al., 2008), and locations where blooms most frequently occur (Liefer et al., 2009;
Wang and Wu, 2009), the novel approached designed throughout this study, identifies *K. brevis* hot spots as statistically significant clusters of high cell count values. This establishes the foundation needed to design an assessment of coastal vulnerability.

The study developed a methodology to identify areas of localized bloom maxima. Identifying regions of bloom hot spots reveals new information about the spatial-temporal trends and patterns characteristic for this almost annually occurring phenomenon. Looking at the intensity of *K. brevis* blooms, and their location with respect to highly populated coastal regions, provides valuable insight on the areas which could be more highly impacted by aerosolized exposure to brevotoxins, areas which are the most vulnerable. As highlighted in Figure 20, recurring areas of *K. brevis* hot spots repeatedly occur, centering on $27^\circ 30' 0''$N, and extending approximately $27^\circ 0' 0''$N. There are a number of factors contributing to this spatial distribution, however they are not fully addressed throughout this study. Among these variables, the movement of ocean currents and their interaction with other physical parameters such as nutrients plays a significant role. Future research should be dedicated in analyzing the physical and biological parameters characteristic of hot spot areas.

**7.1 Assessing the accuracy of the hot spot identification methodology**

As previously mentioned, current interpolation methods (both IDW, as well as kriging) suffer from limitations. These limitations are primarily due to the lack of measurements, or as a result of potentially misreported information. Due to the weight that interpolation gives to each input point, an interpolated surface can be influenced by a singular recording of high *K. brevis* cell counts. This in turn may highlight an area as
having higher cell count values, even though it has a single data point (outlier) which recorded extremely high values. Therefore, the resulting surface may lack accuracy.

As seen in the map presented in Figure 24, bloom surface areas represented in orange are assumed to have high densities of toxic dinoflagellates. However, when overlaying the bloom surface with the point layer created by the GIS Hot Spot Analysis function, some discrepancies become apparent. It becomes obvious that not all bloom surfaces recognized as having high \textit{K. brevis} biomass are located in the same area in which the sampling locations are identified as hot spots. This is due to the fact that interpolation uses all available values and may be influenced by erroneous measurements. Therefore, interpolating only the sampling locations that have an associated 99% confidence level of being bloom hot spots (the red sampling locations), provides a more accurate representation of the spatial extent of the patches of high concentrations of toxic dinoflagellates.

The GIS Hot Spot Analysis function examines the values of a sampling location by also evaluating its value in the context of its neighboring values. This approach can easily identify outlier values, and can facilitate a better understanding of the spatial characteristics of this complex and dynamic biological phenomenon. Subsequently, if a sampling point has high \textit{K. brevis} cell counts and is surrounded by other points which also have high counts, then it is identified as a hot spot. If the point is surrounded by significantly lower values recorded in its neighboring points, then it is classified as Not Statistically Significant. Through this approach, data outliers do not influence the result of the analysis. Ensuring better accuracy, interpolation is used for the sampling locations previously identified as hot spots, not on all the existing sampling locations.
Figure 24: Bloom surface created through the interpolation of all sampling locations monitored during the June – December 2006. Sampling locations classified by their probability of being either clusters of high or low *Karenia brevis* cells
7.2 School absenteeism and bloom hot spots

The marked increase in above average absenteeism levels for all schools recorded during week 36 and 38, and illustrated throughout the graphs presented in Figures 12, 13, and 14, suggests that there was some external factor influencing this change. Week 36 corresponds to the time period starting April 10 through April 14. Week 38 corresponds to the period starting April 20 through April 24. Consequently, other variables could potentially explain these peaks in above average absenteeism rates. Week 36 is the period prior to the Easter Holliday (April 16) in 2006. This may be the reason for the higher absenteeism recorded for all schools. The increase in week 42 may simply be a result of higher absenteeism rates due to the end of the school year. The spike in absenteeism levels registered in week 38 could be caused by the existence of an epidemic. However, according to the Center of Disease control, influenza flu season for the 2006-2007 period was between October 1 2006 and May 19 2007 (MMWR, 2007). This period does not coincide with the spring weeks with overall higher absenteeism rates.

7.3 Minimizing health care costs

The Florida Department of Health has added NSP to the list of reportable diseases. However, irritation as a result of aerosolized brevotoxin exposure is not reported (Kirkpatrick et al., 2004). As previously mentioned in the literature review, heath effects associated with red tides often are unreported or misdiagnosed, making it difficult to fully assess the burden that K. brevis blooms place on health care providers, and the various dimensions of resulting human health impacts. One of the deliverable products of this analysis is the spatial identification of hot spot areas, as well as an
assessments of coastal vulnerability to aerosolized brevotoxins. This information could be employed by Florida Department of Health in monitoring cases of respiratory syndromes reported in areas identified as highly vulnerable. Furthermore, based on the results of the coastal vulnerability assessment, during active red tide periods, supplementary equipment and medical personnel can be assigned to the medical facilities which are expected to experience the highest numbers of patients.

7.4 Limitations of study

The availability of easily accessible data represents one of the main limitations of the research. Small-scale current direction and velocity data were not available. Other physical oceanographic parameters which may have influenced bloom formation and migration (the location of eddies, wind currents, and thermal boundaries within the water column) have not been included. If ocean current data would have been incorporated in the hot spot identification, it may have helped better explain the patterns displayed by the areas of high *K. brevis* concentration.

With respect to the *K. brevis* cell count data, even though there is a large number of measurements which incorporate cell counts, location and depth of measurement, this data was not sampled consistently within specific time intervals and at selected and arbitrary locations. There are no existing stationary monitoring stations through which water quality parameters, along with *K. brevis* cell counts could be recorded on a daily basis. The information on *K. brevis* cell counts was the compilation of data as a result of opportunistic sampling at various locations on the West Florida Shelf.
In the case of the social data incorporated in the analysis, the dataset for school absenteeism was available for only two years, and provided information for only 46 educational facilities. This limitation could have restricted the results of the analysis. If a more comprehensive record of school absenteeism levels, over a larger number of facilities would have been available, then this would have significantly improved the accuracy of the study.

Furthermore, a variety of factors not monitored could have also significantly influenced absenteeism levels. As previously mentioned, certain school have on average higher absenteeism levels compared to others. This difference may be determined by an array of socio-economic considerations. Variables such as the neighborhood in which the school is located, varying income levels, and even the perceived quality of the educational facility, may all act as elements moderating student absenteeism rates. Factors that have a stochastic nature were not accounted for in the analysis. In addition to this, the possible existence of a time lag between biological processes and subsequent impacts may derail the accurate interpretation of available data and could potentially influence the results of the analysis.

7.5 Future recommendations

The accuracy of the hot spot identification methodology can be tested by analyzing if the spatial distribution of high chlorophyll concentrations corresponds with the areas recognized as bloom hot spots. Incorporating satellite chlorophyll data recorded for the defined bloom periods could significantly improve the accuracy of identifying the regions of high bloom concentration.
The study analyzed existing *K. brevis* data spanning from 2001 to 2013. If this time frame would be extended to include a larger number of years, then possible patterns in the geographic location of hot spot areas could become apparent. Moreover, analyzing a larger time period could add certainty to the statement that specific coastal areas are consistently in close proximity to hot spot regions, while others are located further away. Since brevotoxins released by the lysed *K. brevis* cells become aerosolized through air-sea interaction processes and are concentrated in the surf zone, inhabitants of areas further away from intense bloom activity are thought to be less susceptible to suffer from exposure to significant concentrations of aerosolized brevotoxins. This represents key knowledge in the process of assessing coastal vulnerability. Subsequently, by identifying bloom hot spots over a large time frame, it can be observed that vulnerability to aerosolized toxins is not evenly distributed along the west Florida coastline.

Potential avenues for future research could analyze a possible link between income levels and school absenteeism rates in Sarasota County. A visualization of the geographic location with respect to estimated income levels suggests that schools that have overall higher absenteeism rates are located in areas that have lower income levels. Figure 25 displays the location of the schools in various regions characterized by average income. Figure 26 takes a step further illustrating the average absenteeism for 2006 along with the median household income characteristic of the area in which the schools are located. Income levels may be an explanatory parameter used to explain the variation in absenteeism rates.
Figure 25: School locations and median income per household. Income data provided by ESRI
Figure 26: Median household income and average percentage of school absenteeism recorded for the period January through May 2006 symbolized through color coded graduated symbols.
Chapter 8: Conclusion

The identification of offshore regions often characterized by high accumulations of toxic dinoflagellates represents a step further in the process of understanding the characteristics and impacts of *K. brevis* blooms. The inherent dynamic nature of biologic systems requires a multidimensional approach which is based on the understanding of multiple layers of information. The work presented throughout this study sets the groundwork for using ArcGIS as a valuable tool to incorporate and analyze complex physical, biological and social data. The ArcGIS Spatial Analyst modules can be used to explain and understand the spatial and temporal variable processes occurring in the natural world, and their associated range of impacts on human society. In addition to this, GIS Spatial Statistics can be used to understand the spatial relationships found in the data. While trying to understand the multifaceted consequence of red tide events on coastal communities, it is essential to adopt a holistic view and analyze *K. brevis* blooms not only spatially, but temporally as well. Through this respect, a bloom is not only characterized by its geographical extent, but also by its cumulated intensity as illustrated by the bloom maxima identified as a hot spot regions, as well as by its potential annual reoccurrence.

Knowledge on the incidence of seasonal recurring hot spot areas, and their location with respect to the shoreline, provides valuable insight about regions which are most likely to experience high levels of aerosolized brevotoxins. Consequently, the inhabitants of these regions are more prone to experience the adverse impacts associated with the inhalation of the toxins. Therefore, recognizing possible recurring areas of bloom hot spots represents vital information which can be used in a number of ways.
First, mitigation actions and preparedness strategies can be directed towards areas most vulnerable to suffer from a high incidence of health related cases resulting from *K. brevis* coastal blooms. Second, harmful bloom monitoring efforts could be focused towards areas of recognized bloom hot spots. Third, education and outreach measures can be concentrated particularly within communities that are thought to have a higher chance of suffering from red tide impacts. Lastly, it is widely recognized that there is no single “one method fits all” approach used for managing of natural resources, and adopted in coping with complex coastal issues. Therefore, it is essential to look at vulnerability through a spatial context. Not all coastal regions will suffer from the same impacts when an offshore *K. brevis* bloom develops. The functions provided by GIS allow for an accurate identification of areas at a greater risk of brevotoxin exposure compared to others.

If a one size fits all management approach would be adopted, then all beaches along the west Florida coast would be closed due to the fear of adverse health effects resulting from the inhalation of contaminated aerosols. However, this measure would entail significant economic losses for all the business located along the beachfront area. Even areas located far from bloom maxima would be wrongfully perceived as being extremely vulnerable. However, this may not be the case. Recent technological advances, allow researchers not only to attempt to predict the formation of a bloom, but also analyze and identify the recurring trends and patterns characteristic of coastal blooms. This newfound information helps classify coastal areas based on their vulnerability, and facilitate the design of area-specific policies, precautionary procedures and mitigation strategies.
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## Appendix A: Table 1

<table>
<thead>
<tr>
<th>Source</th>
<th>Species</th>
<th>Location</th>
<th>Methodology</th>
<th>Scale</th>
</tr>
</thead>
<tbody>
<tr>
<td>Shuhaibar and Riffat</td>
<td>Dinoflagellates</td>
<td>Kuwait</td>
<td>GIS Interpolation; Map Algebra</td>
<td>Local (10 km)</td>
</tr>
<tr>
<td>(2008)</td>
<td></td>
<td></td>
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</tr>
<tr>
<td>Anderson et al. (2011)</td>
<td><em>Pseudo-nitzschia</em></td>
<td>Central California</td>
<td>Remote Sensing (MODIS-Aqua)</td>
<td>Regional [100 km]</td>
</tr>
<tr>
<td>Wu et al. (2013)</td>
<td>Harmful algal blooms (HAB) events (more than one species)</td>
<td>Bohai Sea (China)</td>
<td>Kernel Desity Estimation; Nearest Neighbour Analysis</td>
<td>Local</td>
</tr>
<tr>
<td>Wang and Wu (2009)</td>
<td>HAB (8 species of toxin-producing algae) and shellfish toxins data</td>
<td>East China Sea</td>
<td>Kernel Desity Estimation; Nearest Neighbour Analysis</td>
<td>Mesoscale (&gt;100 km)</td>
</tr>
<tr>
<td>Das et al. (2010)</td>
<td>Harmful algal blooms (HAB) events (more than one species)</td>
<td>Monterey Bay (California)</td>
<td>Remote Sensing (MODIS)</td>
<td>Local</td>
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<td>Frolov et al. (2013)</td>
<td>Chl-a fluorescence used as a proxy for HAB</td>
<td>US West Coast</td>
<td>Remote Sensing (MODIS) Autocorrelation</td>
<td>Mesoscale</td>
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<tr>
<td>Lewitus and Holland</td>
<td><em>Kryptoperidinium sp.</em>, <em>Pfiesteria piscicida</em>, <em>P. shumwayae</em>, <em>Cryptoperidinopsis sp.</em></td>
<td>South Carolina</td>
<td>Regional HAB Monitoring System</td>
<td>Regional</td>
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<tr>
<td>Steidinger and Haddad</td>
<td><em>Pyrocystis brevis</em>, <em>Pyrodinium bahamense</em></td>
<td>Florida</td>
<td>Hydrographic studies and thermal imagery, remotely sensed data through the coastal zone Color Scanner (CZCS)</td>
<td>Local</td>
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<td>(1981)</td>
<td></td>
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<td>Tester and Steidinger</td>
<td><em>Gymnodinium breve</em></td>
<td>Florida and North Carolina</td>
<td>A thorough description of bloom initiation, transport and dissipation</td>
<td>Mesoscale</td>
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<td>(1997)</td>
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Appendix B: Time series graphs of *K. brevis* counts (2001-2013)
Figure 27: Interpolated surface using K. brevis data from August 2001-to April 2002 overlayed with the results of the Hot Spot Analysis (Getis-Ord Gi*)
Figure 28: Identified areas of hot spots according to the newly designed methodology. The bloom period analyzed extended from August 2001 until April 2002.
Figure 29: January through November 2003 *k*. brevis bloom surface, hot spot locations and coastal population numbers
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Figure 32: Identified hot spot region characteristic of the bloom period spanning from January through March 2004
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Figure 34: Identified *K. brevis* hot spot region for the 2005 bloom period
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Figure 40 January – April 2013 bloom surface, sampling locations characterized as hot spots and coastal population density
Figure 41: Identified area of bloom maxima in 2013