Chapter 17

Living with Harmful Algal Blooms in a Changing World: Strategies for Modeling and Mitigating Their Effects in Coastal Marine Ecosystems

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ABSTRACT

Harmful algal blooms (HABs) are extreme biological events with the potential for extensive negative impacts to fisheries, coastal ecosystems, public health, and coastal economies. In this chapter, we link issues concerning the key drivers of HABs with the various approaches for minimizing their negative impacts, emphasizing the use of numerical modeling techniques to bridge the gap between observations and predictive understanding. We review (1) recent studies on the environmental pressures that promote HABs; (2) prominent strategies for preventing or controlling blooms; (3) modeling methods, specifically addressing harmful algal species dynamics, and their use as a predictive tool to facilitate mitigation; and then (4) highlight several coastal regions where the mitigation of HABs is generally approached from a regional Earth system and observation framework. Lastly, we summarize future directions for "living with" HABs in an era of limited financial resources for ocean observing.

17.1 INTRODUCTION

Decades of research on harmful algal blooms (HABs) in the world's coastal, estuarine, and freshwater environments have revealed immense complexity in

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the conditions that promote bloom development and the diversity of HAB species. Just as the physical features of the coastal zone cannot be represented by a single model across spatial and temporal scales, the biological variability within aquatic ecosystems requires a regional perspective, one that considers indigenous communities (from plankton to humans), habitat connectivity, and the influence of large-scale drivers of change (Cloern et al., 2010). Although levels of devastation experienced by coastal communities during HAB events might not approximate those of many natural disasters, the economic losses are often of great importance to local seafood industries (Imai et al., 2006; Jin et al., 2008; Dyson and Huppert, 2010) as are the risks to public health (Van Dolah et al., 2001). Ecosystem functioning and wildlife populations are also often negatively impacted by HABs, with legacy effects that compound over time (Sekula-Wood et al., 2009, 2011; Paerl et al., 2011; Montie et al., 2012). Understanding the ecological role of harmful algae and their seeming rise to prominence in phytoplankton communities requires that the role of natural variability be teased apart from human disturbance (Hallegraeff, 1993, 2010; Figure 17.1). The field of HAB science has made significant advances in this area, and this ecological knowledge is now informing methods for mitigating the harmful effects of HABs on natural resources and human populations, and in some instances, pushing forward technological advancements with broad application (Anderson et al., 2012b).

A major struggle in the study and management of HABs has been the sheer breadth of species, life histories, ecosystems, and impacts involved. The phytoplankton that are categorized as potentially harmful do not belong to a single, evolutionarily distinct group. Rather, they span the majority of algal taxonomic clades, including eukaryotic protists (armored and unarmored dinoflagellates, raphidophytes and diatoms, euglenophytes, cryptophytes, haptophytes, and chlorophytes) and microbial prokaryotes (the ubiquitous, sometimes nitrogen-fixing cyanobacteria that occur in both marine and freshwater systems). Interestingly, dinoflagellates account for the majority (75 percent) of HAB species (Smayda, 1997). The list of potential impacts from HABs include (1) the production of dangerous phycotoxins that enter food webs, the atmosphere (if aerosolized), fisheries, and the potential contamination of water supplies from freshwater reservoirs or desalination plants; (2) the depletion of dissolved oxygen and/or the smothering of benthic biota as algal biomass decays; and (3) physical damage to fish gill tissue. HABs fall under the umbrella term Ecosystem Disruptive Algal Blooms (EDABs; Sunda and Shertzer, 2012; Sunda et al., 2006), and all HABs or EDABs may impact local ecosystems and economies (e.g., fisheries, tourism, recreation). These impacts include noxious or nuisance blooms such as "brown tides" of pelagophytes *Aureoccocus anophagefferens* and *Aureoumbra lagunensis* (Gobler and Sunda, 2012) or the surfactant-producing *Akashiwo sanguinea* (Jessup et al., 2009). Given this diversity, no single set of conditions or approach to mitigation will apply to all harmful algae, nor is the often-used

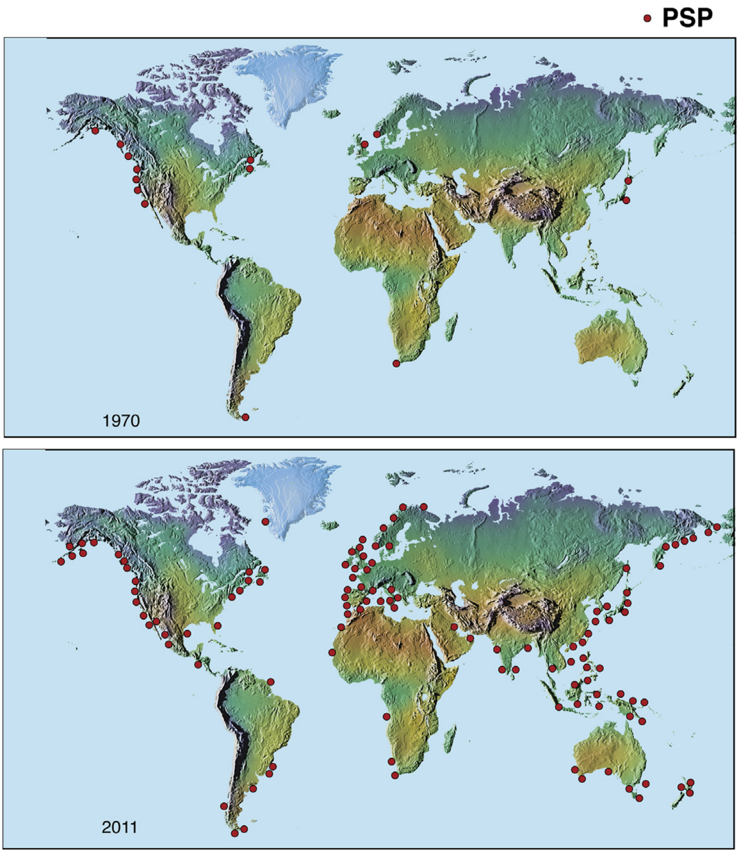

FIGURE 17.1 The expansion of global cases of Paralytic shellfish poisoning (PSP) from 1972 to 2011. PSP is associated with the marine dinoflagellates *Alexandrium* and *Pyrodinium,* several species of which produce saxitoxin, a dangerous neurotoxin that makes its way into the food web and can be lethal. *Map used with permission from the National Office for Harmful Algal Blooms at Woods Hole Oceanographic Institution.*

term “red tide” appropriate for phenomena with a broad range of pigment and spectral qualities generally undetectable to the human eye (Dierssen et al., 2006).

The suite of epidemiological syndromes associated with phycotoxin exposure is itself impressive (see Table 17.1 for symptoms and acronyms); more details on the symptoms associated with these syndromes and the geographic locations where illnesses have been reported can be found in reviews of phycotoxin poisonings (Fleming et al., 2002; Backer et al., 2005; Backer and Moore, 2012). New toxins and syndromes are continually discovered, such as the ecosystem-disruptive yessotoxin (De Wit et al., 2014) produced by the dinoflagellates *Gonyaulax spinifera* (Rhodes et al., 2006), *Protoceratium reticulatum* (Paz et al., 2004; Alvarez et al., 2011), and *Lingulodinium polyedrum* (Howard et al., 2008, Figure 17.2), a bioluminescent

TABLE 17.1 **Human Syndromes Caused by Ingestion or Exposure to Marine HAB Toxins**

Syndrome	Toxin(s)	Causative Organism	Symptoms
CFP	Ciguatoxins	*Gambierdiscus* spp.[b]	Nausea, vomiting, diarrhea, numbness of the mouth and extremities, rash, and reversal of temperature sensation. Neurological symptoms may persist for several months.
PSP	Saxitoxin and its derivatives	*Alexandrium* spp. *Pyrodinium* spp. *Gymnodinium* spp.	Numbness and tingling of the lips, mouth, face, and neck; nausea; and vomiting. Severe cases result in paralysis of the muscles of the chest and abdomen possibly leading to death.
ASP	Domoic Acid	*Pseudo-nitzschia* spp. *Nitzschia navis-varingica*	Nausea, vomiting, diarrhea, headache, dizziness, confusion, disorientation, short-term memory deficits, and motor weakness. Severe cases result in seizures, cardiac arrhythmia, respiratory distress, coma, and possibly death.
AZP	Azaspiracid and its derivatives	*Azadinium* spp.[a]	Nausea vomiting, severe diarrhea, and abdominal cramps
NSP	Brevetoxin	*Karenia* spp.	Nausea, temperature sensation reversals, muscle weakness, and vertigo
DSP	Okadaic acid and its derivatives	*Dinophysis* spp. *Prorocentrum* spp.	Nausea vomiting, severe diarrhea, and abdominal cramps

DSP[e]	Yessotoxin	*Gonyaulax spinifera* *Protoceratium reticulatum* *Lingulodinium polyedrum*	Nausea, vomiting, abdominal cramps, reduced appetite, cardiotoxic effects, respiratory distress
DSP[e]	Cooliatoxin[c]	*Coolia* spp.[b]	Nausea, vomiting, abdominal cramps, reduced appetite, cardiotoxic effects, respiratory distress
Palytoxicosis	Palytoxin and its derivatives[d,f]	*Ostreopsis* spp.[b]	Nausea; vomiting; diarrhea; abdominal cramps; lethargy; tingling of the lips, mouth, face, and neck; lowered heart rate; skeletal muscle breakdown; muscle spasms and pain; lack of sensation; respiratory distress
Lyngbyatoxicosis	Lyngbyatoxin-A and its derivatives	*Lyngbya majuscula*[d,g]	Weakness, headache, lightheadedness, salivation, gastrointestinal inflammation, potent tumor promoter

Note that aside from the diatom *Pseudo-nitzschia* and the cyanobacteria *Lyngbya majuscula* (now *Moorea* spp.), the causative organisms are all dinoflagellates. Freshwater groups such as the hepatotoxin-producing *Microcystis* spp. are not included here. ASP, amnesic shellfish poisoning; AZP, azaspiracid shellfish poisoning; CFP, ciguatera fish poisoning; DSP, Diarrhetic shellfish poisoning; DA, Domoic acid.

[a] *Azaspiracid was first thought to be associated with* Protoperidinium *(Yasumoto 2001; James et al. 2003) but was later shown to be produced by* Azadinium *spp. (Tillmann et al., 2009).*

[b] *Benthic epiphytes.*

[c] *A monosulfated analog of yessotoxin (Rhodes et al., 2000); complete structure uncharacterized (Van Dolah et al., 2013).*

[d] *Produces aerosolized toxins with known health consequences (Osborne et al., 2001; Ciminiello et al., 2010).*

[e] *Yessotoxins and cooliatoxins are grouped with DSP syndrome (Draisci et al., 2000) but may be more like PSP since yessotoxin exposure does not lead to diarrhea (Paz et al., 2008).*

[f] *One of the most toxic natural substances known.*

[g] *Lyngbya majuscula newly classified as* Moorea producens *(Engene et al., 2012).*

Adapted from Table 17.2 in Marques et al. (2010).

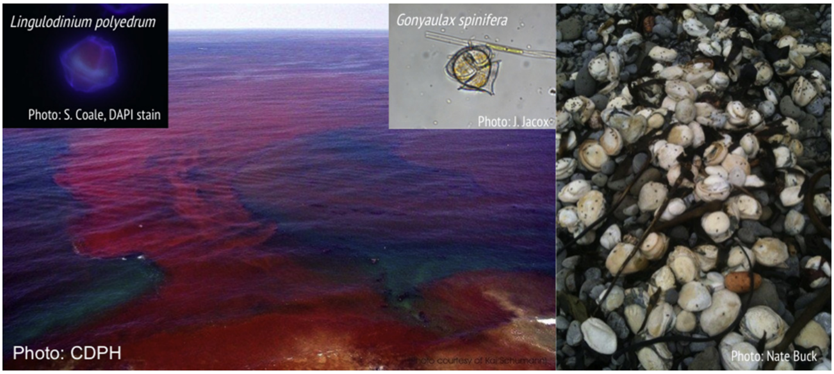

FIGURE 17.2 Sonoma County, California. In 2011, a mass mortality of red abalone, urchins, sea stars, chitons, and crabs (right) was the largest invertebrate die-off recorded for the region (De Wit et al., 2013). Yessotoxin was implicated as the causative agent (De Wit et al., 2014) and is produced by a number of common "red tide" dinoflagellates (inset) in coastal California (left). Red tide photo taken by Kai Schumann.

dinoflagellate common to the US West Coast. Widespread bird mortality caused by blooms of the dinoflagellate *A. sanguinea* is a new threat along the US West Coast (Jessup et al., 2009; Berdalet et al., 2013). Azaspiracid shellfish poisoning, caused by the dinoflagellate *Azadinium,* is another burgeoning disease with a possible worldwide distribution (Salas et al., 2011) after first being noticed in Northern European coastal communities (Krock et al., 2009) and now recently detected in Puget Sound, WA, USA (Trainer et al., 2013). Palytoxicosis is an emerging issue in the Mediterranean where palytoxin, the most toxic marine compound known, has caused extensive seafood poisoning after bioaccumulating in commonly consumed crustaceans and fish that have grazed upon the benthic dinoflagellate *Ostreopsis* (Amzil et al., 2012).

Discussion of HABs in the literature has traditionally focused on the disruptive or even "catastrophic" nature of "red tides" as toxic and/or high-biomass blooms (Margalef, 1978). However, the caveat is often made that such blooms are not new, unnatural phenomena (Cullen, 2008; Hallegraeff, 2010), and they have long been part of a region's local ecology, primary productivity, and important biogeochemical cycling. That said, there is increasing recognition that the effects of HABs on public health, marine and freshwater ecosystems, economies (Hoagland and Scatasta, 2006), and human social structures (Hatch et al., 2013) are worsening (Heisler et al., 2008; Anderson, 2009; Hallegraeff, 2010; Anderson et al., 2012b, Figure 17.1) and require new solutions from collaboration among scientists, the private sector, and governing bodies (Green et al., 2009). The potential causes for this trend have been thoroughly vetted elsewhere (e.g., Hallegraeff, 1993, 2010; Glibert et al., 2006; Anderson et al., 2002, 2008; Heisler et al., 2008; Paerl et al., 2011). Eutrophication, climate change, ballast water dispersal, and improved monitoring are the most cited factors for the increased frequency of reported blooms.

At the interface between HABs and human communities is the socioeconomic outfall around which the majority of impacts are contextualized. The interaction between HABs and humans involves both positive and negative feedbacks to the blooms themselves and to the ability of society to mitigate adverse effects (Figure 17.3). Hoagland (2014) carefully illustrates this process for toxic blooms of *Karenia brevis* on Florida's Gulf coast and describes how "legacies" of indigenous and modern human behavior and the complex history of mitigation strategies inform past and future "policy responses" to HAB events. Ultimately, how these policies are implemented will depend on the cost-effectiveness of mitigation strategies that range from the reduction of exposure risk and illness to fisheries regulation (Heil and Steidinger, 2009; Heil, 2009; Hoagland, 2014). Significant overlap occurs with oil spill response strategies (Liu et al., 2011) that integrate local community impacts with particle tracking models, remote detection techniques, wildlife biology, and regional management mandates. Bringing these socioeconomic, governmental, and traditional science realms together is a challenging but crucial goal for next-generation coastal marine hazard mitigation.

In this chapter, we link issues concerning the key drivers of HABs with the various approaches for minimizing their negative impacts, emphasizing the use of numerical modeling techniques to bridge the gap between observations and predictive understanding. First, we review recent studies on the environmental pressures that promote HABs (Section 17.2); prominent strategies for preventing or controlling blooms (Section 17.3); and modeling methods, specifically addressing harmful algal species dynamics, and their use as a

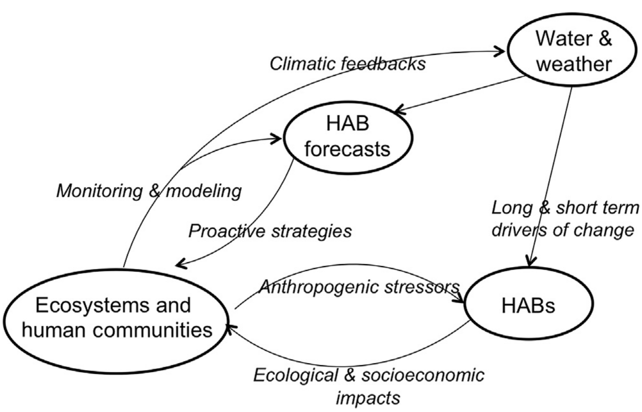

FIGURE 17.3 Schematic diagram illustrating the dynamic links that couple nature (e.g., water and weather conditions), HABs, and human communities. *Modified from Hoagland (2014).*

predictive tool to facilitate mitigation (Section 17.4). Next, several coastal regions are highlighted where the mitigation of HABs is generally approached from a regional Earth system and observation framework (Section 17.5). Such a framework ideally merges traditional monitoring methods, networked arrays, satellite observations, autonomous platforms, predictive models, and local to regional governance to mitigate impacts on human populations and ecosystems (Figure 17.3). In some instances, this approach may necessitate adaptive management for optimal resource use (Section 17.5.4). Lastly, we summarize future directions for "living with" HABs in an era of limited financial resources for ocean observing (Section 17.6).

17.2 ENVIRONMENTAL FORCING OF HABs

Research on the ecological processes that cause HABs and identification of the factors responsible for their worldwide increase has led to the development of predictive tools and mitigation strategies (GEOHAB, 2003, 2006). Highlights from recent studies are summarized in the following subsections to introduce the state of the science rather than duplicate the many exhaustive reviews (e.g., Heisler et al., 2008; Hallegraeff, 2010; Anderson et al., 2012b).

17.2.1 Eutrophication

The ecosystem response to eutrophication (i.e., biomass increases as a result of nutrient overenrichment) in coastal waters is complex and depends on the concentrations of macro- and micronutrients, the chemical form of those nutrients (organic vs inorganic), and the ratio of nutrient supply (Anderson et al., 2002, 2008; Heisler et al., 2008; Glibert and Burkholder, 2011; Kudela et al., 2010). These can all select for phytoplankton functional type (dinoflagellate, diatom, flagellate, cyanobacteria) as well as promote toxicity in toxigenic HAB species (Howard et al., 2007; Cochlan et al., 2008; Kudela et al., 2008). One compelling line of evidence from eutrophication studies is that land-based runoff and associated alteration of nutrient ratio supply (particularly Si:P and Si:N) away from the mean Redfield ratios selects for flagellates relative to diatoms (Smayda, 1997). This resource-mediated community composition shift is well-documented (reviewed in Anderson et al., 2002; Glibert and Burkholder, 2006) and now buttressed by increasing recognition that organic nutrients and reduced forms of nitrogen such as urea can modulate phytoplankton growth and toxicity (reviewed in Glibert et al., 2006; Kudela et al., 2010). This is important when we consider that industrial nitrogenous fertilizers are now predominantly composed of urea over nitrate (Glibert and Burkholder, 2006; Glibert et al., 2006). The role of groundwater in driving and regulating bloom development is also an important but understudied theme (Paerl, 1997). For example, Liefer et al. (2009, 2013) showed that dense blooms of toxigenic *Pseudo-nitzschia* species in the Northern Gulf of Mexico cluster near rivers known to transport high volumes of nitrate-rich discharge.

Davidson et al. (2012) challenged the rationale of some of the most canonical studies (e.g., "red tides" in Hong Kong; Hodgkiss and Ho, 1997) that link the process of nutrient enrichment with the effect of eutrophication and increasing HABs (Smayda, 2008). Although somewhat selective in its critique, the review provides a useful summary of the theoretical controls on nutrient uptake kinetics. It also reminds us of the caveats in applying nutrient limitation models to field scenarios where the role of organic nutrients (Howard et al., 2007), cell quotas/thresholds (Flynn, 2010), mixotrophy (Stoecker, 1998; Mitra and Flynn, 2010), "luxury" consumption of nutrients (Roelke et al., 1999), and interspecific competition for limiting resources are still poorly understood. Indeed, the interplay between cellular nutrient stoichiometry, exogenous nutrient pulses, and toxin production is nicely illustrated for *Alexandrium tamarense,* a paralytic shellfish poisoning (PSP)-causing organism that may have a high capacity for luxury phosphorous storage, thereby altering its response to ambient N:P ratios depending on its prior nutrient history (Van de Waal et al., 2013).

Despite this physiological complexity, nutrient loading from terrestrial environments into coastal and freshwater systems that are experiencing severe N and/or P limitation often appears directly related to the development of algal blooms (e.g., Glibert et al., 2001; Beman et al., 2005; Glibert, 2006; Paerl et al., 2011). The extent to which these blooms manifest as dense accumulations of biomass or as sources of harmful toxins depends on ecosystem responses and interactions. For instance, algal proliferation is heavily regulated by grazing pressure from zooplankton, with trophic cascades representing an often understudied component of bloom development and persistence (e.g., Gobler et al., 2002; Turner and Graneli, 2006; Smayda, 2008) relative to bottom-up effects or the pervasive influence of physical processes (Franks, 1992; Donaghay and Osborn, 1997; Ryan et al., 2008; Stumpf et al., 2008; Pitcher et al., 2010). Eutrophication may exert an indirect effect on zooplankton grazing efficiency such that at higher nutrient levels, grazing control of phytoplankton becomes saturated (Kemp et al., 2001). Mitra and Flynn (2006) further demonstrate that high nutrient conditions not only promote HAB species but also suppress grazing by enhancing the production of toxin grazing deterrents, a positive feedback that intensifies negative impacts of HABs (Sunda et al., 2006). Although we should be cautious about implicating the increase in HAB events specifically to eutrophication or to changes in nutrient ratios and specific nutrient compounds, it is clear that nutrient availability strongly modulates many aspects of HAB ecology. Ultimately, investigators will need to integrate nutrient dynamics at the land—sea interface, coastal and estuarine physics, and food web interactions to successfully model, predict, and forecast coastal HABs in a changing climate (Glibert et al., 2010).

17.2.2 Climate Change

The recently released Fifth Assessment Report by the Intergovernmental Panel on Climate Change (IPCC) verifies the role the ocean has played as a major heat sink, absorbing 90 percent of Earth's net energy increase over the past 40 years with an almost 4 °C increase in the upper 75 m of the water column (IPCC, 2013). Although internal variability remains a dominant governing force of regional climates, warming of the top 100 m of the ocean by as much as 2 °C is expected by the end of the twenty-first century (Stocker et al., 2013). Moore et al. (2008), Hallegraeff (2010), and Anderson et al. (2012b) examine the observed and expected consequences of warming sea surface temperatures, climate trends, and large-scale variability on phytoplankton. These consequences range from changing phenologies, "match—mismatch" in marine food webs, proliferation of HAB species into newly primed environments, potential adaptation to rapid adjustments in physicochemical conditions, and surprising range expansions. For the latter, debate still exists about whether observed expansions are driven by climate-mediated ocean circulation patterns or ship ballast water dispersal (Hallegraeff, 1993, 2010; Smayda, 2007). Warmer temperatures are projected to broaden the seasonal period over which phytoplankton can grow, i.e., phenology, thereby enhancing the risk of negative impacts and exposure to dangerous toxins (Moore et al., 2008, Figure 17.4). Natural decadal cycles of variability such as the El Niño Southern Oscillation (ENSO), North Atlantic Oscillation, Pacific Decadal Oscillation, North Pacific Gyre Oscillation, and the Madden—Julian Oscillation are also known regulators of phytoplankton primary production through their modulation of atmospheric patterns, water column mixing, stratification, circulation, and surface

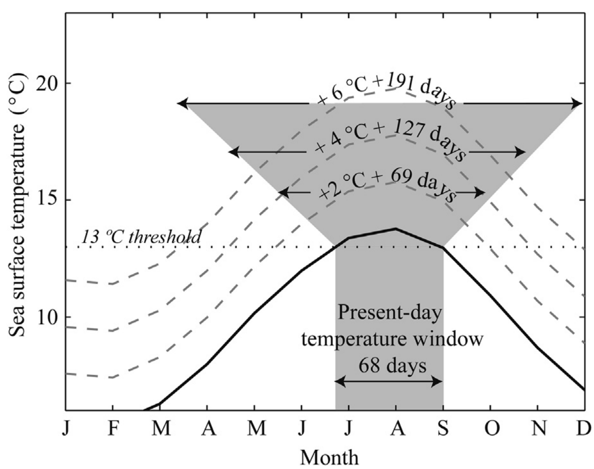

FIGURE 17.4 Puget Sound, Washington. The annual temperature window for accelerated growth of *Alexandrium catenella* for the present-day and in response to a 2, 4, and 6 °C increase in sea surface temperature. *Modified from Moore et al. (2008).*

nutrient delivery (Barton et al., 2003; Waliser et al., 2005; Di Lorenzo et al., 2008; Moore et al., 2008; Cloern et al., 2010). In the absence of long-term data, however, decadal and subdecadal oscillations in phytoplankton abundance and species composition (Jester et al., 2009) can camouflage secular trends.

17.2.3 Ocean Acidification

Anthropogenic CO_2 inputs to the atmosphere are overwhelming the buffering capacity of the ocean's carbonate system, leading to a corrosive environment for calcified organisms (e.g., Fabry et al., 2008; Feely et al., 2008). More counterintuitive is the effect that this change in aquatic pCO_2 will have on noncalcareous phytoplankton. Laboratory experiments demonstrate an increase in toxicity by the domoic acid (DA)-producing diatoms *Pseudo-nitzschia multiseries* and *Pseudo-nitzschia fraudulenta* and the saxitoxin-producing *Alexandrium catenella* after simulating projected pCO_2 levels in semicontinuous cultures (Sun et al., 2011; Tatters et al., 2012, 2013). This is caused by currently unexplained mechanisms tied to growth and toxin production. The effect will need to be verified and extended to other toxigenic HAB organisms, given the potentially complex, multifactorial response expected for natural ecosystems. As ocean acidification alters the saturation states of CO_2, HCO_3^-, and CO_3^{2-}, it will also interact with variability in temperature, salinity, and nutrient fields, leading to difficult-to-predict consequences for the phytoplankton (Moore et al., 2008), not to mention possible biophysical feedbacks that could amplify greenhouse gas emissions (Woods and Barkmann, 1993; Paerl et al., 2011). Cyanobacterial HABs that span a range of environments are expected to respond favorably to rising global temperatures, preferentially growing in warmer waters and outcompeting other phytoplankton for carbon because of their enhanced ability to acquire aqueous CO_2 over the more energetically expensive HCO_3^- and CO_3^{2-} (Paerl et al., 2011). While we are reminded that natural variations experienced by many coastal environments already expose phytoplankton to pH and pCO_2 concentrations well beyond long-term projections for the open ocean (Talmage and Gobler, 2009), pH levels in the Arctic, Southern Ocean, and coastal California are now on the verge of exceeding their "preindustrial variability envelopes" (Hauri et al., 2013). The synergistic effects of ocean acidification and eutrophication (Cai et al., 2011) on HABs (Figure 17.5) are severely stressing nearshore fin- and shell fisheries (Waldbusser et al., 2011).

17.3 BLOOM CONTROL AND PREVENTION

The desire to protect valuable fisheries and natural resources has motivated extensive research on methods for directly modifying blooms. Kim (2006) classifies these mitigation strategies for HABs into two categories,

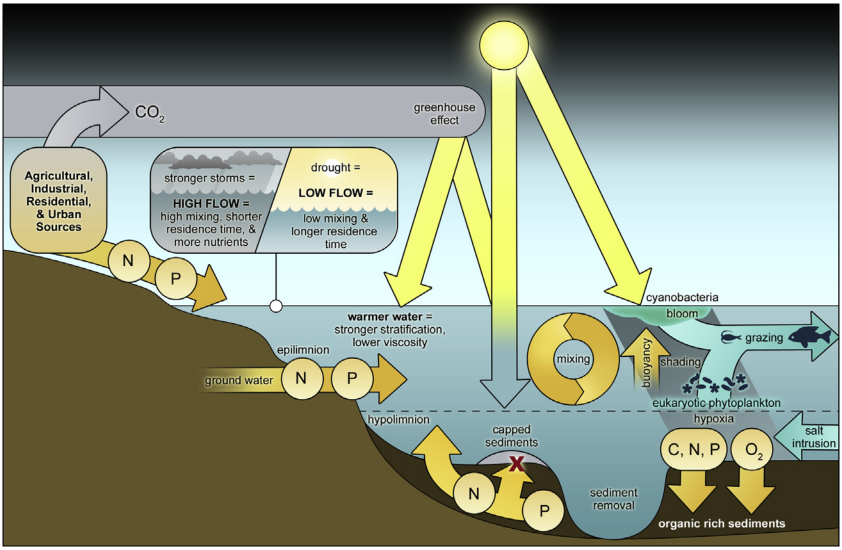

FIGURE 17.5 Conceptual diagram of cyanobacterial bloom development that can be generalized to a wide variety of algal blooms including HABs. The arrows indicate relationships between major biogeochemical processes found in both marine and freshwater environments; humans influence HAB development through modulation of nutrient sources at the land–sea interface and in the benthic zone where some mitigation strategies target the remineralization of limiting nutrients back into the water column. *Figure reproduced with permission from Paerl et al. (2011).*

precautionary impact preventions and *bloom controls*. Precautionary impact preventions refer to monitoring, predictive, and emergent actions. Bloom control involves both direct controls applied after an HAB has begun and indirect controls dealing with preventive strategies, including management of land-derived nutrient inputs. In this section, the distinction is made between (1) approaches to prevent and control a bloom and its impacts (Section 17.3.1) and (2) prediction, detection, and modeling capabilities (Section 17.3.2), which will form the backbone of future mitigation strategies within a regional Earth system framework (Section 17.3).

17.3.1 Biological and Chemical Control Methods

Biological and chemical controls refer to direct application or stimulation/suppression of factors that modify the biological (e.g., growth, grazing, mortality) or chemical (e.g., pH, inhibitors) composition or function of the ecosystem. These controls are often administered as emergency measures for suppressing blooms that threaten aquaculture facilities, or other spatially restricted regions, and their use can significantly accelerate the demise of a bloom or rid the water of toxins. These methods are most successful over small spatial scales within confined fish farms, reservoirs, desalination plants, or lakes and involve the manipulation of the environment and/or causative organism (Anderson et al., 2001; Kim, 2006). Biological agents such as grazers, parasites (Kim et al., 2008; Mazzillo et al., 2011), viruses (Nagasaki et al., 1999), and algicides (e.g., Jeong et al., 2003; Kim et al., 2009) are often host specific (Kodama et al., 2006) targeting a particular HAB species. Other moieties such as clays are used to promote flocculation and settling of algal particles to the sediment. Everything from microbial biosurfactants called sophorolipids (Sun et al., 2004; Lee et al., 2008) to algicidal bacteria (Imai et al., 1998; Doucette et al., 1999; Gumbo et al., 2008; Kang et al., 2008; Roth et al., 2008; Kim et al., 2009) and fungi (Jia et al., 2010) can be effective, at least in laboratory settings. The most extensively studied biocontrols target the PSP-producing *Alexandrium* spp. (Nakashima et al., 2006; Amaro et al., 2005; Bai et al., 2011; Su et al., 2007, 2011; Wang et al., 2010, 2012) or the fish-killing *Cocholidinium* spp. (Jeong et al., 2003; Kudela and Gobler, 2012), *Heterosigma akashiwo* (Nagasaki and Yamaguchi, 1997; Lovejoy et al., 1998; Imai et al., 1998; Jin and Dong, 2003; Kim, 2006), and *Chatonella* spp. (Imai et al., 2001). Zhou et al. (2008) achieved 80 percent inhibition of several species of *Alexandrium* in culture after applying garlic extract above 0.04 percent and attributed this effect to the active ingredient, diallyl trisulfide. This sort of "environment–friendly" approach to bloom control is appealing given the uncertainty and risk surrounding the use of toxic chemical agents that endanger a variety of aquatic flora and fauna. These compounds also minimize the issues associated with more environmentally damaging mitigation methods such as the use of copper sulfate ($CuSO_4$) on *K. brevis* blooms in the 1950s (Rounsefell and Evans, 1958 as cited in Kim, 2006). However, $CuSO_4$ and chlorination are still used routinely to rid drinking water reservoirs of nuisance algae and toxins (McKnight et al., 1983; Zamyadi et al., 2012).

Clay minerals such as kaolinite and loess compounds have been used effectively to control blooms in Asia, Europe, and the United States. Suspensions of the clay are sprayed onto the surface layer of a bloom (Figure 17.6), resulting in scavenging and flocculation of algal cells with over

FIGURE 17.6 Southern Sea of Korea. Clay dispersal used to mitigate blooms of *Cochlodinium polykrikoides. Photos by S. Moore.*

80 percent removal efficiency from surface waters in some cases (Sengco and Anderson, 2004). Phoslock® (lanthanum-modified bentonite) and chitosan have been applied to cyanobacterial blooms but prove too costly and impractical for routine management in the United States (Sellner et al., 2013), and in the case of Phoslock®, can lead to phosphorous limitation and increased ammonium regeneration (Sellner et al., 2013), further promoting cyanobacteria that respond to both P and N inputs (Paerl et al., 2011). Bloom removal is often successful only at very high clay and chitosan concentrations, with HAB species, pH (i.e., time of day), growth phase, and chitosan quality influencing results (Sellner et al., 2013). In lakes and ponds, barley straw and its extract can be cost-effective alternatives to controlling toxic cyanobacterial blooms and subsequent regrowth (Sellner et al., 2013; references in Brownlee et al., 2003), but it may have limited use in coastal marine environments where only a few dinoflagellate species appear susceptible (Terlizzi et al., 2002; Brownlee et al., 2003; Hagstrom et al., 2010). Peroxide additions are also effective (e.g., Matthijs et al., 2012) but limited due to cost and hazardous chemical permitting (particularly in the United States). In addition, little is known about the effects that this removal of toxic phytoplankton to the benthos has on the biota (Shumway et al., 2003) or on the potential for anoxic conditions in deeper waters (Imai et al., 2006). The list of physical disturbance methods now being tested is long, and most do not translate well to open coastal zones despite success in lakes and fjords; these include sediment capping (Pan et al., 2012), dredging (Lurling and Faassen, 2012), and even solar-powered circulation (Hudnell et al., 2010). A novel and potentially environmentally benign approach to control of blooms of cyst-forming HAB species (e.g., *Alexandrium)* in shallow, localized systems is being explored wherein manual mixing of bottom sediments can bury cysts uniformly throughout the disturbed layer, greatly reducing the number of cysts in the oxygenated surface layer, and thus the potential inoculum for future blooms (D. Anderson and D. Kulis, pers. comm.).

Viral and bacterial lysis appear to play a natural role in regulating phytoplankton communities and carbon flux (e.g., Fuhrman and Azam, 1980; Salomon and Imai, 2006). Capitalizing on this natural pathogenicity seems like a logical, cost-effective solution to HAB control. However, society has grown weary of runaway experiments with nature that introduce foreign, potentially invasive species or irreversibly alter natural assemblages in an ecosystem (Sanders et al., 2003; Secord, 2003). Given how poorly we understand phytoplankton community ecology, let alone viral and bacterial systematics and ecological interactions, Secord (2003) warns of the possibility for evolving host specificity in introduced viral and bacterial biocontrols that may not only prey switch but also could become less effective as their HAB hosts start to develop resistance. In a thought-provoking review on algicidal bacteria, Mayali and Azam (2004) considered the broader ecological context of microbial interactions in phytoplankton communities. Despite the many laboratory studies demonstrating the harmful predatory effects of heterotrophic bacteria on algal species, they argued that most field studies have failed to show conclusively the causal relationship between the decline of a bloom in natural ecosystems and the behavior of an introduced, algicidal bacterium. Moreover, translation from laboratory conditions to the field is inherently complex, given the flexibility of predator–prey dynamics mediated by the presence or absence of other algal species (Mayali and Azam, 2004) and the potential for toxicity effects due to HAB–microbe interactions (Moore et al., 2008).

17.3.2 Preventive Measures

The ultimate management strategy for preventing many algal blooms, particularly cyanobacterial blooms, is the reduction of nutrient inputs and the promotion of biodiversity. The rise of toxic *Nodularia spumigena* blooms in the Baltic Sea and their subsequent control after the Helsinki Convention in 1974 remains one of the strongest supporting narratives for curbing land-based nutrient pollutants (Elmgren and Larsson, 2001). The Baltic Sea is a complex network of contiguous basins bordering 12 nations. It has a long and ongoing history of hypoxia and fish kills associated with cyanobacteria blooms that are modulated by long-term climatic change and human land use practices (Zillen et al., 2008). Regions of both N and P limitation are separated in space and time with internal sources of phosphorous, an important regulator of offshore Baltic biogeochemistry (Vahtera et al., 2007). This not only necessitates but also complicates the dual reduction of N and P inputs to the system (Elmgren and Larsson, 2001; Conley et al., 2002; Vahtera et al., 2007). The largest source of nitrogen entering the Baltic is agriculture, but point-source discharge of sewage makes up a significant fraction. Sweden has adaptively managed sewage outflow by removing 80–90 percent of N and 95.5 percent of P to bring down overall phytoplankton biomass (Figure 17.7). They intermittently release more N into surrounding waters when there is a high risk of encouraging potentially toxic blooms of cyanobacteria species (called N_2 fixers or diazotrophs). Because diazotrophs can "fix" nitrate from elemental nitrogen in the atmosphere, they respond to low N:P ratios and thus will likely not bloom if additional N is supplied to the system (Elmgren and Larsson, 2001). This ecological strategy is stated in the joint initiatives management plan of the forward-thinking Helsinki Commission that advocates both N and P reductions and maintenance of biological diversity (HELCOM-BSAP, 2007) with the goal of returning the Baltic to a pristine state (Ronneby Declaration of 1990; Ehlers, 1994). The perennial problem noted by Elmgren and Larsson (2001) is the minimal involvement of local and regional stakeholders in decision making by most European Union (EU) directives and the lack of a clear end goal for determining restoration. One lesson learned is that dual reduction of N and P loads (Figure 17.7; see reviews by Conley et al., 2009; Paerl et al., 2011) as well as periodic control of N:P ratios appears appropriate for this region despite the theoretical limitations that

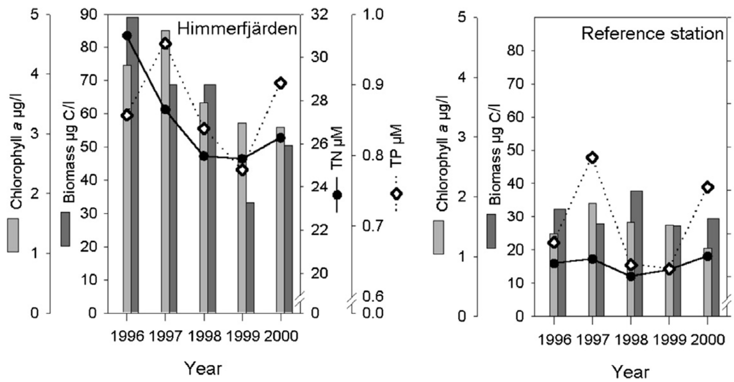

FIGURE 17.7 Baltic Sea. Reduction in the annual mean phytoplankton biomass in the upper mixed layer of Himmerfjärden, Sweden (left) after 1997 following N removal from the sewage treatment plant and subsequent declines in total nitrogen (TN) and dissolved inorganic nitrogen. As N:P ratios decreased, populations of N_2-fixing cyanobacteria rose in summer leading to an adaptive management strategy to control potentially toxic N_2 fixers. In contrast, phytoplankton biomass did not decrease at the open coastal reference station (right), nor did the annual mean TN and total phosphorus (TP). *Figure reproduced with permission from Elmgren and Larsson (2001).*

an exogenous nutrient ratio approach has been shown to impose on nutrient uptake by phytoplankton (Flynn, 2010).

Lake Erie, the shallowest, warmest, and most anthropogenically impacted of the Laurentian Great Lakes, poses another unique condition. Although it is a freshwater system, its large size and far-reaching impacts make it a good case study for marine HAB mitigation. In the mid-1960s to the 1970s, extensive cyanobacterial blooms, with associated hypoxic/anoxic conditions, were indicators of eutrophication within the shallow stratified portions of the western lake (Millie et al., 2009). Assemblages of other cyanobacteria species do occur, but the predominant bloom species in this region is *Microcystis aeruginosa,* a producer of the hepatotoxin microcystin. Phosphorus abatement strategies in the late 1970s successfully terminated blooms of cyanobacteria. However, following an invasion of foreign *Dreissena* mussels (zebra/quagga), cyanobacterial blooms began to reoccur in 1995 (Budd et al., 2001; Juhel et al., 2006). Zebra mussels were purportedly responsible for increased water clarity in the lake, but the consequence is that they selectively prey on eukaryotic phytoplankton, leaving cyanobacteria to thrive. Like clockwork, summer—fall blooms of *M. aeruginosa* have plagued the western basin on an annual basis ever since (Brittain et al., 2000; Vanderploeg et al., 2001), significantly impacting Ohio's beaches and water suppliers, with occasional effects in Michigan and Canada. In 2013, Carroll Township's water treatment facility in Ohio detected microcystin at concentrations more than threefold higher than the World Health Organization threshold of 1.0 part per billion in finished drinking water, forcing a shutdown of the municipal water supply (Henry, 2013). The chronic effects of human exposure to microcystin are poorly documented, and acute exposure is routinely implicated in deaths of domestic dogs and livestock shortly after exposure (Backer et al., 2013). As a result of exposure through recreational contact with water, contact dermatitis, nausea, and respiratory irritation (through inhalation of contaminated lake water) have been reported (Backer and McGillicuddy, 2006). The watershed surrounding the western basin is primarily represented by agricultural areas and drains into western Lake Erie by the Maumee River. The effluent of the Maumee River has elevated nutrients (particularly phosphorus), further exacerbating the cyanobacterial blooms (Stumpf et al., 2012). Unfortunately, as a consequence of climate change and resulting increases in water temperature, it is anticipated that toxic cyanobacterial events will increase in magnitude and frequency (Paerl and Huisman, 2008). Efforts to launch an operational forecasting system for cyanoHABs in Lake Erie are currently underway at the US National Oceanic and Atmospheric Administration (NOAA) as part of the Harmful Algal Bloom Operational Forecasting System (NOAA HAB-OFS; Wynne et al., 2013).

Biological diversity, although more difficult to assess, is an important determinant of water quality. Cardinale (2011) demonstrated that enhanced niche partitioning by benthic diatoms increased nitrogen uptake, providing a natural "buffer" against nutrient enrichment relative to less diverse communities associated with spatially homogenous environments. Promoting algal biodiversity and habitat preservation may then facilitate greater nutrient uptake capacity, particularly in protected environments where physical advection processes do not dominate phytoplankton turnover rates. Allelopathic interactions introduced when algae exude dissolved phycotoxins into the environment are an indicator of interspecific competition for limiting resources (Graneli and Hansen, 2006). It may also be that as species diversity increases, the ability of a given toxic species to dominate its competitors is suppressed by the wider array of competitive strategies present in the community. As marine ecosystem models become more sophisticated and include realistic phytoplankton biodiversity (Follows et al., 2007; Goebel et al., 2010), varying management strategies can be assessed in relation to community composition, competitive interactions, and nutrient dynamics.

17.4 MONITORING AND MODELING HABS

17.4.1 Ocean Observing

Once the far-reaching pressures of global climate change are superimposed on human impacts at regional scales (Figure 17.5), the projected response by phytoplankton communities becomes a seemingly intractable problem that can only be tackled through vigilant observation. This need for constant monitoring is a recurring mantra in the scientific and resource management communities. Baseline patterns cannot be distinguished from secular or decadal trends without consistent time series (McQuatters-Gollop et al., 2011). In particular, observations of species composition, phycotoxin loads throughout the food web, and ancillary measures of physical and chemical constituents are needed. These measurements are broadly defined into point, transect, and synoptic categories, all of which are necessary and require thoughtful integration for adequate HAB tracking and prediction (Stumpf et al., 2010; Jochens et al., 2010). It has been argued that at least 30 years of consistent monitoring data of HABs are required to discern climate-scale effects (Dale et al., 2006). One such record is provided by the 75-year time series of phytoplankton captured by the Continuous Plankton Recorder (CPR) in the North Sea. Using CPR data, a large-scale regime shift in open ocean phytoplankton was identified in the mid-1980s (McQuatters-Gollop et al., 2007). This "alternate resilient state" typified by anomalously high chlorophyll concentrations was found to be closely tied to climatic variability in the North Atlantic and decoupled from the significant reductions in nutrient loading implemented by the EU in the 1980s and the 1990s. Trophic cascades initiated by overfishing may also contribute to this rise in biomass (McQuatters-Gollop et al., 2007). Only via a fully integrated assessment of these pressures (using a combination of models and time series analysis) can the various factors be teased apart (Stumpf et al., 2010; Tett et al., 2013).

Efforts to codify public policy on reducing the impacts of HABs on human populations, wildlife, fisheries, aquatic ecosystems, aquaculture facilities, and drinking water supply (Bauer, 2006, Jewett et al., 2008) have been part of a growing movement by scientists and managers in the United States to "harness" monitoring and prediction capabilities through targeted research priorities aimed at holistic mitigation (HARRNESS, 2005). Federal investment in short- and long-term studies was mandated by the Harmful Algal Bloom and Hypoxia Research and Control Act (HABHRCA) of 1998, followed by the Harmful Algal Bloom and Hypoxia Amendments Act of 2004. While severe reduction in funding these programs has disrupted regional HAB monitoring in the United States, HABHRCA was recently reauthorized through 2018 indicating renewed interest in supporting HAB research. Many of the current and future efforts to apply technological advancements and Earth system frameworks in ocean observing to HAB ecology leverage the US Integrated Ocean Observing System (US IOOS) to bridge regional monitoring networks and sensor arrays with biological measurements (Green et al., 2009; Jochens et al., 2010; IOOS, 2013; Kudela et al., 2013).

Integrated observing systems to address HABs have been developed in several countries (See Section 17.5.3; Stumpf et al., 2010; Bernard et al., 2014). At the international level, the Global Ocean Observing System (GOOS) sponsored by the International Oceanographic Commission (United Nations Educational, Scientific and Cultural Organization) offers near real-time measurements of the state of the ocean (e.g., the successful Argo float program). It is part of a "permanent global collaborative system" with regional alliances comprising government and nongovernmental entities (GOOS, 2013). Fundamental gaps exist with respect to HABs in the initial design of most observing systems since there is greater emphasis on physics and meteorology than on biology (Frolov et al., 2012; Kudela et al., 2013; see also Section 17.6.1). The focus will be on leveraging those existing assets to create an end-to-end predictive system for HABs and other coastal hazards (Kudela et al., 2013), since the regional ocean observing networks now represent the best option for sustained HAB monitoring and forecasting in coastal waters.

17.4.2 Numerical Approaches to HAB Prediction

The number of approaches for monitoring, detecting, predicting, and forecasting the onset, fate, and demise of algal blooms is arguably comparable to the diversity of species being studied. Over the past two decades, there has been an increasing desire to apply our heuristic understanding of bloom ecology toward practical, numerical methods that will alert managers and communities of impending dangers (see McGillicuddy, 2010). An ideal alert system provides quantitative predictions of HAB likelihood, intensity, and movement or potential landfall along coastal margins. These approaches rely on a range of platforms from space-based, airborne, and in-water optical sensors, to traditional environmental sampling, to purely computational methods. Here, we focus our summary on the prediction of HABs using models or creative combinations of models, satellite observations, and in situ sampling (Table 17.2). We do not address the large body of work that directly associates aquatic optical properties with algal constituents nor the development of remote sensing indices for HAB detection (see recent review chapters in Pettersson and Pozdnyakov, 2013; the "HABWatch" volume, Babin et al., 2008; Stumpf and Tomlinson, 2005). Several regions are examined in detail in Section 17.5 to provide examples of how geographical variation in HAB species, monitoring programs, available satellite and modeling products, and resource management issues dictate the most effective mitigation strategy.

17.4.2.1 Empirical Models

Empirical or statistical methods range from fairly simple, steady-state regression techniques to more deterministic numerical solutions that draw from machine learning, such as artificial neural networks (ANN) and genetic programming (GP), or logic and rule-based reasoning, such as fuzzy logic. Some successful applications of linear regression to the prediction of HABs are found for toxigenic *Pseudo-nitzschia* populations (amnesic shellfish poisoning organism), beginning with a study that built several models of cellular DA concentration from cultures (with some field data) of *Pseudo-nitzschia pungens* using stepwise multiple regression (Blum et al., 2006). Anderson et al. (2009, 2010) and Lane et al. (2009) achieved similar success (~75 percent accuracy)

TABLE 17.2 Summary of Numerical Models Used to Predict Target HAB Species; in Some Cases, These are Forced with Output from (or Coupled to) 3D Circulation Models, and a Few are Involved in (or Moving Toward) Operational Use

Type of Model	Target Species	Region	Specific Approach	Forced with Other Regional Models, Observations	Source
Empirical/ statistical	Cyanobacteria	Japan, Finland, Australia	ANNs		Recknagel et al. (1997)
	Skeletonema spp.	Hong Kong	ANNs		Lee et al. (2003)
	Pseudo-nitzschia	Cardigan Bay, Canada	Multiple linear regression to predict toxins (DA)		Blum et al. (2006)
	Nodularia spumigena, Alexandrium minutum, Dinophysis spp., Karenia mikimotoi	Baltic sea, Gulf of Finland, Sweden, Ireland, United Kingdom, Netherlands	Fuzzy logic	HABES project	Laanemets et al. (2006), Blauw et al. (2006)
	Phaeocystis globosa	Dutch coast, Netherlands; United Kingdom	Decision tree; nonlinear regression; fuzzy cellular automata; fuzzy logic	Delft3D-WAQ (HABES project)	Chen and Mynett (2004), Chen and Mynett (2006), Blauw et al. (2006), Blauw et al. (2010)
	Dinophysis acuminata	Western Andalucia, Spain	ANNs		Velo-Suarez and Gutierrez-Estrada, (2007)

	Lyngbya majuscula	Deception Bay, Queensland, Australia	Bayesian model averaging		Hamilton et al. (2009)
	Pseudo-nitzschia spp.	Santa Barbara Channel, CA, USA; Monterey Bay	GLM (logistic), multiple linear regression to predict abundance and toxin concentration (DA)	ROMS-CoSiNE (CCS), HYCOM-CoSiNE (CCS), MODIS ocean color, HFR	Anderson et al. (2009, 2011), Lane et al. (2009), Anderson et al. (in review)
	Pseudo-nitzschia spp.	Chesapeake Bay	GLM (logistic)	ChesROMS-Fennel ecosystem model	Anderson et al. (2010)
	Karenia brevis	Gulf of Mexico	Supported vector machine learning		Gokaraju et al. (2011)
	Karlodinium veneficum, Microcystis aeurginosa, Prorocentrum minimum	Chesapeake Bay	ANNs, GP, GLM (logistic)	ChesROMS-Fennel ecosystem model	Brown et al. (2013)
Mechanistic	*Alexandrium fundyense*	Gulf of Maine	Deterministic cyst germination and growth model	HYCOM-ROMS	Stock et al. (2005), He et al. (2008), Mcgillicuddy et al. (2005, 2011)
	Karenia brevis	West Florida Shelf	Deterministic nutrient-limited growth model	HYCOM with MODIS FLH and LCS method	Olascoaga et al. (2008)

(Continued)

TABLE 17.2 Summary of Numerical Models Used to Predict Target HAB Species; in Some Cases, These are Forced with Output from (or Coupled to) 3D Circulation Models, and a Few are Involved in (or Moving Toward) Operational Use—cont'd

Type of Model	Target Species	Region	Specific Approach	Forced with Other Regional Models, Observations	Source
	Gambierdiscus spp.	Hawaii, Big Island	Deterministic nutrient-limited growth and export model		Parsons et al. (2010)
	Pseudo-nitzschia seriata; Psuedo-nitzschia spp.	Cultured from Scottish waters; Monterey Bay, CA	Deterministic nutrient-limited growth-mortality-toxin production model		Terseleer et al. (2013), Anderson et al. (2013)
Physical indices and Lagrangian particle tracking	*Psuedo-nitzschia spp.*	Galician Coast, Spain; Lisbon Bay, Portugal	Upwelling index; SST and UI; wind current patterns	AVHRR SST and SeaWiFS chlorophyll	Sacau-Cuadrado et al. (2003), Palma et al. (2010)
	Karenia brevis	Texas Shelf; Tampa Bay, FL, USA (Gulf of Mexico)	Passive tracer advection diffusion; trajectory/transport modeling from physics; LPT applied ex post facto to an identified *K. brevis* event	ROMS; HYCOM-ROMS-FVCOM with HFR; POM	Hetland and Campbell (2007), Weisberg et al. (2009), Havens et al. (2010)
	Dinophysis acuminate	Bantry Bay, Ireland; Bay of Biscay, Spain	Wind index; LPT (Ichthyop) to simulate *D. acuminate* bloom	MARS3D-Ichthyop	Raine et al. (2010), Velo-suarez et al. (2010)

	Pyrodinium bahamense (Phaeocystis globosa, Gymnodinium mikimotoi, Prorocentrum minimum)	South China Sea—Vietnam; Manila bay	Rudimentary growth model & passive tracer advection diffusion; LPT applied ex post facto to an identified HAB event	POM-SWAN; POM	Villanoy et al. (2006), Dippner et al. (2011)
Ecosystem/ biogeochemical	*Karenia brevis*	West Florida Shelf, Gulf of Mexico	Complex N-P-Z-D model with explicit *K. brevis* box and aerosolized brevetoxins	POM; FVCOMS, ROMS, HYCOM	Walsh et al., (2001, 2002)
	Potentially toxic cyanobacteria	Baltic Sea	Ensemble forecasting of C:Chl for cyanobacteria	Finnish Meteorological-Institute-coupled physical—biological model	Roiha et al. (2010)
	Pseudo-nitzschia spp.	Pacific Northwest	Particle tracking and wind index from a fully validated ecosystem model	ROMS (Eastern Pacific)	Giddings et al. (2013)

FLH, fluorescence line height; FVCOM, finite volume community ocean model; LCS, lagrangian coherent structures; MODIS, moderate-resolution imaging spectroradiometer; AVHRR, advanced very high resolution radiometer; C:Chl, carbon to chlorophyll ratio; HFR, high-frequency radar, SWAN, simulating waves nearshore; SST, sea surface temperature; UI, upwelling index; SeaWiFS, sea-viewing wide field-of-view sensor; WAQ, water quality. Empirical models relate the species distribution and abundance patterns of a particular algal taxonomic group to combinations of physical, chemical, biological, and optical environmental indices using varying levels of statistical complexity. Mechanistic models strive to numerically parameterize fundamental physiological and life history traits of the target organism to predict its abundance and/or toxicity. Physical methods range from statistical relationships between HAB species and physical indices to LPT methods that rely on sophisticated numerical solutions of the physical circulation to predict particle trajectories. LPT is a general method that is widely applied in ecological forecasting with some HAB examples cited here. The broad field of ecosystem or biogeochemical modeling has not historically focused on HAB prediction, but there are now several examples of direct incorporation of HAB species into model design or model analysis. For a comprehensive discussion of 3D physical—biological models applied to both HAB and non-HAB algal groups, see Petersson and Pozdynkaov (2013).

when applying a range of stepwise linear and logistic regression (as generalized linear models, GLMs) to time series of in situ physicochemical parameters to predict both DA and *Pseudo-nitzschia* blooms in the Chesapeake Bay (Anderson et al., 2010) and coastal California (Lane et al., 2009; Anderson et al., 2009; more in Section 17.6). An advantage of these simple models is their reproducibility and retuning by other investigators as data sets lengthen as well as the easily interpreted, ecological relationships between variables.

Somewhat more obscure are the numerical approaches that use artificial neural networks to model biological phenomena. ANN mimic complicated nonlinear neuronal connections, and thus are expected to capture the chaotic component of ecological patterns by deterministically modeling the inherent nonlinearity of the system. Time series data are generally divided into "learning" and validation sets for training the ANN to recognize patterns that connect the response and predictor variables, an approach also used for support vector machine learning techniques (Gokaraju et al., 2011; Ribeiro and Torgo, 2008). An early application of ANN was conducted by Recknagel et al. (1997) to predict algal blooms in four lake systems. Velo-Suarez and Gutierrez-Estrada (2007) were very successful ($r^2 = 94-96$ percent) in predicting *Dinophysis acuminata* blooms (diarrhetic shellfish poisoning (DSP) organism) over short timescales in Spanish coastal waters using ANN. Muttil and Lee (2005) applied GP evolutionary algorithms to chlorophyll data sets from Tolo Harbor, Hong Kong, a site with a long history of HAB events (Hodgkiss and Ho, 1997), and achieved good correspondence between observed and predicted chlorophyll (86 percent). Bayesian model averaging and similar techniques are becoming more popular in ecological studies due to their ability to stringently quantify uncertainty over all possible model forms and parameter estimates, as described by Hamilton et al. (2009) for *Lyngbya majuscula* blooms (now *Moorea producens)* in Australia. Fuzzy logic approaches include the HABs Expert System (HABES, http://habes.hrwallingford.co.uk) sponsored by the EU Fifth Framework Program. HABES predicted (using "Ecofuzz"; an open source model) a suite of HAB species at seven EU coastal sites (Blauw et al., 2006). The program illustrates the many regional considerations necessary when attempting to encompass regional diversity of HAB issues including *N. spumigena* in the Gulf of Finland (Laanemets et al., 2006) and nuisance blooms of *Phaeocystis globosa* along the Dutch coast (Blauw et al., 2010; Chen and Mynett, 2004, 2006).

17.4.2.2 Physical Models and Particle Tracking

A number of investigators have examined bloom formation and duration with hydrodynamic circulation models to constrain the physical processes controlling bloom dynamics. The numerically least intensive approaches use physical indices or relationships to predict conditions likely to promote HABs such as upwelling (Palma et al., 2010; Sacau-Cuadrado et al., 2003) or favorable winds (Raine et al., 2010). Using this empirical approach and recognizing that DSP-causing *Dinophysis* blooms (Table 17.1) on the southwestern Ireland coast occur during summer when offshore water is advected into the highly stratified nearshore, Raine et al. (2010) developed a model based on the wind index as a proxy for wind-driven exchange of water and HAB probability onto the shelf. This simple but elegant model has proven helpful for understanding the dynamics of DSP intoxications that have greatly impacted the shellfish in Bantry Bay.

Once a bloom has been positively identified through environmental sampling, satellite algorithms, or models, its trajectory can be mapped using particle transport (Lagrangian particle tracking (LPT)) coupled to either a two-dimensional or three-dimensional (3D) circulation model. Widely used in oil spill tracking and studies of fish larval transport, LPT is seeing growing popularity for HAB risk management. Because many blooms originate offshore and are advected into the nearshore environment via physical processes like mesoscale eddies, LPT can be a powerful tool for estimating the timing and spatial impact of landfall. Wynne et al. (2011) evaluated LPT applied to satellite data for cyanobacterial blooms in Lake Erie and confirmed that the model improved the accuracy of forecasted bloom locations. Another study tracked passive particle transport of a *K. brevis* bloom in Tampa Bay with LPT coupled to the Princeton Ocean Model (POM) to identify zones most likely to be affected, but was unable to adequately validate predictions with monitoring data (Havens et al., 2010; more on *K. brevis* particle tracking in Section 17.5). Velo-Suarez et al. (2010) determined the physical processes responsible for the demise of a *D. acuminata* bloom in the Bay of Biscay using an LPT model ("Ichthyop") coupled to a downscaled regional ocean model (MARS3D, Model for Application at Regional Scale), illustrating the importance of retention–dispersion patterns driven by the physics of the bay. Summer southwest monsoon patterns were shown to drive transport of HABs into sensitive aquaculture and coral reef zones along the Vietnamese coast of the South China Sea with a Lagrangian model coupled to the Hamburg Shelf Ocean Model (Dippner et al., 2011). Also focusing on the SW monsoon season, Villanoy et al. (2006) incorporated the physical–biological interaction into their LPT-POM coupled model by including a rudimentary individual-based growth model (IBM) for *Pyrodinium* cyst resuspension and transport in Manila Bay, similar to the treatment by McGillicuddy et al. (2003) to determine the offshore initiation of *Alexandrium fundyense* blooms from dormant cysts in the Gulf of Maine (both are PSP organisms). An advantage to IBMs is the ability to include diel vertical migration, a fundamental nutrient-acquisition strategy in dinoflagellates (Kamykowski et al., 1999; Peacock and Kudela, 2014) that may greatly affect passive tracer behavior if correctly applied to LPT models (Henrichs et al., 2013).

17.4.2.3 Coupled Physical–Biological Models

In the 17 years since Franks (1997) showcased the potential utility of coupled physical–biological models to HAB ecology, the fields of ecosystem modeling and data assimilation have advanced significantly. At the same time, a growing recognition has occurred that satellite observations for real-time HAB prediction are limited due to the poor temporal and spatial resolution of ocean color imagery; large uncertainty in chlorophyll-*a* (chl-a) estimates for coastal, optically complex waters; and the lack of taxonomic specificity that can be extracted from current sensors (e.g., Allen et al., 2008; Stumpf et al., 2009). Petersson and Pozdynkaov (2013) reviewed the current state of satellite methods and coupled physical-ecosystem models available for use in HAB studies. Many of these models predict bulk chlorophyll biomass rather than species-specific biomass pools (e.g., Allen et al., 2008; ERSEM model, European Regional Seas Ecosystem Model), highlighting the limitation that few models explicitly simulate HAB species dynamics. An additional take-home message is the tight symbiosis between observations and models, echoed by both Franks (1997) and Weisberg et al. (2009), who noted this joint utility in the design of ocean observing systems and the fine-tuning of predictive models. Despite model advances, some of the major hurdles outlined by Franks (1997) remain: (1) assimilation of biological and chemical observations to improve ecosystem model performance (a crucial role for satellite observations, see Gregg et al., 2009); and (2) uncertainty in initial conditions and multispecies interactions. Moreover, limitations still exist for most HAB species in understanding the mechanisms responsible for bloom initiation, termination, and toxicity—the factors most useful to managers. These limitations will persist so long as the large-scale observing systems continue to focus on variables with limited applicability to understanding species-specific dynamics (see Section 17.4.1).

The descriptive term often used for a wide variety of basic to complex deterministic formulations that examine the dynamical interaction of these *biogeochemical* compartments in zero-dimensional to 3D settings is nitrogen-phytoplankton-zooplankton-detritus (N-P-Z-D) model. Walsh et al. (2001) subdivided the phytoplankton state variable in an N-P-Z-D model into six functional/taxonomic groups, including an explicit HAB "box" for *Gymnodinium breve,* now classified as *K. brevis.* They then predicted (hindcasted) transport/landfall for the well-documented 1979 event on the West Florida Shelf by combining this one-dimensional model with a POM circulation model and light-mediated vertical migration behavior and proposed that the bloom was regulated by organic nutrients (Walsh et al., 2002). Olascoaga et al. (2008) applied a new technique, also for the West Florida Shelf, that isolates distinct regions in the flow termed Lagrangian coherent structures to back-calculate the origin of a satellite and field-detected *K. brevis* bloom. This latter approach is only possible where a bloom can be preverified and is in contrast to the forecasting efforts of Walsh et al. (2001) who also noted the "real-world" limitations of their complex model and a reliance on in situ biooptical sensors for model evaluation. Giddings et al. (2013) recently improved predictive skill of toxic DA events in the Pacific Northwest of the United States using a fully validated ecosystem model coupled to a Regional

Ocean Modeling System (ROMS) by tracking particle advection of simulated *Pseudo-nitzschia* particles (represented by the "large phytoplankton" size class in their model). They filtered out false positive values by sequentially applying a wind index and the presence of appropriate size classes of cells to classify favorable periods for onshore HAB transport.

17.4.2.4 Mechanistic HAB Models and Blended Dynamical Approaches

Mechanistic models that simulate HAB population dynamics or toxin production (as observed for a particular species or genus) are still rare (Parsons et al., 2010; Stock et al., 2005; Anderson et al., 2013; Terseleer et al., 2013), but they are arguably a key component to HAB forecasting from ecosystem models where, if not too complex, they can function as a tracer or a fully integrated state variable. In the Gulf of Maine, *A. fundyense* population dynamics is parameterized for cyst germination, growth, and mortality (McGillicuddy et al., 2005; Stock et al., 2005) and treated as a tracer within a regionally downscaled ROMS model (He et al., 2008) to make real-time, weekly *A. fundyense* forecasts during the bloom season as well as seasonal ensemble forecasts (McGillicuddy et al., 2011). Based on years of resting cyst abundance data for the region, models initiated with the previous year's cyst bed data were sufficient for estimating a climatological bloom horizon for the following year to alert stakeholders and resource managers of potential PSP outbreaks (Figure 17.8; Anderson et al., 2005; Li et al., 2009). McGillicuddy et al. (2011) candidly described the failure of this relationship to manifest a correct seasonal prediction for the western Gulf of Maine in 2010 after historically high cyst abundance in 2009 indicated otherwise (Figure 17.8). Nonlinearities in the dynamic system may be to blame, and the scenario is likened to that of the 1990s when poor ENSO model performance arose from shifts in the underlying ocean state far outside those used for model construction (McGillicuddy et al., 2011). This case study also demonstrates that ensemble forecasts from varying boundary conditions, while a potentially powerful management tool for creating model uncertainty envelopes and conducting sensitivity analyses (Roiha et al., 2010), are not immune to these nonlinearities. This emphasizes the need for advanced data assimilation techniques if ecosystem models are to be used operationally (McGillicuddy et al., 2011). Statistical models would likely also fail when the underlying ocean state shifts outside that used for model construction, highlighting the sensitivity of both these "simple" and more complex modeling approaches. Clearly, a need exists for close coordination between observation and modeling efforts.

Approaches that blend empirical and dynamic methods leverage the practicality of statistical HAB models with the sophistication of coupled hydrodynamic-ecosystem models (e.g., Anderson et al., 2010, 2011). The Chesapeake Bay Ecological Prediction System (CBEPS) is one such project, currently generating nonoperational nowcasts and 3-day forecasts for several HAB species (unpublished ANN and GLM empirical models for *Karlodinium*

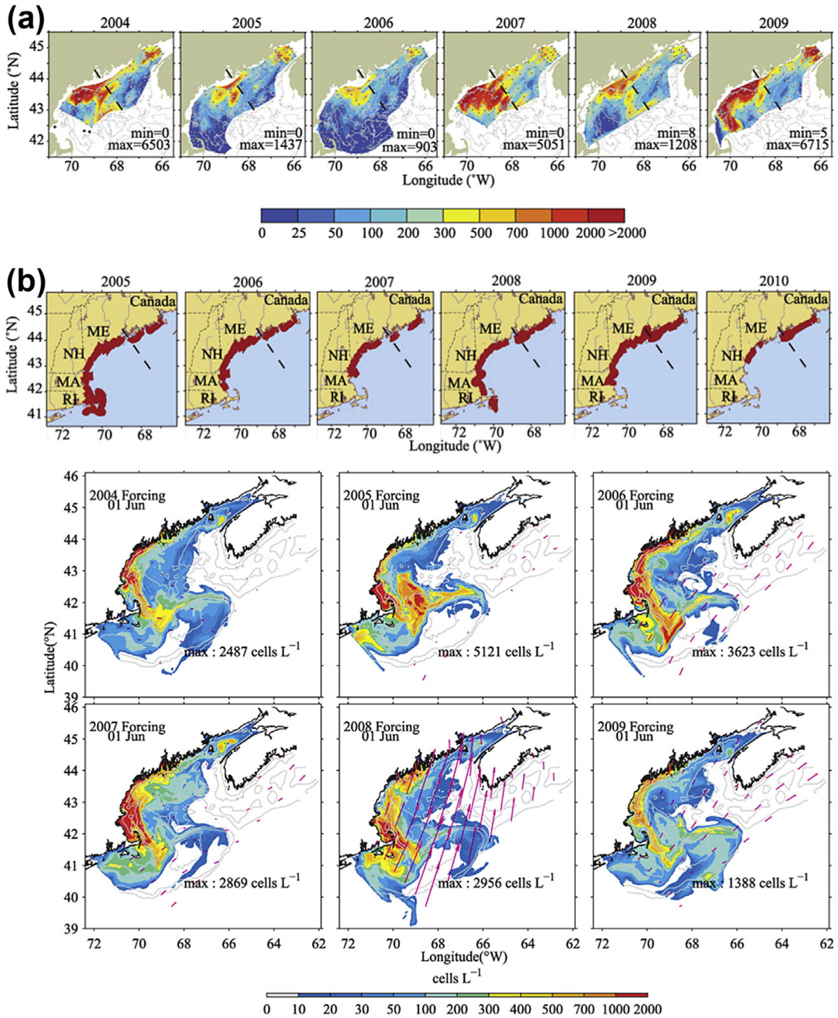

FIGURE 17.8 Gulf of Maine. Top panel: (a) Contour maps created from sediment samples of *Alexandrium fundyense* cysts collected from 2004 to 2009 (open circles). (b) Cyst abundance is paired with corresponding maps of paralytic shellfish poisoning (PSP) closures for the following year, i.e., 2005–2010. Bottom panel: Ensemble forecast of *A. fundyense* cell abundance generated from 2009 cyst data and a hydrodynamic (ROMS) model for 2004–2009 to constrain the variability in physical forcing each year while holding the biology (i.e., cyst distribution) constant. Predictive skill broke down in 2010 when water mass anomalies fell outside the "envelope of variability" used to train the model. *Figures reproduced with permission from McGillicuddy et al. (2011).*

veneficum, M. aeruginosa, and *Prorocentrum minimum),* stinging jellyfish called seanettles (Decker et al., 2007), pathogens such as *Vibrio cholerae* (de Magny et al., 2009), and dissolved oxygen content for the largest estuarine system in the United States (Brown et al., 2013). The CBEPS uses a downscaled ROMS

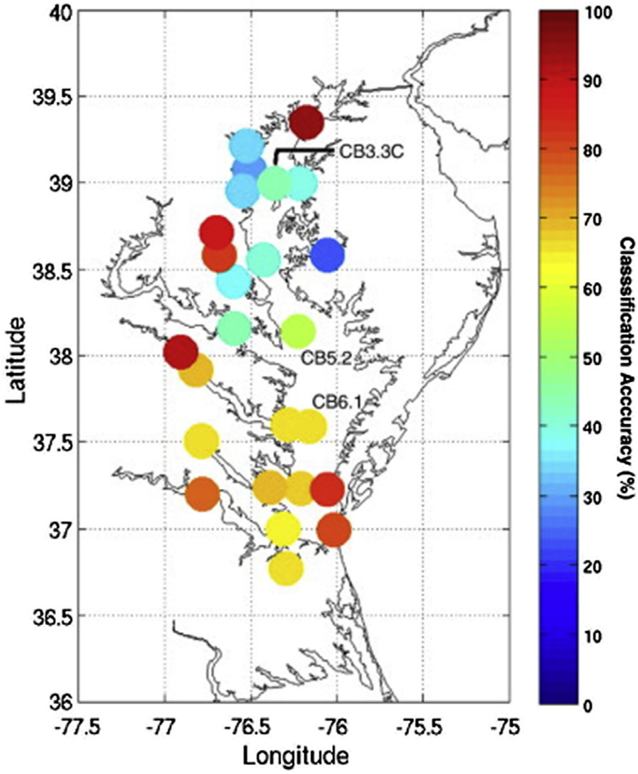

FIGURE 17.9 Chesapeake Bay. Skill assessment of *Karlodinium veneficum* simulations created from empirical HAB models and forced with a coupled ROMS and biogeochemical model for 2007–2009. Accuracy measures are based on comparisons with in situ data from 24 stations monitored by the Chesapeake Bay Program. *Figure reproduced with permission from Brown et al. (2013).*

("ChesROMS") coupled to an N-P-Z-D model (Fennel et al., 2006; Xu and Hood, 2006) that includes inorganic P and N, organic N, and dissolved oxygen. The ChesROMS configuration considers United States Geological Survey (USGS) river discharge and atmospheric deposition of nutrients, but does not currently run the real-time data assimilation routines developed for the region (Hoffman et al., 2012; Zhang et al., 2010). CBEPS is moving toward rigorous evaluation of model skill (Brown et al., 2013), a fundamental goal for all applied modeling systems (see Stow et al., 2009). Brown et al. (2013) report a mean accuracy of 59 percent for the *K. veneficum* nowcasts (Figure 17.9). Given that the only significant predictor variables are month, salinity, and temperature, all of which are well-validated for ChesROMS (Warner et al., 2005), this implies that the model may be too simple to sufficiently capture *K. veneficum* variability. Forthcoming endeavors to evaluate HAB models and assimilate biological data for this project and others, although extremely difficult, are imperative for strengthening the role of HAB forecasting in potential mitigation.

17.4.2.5 Valuation of Models for HAB Mitigation

The societal goal for all HAB modeling efforts should be the mitigation of negative impacts. The costs for developing an operational forecast system are ideally balanced by the socioeconomic gains and protection of living marine resources, or they should at least provide significant added value. These operational forecast systems also add value to the often significant investment in underlying observational infrastructure, costs incurred whether or not the data are used for HAB applications. One of the few (or perhaps only) such cost–benefit analyses that evaluates the relative investment of HAB model prediction looks at commercial finfish and shellfisheries in New England with respect to the *A. fundyense* forecast and tracking system discussed above for the Gulf of Maine (Jin and Hoagland, 2008). A unique advantage of a forecasting system for fishermen and shellfish growers is the fine-tuned spatial and temporal prediction of bloom or toxin presence and movement, which would enable targeted, proactive harvests and even geographic shifts in fishing effort (e.g., offshore to Georges Bank). In their study, Jin and Hoagland (2008) modeled the economic impacts of predictions in terms of (1) harvest loss if no prediction is made, (2) the value of HAB prediction over a range of possible skill levels, (3) the annual economic value to a public or private decision maker if action is or is not taken given a particular HAB prediction; and (4) the total value of a prediction. By examining a range of HAB frequency (from 2- to 30-year events) and model accuracy, the study elegantly estimated the variation in monetary value for responses to a given scenario. Not surprisingly, model accuracy is a leading factor driving prediction value, but so is the frequency of HABs, i.e., the value of a prediction increases when blooms are more common. For example, the model yields a 30-year maximum net value of $51.3 million when forecasts are completely accurate and PSP events occur every 2 years (Jin and Hoagland, 2008). Of course, one crucial aspect not captured in this study is the ecosystem service value of a functioning ecosystem and healthy wildlife populations, and as the authors note, spillover effects to other industries such as tourism or nontargeted fisheries.

17.5 REGIONAL EARTH SYSTEM FRAMEWORK

Whether predicting when a potentially dangerous bloom will strike or tracking its path, models should always be anchored to the regional chemistry, physics, and biology. Alert systems and mitigation strategies will be dictated by the history of human resource use in the region and will hinge on local to federal government mandates for protecting those resources. For these reasons, a "one-size-fits-all" approach for modeling HABs is not practical. This section highlights several regional narratives in the United States and EU that integrate observation networks and predictive models in idiosyncratic ways to meet society's challenge of mitigating the negative consequences of HABs.

17.5.1 Pacific Northwest of the United States

The Earth system framework for detecting and forecasting HABs in the PNW is composed of a diverse range of elements with varying degrees of complexity to overcome the challenges that are associated with the environment. For example, cloud and fog prevent bloom detection using satellites over much of the year. Furthermore, the toxic HAB species "bloom" in the PNW makes up only a small percentage of the total phytoplankton biomass. This renders the use of satellite-derived chlorophyll ineffective as a direct indicator of these events (e.g., Trainer et al., 2009). Direct observations of fish-killing HABs that form visible surface water accumulations are at some places made by small aircraft, but this is not effective for the toxic HABs that contaminate shellfish because they rarely discolor the water. Therefore, in situ observations are (necessarily) more commonly used for HAB detection, although progress is being made through the use of coupled satellite and modeling efforts (Giddings et al., 2013). In situ observations are obtained by manually collecting and analyzing samples using traditional methods, and also using advanced robotic sensors such as the Environmental Sample Processor (ESP). The coupled nature–human (CNH) system that contextualizes the impacts of HABs is also unique in the PNW. This is because of the cultural, spiritual, and economic significance of shellfish for over a dozen Native American tribes in the region. Shellfish feature so prominently in tribal customs that the native language of one coastal tribe includes a phrase that means "clam hungry." It stands to reason that the tribal people of the PNW may be disproportionately impacted by HABs and their toxins.

17.5.1.1 Puget Sound

Puget Sound is a large coastal estuary (2,330 km^2) in Washington State with long and branching basins and a complex coastline (Figure 17.10). A heuristic model of toxic blooms of *Alexandrium* was developed for Puget Sound using long-term records of PSP toxin concentrations in shellfish tissues. Blue mussels (*Mytilus edulis*) were used as a sentinel for toxic bloom activity because they readily acquire and accumulate toxins to high levels during a bloom, and they also rapidly depurate the toxins in the absence of toxic cells (Bricelj and Shumway, 1998). The model was based on toxin dynamics at "hot spot" sites where mussels most frequently attained the highest concentrations of toxin in their tissues. By examining daily time series of environmental conditions leading to the most toxic events at these hot spot sites, a specific combination of environmental conditions was identified that appeared to favor bloom development. These conditions are warm air and water temperatures,

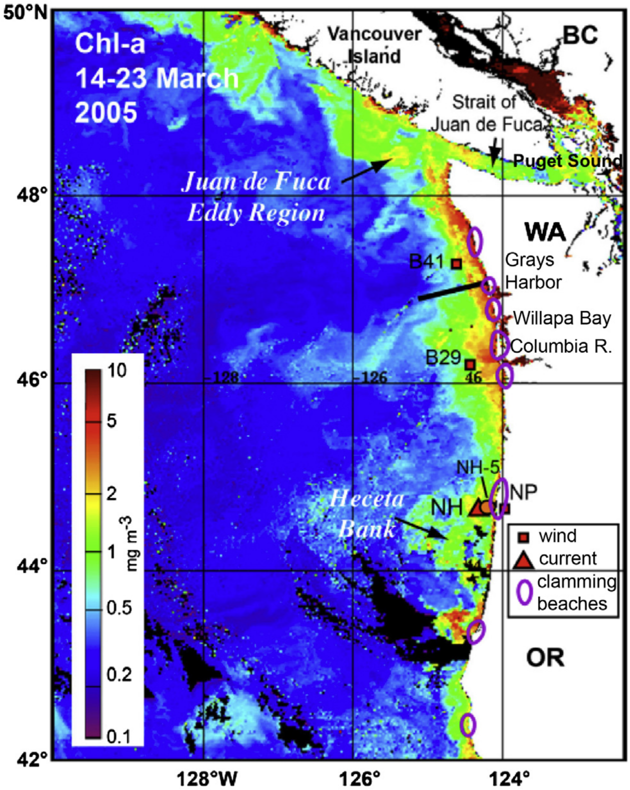

FIGURE 17.10 US Pacific Northwest. Coastal variability in algal blooms can be seen from this satellite-derived chlorophyll image (moderate-resolution imaging spectroradiometer-Aqua sensor) smoothed over a 10-day window. Major physical features such as the Juan de Fuca Eddy and Heceta Bank are sites of active research since they are associated with elevated primary production. Puget Sound is connected to coastal waters via the Strait of Juan de Fuca. Symbols denote observation platforms for monitoring coastal winds, surface currents, and clamming beaches to assess environmental forcing of HABs. *Modified and used with permission from Hickey et al. (2013); MODIS image courtesy of R. Kudela.*

weak winds, low streamflow, and small tidal variability. A temporal "window of opportunity" exists for toxic blooms of *Alexandrium* when these conditions occur in combination, and a wider window (i.e., more days) indicates increased bloom risk.

The window of opportunity for *Alexandrium* in Puget Sound can be used to evaluate past and future bloom scenarios (Moore et al., 2011). The caveat of this approach is the assumption that the environmental conditions that favor present-day blooms of *Alexandrium* have not changed from past conditions and will continue to favor blooms in the future. Moore et al. (2011) examined future *Alexandrium* bloom scenarios using the IPCC climate change projections for the PNW. Perturbations to the local environmental conditions that comprise the window of opportunity were calculated using climate projections from global climate models. The resulting forecast indicates that by the end of the twenty-first century, *Alexandrium* blooms may begin up to two months earlier in the year and persist for one month later compared to the present day. Changes to the duration of the bloom season (phenology) appear to be imminent and may be detectable within the next 30 years.

A framework that incorporates the heuristic model for *Alexandrium* with weather forecasts and in situ observations could inform managers and shellfish growers of increased HAB risk in Puget Sound (Figure 17.11). The advanced warning provided by this framework is of the order of a few days to a week, the timescale that has been identified by end users to be the most useful for putting mitigation measures in place to protect human health and reduce economic impacts. Mitigation measures for shellfish growers, and the cost savings associated with these measures, have been identified by Jin and Hoagland (2008) for the shellfish industry in the Gulf of Maine and include selectively harvesting different growing areas or increasing prebloom harvests to partially offset losses during bloom periods (Section 17.4.2.4). Public health managers can also better allocate limited resources to monitoring by targeting "hot spot" locations during time periods with increased risk for a bloom, or closing-growing areas during bloom periods more selectively than they would without a forecast.

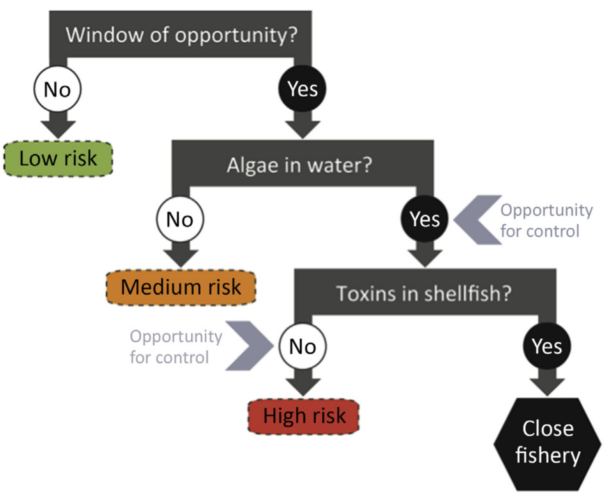

FIGURE 17.11 A risk-based approach to managing HABs in Puget Sound that provides advanced warning of outbreaks and identifies opportunities to mitigate impacts. The framework includes forecasts of the environmental conditions that favor bloom development (i.e., the window of opportunity) and timely observations of algae in the water to inform targeted and timely testing of shellfish for toxins.

A key component of the risk-based framework shown in Figure 17.11 is timely observations of harmful algae in the water. To overcome sampling challenges, in situ observations of harmful algae are provided by a citizen science program called SoundToxins (www.soundtoxins.org), which is a partnership of shellfish growers, fish farmers, tribes, environmental learning centers, and the general public. Participants are provided equipment and microscopes to collect and analyze water samples for HABs near their growing areas or near their homes, and the information is entered into a real-time database where all partners can assess the risk of imminent HABs. This program is an effective way to obtain observations of HABs from locations all around Puget Sound, but since participation is voluntary, the frequency of observations at most sites is limited to weekly. In contrast, autonomous in situ observations by an advanced biosensor, the Environmental Sample Processor (ESP), can provide high-frequency information on HAB abundance at key locations that complement the spatial coverage offered by SoundToxins observations. The ESP uses sensitive and specific molecular assays to quantitatively detect HABs and their toxins (Scholin et al., 2009). The results of the assays are captured in a photograph that is relayed via telemetry in near-real time. The entire process, from sample collection through results delivery, can occur in as little as 3 h. The ESP was first deployed in Puget Sound in 2012 and has been used to provide advanced warning of HABs at a commercial shellfish farm and a tribal shellfish hatchery as well as to answer research questions related to the ecology and oceanography of HAB species. The ESP is a new and powerful asset in the Earth system framework for detecting and forecasting HABs in the PNW.

17.5.1.2 Outer Washington—Oregon Coast

A mechanistic understanding of toxic *Pseudo-nitzschia* blooms on the outer Washington—Oregon coast underpins the approach used to forecast these HABs. *Pseudo-nitzschia* spp. are a common and natural component of the marine phytoplankton community in the PNW and are generally not toxic. However, when they are toxic they can have significant impacts; a single toxic bloom can cost as much as $22 million in lost revenue (Dyson and Huppert, 2010). A series of multiyear studies discovered two sources of toxic cells that are associated with retentive oceanographic features: the seasonal Juan de Fuca eddy located off the northern Washington coast and Heceta Bank located off the central Oregon coast (Hickey and Banas, 2003; Trainer et al., 2009). By examining measured and modeled (ROMS) ocean currents in relation to razor clam toxicity at coastal beaches, it has been shown that the Juan de Fuca eddy is the source of toxic cells of *Pseudo-nitzschia* in the summer and fall, whereas Heceta Bank is the source in the spring (Hickey et al., 2013). From the Juan de Fuca eddy, toxic cells can escape and be transported southward during periods of upwelling-favorable winds (MacFadyen et al., 2005) or transported onshore to coastal beaches during downwelling-favorable conditions (i.e., storm events; MacFadyen et al., 2005; Trainer et al., 2002). The transport of toxic cells from Heceta Bank to the Washington coast is complicated by the buoyant Columbia River plume, which during the summer and fall, acts as a barrier to onshore transport of toxic cells to Washington's beaches, but in the spring, acts primarily as a conduit (Hickey et al., 2013).

Data describing the environmental conditions that are known to bring toxic cells from the offshore source regions to the coastal beaches comprise the basis of the HAB forecasting framework for *Pseudo-nitzschia* on the outer Washington–Oregon coast. These data are examined and synthesized by local experts, and forecasts are based on the risk or likelihood of toxic cells being transported onshore. Risk factors are assessed using prior 10-day winds, observations, and numerical forecasts of regional weather, surface currents, and the Columbia River plume. A more detailed description of the complete set of models and environmental conditions that are used by the framework is given by Brown et al. (2012a). The overall risk of toxic cells contacting the coastal beaches is communicated via the PNW HAB Bulletin (http://www.pnwhabs.org/pnwhabbulletin/). The level of risk is conveyed using a "traffic light" approach, where a green symbol indicates a low risk of a toxic bloom occurring, and conversely, a red symbol indicates a high risk. The Bulletin is made available to managers and coincides with scheduled openings of the coastal razor clam beaches. As comanagers of the coastal clam resource, Washington State and Native American tribes use the Bulletin to inform their communications with stakeholders, such as sport razor clammers, coastal tourist businesses, and commercial crab fishers and processors, so that they may plan a productive season. The Bulletin also contains a narrative of the rationale behind the forecast which has helped to make the science accessible to managers.

A critical component of the PNW HAB Bulletin is information on *Pseudo-nitzschia* abundance and toxicity obtained from biweekly monitoring at six coastal beaches coordinated by the Olympic Region Harmful Algal Bloom (ORHAB) program (www.orhab.org; Trainer and Suddleson, 2005), a partnership of academic, federal, tribal, and state researchers. When concentrations exceed a size-dependent threshold (50,000 cells/l for large cells and 1 million cells/l for small cells), toxin testing of seawater and shellfish is triggered. The synergistic management approach provided by ORHAB and the PNW HAB Bulletin allows for effective and timely management of the coastal clam resource.

17.5.2 Gulf of Mexico

Over the past two decades, blooms of *K. brevis* have occurred almost annually along the Gulf Coast of Florida, intermittently along the Texas and east Florida coasts, and rarely along the coasts of Louisiana, Mississippi, and Alabama. As these blooms affect large sections of coastline, the most effective form of mitigation is to use a large synoptic framework to prevent exposure to the toxins. The Earth system framework for forecasting toxic *K. brevis* blooms comprises a combination of satellites, buoys, autonomous underwater vehicles (AUVs) and other remote technologies, along with shipboard observations to identify the initial presence of a bloom. Once *K. brevis* is identified and confirmed by water samples, blooms are monitored through the use of this system. Several models have been developed for understanding bloom dynamics and physical transport (see Table 17.1). These include an upwelling prediction model (Lanerolle et al., 2006), a biophysical model developed by Walsh et al. (2006), and a physical circulation model for transport (Weisberg et al., 2009). While complex ecosystem and high-resolution hydrodynamic models are extremely important for understanding bloom dynamics, they are not always conducive to real-time forecasting. Often, a simpler approach can provide improved guidance for mitigating bloom impacts, as the data streams and resolution are not always available in real time.

The two major human health concerns from *K. brevis* are neurotoxic shellfish poisoning (NSP) and respiratory irritation. Florida Department of Agriculture and Consumer Services (FDOACS) use the regulatory limit of 5,000 cells/l for shellfish closures to minimize the risk of NSP. In a comprehensive review on health effects associated with Florida red tide, Kirkpatrick et al. (2004) indicated that once this level is reached, beds remain closed until cell counts remain below this level for over 2 weeks and mouse bioassays indicate that levels in shellfish are below 20 MU/100 g (MU = mouse units). Current remote monitoring systems are not conducive to detection at that level and still rely on the state's system of field water sampling. As opposed to regulating NSP incidents, no regulatory limit exists for exposure to brevetoxin in seawater or air at this time, and a routine monitoring program for brevetoxin does not exist. In Florida, where the blooms occur annually, beaches are not closed even during active nearshore bloom events (Kirkpatrick et al., 2004). The abundance of *K. brevis* that typically leads to respiratory irritation in most people is >50,000 cells/l, densities that can be detected with remote sensing (Tomlinson et al., 2009; Tester et al., 1998). In an effort to predict the impact of *K. brevis* blooms, NOAA's Harmful Algal Bloom Operational Forecast System (NOAA HAB-OFS) was established and has provided HAB forecasts twice a week during the bloom season since 2004 (Stumpf et al., 2009, Figure 17.12). This system is the only operational HAB forecast system within the United States; however, several others have been developed and are being provided through crucial research programs (McGillicuddy et al., 2011). It is important to note that by being operational in the United States, the systems are "sustained, systematic, reliable and robust mission activities with institutional commitment to deliver appropriate, cost-effective products and services" (NOAA, 2008; Wilson, 2011). Although the investment in developing operational HAB forecast efforts is not trivial, significant costs can also occur in system maintenance. Operational systems can also be somewhat static, so planning improvements such as transition of new research tools into operations is crucial.

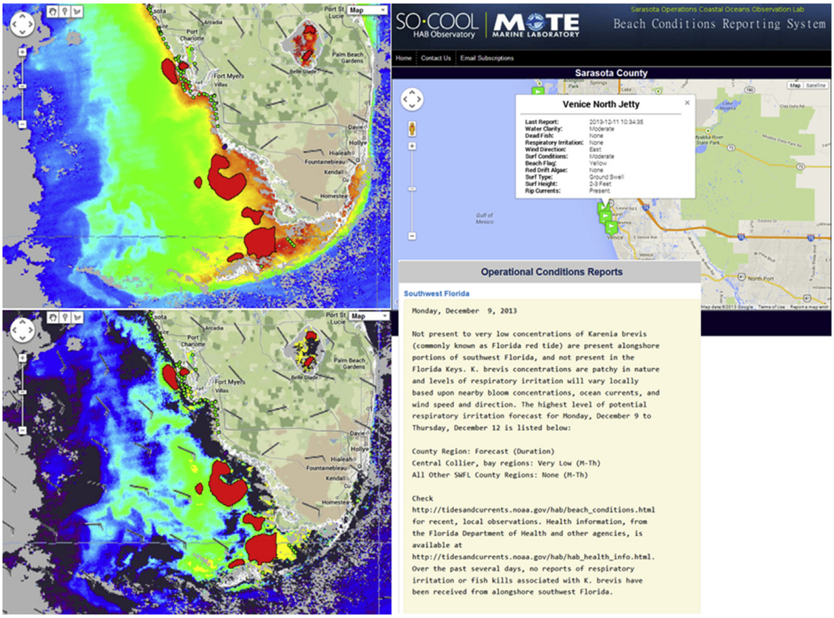

FIGURE 17.12 Western Gulf of Mexico. HAB Operational Forecast System for *Karenia brevis* blooms and brevetoxin events. Top left panel shows chl-*a* imagery from moderate-resolution imaging spectroradiometer-Aqua, with overlaid red polygons indicating likely *K. brevis* bloom due to anomalously high chlorophyll. Bottom right shows chlorophyll anomaly image used to create red polygon features as described in (Stumpf et al. 2013). The beach condition report shown in the top left, provided by Mote Marine Laboratory, provides information on respiratory irritation at individual beaches which, along with imagery and field samples, are used to produce the Operational Conditions Report in the bottom right panel.

The details regarding the development of the forecast have been addressed before (Tomlinson et al., 2004; Fisher et al., 2006; Stumpf et al., 2008, 2009; Wynne et al., 2005). The current forecast for Florida requires a combination of a satellite-derived chlorophyll anomaly product, wind speed and direction from NOAA's buoy system, and field validation and counts of *K. brevis* (provided by the Florida Fish and Wildlife Commission and shellfish bed sampling efforts by FDOACS). Since continental shelf circulation is mostly wind driven out to 50–60 m depth (Wiseman and Sturges, 1999), surface winds (rather than circulation models) are used to predict when the blooms will affect the coast, and how they will move along Florida's Gulf coast. In addition, a combination of cell concentration and wind speed and direction are used to predict the level of the respiratory effects at beaches (Stumpf et al., 2009). The forecasts are issued twice a week and the spatial resolution is at a half-"county" level. Ideally, forecasts would be issued on a beach-by-beach basis to account for the diurnal effect of sea breeze on aerosol contamination. This capability is limited by available technologies and resources (Fisher et al., 2006; Stumpf et al., 2009). Nevertheless, the current forecasts provide guidance for state sampling programs and give the public a general idea where blooms are anticipated to impact beaches. Using this information, individuals can reduce their exposure to the blooms by choosing to visit beaches that are not affected or traveling inland, remaining indoors, and/or changing vacation plans.

A unique aspect of this Earth system framework is that a human sentinel system has been established, where professional lifeguards are equipped with personal data assistants, to provide beach data regarding probable respiratory irritation intensity (i.e., audible coughing), dead fish, water color, wind direction and surf conditions at individual beaches (Kirkpatrick et al., 2008). These data are uploaded in near-real time and used in the analysis reported in the HAB forecasts. An instrument known as the BreveBuster (Kirkpatrick et al., 2000), which analyzes the optical signature of the water column, has been installed at Venice and Naples Piers, FL, USA, to facilitate monitoring. NOAA also purchased a Slocum glider equipped with a BreveBuster to locate the presence of the blooms offshore and subsurface. However, insufficient funding prevents the personnel-intensive AUV running, and these data have been unavailable for improving the forecasts. Even though weather forecasts are issued at an institutional level and significant resources are allocated for better accuracy of the forecasts, marine ecological forecasts are decades away from reaching this goal.

When looking at the cost of respiratory illnesses associated with *K. brevis*, Hoagland et al. (2009) found that just for Sarasota County, FL, USA the capitalized costs of emergency department visits were \$0.5−4 million, depending on the magnitude of the bloom. Since this estimate only takes into account the costs based on respiratory illness, it clearly underestimates the total costs for the region. In a study looking at the loss of revenue for restaurant and lodging sectors near the Ft. Walton Beach and Destin areas of Florida, red tide accounted for the most significant losses compared with tropical storms and precipitation events. For example, average restaurant revenue dropped by 2.9 percent per month during red tide events compared to 4.1−5.7 percent reduction due to hurricane or tropical storm events (Larkin and Adams, 2007). Direct losses to fishing and tourism sectors, including cleanup and subsequent costs, were \$18 million following a bloom event in Galveston County, Texas, in 2000 (Evans and Jones, 2001; Larkin and Adams, 2007). A single 1997−1998 event of *K. brevis* in North Carolina, USA, cost over \$30 million to the fisheries industries (Stumpf and Tomlinson, 2005). Additional costs associated with animal deaths, tourism, increased sampling efforts, to name a few, have not yet been accounted for. Mitigation strategies that communicate possible risk (through poison control center hotlines, signage, education, and outreach materials), facilitate natural resource management (shellfish bed closures, beach cleanup efforts), and guide nutrient control efforts all entail significant costs as well (Hoagland et al., 2009).

Through a CNH system, Hoagland (2014) used *K. brevis* blooms in Florida to describe human interactions with HABs. Although he acknowledged that the role of anthropogenic nutrients in stimulating *K. brevis* blooms continues to be a subject of scientific debate, policies associated with nutrient reduction were suggested to prevent blooms. Mechanisms for reducing nutrients through erosion control, fertilizer reductions, holding ponds for rainwater, and improvements to septic systems and tertiary municipal wastewater treatment plants may be effective. A second policy to reduce human exposure to phycotoxins involves monitoring and forecasts of blooms and increasing efforts to alert the public. The beach condition report that NOAA provides is just one aspect of such a policy that aims to reduce human exposure to brevetoxins in Florida. Other efforts are coordinated by Solutions to Avoid Red Tide and Mote Marine Laboratory to provide educational materials, effective beach signs, and public service announcements; the Aquatic Toxins Hotline established through collaboration with Florida Department of Health and Poison Control Center/Miami; and the "Beach Conditions Report" provided by Mote Marine Laboratory.

17.5.3 Northern European Continental Shelf

A EU project called Applied Simulations and Integrated Modelling for the Understanding of Toxic and Harmful Algal Blooms (HABs) (ASIMUTH) developed short-term forecasts of HAB events along Europe's Atlantic coast from 2010 to

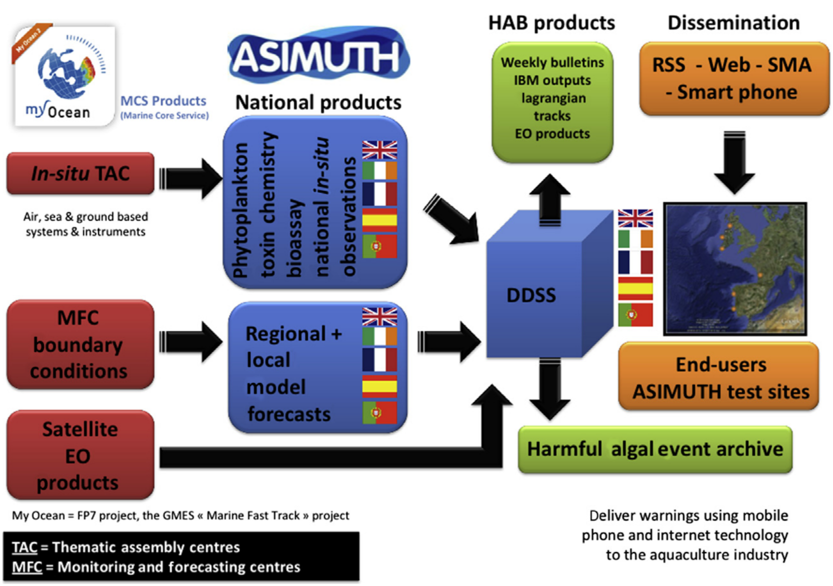

FIGURE 17.13 Northern Europe. Conceptual construct of the ASIMUTH forecasting system that compiles satellite Earth observation products with in situ monitoring and regional models to produce HAB forecasts with feedback to a network of end users in the aquaculture industry across five countries. EO, Earth Observations; RSS, Really Simple Syndication; DDSS, Distributed Decision Support System.

2013 (Figure 17.13), targeting a large range of HAB species and phycotoxins throughout the region (www.asimuth.eu). The project consortium was spread along the Atlantic coast of Europe—Portugal, Spain, France, Ireland, and Scotland—and included research agencies across the EU that are responsible for monitoring and regulating shellfish biotoxins and phytoplankton programs. Operational HAB model forecast systems were developed to track the regional distribution of selected phytoplankton species considered harmful and/or toxic to fin- and shellfish produced commercially by the aquaculture industry. Although local differences occur in existing model structures, physical oceanographic conditions, and species of interest, an important part of the process was the exchange of information (e.g., computer routines, methodologies, HAB alerts between subregions when blooms were likely to enter a neighboring domain) between partners in each EU member state. The operational system was run for a test period in 2013, and several partner countries continue to incorporate the system into operational activities past the lifetime of the ASIMUTH project.

The HAB groups common to all regions are *Dinophysis, Pseudo-nitzschia, Alexandrium,* and *Karenia mikimotoi.* The project sought to establish a new 3- to 4-day forecast service to the European Atlantic aquaculture industry making better use of historical data, current monitoring, and novel technologies. The forecast was delivered as a series of weekly HAB regional alert bulletins published online (http://www.asimuth.eu) with the overarching aim of providing the aquaculture industry and regulatory authorities with an assessment of areas at risk. To achieve this, a fusion of all relevant information from models (hydrodynamic, biogeochemical, biological), remote sensing (satellite and airborne), and in situ observations (monitoring stations) for the northeast Atlantic was assembled with local, experienced individuals in the field interpreting the information from the above data streams to produce a regular HAB bulletin for stakeholders.

17.5.3.1 Hydrodynamic Models

Each partner country developed hydrodynamic models to describe the physical processes in their selected geographical domain. In Ireland, France, and Spain, these models were based on ROMS; in Scotland, the Finite Volume Community Ocean Model (FVCOM) was used to account for Sea Lochs; and the Portuguese Coast Operational Model System/Modelo Hidrodinamico was developed in Portugal. Outputs from the French Mercator-Ocean (system name: PSY2V4), an operational model for the entire North Atlantic, were used for regional model boundary conditions and model initialization. This model provides daily predictions of ocean circulation, the mesoscale features, and ocean water properties (e.g., temperature, salinity, sea surface height). Regional models were run to produce hydrodynamic and ecological predictions, whereas Lagrangian (LPT) models are considered important in the interregional alert systems to track bloom progression between adjacent subregions. In the model domains, HABs were treated as particles and were tracked using the LPT approach, which has proven successful for tracking known HAB populations in the field (Section 17.4.2.2; Velo-Suarez et al., 2010; Mateus et al., 2012). In these cases, particle release and tracking were executed at monitoring stations and their progress modeled to aid assessment of risk to aquaculture operations. Upwelling events, coastal currents, and advection of water masses into aquaculture-producing bays were incorporated into the 3- to 4-day forecasts generated in each country.

17.5.3.2 Biogeochemical Models

Particle tracking is particularly useful for tracking HABs when little is known about aspects of HAB biological behavior. For example, sexual reproduction and resting life cycle stages are still unknown for many species. Where possible, efforts were made to produce models with biological behaviors to use in the forecast system. Ireland and Scotland developed *K. mikimotoi* functional models. Physical parameters including advection, diffusion, and shear were incorporated with biological processes of growth and mortality based on the algorithms developed by Gentien et al. (2007) to estimate progression of these blooms. The Irish model was subsequently modified to include additional behavioral procedures such as diel vertical migration, response to inorganic nutrients and oxygen, preference for ammonia as a source of nitrogen, an ability to kill other species of phytoplankton, and variation in swimming speeds depending on the temperature at depths where growth is most favorable. Mortality rates derived from turbulence, autotoxicity, and sinking were also included. Spain and Ireland use the biogeochemical model developed by Fennel et al. (2006) (also used in the Chesapeake Bay, CBEPS). In Portugal, a biomass-based pelagic biogeochemical model developed by Baretta-Bekker et al. (1995, 1997) is under development to account for all major phytoplankton groups, and in the context of this project, reflects the dynamics of the major HAB species/groups in Portuguese waters.

17.5.3.3 Satellite Remote Sensing

Satellites are an effective platform for obtaining a synoptic view of various water surface characteristics over large spatial areas, and to this end, the European Earth Observation Programme, operated by Copernicus, supports and develops downstream services such as those provided by the ASIMUTH project. Ocean color chl-*a* data are used to detect phytoplankton blooms from space from Moderate Resolution Imagine Spectroradiometer (MODIS) aboard National Aeronautics and Space Administration "Aqua" satellite. With chl-*a* as a proxy for phytoplankton biomass, the location of dense phytoplankton blooms can be detected. Since Northern Europe experiences considerable cloud cover, the North Atlantic merged chlorophyll product developed by French Research Institute for Exploration of the Sea (IFREMER) (Gohin et al., 2002; Saulquin et al., 2011) is used. This product interpolates daily cloudless

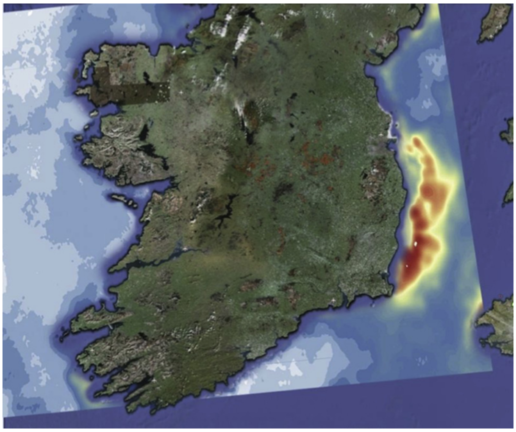

FIGURE 17.14 East Coast of Ireland. The spatial extent of a large *Phaeocystis* bloom in the Irish Sea is apparent in this satellite-derived chlorophyll-a image (moderate-resolution imaging spectroradiometer) from June 2013.

fields of chl-*a* to minimize gaps created by cloud interference, allowing ASIMUTH to identify high-biomass blooms with a potential to cause harm. Investigative work aboard research vessels and monitoring programs validated chl-*a* levels and identified the causative organism. Chl-*a* anomaly routines developed by the Gulf of Mexico *K. brevis* forecast system (Section 17.5.2; Stumpf et al., 2003; Tomlinson et al., 2004) were also used in a modified form to identify new blooms at the surface, whereas satellite-derived sea surface temperature helped define upwelling events and the location of oceanic frontal zones. An example of how Earth observation data were used in ASIMUTH is presented in Figure 17.14; high chl-*a* levels that extended from County Dublin on the east coast of Ireland as far south as County Wexford on the southeast were confirmed from shipboard observations to be *Phaeocystis* spp., and the extent confirmed by airborne observations. The bloom persisted for a month and was monitored using satellite tools. Although it was more of a nuisance (i.e., EDAB) than an HAB, coastal communities were informed of its presence and their concerns were addressed through local and national media. It is anticipated that higher spatial/temporal resolution and number of spectral bands that can detect phytoplankton composition (i.e., functional types) will be fulfilled with the launch of the European Space Agency's Sentinel-3 in 2014.

17.5.3.4 In situ Monitoring

Each European state has a legal obligation to monitor marine HAB species and associated phycotoxins in shellfish. Weekly marine phytoplankton and shellfish samples are collected along the Atlantic coastline, and laboratory data are stored by government institutions. Data were made available to the project by each national monitoring program and were assessed and incorporated into the national forecast bulletins by the local ASIMUTH expert. Additional monitoring is carried out for fish-killing phytoplankton by aquaculture operators

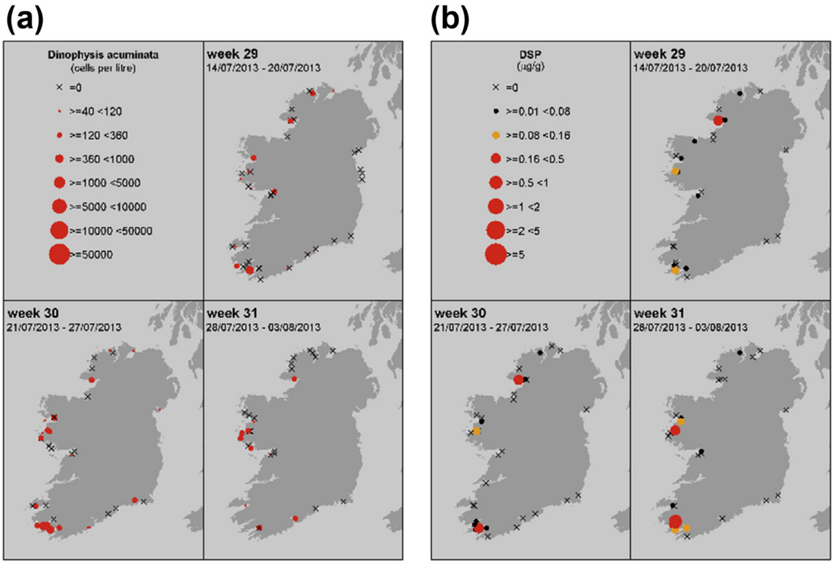

FIGURE 17.15 Irish Coast. Maps of *Dinophysis acuminata* abundance and its associated DSP-producing biotoxin, okadaic acid. (a) *Dinophysis acuminata* levels and (b) okadaic acid levels.

and private laboratories. ASIMUTH used these in situ marine data sets to complement satellite and modeled simulation products on the current state of the marine system, thereby producing time and space distribution maps for the public (Figure 17.15).

17.5.3.5 HAB Reports/Forecasts

A synopsis of each region was prepared using hydrodynamic and biogeochemical simulations, combined with satellite and in situ observations. These were assessed and weekly forecasts prepared, taking other information into account such as historical trends, extent of local events, bloom progression, and ad hoc information from social media streams. Bulletins were produced and made available on a frequent basis when an HAB risk was present (Figure 17.16), and custom-built weekly reports were produced for the target areas in Portugal, Spain, France, Ireland, and Scotland. Aquaculturists deem HAB forecasts a priority; therefore, the bulletin's primary intent was to give an assessment of the current HAB risk to the industry in order to assist in day-to-day management activities. Feedback indicated that: 80 percent of growers who filled out a satisfaction questionnaire were already using the information presented in the regional forecasts; 9 percent of respondents felt that the bulletin contained enough information to make it a useful tool; and 8 percent felt that the ideal forecast would be between 3 days and 1 week (as opposed to 3–4 days). The forecast was very well received, with 6 percent of respondents giving it a "good" or "very good" ranking and the remainder

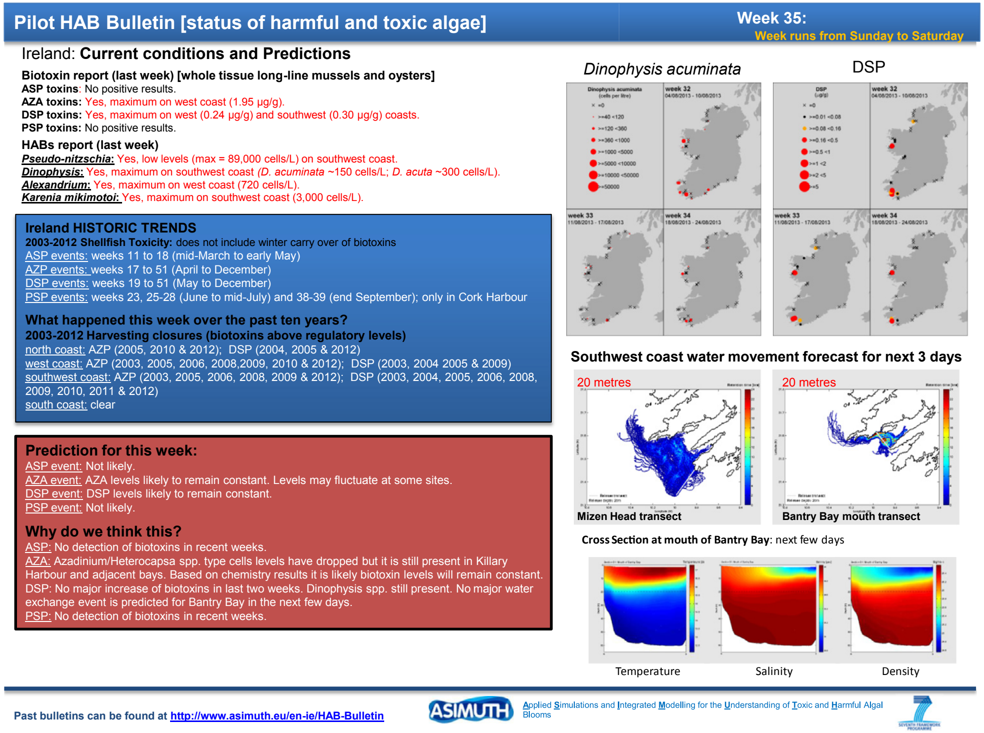

FIGURE 17.16 Excerpt of an ASIMUTH bulletin for the coast of Ireland. HAB and biotoxin summaries for the previous 3 weeks are provided along with summaries of modeled water movement for the region and vertical transects of physical properties measured in the HAB hot spot, Bantry Bay. Historic trends on harvest closures (blue box) and biotoxin predictions for the following 4 days (red box) provide context for end users to interpret forecast significance. ASP, amnesic shellfish poisoning; AZP, azaspiracid shellfish poisoning.

scoring it as "excellent." This was the first time that operational HAB forecasting was made available across the Atlantic countries of the EU, and industry end users confirmed that the ASIMUTH approach to forecasting and information dissemination is a tool that aquaculturists and industry find beneficial in planning and decision making.

17.5.4 California: A Testbed for Integrating Models, Optimal Network Design, and Adaptive Sampling

Research on HABs in coastal California has mostly focused on the DA-producing diatom *Pseudo-nitzschia* that is present throughout the California Current System (CCS; includes the PNW), although *Alexandrium, Dinophysis, Cochlodinium, Gonyaulax, Protoceratium, A. sanguinea, H. akashiwo,* and *Microcystis* (from coastal freshwater sources) also pose a threat. DA poisoning leads to particularly alarming phenomena in aquatic life when it enters marine food webs in the CCS (Scholin et al., 2000; Lefebvre et al., 2002; Bargu et al., 2012), resulting in seasonal strandings or beachings of sea lions, cetaceans, and birds on local beaches. This and the fact that *Pseudo-nitzschia* abundance and DA production can be high during spring and summer phytoplankton blooms has led to preferential treatment of *Pseudo-nitzschia* in HAB modeling studies (Anderson et al., 2009, 2006; Kudela et al., 2010; Schnetzer et al., 2007; Sekula-Wood et al., 2011). Recent research on the detrimental effects of chronic exposure to DA on the brains and reproductive fitness of sea lions has raised new concerns regarding human exposure to seasonally occurring low levels (i.e., detectable but below the regulatory limit for human consumption) of DA in shellfish (Montie et al., 2012). The California Department of Public Health (CDPH) Biotoxins Monitoring program periodically monitors ~50 shore stations for HAB species and phycotoxins (DA and saxitoxin) and also issues a proactive seasonal closure of recreational shellfish harvests. Commercial shellfish growers closely communicate with the CDPH, and some self-monitor their product. However, ever-tightening state and federal budgets have restricted how frequently the CDPH can sample, leading researchers to test alternative methods for alerting the public of HABs and for dually assessing impacts to the ecosystem at large.

Ocean color satellite imagery has been shown to provide good synoptic coverage of chl-*a* biomass in California, particularly for the southern portion of the state (Frolov et al., 2012), but no optical "smoking gun" has been found for inferring *Pseudo-nitzschia*- or DA-specific signatures from chl-*a* retrievals. Anderson et al. (2009, 2011) proposed a second-best solution by mining the statistical relationships between satellite reflectance measurements, *Pseudo-nitzschia* spp. abundance, and DA levels, while also accounting for the more physiologically relevant nutrient and physical properties (such as coastal upwelling) associated with toxic blooms (Section 17.4.2.1). From these and others studies (Anderson et al., 2006; Marchetti et al., 2004; Ryan et al., 2008;

Schnetzer et al., 2007; Trainer et al., 2000), several HAB biomass hotspots within retentive circulation features have been identified in the CCS. Research is now focused on blending satellite observations, hydrodynamic models, and statistical models for CA to spatially map and predict toxic blooms along the coast (Anderson et al., 2011). Physical circulation models already available for use are the ROMS (http://ourocean.jpl.nasa.gov/) and Navy Coastal Ocean Model (NCOM). This capability was evaluated using hindcasts of NCOM coupled to the ecosystem model Carbon, $Si(OH)_4$, Nitrogen Ecosystem model (CoSiNE) (Chai et al., 2002; Lui and Chai, in press), an approach that eliminates the need for satellite imagery and allows predictions to be based on empirical relationships between blooms and nutrient supply. Limitations in the realistic simulation of nutrients and physical fields hinder the immediate application of NCOM-CoSiNE, but a coupled physical−biological approach will be an asset for synoptic forecasts in the future (Figure 17.17(a)).

The modeling methods described here are only one aspect of an alternative approach to an HAB alert system that relies predominantly on shore-based monitoring. Two regional IOOS partnerships offer the ideal opportunity to merge oceanographic observation networks (moorings, HF radar, gliders/AUVs) and state-of-the-art models for managing coastal hazards such as HABs—these are the Central and Northern California Coastal Ocean Observing System (CeNCOOS) and the Southern California Coastal Ocean Observing System (SCCOOS) (Jochens et al., 2010). Kudela et al., (2013) recently identified these IOOS assets as the "most reasonable venue" for improving our HAB forecasting capability, contingent on future investment into IOOS resources. This assessment was partly based on the results of a study that evaluated the spatial and temporal variability of blooms in the CCS relative to existing monitoring from either satellite sensors, shore-based stations, or nearshore moorings (Frolov et al., 2012). Interestingly, the CDPH shore-based monitoring captures more of the regional variability in blooms than either long-term moorings (MBARI and LTER) or pier monitoring conducted by CeNCOOS and SCCOOS but with considerably more personnel effort to routinely cover those 50 stations. Frolov et al. (2012) propose an optimized network after calculating decorrelation scales and showing that blooms more than 4 km offshore are decoupled from those nearshore. The resulting network optimizes placement of offshore moorings (used for targeting the onset of HABs) and minimizes the number of shore-based stations (used for assessing threats to aquaculture) that are necessary to gain the most realistic representation of regional bloom dynamics (Figure 17.17(b)). Although new resources would be required to implement the proposed design, particularly if offshore moorings were to be equipped with expensive ESPs or a similar technology for identifying HAB species, the implication is that over time, this monitoring network would be more cost-effective and helpful for decision making than the current shotgun approach (Frolov et al., 2012).

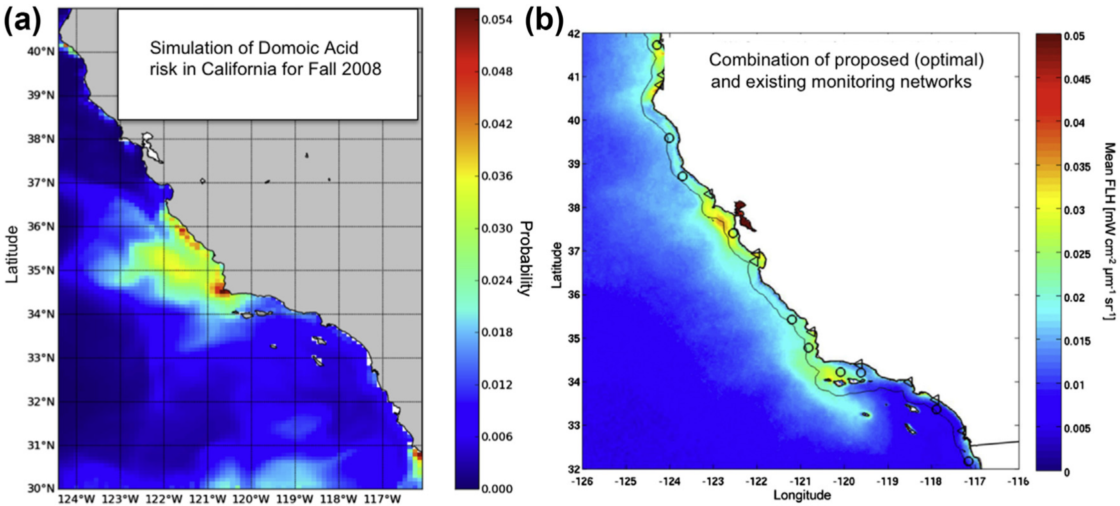

FIGURE 17.17 California. (a) Seasonal hindcast of the probability of a toxic DA event from *Pseudo-nitzschia* blooms created by forcing empirical toxin models with output from a hydrodyanmic model (NCOM) coupled to a complex biogeochemical model (CoSiNE; Anderson et al., 2012a). (b) A map of the existing network of monitoring stations (triangles) and those proposed based on an optimal sampling analysis (open circles) overlaid on the mean Fluorescence Line Height (FLH) (a proxy for phytoplankton blooms) derived from moderate-resolution imaging spectroradiometer- Aqua imagery. An optimal observation network design maximizes how much realistic bloom variability is captured while minimizing effort and cost. *Modified and used with permission from Frolov et al. (2013).*

The combination of an optimal observing system for HABs and operational forecast models with data assimilation (aided by on-going efforts of CeNCOOS and SCCOOS) will open the door for a fully operational early warning system in California. Recognizing the importance of this tight symbiosis between observations and model predictions, the Controlled, Agile, and Novel Observing Network (CANON) is merging these realms during regional process studies that bring together autonomous underwater vehicles, ESP sensors, drifters, numerical models, field experiments, and decision support systems (http://www.mbari.org/canon/). At the event scale, adaptive sampling techniques are being tested with the goal of tuning the models and better directing resources toward the focal point of a targeted feature such as an HAB. In order to smartly guide robotics for high-resolution coastal surveys, Das et al. (2010) culled the available CANON resources to simulate real-time bloom trajectories. They used HF radar surface current data and ROMS output for the Monterey Bay to project the movement of high-biomass features identified with ocean color imagery (Figure 17.18). This is just one example of how a fully integrated observation network could potentially be applied to adaptively sample and manage the impacts of an emergent HAB from its incipient stages offshore to its advection into nearshore environments through optimizing the efficiency of all available resources.

17.6 LIVING WITH HABs

We will likely never eradicate nuisance and harmful algae from aquatic ecosystems. As algal species expand into new territory and adapt to a changing climate, humans will also need to adapt and cope. Population levels along US coasts alone are projected to increase 10 percent by 2020 (NOAA, 2013). With the explosion in coastal development comes a higher likelihood for negative impacts of coastal marine hazards, including HABs. A state space method much like that used by Ramon Margalef in his phytoplankton "mandala" (Margalef, 1978) has recently been proposed to holistically manage our marine resources and promote ecosystem resilience at the regional level (Tett et al., 2013). This approach advocates the use of numerical models to understand decadal trends and to define the boundaries of a useful and functioning ecosystem for environmental managers. At the same time, it is important to realize that traditional boundaries, such as the land−sea interface, are "leaky," providing not just fluxes of nutrients to the coast through both fluvial and groundwater discharge but also transport of freshwater toxins, whereas marine toxins are "transported" inland via the food web and human consumption.

What lessons can we learn from the case studies presented in this chapter? First, all of the successful semi-operational and operational forecasting efforts rely on a close relationship between observations and models. Second, these programs rely on years (if not decades) of research leading to the development of a forecasting capability. Third, despite this research, there is a clear need for

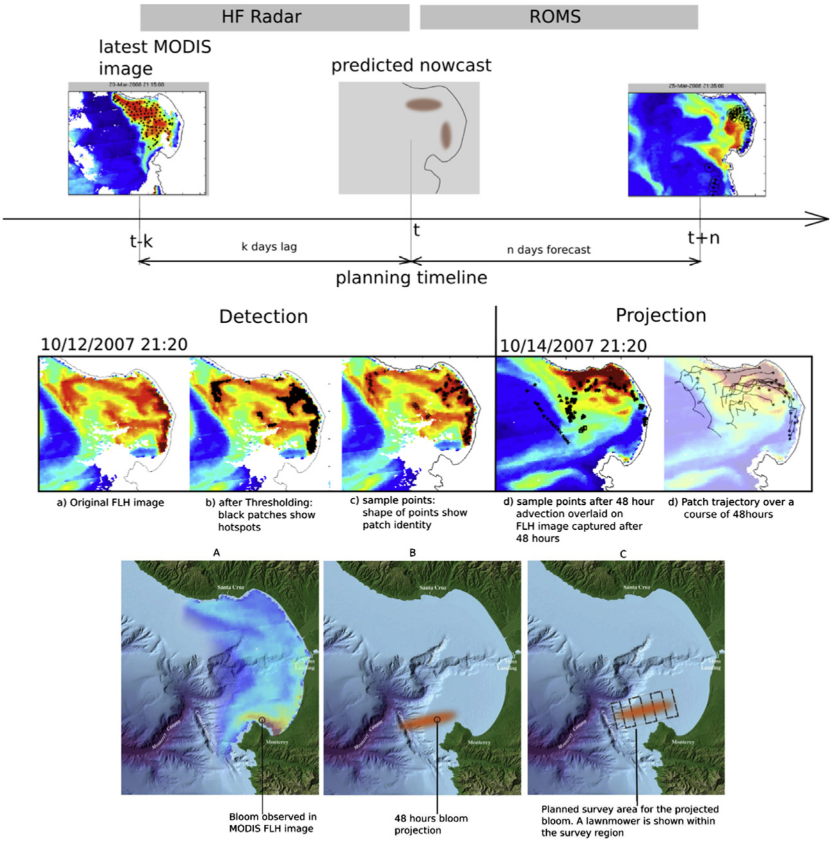

FIGURE 17.18 Monterey Bay, California. Top panel: Conceptual workflow for combining satellite ocean color imagery (MOIDIS-FLH), HF radar, and model (ROMS) platforms to identify a bloom, predict its current location, and project the advection of a high-biomass patch. Middle panel: This method is used to project an October 2007 bloom. Bottom panel: A hypothetical scenario for applying the methodology to adaptively sample a bloom using AUV robotics optimally positioned over a bloom footprint. *Modified and used with permission from* Das et al. (2010).

improved understanding of the underlying ecophysiological mechanisms leading to HABs; this will not be achieved through reliance on the bulk indices (e.g., chl-a, temperature, salinity) initially targeted by GOOS, IOOS, and other regional observing efforts. And finally, although there are many examples for individual regions, we clearly need a comprehensive assessment of the true cost and added value of these systems to adequately articulate the societal benefit of maintaining these efforts.

In summary, models, together with time series observations, are increasingly viewed as tightly coupled to management practices. Building sophisticated decision tools around an Earth system framework that properly accounts for model uncertainty and feedbacks to end user needs requires significant investment from funding agencies. However, many of the advancements are already in place if we consider economies of scale (Green et al., 2009; Weisberg et al., 2009). In the case of HAB mitigation, an integrated Earth observation-modeling framework would not only enhance our understanding of fundamental ecological relationships for constructing better models but also form the backbone of an early warning system, the goal of which is the protection of livelihoods and living resources.

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