The Chesapeake Bay Ecological Prediction System

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Ecological Forecasting

- Predicts the likely changes in ecosystems and their components in response to alteration in the environment
- Helps people, coastal managers and scientists make better decisions
- Extremely challenging: requires integration of physical, chemical, biological, economic, and social factors
- Feasible only recently with improvements in ecosystem understanding, observing systems, modeling, computing, and telecommunications
Ecological Forecasting: Time & Space Scales

Frequency of Forecast

- Year
- Season
- Months
- Weeks
- Days

Spatial Extent of Forecast

- Local
- Regional
- Global

- Climate Impacts
- Ecosystem Change
- Exposure Risk
- Habitat Migration
- Species Abundance
- Invasive Spread
- Disease Transmission
- Hypoxia Formation
- Shellfish Closures
- Spill Response
- Beach Advisories
- Exposure Risk
- Ecosystem Change
- Hypoxia Formation
- Climate Impacts
- Spill Response
- Beach Advisories
- Exposure Risk
Motivation of Ecological Forecasts in Chesapeake Bay

- Chesapeake Bay represents an extremely valuable regional resource

- Noxious conditions and organisms afflict the Chesapeake Bay, adversely effecting aquatic and human health, and local economies

- Predicting the timing and location of these conditions and events will improve monitoring capabilities and aid in mitigating their effects
List of Forecasts

• Physical
  o Temperature
  o Salinity
  o Current velocity
  o Sea Surface Height

• Biogeochemical
  o Nutrient concentrations
  o Phytoplankton, Zooplankton
  o Dissolved oxygen concentrations

• Organismal
  o Sea Nettles (Chrysaora quinquecirrha)
  o Harmful algal blooms
  o Water-borne pathogens

Chesapeake Bay Ecological Prediction System (CBEPS)
Tidal Harmonics

Conditions at Bay’s Mouth
- Near-real time water level
- Monthly climatological vertical profiles of temperature, salinity, and $[\text{NO}_3], [\text{PO}_4], [\text{O}_2]$
ChesROMS Hydrodynamic Model

- 3-D
- Sigma coordinate
- Coarse mesh (100*150*20)
- Horizontal spatial resolution (0.5 – 5 km)
- Validated w/15-year hindcast

ChesROMS grid and bathymetry.
RMS Error of Surface SST & SSS
Empirical - Mechanistic Approach

Using real-time and forecast data acquired and derived from a variety of sources and techniques to drive multi-variate empirical habitat models that predict the abundance or presence of the target species.
Motivation for Hybrid Approach

• Few existing methods work well and in near-real time
  – Satellite remote sensing: low taxonomic resolution
  – In-situ probes: spatially and/or temporally limited
  – Mechanistic modeling: biology of most species not well known
Statistical – Mechanistic Approach

• Based on concept of niche
  – Identifies the geographic locations where ambient conditions coincide with the habitat of target organism

• Feasible
  – Many relevant variables can be acquired, estimated, or simulated in near-real time and forecast

• Approach can be generalized to any location and any organism if sufficient habitat data and access to near-real time environmental data exists
Empirical Model Limitations

• Geographically and temporally limited
• Does not provide insights into the various processes
## Habitat Models Used in CBEPS

<table>
<thead>
<tr>
<th>Species</th>
<th>Model Type</th>
<th>Input Variables</th>
<th>Forecast</th>
<th>Accuracy (correct forecasts/n)</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><em>Chrysaora quinquecirrha</em></td>
<td>Logistic Regression</td>
<td>SST, SSS</td>
<td>Probability of Occurrence</td>
<td>87%</td>
<td>Decker et al., 2007</td>
</tr>
<tr>
<td><em>Karlodinium veneficum</em></td>
<td>Artificial Neural Network</td>
<td>SST, SSS, Month</td>
<td>Relative Abundance</td>
<td>84%</td>
<td>Brown et al., In prep.</td>
</tr>
<tr>
<td><em>Microcystis aeruginosa</em></td>
<td>Artificial Neural Network</td>
<td>SSS, DO, Chla, DIN, TN, NH4, TSS, Kd</td>
<td>Probability of Bloom Occurrence</td>
<td>90%</td>
<td>Ramers et al., Unpublished</td>
</tr>
<tr>
<td><em>Prorocentrum minimum</em></td>
<td>Logistic Regression</td>
<td>Chla, NH4, TON, TSS, Month</td>
<td>Probability of Bloom Occurrence</td>
<td>88%</td>
<td>Ramers et al., Unpublished</td>
</tr>
<tr>
<td><em>Vibrio cholerae</em></td>
<td>Logistic Regression</td>
<td>SST, SSS</td>
<td>Probability of Occurrence</td>
<td>77%</td>
<td>Constantin de Magny et al., 2009; Louis et al., 2003</td>
</tr>
<tr>
<td><em>Vibrio parahaemolyticus</em></td>
<td>Logistic Regression</td>
<td>SST, CHL</td>
<td>Probability of Occurrence</td>
<td>82%</td>
<td>Jacobs et al., In prep.</td>
</tr>
<tr>
<td><em>Vibrio vulnificus</em></td>
<td>Logistic Regression</td>
<td>SST, SSS</td>
<td>Probability of Occurrence</td>
<td>93%</td>
<td>Jacobs et al., 2010; Jacobs et al., In prep.</td>
</tr>
</tbody>
</table>

Chla = chlorophyll-a concentration; SST = sea-surface temperature; SSS = sea-surface salinity; TON = total organic nitrogen; ISS = Inorganic suspended solids
**K. veneficum Habitat Model**

- **Training / Testing Data Set** (n= 151): MD DRN PP
- **Live Count**
- **Habitat Model: Neural Network**
- **Input variables:**
  - Sea-surface temperature
  - Sea-surface salinity
  - Month
- **Output: Relative abundance** (low (0 - 10 cells/ml), medium (10 - 2000 cells/ml), and high or "bloom" (> 2000 cells/ml)

### Validation Confusion Matrix (n=81):

<table>
<thead>
<tr>
<th>Predicted</th>
<th>Low</th>
<th>Med.</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Low</td>
<td>81%</td>
<td>28%</td>
<td>0%</td>
</tr>
<tr>
<td>Med.</td>
<td>13%</td>
<td>61%</td>
<td>0%</td>
</tr>
<tr>
<td>High</td>
<td>6%</td>
<td>11%</td>
<td>100%</td>
</tr>
</tbody>
</table>
K. veneficum Forecasting Skill

Nowcasts

3-Day Forecasts
Predicted *K. veneficum* Relative Abundance
Animation of predicted daily *Karlodinium veneficum* relative abundance from January 1 – December 31, 2005 using the preliminary *K. veneficum* habitat model
Interannual Variability

Hindcasts depicting probability of occurrence of *V. vulnificus* in wet (1996) and dry (1999) years. Both figures represent conditions present on August 1st of each year. Color scale represents probability of occurrence with red high (100%) and blue low (0%).
Next Steps

• Continue validating forecasts
• Develop and incorporate mechanistic models to account for the relevant biotic and abiotic processes
• Predict toxicity and virulence associated with HABs and pathogens
• Assimilate additional sources of environmental information into prediction system
  – Satellite imagery
  – In-situ observations
• Include socio-economic models
• Transition vetted products to NOAA operations
Regional Earth System Model

**Objective**
- Revive and expand the Chesapeake Bay Forecast System -- a fully integrated, ecosystem model of the Chesapeake Bay and its watershed that assimilates *in-situ* and satellite-derived data by adapting and coupling existing models

**CBFS System Components**
- **Air**: Atmosphere - Weather Research and Forecasting (WRF) Model
- **Land**: Land - Soil and Water Assessment Tool (SWAT)
- **Coastal Ocean**: Regional Ocean Modeling System (CBEPS)

**Partners**: UM System, NASA, NOAA
Backup Slides
Forecast Availability

Predictions are generated daily and are available as data files and on the World Wide Web

Sea nettle forecasts: http://chesapeakebay.noaa.gov/remote-sensing-for-coastal-management/forecasting-sea-nettles
## Forecasts Generated by the CBEPS

<table>
<thead>
<tr>
<th>Physical</th>
<th>Biogeochemical</th>
<th>Organismal</th>
</tr>
</thead>
<tbody>
<tr>
<td>Temperature</td>
<td>Nitrate (NO$_3$)</td>
<td><em>Chrysaora quinquecirrhra</em> (scyphomedusa)</td>
</tr>
<tr>
<td>Salinity</td>
<td>Ammonia (NH$_4$)</td>
<td><em>Karlodinium veneficum</em> (dinoflagellate)</td>
</tr>
<tr>
<td>Water density</td>
<td>Dissolved Organic Nitrogen</td>
<td><em>Prorocentrum minimum</em> (dinoflagellate)</td>
</tr>
<tr>
<td>Current velocity (u, v, w)</td>
<td>Chlorophyll</td>
<td><em>Microcystis aeruginosa</em> (cyanobacteria)</td>
</tr>
<tr>
<td>Sea Surface Height (tidal and non-tidal water level)</td>
<td>Inorganic suspended sediments</td>
<td><em>Vibrio cholerae</em> (bacteria)</td>
</tr>
<tr>
<td>Turbulent eddy viscosity</td>
<td>Detritus (small and large component)</td>
<td><em>Vibrio parahaemolyticus</em> (bacteria)</td>
</tr>
<tr>
<td>Turbulent kinetic energy</td>
<td>Dissolved Oxygen</td>
<td><em>Vibrio vulnificus</em> (bacteria)</td>
</tr>
<tr>
<td>Diffuse attenuation coefficient</td>
<td>Phytoplankton</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Zooplankton</td>
<td></td>
</tr>
</tbody>
</table>
K. veneficum Habitat Model Development

- Neural Network (NN) employs sea surface temperature, salinity and month to predict the relative abundance of K. micrum at low, medium and high or “bloom” concentrations.
- NN trained with samples (n = 151) of in-situ K. micrum abundance and various environmental variables.
- A test data set (n = 81) was extracted from the available data to assess the model’s performance.
K. Veneficum Nowcasting Accuracy
Comparison of observed (○) and nowcast (Δ) *K. veneficum* relative abundance at Chesapeake Bay stations in the upper (CB3.3c), mid (CB5.2), and lower (CB6.1) Chesapeake Bay from January 2007 to October 2009.
Predicted *K. veneficum* Relative Abundance

Fish kill in Middle River this November (Bay Journal, Rona Kobell, 11/17/2015)
Enhance Ecological Forecasting

1. Ecological Event Outlook
2. Ecological Event Prediction
3. Ecological Event Forecast
4. Ecological Event Warning

Recovery

Forecast Uncertainty

Minutes
Hours
Days
Weeks
Months

Planned Response
Preparation: Control, Mitigate
Water-Borne Pathogens

• Vibrio Forecasts
  – *V. cholerae*
  – *V. vulnificus*
  – *V. parahaemolyticus*

Courtesy of safeoysters.org
Observed medusa abundance

Temperature (°C)

Salinity

Date

CBL

HPL

Predicted likelihood of occurrence (%)

Observed

Predicted

Forced

CBL HPL
P. minimum Habitat Model

- Training / Testing Data Set: CBP (Morgan State)
- Habitat Model: Logistic Regression
- Input variables:
  - “APR-MAY”
  - Chl a
  - NH4
  - TON
  - TSS
- Output: Probability of Bloom, where a bloom $\equiv$ cell counts $> 3,000$ cells/ml

*Probability of Detection
**M. aeruginosa Habitat Model**

- **Training / Testing Data Set:** MD DRN PP Live Count
- **Habitat Model:** Hierarchical Decision Tree
- **Input variables:**
  - Chlorophyll concentration
  - Sea-surface salinity (SSS)
- **Output:** Probability of Bloom ($P_{blm}$), where bloom $\equiv$ cell counts $> 10,000$ cells/ml
Examples of Chesapeake Bay Species Forecasts

**Sea Nettle**

Predicted likelihood of encountering sea nettles on 17 August 2007.

**Water-borne Pathogen**

Predicted likelihood of *Vibrio vulnificus* on 20 April 2011.

**Harmful Algal**

Predicted relative abundance of *Karlodinium veneficum* on 20 April 2005.
Current Chesapeake Bay HAB Forecasts

**Karlodinium veneficum**

**Prorocentrum minimum**
- Predicted probability of a *P. minimum* bloom on June 20, 2011. Bloom: ≥ 3,000 cells/ml.

**Microcystis aeruginosa**
- Predicted probability of a *M. aeruginosa* bloom on June 20, 2011. Bloom: ≥ 10,000 cells/ml.
Current Chesapeake Bay HAB Forecasts

**Karlodinium veneficum**
- Predicted relative abundance of *K. veneficum* on March 23, 2013

**Prorocentrum minimum**
- Predicted probability of a *P. minimum* bloom on March 23, 2013

**Microcystis aeruginosa**
- Predicted probability of a *M. aeruginosa* bloom on March 23, 2013
Operational Status of Ecological Forecasts in Chesapeake Bay

• Sea Nettles: operational demonstration (NOAA Chesapeake Bay Office)

• Vibrios:
  – *V. cholerae*: research
  – *V. parahaemolyticus*: research
  – *V. vulnificus*: operational demonstration (NCEP)

• HABs: research