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Estimating Productivity Loss Attributed to Deepwater Horizon for Alabama Nearshore Environments

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Estimating Productivity Loss Attributed to Deepwater Horizon for Alabama Nearshore Environments

DRAFT REPORT

OCTOBER, 2015
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Prepared for

Alabama Department of Conservation and Natural Resources
Geological Survey of Alabama

October, 2015
Contents

1 Approach to the Assessment

1.1 Model Selection

1.1.1 AQUATOX Strengths

1.2 Study Area

1.3 Habitats Modeled

1.3.1 Calibration Sites

2 Baseline productivity assessment

2.1 AQUATOX Release 3.1 NME

2.2 Food-web elements

2.3 Input Data

2.4 Salinity and Physical Drivers

2.5 Feeding preferences

2.5.1 Trophic Level Assessment

2.6 Calibration, Verification, and Validation

2.7 Verification of Baseline Productivity—Scientifically Valid Methodology

2.8 Baseline Productivity Verification

2.8.1 Soft-bottom, Open Waters

2.8.2 Oyster Reef

2.8.2.1 Partial Validation (or Verification) followed by Additional Calibration

2.8.3 Marsh Edge

2.8.3.1 Vegetated

2.8.3.2 Unvegetated

2.8.4 Beaches

2.8.4.1 Exposed Beach

2.8.4.2 Protected Beach (with and without seagrass)

2.9 Overview of Baseline Productivity by Site

3 Exposure

3.1 TPAH components

3.1.1 Kow bins selected

3.2 Sediment

3.2.1 Data Sets

3.2.2 Background Levels

3.2.3 Maximum Likelihood Estimation
1 Approach to the Assessment

1.1 Model Selection

The Alabama work follows an application of the AQUATOX model to Mississippi state waters (Clough et. al., 2015). A 22-member technical working group first selected the most appropriate model to estimate productivity losses from the DWH spill incident.

To ensure transparency in the model evaluation and model selection process, a two-part procedure was proposed by the modeling group consisting of a screening step and a numerical evaluation step for those models that passed through the initial screening. Screening criteria were defined by the working group and proposed to the full 22-member team. Any comments received by the larger team were thoroughly incorporated into the screening criteria. The final list of criteria can be found in Table 1 of this document. The central question to be answered by the screening criteria was “What is the best tool that can be applied in terms of the living resources of the MS Sound?” If there was uncertainty as to whether a model should pass a certain screening criteria, the model was generally passed to move on to a more stringent appraisal in the second round of evaluation. Screening criteria were used to evaluate whether a model met the minimum requirements for modeling; models needed to pass all of the screening criteria in order to be considered in the numerical evaluation.

Next, numerical criteria were derived to evaluate the strengths and weaknesses of the models pertaining to the specific needs of the project. There were four primary categories for consideration in the numerical evaluation, considered to have equal weighting:

- Demonstrated model acceptance;
- Thorough characterization of pollutant effects;
- Compatibility with available data; and,
- Availability of technical expertise and resources to adapt the model.

Each of these categories included several considerations as enumerated in Table 1 of this document.

Ten models or suites of models were nominated for consideration by the working group and the larger group. Individuals most familiar with each model evaluated that model based on the screening criteria. The working-group reviewed the screening results and came to consensus about the results. Three models passed through the screening and were subject to a more thorough numerical consideration.

Methods used to assess the models numerically follow. Each model was assigned a “data lead” to gather information on the model to present to the working group. The group then discussed each general category and points of consideration and came to consensus as to the model score for each category. Because two members of the working group had extensive experience working with the AQUATOX model, and a potential conflict of interest, they did not vote on the
numerical score for the AQUATOX model, which was scored exclusively by members of the USM department of Marine Science. The AQUATOX model was also scored last to ensure that considerations of its score did not affect the scoring of the other two models.

Of the three models under consideration RAMAS GIS scored 47 out of a possible 100 points. Some weaknesses of this model include the fact that RAMAS GIS is more of a modeling tool rather than a fully-parameterized model which puts the burden of model creation entirely on the end users. Also ecotoxicology constructs are not directly integrated into the RAMAS GIS model but need to be externally input (for example as limitations to growth rates or increases in mortality rates).

The CASM model scored 67 out of a possible 100 points. CASM is a strong tool in terms of characterization of direct effects and compatibility with available data. Some weaknesses of the CASM model included the lack of a publicly available peer-review panel, incomplete characterization of indirect effects of chemical contamination, limited publicly-available technical documentation, and the proprietary nature of the code base.

The AQUATOX model scored 91 out of a possible 100 points. Some weaknesses of the AQUATOX model included model operating-system or platform flexibility (the software is Microsoft-Windows based) and only moderate regulatory acceptance. The model strengths include thorough characterization of contaminant effects, documentation, transparency, several publicly available peer reviews, and the open-source nature of the code base.

During a one-day meeting of the technical team, after a thorough discussion of modeling domain, data requirements and data needs, the group came to the consensus that future modeling work by this group to model impacts of MC252 should utilize the AQUATOX model.

1.1.1 AQUATOX Strengths

In 1987, the U.S. Environmental Protection Agency (EPA) sponsored a workshop in Baltimore on modeling the fate and effects of toxic organics. The specifications for the AQUATOX model came out of this workshop, and the first paper on the modeling concept was published soon after. Since then, over a 28-year period, the US EPA has developed, documented, and supported the model for wide use at no charge, making the open-source code available through a Common Public License. Subsequently, modeling groups around the world have published a wide range of applications (Figure 1), demonstrating the generality and acceptance of AQUATOX. Furthermore, the model has undergone three successful reviews by independent peer review panels appointed by the EPA (EPA 2015). We built on these demonstrated strengths in adapting the model for the present project.
Figure 1. Worldwide AQUATOX Applications
Table 1. Summary data from Model Selection Process

<table>
<thead>
<tr>
<th>Criteria</th>
<th>AQUATOX</th>
<th>RAMAS GIS</th>
<th>CASMI</th>
<th>C4S</th>
<th>RIVETOX</th>
<th>EcoSim</th>
<th>EFDC linked to Connolly</th>
<th>BASS</th>
<th>EROD, GEQAL-ICM</th>
<th>CSIRO Atlantis</th>
</tr>
</thead>
<tbody>
<tr>
<td>Quantified results can be monetized</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Nearshore marine ecosystem can be characterized</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Keystone &amp; commercial spp. Can be modeled</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Acute &amp; chronic effects of oil &amp; dispersants can be represented</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Can be linked with NOAA models</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Model support available with documentation / equations available in open literature</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>History of successful application to ecotoxicological problems</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Technical expertise available to modify &amp; run model</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Pass to second level?</td>
<td>PASS</td>
<td>PASS</td>
<td>PASS</td>
<td>FAIL</td>
<td>FAIL</td>
<td>FAIL</td>
<td>FAIL</td>
<td>FAIL</td>
<td>FAIL</td>
<td>FAIL</td>
</tr>
</tbody>
</table>

If all screening-level criteria are satisfied then fill in weighted numeric criteria

<table>
<thead>
<tr>
<th>Demonstrated acceptance (25%)</th>
<th>22%</th>
<th>7%</th>
<th>16%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Characterization of effects (25%)</td>
<td>24%</td>
<td>6%</td>
<td>18%</td>
</tr>
<tr>
<td>Compatibility with available data (25%)</td>
<td>21%</td>
<td>18%</td>
<td>19%</td>
</tr>
<tr>
<td>Can represent desired spatial-temporal domain</td>
<td>24%</td>
<td>16%</td>
<td>14%</td>
</tr>
</tbody>
</table>

Four numbers to be filled in for each model; the sub categories indicate considerations when scoring 0-25% by subgroup consensus.
1.2 Study Area

The study area is comprised of Alabama state waters, and is limited to those locations that were subject to observed Deepwater Horizon oiling. Data used to locate the presence of oil include SCAT surveys, NESDIS satellite data products, and oil samples taken from sediment and the water column. The northern portion of Mobile Bay was omitted from the study. The study area is composed of 576 square miles (1491 square kilometers) within Alabama (Figure 2).

1.3 Habitats Modeled

Habitat types for inclusion in the model were delineated using sourced data in a geographic information system (GIS). Three primary habitat categories with multiple subtypes for the shoreline were created to spatially apply modeled results. These include:

1) Soft Bottom
2) Oyster Reef
3) Shoreline
   a. Exposed Beach
   b. Protected Beach with seagrass
   c. Protected Beach without seagrass
   d. Marsh
   e. Marsh with seagrass

One additional mainland feature ("Bulkhead/Riprap") was created to represent hardened shoreline, but was not used in the modeling process. Soft bottom habitat was considered to be all subtidal space greater the one meter depth within the state waters of Alabama and not containing oyster reef or seagrass beds. Bathymetric data was obtained from NOAA and post-processed to a vertical datum of Mean Low Water (MLW) using the NOAA software program VDatum.

Oyster reef habitat in the study area was spatially defined by data obtained from the State of Alabama. The data represent polygon areas where subtidal reef is known to occur based on multiple surveying efforts. A one-hundred meter buffer was added to the outer boundary of the reef habitats to include near-reef habitats with similar biotic characteristics.

The shoreline habitats were initially defined as all area in between the mainland shoreline (Mean High Water – MWH) and the one meter depth contour (-1 m) and then refined based on shoreline type. The estuarine wetland layer from the NWI as well as the USGS marsh type data, and CCAP landcover were used to define locations of coastal marsh. Geographic locations of beach and hardened shoreline were digitized using up to date, high-resolution aerial imagery and a digital polyline database obtained from the Geological Survey of Alabama that represents shoreline type across the Alabama coast. Marsh areas with adjacent seagrass were delineated using seagrass spatial data obtained from the State of Alabama.

Exposed beach represents the sections of the shoreline that are exposed to the Gulf of Mexico. “Protected beach” characterizes beach habitat that is adjacent to the Mississippi Sound and
Mobile Bay on the north side of barrier features. The “Protected beach” category was further delineated into areas that have seagrass and those that do not. Two additional small mainland beach areas in a protected lagoon (east side of study area) and near Point aux Pins (west side of study area) were combined with protected beach due to the small spatial extent of these habitats.

The designated habitats were modeled within four primary simulation types: Marsh, Beaches, Soft Bottom, and Oyster Reefs. Table 2 presents the breakdown of the total study area by habitat in acres and as a percentage of the total aerial coverage. Figure 2 shows the spatial locations of designated habitats.

Table 2. Alabama study area broken down by Habitat Type

<table>
<thead>
<tr>
<th>Habitat Type</th>
<th>Acres</th>
<th>Percentage</th>
</tr>
</thead>
<tbody>
<tr>
<td>Soft Bottom</td>
<td>352,637</td>
<td>95.73%</td>
</tr>
<tr>
<td>Oyster Reef</td>
<td>5,013</td>
<td>1.36%</td>
</tr>
<tr>
<td>Marsh (Vegetated/SAV)</td>
<td>4,524</td>
<td>1.23%</td>
</tr>
<tr>
<td>Marsh (Unvegetated)</td>
<td>2,591</td>
<td>0.70%</td>
</tr>
<tr>
<td>Exposed Beach</td>
<td>1,634</td>
<td>0.44%</td>
</tr>
<tr>
<td>Bulkhead/Riprap</td>
<td>773</td>
<td>0.21%</td>
</tr>
<tr>
<td>Protected Beach Vegetated</td>
<td>643</td>
<td>0.17%</td>
</tr>
<tr>
<td>Protected Beach Unvegetated</td>
<td>561</td>
<td>0.15%</td>
</tr>
</tbody>
</table>
Figure 2. Habitat categories for Alabama AQUATOX

1.3.1 Calibration Sites

For each habitat type, model calibration was carried out in locations with the best combined set of physical-driving data and biotic data to verify primary and secondary productivity estimates (Figure 3)

- One soft-bottom site was chosen towards the center of the system and MODIS data were specifically extracted for that location (labeled “Mobile Bay 3” in Figure 3). Data from Pennock (2002) were available for nutrients loadings. Salinity and temperature were available from the Dauphin Island Sea Lab/ Mobile Bay National Estuary Program dataset (2015) taken from the Dauphin Island site at the mouth of Mobile Bay;
- The dominant oyster-reef site in Alabama (Cedar Point Reef) was chosen and oyster productivity data were available at that site (Gregalis et. al., 2009);
- The dominant marsh system within the AL study area is Point Aux Pins marsh to the northwest of the study area. Extensive data are available from Grand Bay Marsh, within ten kilometers of the study area. The marsh system was therefore calibrated using Grand Bay physical data from Grand Bay NERRS long-term water quality studies (NERRS 2015) and biotic data from Shervette and Gelwick (2008);
Barrier Island calibrations took advantage of rapid-assessment biotic data (Heard and Rakocinski 2012) available just to the east and west of the study area;

More information about model calibration can be found in the section titled “Baseline Productivity Verification” below.

2 Baseline productivity assessment

2.1 AQUATOX Release 3.1 NME

Minor modifications to the latest EPA release of AQUATOX (Release 3.1) were required to improve capabilities for a model of the nearshore marine environment. While no part of Release 3.1 was removed from this version, there were several changes made to the model. The most notable changes in the new version include:

- Additional equations to model the physical complexity of oyster reefs and the marsh-edge environment;
- The capability to model size-classes of oysters (Figure 4) and crabs within the model; and,
- New invertebrate-modeling capabilities including allometric bioenergetics equations and burrowing refuge from predation.
A full accounting of new features in Release 3.1 NME can be found in the Technical Documentation for this version (Blancher et al. 2015). AQUATOX Release 3.1 NME also underwent successful peer review by EPA (EPA 2015).

![Oyster Model Diagram]

Figure 4. Schematic of the AQUATOX 3.1 NME Oyster Size-Class Model

### 2.2 Food-web elements

AQUATOX is intended to be applied as a reasonably detailed food-web model, representing all important taxonomic groups and guilds. Specification of representative groups involved the collective experience of all members of the modeling team, who sought the simplest configuration while still covering the complexities of biotic interactions and susceptibility to toxic effects. Although we tried to develop a comprehensive food web, we recognized that one structure would not cover all habitats. Figure 5 demonstrates the complexity of the implementation. As noted above, in many cases, individual species acted as representatives for larger groups of invertebrates or fish within the food web. Figure 6 includes photos for each of the biotic compartments modeled in these simulations.
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Figure 5. Typical food web modeled in Alabama nearshore waters. Hard bottoms (oyster reefs), marsh edge, and low- and high-energy beaches differ somewhat from the general open-water, soft-bottom configuration shown here.

Figure 6. Photographs of Alabama foodweb components that were modeled.
2.3 Input Data

AQUATOX accepts several forms of input data, a partial list of which follows:

- Point-estimate parameters describing animals, plants, chemicals, sites, and remineralization. Default values for these parameters are generally available from included databases (called “libraries”).
- Time series (or constant values) for nutrient-inflow, organic matter-inflow, and gas-inflow loadings.
- Time series for inorganic sediments in water, water volume variables, and the pH, light, and temperature climates.
- Time series of chemical inflow loadings and initial conditions.
- A trophic matrix must be specified to describe the potential food preferences and quality of food in the simulation.
- Additional parameters may be required depending on which submodels are included (e.g. additional sediment diagenesis parameters.)
- Nearly all point-estimate parameters may be represented by distributions if the model is run in uncertainty mode.

Data used in assessment of the Deepwater Horizon oil spill incident have been subjected to quality assurance.

2.4 Salinity and Physical Drivers

The following data sets were used for salinity, nutrients, and other driving variables:

- **Total Ammonia as N, Nitrate as N, and Total Soluble P**: Site-specific nutrient data from Mobile Bay cruises were used to define the nutrient characteristics for soft-bottom and reef studies (Pennock et al. 2002). From these Mobile-Bay cruises, data stations were selected that were spatially relevant to each study area and averaged. Data from the Northern Gulf Institute (NGI, 2013) were used for beach calibrations. For Point aux Pins marsh, data were taken from Grand Bay NERR long-term water quality studies (NERRS 2015).
- **Carbon Dioxide**: All studies used MS-Sound data from (Pennock et al. 2002). The model is not sensitive to CO$_2$ concentrations in CO$_2$-rich study areas such as found in Alabama coastal waters.
- **Total Suspended Solids**: For soft bottom, marsh and reef simulations, TSS concentrations were estimated using remotely sensed data (MODIS extractions).
- **Salinity**: Time-series observed data were used for all sites. For soft bottom, data from Dauphin Island Sea Lab were available (Dauphin Island Sea Lab/Mobile Bay National Estuary Program, 2015). For beaches data were from USGS East Ship Island. Marsh simulations used data from Grand Bay NERR (NERRS 2015); reefs used data from at Cedar Point, AL (Dauphin Island Sea Lab/Mobile Bay National Estuary Program, 2015).
• **Organic Matter:** For soft-bottom, reef, and marsh simulations, data from Mobile Bay cruises were available that broke down water-column organic matter into dissolved and particulate components (Pennock *et al.* 2002). For beaches, site-specific data were obtained from MS DEQ.

• **Temperature:** For soft bottom, data from Dauphin Island Sea Lab/Mobile Bay National Estuary Program (2015) at the Dauphin Island Site. For beaches, data were from USGS East Ship Island (USGS 2015). Marsh simulations used data from Pennock *et al.* (2002) and reef simulations used data from Dauphin Island Sea Lab/Mobile Bay National Estuary Program (2015) at Cedar Point.

• **Wind Loading:** For beaches, soft bottom and marshes, data from NOAA Bay-Waveland Yacht Club was used. For reefs, wind loadings were from NOAA Pleasure Pier data collected 1999-2001.

• **Light:** Average light and annual light range were set to be the same for all sites based on NASA Surface meteorology and solar energy data.

• **pH:** For marshes, pH levels were set based on Grand Bay long-term water-quality monitoring. For other sites, a constant pH of 7.5 was assumed. The model is not sensitive to pH loadings.

### 2.5 Feeding preferences

A unique food-web was specified for each habitat type and thoroughly vetted by the ecologists on the technical team. AQUATOX calculates food ingestion as a function of the preference a predator has for a prey and also the abundance of that prey item at a given time. Relative preferences are represented in AQUATOX by a matrix of preference parameters. Higher values indicate increased preference by a given predator for a particular prey compared to the preferences for all possible prey (Table 3).
Table 3. Food web excerpt showing feeding preferences for selected fish within marsh habitats

<table>
<thead>
<tr>
<th>Prey Items</th>
<th>Sm. Seatrout Preferences</th>
<th>Pinfish Preferences</th>
<th>Toadfish Preferences</th>
<th>Menhaden Preferences</th>
<th>Seatrout Preferences</th>
</tr>
</thead>
<tbody>
<tr>
<td>Labile Detritus in Sediment</td>
<td>60.1%</td>
<td></td>
<td></td>
<td></td>
<td>9.2%</td>
</tr>
<tr>
<td>Particulate Labile Detritus</td>
<td>10.0%</td>
<td>12.0%</td>
<td>20.0%</td>
<td>9.2%</td>
<td></td>
</tr>
<tr>
<td>Skeletonema</td>
<td></td>
<td></td>
<td>20.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Guinardia</td>
<td></td>
<td></td>
<td>20.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Green, Nannochlorops</td>
<td></td>
<td></td>
<td></td>
<td>20.0%</td>
<td></td>
</tr>
<tr>
<td>Cladophora</td>
<td></td>
<td></td>
<td></td>
<td>9.2%</td>
<td></td>
</tr>
<tr>
<td>Synechococcus</td>
<td></td>
<td></td>
<td></td>
<td>20.0%</td>
<td></td>
</tr>
<tr>
<td>Tanaid Crustacean</td>
<td></td>
<td></td>
<td>6.3%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Amphipod, Ampelisca</td>
<td>6.0%</td>
<td>6.3%</td>
<td>2.3%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Acartia, Copepod</td>
<td>20.0%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Aurelia, Large</td>
<td></td>
<td></td>
<td>9.2%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mediomastus, Polych</td>
<td>1.5%</td>
<td>6.3%</td>
<td>3.7%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Streblospio (sionid) Polych.</td>
<td>20.0%</td>
<td>1.5%</td>
<td>6.3%</td>
<td>3.7%</td>
<td></td>
</tr>
<tr>
<td>Neritina Snail</td>
<td></td>
<td>6.3%</td>
<td>0.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oyster Drill</td>
<td></td>
<td>6.3%</td>
<td>0.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Brown Shrimp</td>
<td>9.9%</td>
<td>6.3%</td>
<td>23.0%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mud-Stone Crab</td>
<td>1.5%</td>
<td>6.3%</td>
<td>3.7%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Blue Crab</td>
<td>1.0%</td>
<td>3.0%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grass Shrimp</td>
<td>6.0%</td>
<td>3.0%</td>
<td>3.2%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anchovy</td>
<td>20.0%</td>
<td></td>
<td></td>
<td>8.3%</td>
<td></td>
</tr>
<tr>
<td>Menhaden post-larval</td>
<td>20.0%</td>
<td>6.3%</td>
<td>2.3%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goby</td>
<td></td>
<td>6.3%</td>
<td>1.8%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Silverside</td>
<td>5.2%</td>
<td>6.3%</td>
<td>1.8%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Spot</td>
<td></td>
<td>6.3%</td>
<td>1.8%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Killifish</td>
<td>5.2%</td>
<td>6.2%</td>
<td>1.8%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sm. seatrout</td>
<td></td>
<td>6.3%</td>
<td>0.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Pinfish</td>
<td></td>
<td>6.2%</td>
<td>0.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Toadfish</td>
<td></td>
<td></td>
<td>0.9%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Menhaden</td>
<td></td>
<td></td>
<td>0.9%</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

2.5.1 Trophic Level Assessment

Further verification of appropriate food-web setup was derived from AQUATOX output of Trophic Level for each organism. This can be verified against observed trophic levels measured from natural dietary markers. For example, Rooker et al. (2006) used stable isotopes and fatty acids to estimate blue-crab trophic levels at 3.4. This value falls nicely within the modeled range of trophic levels for that species (3.0 to 3.8).
2.6 Calibration, Verification, and Validation

Rykiel (1996) defines calibration as “the estimation and adjustment of model parameters and constants to improve the agreement between model output and a data set” while “validation is a demonstration that a model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model.” A related process is verification, which is “a subjective assessment of the behavior of the model” (Jørgensen 1986). The terms are used in those ways in our applications of AQUATOX.

Endpoints for comparison of model results and data should utilize available data for various ecosystem components, preferably covering nutrients, dissolved oxygen, and different trophic levels, and toxic organics if they are being modeled. Although AQUATOX models a complete food web, often only limited biotic data are available.

Verification should consider process rates to confirm that the results were obtained for the correct reasons (Wlosinski and Collins 1985). Rate information that can be compared with observations includes the fluxes of phosphorus, nitrogen, and dissolved oxygen, and all biotic process rates.
There are several measures of model performance that can be used for both calibrations and validations (Bartell et al. 1992, Schnoor 1996). The primary difficulty is in comparing general model behavior over long periods to observed data from a few points in time with poorly defined sample variability. Recognizing that evaluation is limited by the quantity and quality of data, stringent measures of goodness of fit are often inappropriate; therefore, we follow a weight-of-evidence approach with a sequence of increasingly rigorous tests to evaluate performance and build confidence in the model results:

- Reasonable behavior as demonstrated by time plots of key variables—is the model behavior reasonable based on general experience? Are the end conditions similar to the initial conditions? Reasonableness is highly subjective and is not desirable as a line of evidence (see next section), but when observed data are lacking or are sparse and restricted to short time periods it provides a limited reality check, especially during calibration.
- Visual inspections of data points compared to model plots—do the observations and predictions exhibit a reasonable concordance of values? Visual inspection can also take into consideration if there is concordance given a slight shift in time—which is difficult to quantify statistically.
- Do model curves fall within the error bands of observed data? Alternatively, if there are limited replicates, how do the model curves compare with the spread of observed data?
- Do point observations fall within predicted model bounds obtained through uncertainty analysis? This has the limitation of being dependent on the precision of the model; the greater the model uncertainty, the greater the possibility of the data being encompassed by the error bounds.
- Regression of paired data and model results—does the model produce results that are free of systematic bias, as indicated by a non-zero slope with a correlation statistically less than 1?
- Overlap between data and model distributions based on relative bias (rB) in combination with the ratio of variances (F)—how much overlap is there? (See Figure 8) Isopleths assume normal distributions. Relative bias is a robust measure of how well central tendencies of predicted and observed results correspond; a value of 0 indicates that the means are the same (Bartell et al. 1992). The F test is the ratio of the variance of the model and the variance of the data. A value of 1 indicates that the variances are the same.
2.7 Verification of Baseline Productivity—Scientifically Valid Methodology

Because of the scope of the damage assessment, one should not think in terms of overall validation. Instead we are following process-level verification of each step in the model application with limited site validation using independent data from Alabama. In this way we can demonstrate that the model constructs and application are scientifically valid as implied by the Federal Rules of Evidence. The Supreme Court in Daubert v Merrell Dow Pharmaceuticals, Inc. (113 Sup. Ct. 2786 [1993]) “analyzed the language of Rule 702 and found that nothing in the text of the rule ‘establishes ‘general acceptance’ as an absolute prerequisite to admissibility” (Hacker et al. 1998). “Instead, the Court held that, for expert testimony on a scientific matter to have evidentiary reliability, i.e., trustworthiness, the expert’s testimony must be based on information that has scientific validity, i.e., it must be based on the scientific method” (Hacker et al. 1998).
The step-by-step verification and validation of the baseline simulations will be based on the measures described in section 2.6, especially:

- Visual comparison of model predictions of biomass with available observed data for sites in Alabama nearshore waters and similar sites as used in calibration; these will only be used for data taken prior to the first oiling in the study area (assumed to be June 1, 2010);
- Do model curves fall within the error bands of observed data, taking into consideration sources of uncertainty due to biomass conversions and spatial and temporal averaging?
- Do the observed data and simulated results represent statistically similar distributions based on relative bias (relB) in combination with the ratio of variances (F)?

2.8 Baseline Productivity Verification

2.8.1 Soft-bottom, Open Waters

Simulation of biota in soft-bottom open-water habitat utilized a calibration set from Mississippi Sound, with minor adjustments to represent the different salinity regime of Mobile Bay, especially Station “Mobile Bay 3” (Figure 9). In general, simulation results compared favorably with available data including chlorophyll a and biomass of algal groups, zooplankton, zoobenthos and fish.

Figure 9. Location of Soft-bottom studies in Mobile Bay, Mobile Bay 3 was used for initial verification.
Figure 10. Initial calibration of Soft-Bottom study involved fitting simulated chlorophyll a and simulated biomass of algal groups to observed values.
Figure 11. Simulated zoobenthos, zooplankton, and fish biomass compared favorably with available biomass data including means and error bars for copepods and menhaden. Because of their importance in the Northern Gulf of Mexico, estimates of menhaden biomass involved statistical stock reconstruction based on the Gulf Menhaden Stock Assessment (SEDAR32 2013) adjusted for area, including locations of the fishing fleet from the Captains’ Daily Fishing Reports (Leaf and Park 2014).
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Figure 12. Simulated fish were compared with available data for both Mississippi and Alabama, keeping in mind uncertainties in converting density (numbers/trawl) to standing stock (g/m²). Occasional low salinity in Mobile Bay may have affected some fish species.
2.8.2 Oyster Reef

2.8.2.1 Partial Validation (or Verification) followed by Additional Calibration

The initial set of reef parameters from Mississippi was partially validated using data from Cedar Point oyster reef, Alabama (Figure 13), followed by additional calibration. The steps taken were as follows:

- **Partial validation**
  - Used calibrated Pass Marianne, MS study as basis. Changed only boundary conditions:
    - Salinity time series;
    - Temperature time series;
  - Plotted observed Cedar Pt., AL oyster biomass as partial validation (Figure 14);
- **Additional calibration**
  - Recalibrated several invertebrates and fish on basis of additional data. (Figure 15 to Figure 17)
  - Applied revised calibration set to Mississippi reefs and found the results to be an improvement (Figure 18 to Figure 20).
  - Revised calibration set was accepted as final.

Figure 13. Cedar Point Reef Location used in model Validation
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Figure 14. Oyster reef parameter set was partially validated by applying to Cedar Pt. Reef AL with only changes in the salinity and temperature boundary conditions. The mean simulated oyster biomass was an acceptable match to the mean observed data.

Figure 15. Additional biomass data were available for several zoobenthic and fish groups (Gregalis et al. 2009), and these were used for additional calibration of the Cedar Point parameter set and revised application to Miss. reefs.
Figure 16. Recalibration increased predation pressure on oysters from toadfish.

Figure 17. Additional calibration with Cedar Point fish data also improved fit of the simulation.
In the graphs that follow, the Aug. 10 simulation results for each of three Miss. reefs are compared with those of Aug. 18, starting with Pass Marianne Reef with the revised parameter set used for Cedar Point. In each case, with the revised parameter set, there is a better fit of simulated zoobenthos and fish, and simulated oyster biomass fits the very low observed biomass that occurs periodically.

Figure 18. Increased predation pressure lowers mean biomass for each size class of oysters; simulated seasonal low sack oyster biomass now fits observed Pass Marianne data much better.
Figure 19. The revised reef parameter set yields a better fit to the seasonal low observed oyster biomass in the Pass Christian Reef than the previous parameter set.

Figure 20. The revised parameter set gives a better fit to the seasonal low observed oyster biomass on St. Joseph Reef than the previous set.
Because the goodness of fit has improved across the three reefs, the revised parameter set for oysters was accepted and is available for simulation of additional oyster reefs in both Mississippi Sound and in Alabama coastal areas.

Figure 21. The simulated and observed distributions of sack oysters are similar based on means and, to a lesser extent, variances. In order to obtain a true baseline for analysis, the comparisons are for 1/1/2006 to 5/31/2010, ending just before the first exposure to DWH oil.

2.8.3 Marsh Edge

2.8.3.1 Vegetated

Marsh-Edge Studies were primarily calibrated using data from Grand Bay Marsh, which is in the eastern part of Mississippi Sound, just to the west of the Alabama study area, and contiguous to the largest marsh areas modeled within Alabama. Seagrass or submerged aquatic vegetation (SAV) was present at some sites and absent at others. First we will consider simulations of sites with SAV.
Figure 22. Although several macrophyte species occur in the adjacent bays, *Halodule* was used as a typical seagrass that is fairly tolerant of salinity fluctuations but that dies back in the winter. Periphytic algae occur on the macrophytes as well as on bare sediment.

Figure 23. Grass shrimp, and penaeid (brown and white) shrimp are important constituents of the Marsh Edge Habitat. Shrimp harvesting was based on NMFS Shrimp Stock Assessment Forecast (accessed online in 2014), with allowance for closure of the fishery during oiling. Diverse zoobenthos includes blue crabs, mud crabs, polychaetes, and amphipods; they are predicted to occur at about the same order of magnitude as observed data from Point aux Pins.
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Figure 24. The model represents a diverse fish community at Point aux Pins with an acceptable fit to limited total fish biomass data. Total biomass of SAV and fish fluctuate seasonally and exceed the biomass of invertebrate zoobenthos and nekton by factors of 2 to 5.

2.8.3.2 Unvegetated

The same marsh sites were simulated with *Halodule* set to 0 so that there was no SAV in the simulation. SAV is known to provide shelter from predation to many invertebrates and small fish, so it is not surprising that the model predicts lower biomass without SAV than with it. However, based on site observations, the mean depth in the simulations was also changed from 0.33 m, which was characteristic of the SAV sites, to 0.72 m, characteristic of sites without SAV, and this change could have affected the results as well.

Figure 25 Simulated and observed grass shrimp and brown shrimp exhibit lower biomass in the absence of SAV compared to the prior simulations with SAV.
Figure 26. Likewise, there is less fish biomass in the absence of SAV.

Figure 27. By putting the biomass summary graphs from Figure 24 and Figure 26 side-by-side, one can easily see some of the broad impacts that the presence or absence of SAV has within the marsh-edge ecosystems. For example, without SAV to provide additional substrate, periphyton biomass is lower; however, without competition for light, phytoplankton biomass is greater.

2.8.2.3 Application of AQUATOX in Restoration Phase

Although AQUATOX is an ecosystem biomass model, it is capable of representing some important habitat characteristics. In particular, the model can take into account the structural characteristics of the habitat in providing refuge from predation, as documented in the Technical Documentation (Park and Clough 2012).

One such refuge is provided by tidal creeks and the diffuse interface between marsh and water. The irregularity of the marsh-water interface can be represented as a fractal dimension. If the interface were a straight line it would have a fractal dimension of 1.0, corresponding to the Euclidean integer dimension; this is characteristic of coastlines subjected to erosional retreat. Healthy marshes have a fractal dimension in excess of 1.0 (intermediate between the Euclidean
dimensions of a line and a surface). Examples of marsh areas with measured fractal dimensions are taken from Grand Bay on the border between Mississippi and Alabama, as shown below. This capability is used in an example of the potential application of AQUATOX in guiding the restoration of marshes as part of the Natural Resources Damage Assessment (NRDA) process.

Figure 28. A complex marsh-water interface (FD >1) provides refuge from predation; an erosional margin (FD ~ 1.0) offers no additional protection from predation; a marsh that is being inundated may break up into fragments (FD < 0.875) with enhanced predation.

Oyster-reef restoration project at Point aux Pins (Moody et al. 2013) was used as an example of application of AQUATOX model in analyzing the changes in biomass to be expected from differing levels of complexity of the marsh-water interface, represented as the fractal dimension (FD) of that interface. FD of erosional margin = 1.0 (a straight line); FD of complex margin characterized by numerous tidal creeks = 1.5.

Figure 29. An oyster-reef restoration project at Point aux Pins, with restored marsh protected by constructed oyster reefs, sets the stage for analysis of the additional biomass that might be generated because of construction of a more complex marsh edge behind the oyster-reef wave baffles.
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Figure 30. Grand Bay Marsh complex with numerous tidal creeks; AQUATOX represents the complexity of the marsh-water interface with the fractal dimension (FD); the healthy marsh has an FD of 1.47; the straight-line erosional margin, where the marsh borders on Grand Bay, has an FD of 1.01.

Figure 31. Northern part of Grand Bay Marsh complex; the marsh-water interface has a measured FD of 1.52.
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Figure 32. Construction of a sequence of increasingly complex marsh-water interfaces, with changes of FD from 1.1 to 1.5, favors shrimp and other animals that can benefit from the refuge offered by more tidal creeks. Overall, fish are predicted to decline slightly because of disruption of the predator-prey relationships. Comparisons of simulation results for shrimp and fish are based on difference plots to emphasize the progressive increase in protection from predation and the slight negative effect on the predators (especially fish).

Figure 33. The model predicts higher overall biomass for fish in the absence of seagrass (when compared with Figure 32). This is a measure of the more efficient predation when there is no sheltering vegetation—a factor that is simulated in AQUATOX.
2.8.4 Beaches

The barrier islands were the first habitats exposed to DWH oil, and they are an integral part of the application of the model. Beach habitats include Exposed and Protected Beaches, with and without SAV. Because much of the biological data used to calibrate the model were taken from studies of the barrier island systems from Alabama and Mississippi, the calibration of the beach habitats can be assumed to apply to both coasts.

Figure 34. Horn Island, Mississippi is a good example of a barrier island with both exposed and protected beaches and adjacent seagrass meadows. This is comparable to Dauphin Island and Fort Morgan Peninsula, Alabama.

2.8.4.1 Exposed Beach

The exposed beach ecosystem has several characteristics of interest:

- Both detrital- and periphyton-based
- Wave energy is a key factor
- Depth varies with waves
- Greater wave energy implies greater:
  - Detrital loadings
  - Resuspension
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

- Wrack transport
- Periphyton scour

### Beach Calibrations, Exposed Barrier Beach with wave-energy effects implicit in loadings

![Graphs and charts](image)

Figure 35. The range of biomass observed in *Donax*, a fast-burrowing clam characteristic of exposed beaches, indicates the range of wave energy on these beaches. Lower left: the range of *Donax* predicted matches available observations. Lower right: the model exhibits an acceptable fit to other zoobenthic data from exposed beaches.
2.8.4.2 Protected Beach (with and without seagrass)

Figure 36. Beaches that are protected from wave action, such as on the back sides of barrier islands, were successfully modeled with observed detrital loadings.

Figure 37. Protected beaches without adjacent seagrass meadows are assumed to have the same detrital loadings as protected beaches with seagrass; however, without seagrass the total available detritus is less and less productivity is supported, especially fish.
2.9 Overview of Baseline Productivity by Site

All injury assessments for DWH oiling were made by comparing post-oiling TPAH exposures with simulations run at background levels of TPAH exposures. Figure 38 shows the total background secondary productivity for each habitat modeled in units of grams of ash-free dry weight per meter squared per year. When normalized by surface area, the reef habitats are predicted to be most productive followed by the exposed beach, and then the soft-bottom and marsh with SAV habitats. These productivity estimates are comparable to those measured in literature for various estuarine environments (Peterson *et al.* 2009). Productivity estimates can also be considered to be valid based on the calibration of the model to extensive biomass data as discussed above.

![Background secondary productivity by site](image)

Figure 38. Background secondary productivity by site, with relative contributions from Fish and Invertebrate categories.

For each site modeled, the relative contribution to secondary productivity by species/taxon can also be estimated from the analysis. For example, the pie chart below (Figure 39) shows that grass shrimp are the most productive species in terms of secondary production in marsh habitats. In contrast, Figure 40 shows that mud crabs, oysters, and brown shrimp are the most productive elements on the oyster reefs, which is predicted to be much more productive than marsh overall.
Figure 39. Baseline Productivity for Marsh edge (with and without SAV) by species

Figure 40. Baseline productivity for oyster reef by species
3 Exposure

3.1 TPAH components

Total Polycyclic Aromatic Hydrocarbons (TPAH) consists of dozens of analytes that can differ with respect to their volatility, partitioning to organic matter, and toxic effects. To model TPAH with more precision, individual analytes were binned into six different categories using the octanol-water partition coefficient (Kow). The heavier-weight Kow analytes tend to behave similarly in terms of organic-matter partitioning and food-web toxicity is also closely correlated to Kow (see Figure 56 based on Battelle 2007).

3.1.1 Kow bins selected

Based upon available toxicity data, six analytes were initially chosen to represent a range of TPAH Kow values within Alabama water, sediment, and biota. Other PAH analytes were assigned to these categories based on their Log Kow values. NOAA databases of surface sediment TPAH (DIVER Explorer) were analyzed to assign TPAH into these six Kow bins (Figure 41). Table 4 indicates the percentage of AL surface sediment that were found in each Kow bin based on post-DWH AL-specific surficial sediment data.
Table 4. Percentage of TPAH in AL Surface Sediment assigned to each Kow Bin

<table>
<thead>
<tr>
<th>Nominal Assignment</th>
<th>Representative Kow</th>
<th>Percent of TPAH in AL Surface Sediment</th>
</tr>
</thead>
<tbody>
<tr>
<td>“Fluoranthene” bin</td>
<td>5.22</td>
<td>18.34%</td>
</tr>
<tr>
<td>“Benzo(a)pyrene” bin</td>
<td>6.04</td>
<td>45.05%</td>
</tr>
<tr>
<td>“Chrysene” bin</td>
<td>5.79</td>
<td>21.01%</td>
</tr>
<tr>
<td>“Pyrene” bin</td>
<td>5.18</td>
<td>8.22%</td>
</tr>
<tr>
<td>“Anthracene” bin</td>
<td>4.54</td>
<td>5.45%</td>
</tr>
<tr>
<td>“Phenanthrene” bin</td>
<td>4.36</td>
<td>1.93%</td>
</tr>
</tbody>
</table>

As discussed below, sediment-exposure data were simplified to time-series of TPAH for each habitat modeled. The above percentages were then used to break up the TPAH exposures into each of the six Log Kow categories. The most toxic Kow bin (Kow of 6.04) was found to have the highest percentage of TPAH in surface sediments. However, the Log Kow used for toxicity determination (6.04) was close to the minimum Kow in the bin (6.0 to 8.1), meaning that toxic-effects calculations for this bin remain conservative.

3.2 Sediment

3.2.1 Data Sets

Oil-in-sediment data were taken from 2010, 2011, and 2012 post-oiling surface-sediment data within the NOAA NRDA database. Additionally, NOAA provided guidance as to which data should be considered “post-oiling” in 2010 and as to which data would be representative for surface-sediment oil exposures in AL nearshore waters (Personal Communication, Sharock Rouhani, 2014). “Tox PAH 50” data were extracted from the NOAA NRDA database and used to characterize the Kow content in surface sediments, as discussed above, and a spatial and temporal accounting of Total PAH contamination in sediment.

Samples were assigned to habitat designations if they fell within the defined habitat polygon. Unassigned samples within 100 meters of an existing habitat area were also automatically included; a visual inspection of these samples ensured that proper assignment had been made and that the samples were representative of the modeled habitat (Figure 42).
The resulting data set consisted of 312 surface sediment samples relevant to the study area from 2010 to 2012. These samples were binned by habitat-type and year and evaluated using maximum-likelihood estimation as discussed below.

### 3.2.2 Background Levels

Historical oil-in sediment data were extracted from the NOAA NRDA database. 319 historical TPAH surface sediment samples were available in AL ranging in date from 1990 to 2006 with a mean concentration of 62.28 mg/kg (the sum of detected concentrations only). For conservatism and for consistency with MS simulations, 70 mg/kg was used as the baseline TPAH-in-sediment concentration. Simulations run with baseline TPAH concentrations were ultimately compared to simulations run with increased TPAH concentrations following oiling from Deepwater Horizon.

### 3.2.3 Maximum Likelihood Estimation

The “Tox PAH 50” calculation is produced by summing data for up to 50 individual PAH analytes. For these samples, often some of the analytes were detected and others were not detected. This causes a question of how to handle the non-detects within the data set, given knowledge of the “detection limit” for the laboratory method.

Within the study area, some TPAH data were processed with high-precision laboratory methods (resulting in low detection limits) and some were processed with lower precision methods (resulting in much higher detection limits and therefore more uncertainty.) For low-precision samples, assuming either that non-detected samples should be set to zero, or that they should
be set to the detection limit (or half of the detection limit), has the potential to provide misleading information.

Assuming log-normality of these data sets, a maximum-likelihood method estimates the parameters for the distribution that is most likely to fit the observed data, considering both which samples were detected and the detection limits at which the test was conducted (Antweiler and Taylor 2008). This method therefore provides an elegant manner of dealing with the non-detect problem discussed above as it takes into account the precision of each sample. In the case of the “Tox PAH 50” calculation, the estimation can take into account whether a sample with a minimum value (assuming that non-detects equal zero for all analytes) and a maximum value (non-detects equal the detection limit) would fit the distribution. Many different distributions would have a high probability of including a low-precision sample, so the “power” of these samples is reduced within the estimation, though these samples are not discarded.

The maximum-likelihood method requires an assumption of log-normality with the exposure data. In the data-sets with the most available data, this assumption of log-normality was well borne out by the data. For example, marsh samples in 2011 were the bin with the highest number of samples and the most high-precision sampling. Plotting the log-concentration against the z-score would result in a linear fit to a log-normal distribution, and these samples fit a log-normal distribution closely (Figure 43).

![Figure 43. Log-concentrations for “Marsh 2011” plotted against their Z-score, suggesting a log-normal data set.](image)

Using the ML methods, parameters were assigned to log-normal distributions for each set of samples binned by year and habitat.
3.2.4 Percentile Approach

Rather than using a single central tendency to model contamination effects, multiple percentiles were run for each habitat. For example, the 99th percentile sediment concentration was assumed to represent the 1% of habitat that was most contaminated. This method ensured effects from highly-contaminated areas are accounted for, and scaled to the appropriate square-meters, based on observed data. Only the more contaminated percentiles were run and productivity results were compared to background predicted productivity. Based on the difference from background concentrations, twenty-five percentiles were run for each habitat-type modeled (Table 5, Table 6).

Table 5. Accounting of percentiles run for each habitat

<table>
<thead>
<tr>
<th>Percentile</th>
<th>75th percentile</th>
<th>80th percentile</th>
<th>85th and 90th percentiles</th>
<th>95th percentile</th>
<th>97.5th percentile</th>
<th>99th percentile</th>
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</thead>
<tbody>
<tr>
<td>Fraction of Surface Area Represented</td>
<td>represents 5% (75th to 80th)</td>
<td>represents 5% (80th to 85th)</td>
<td>each represent 5%</td>
<td>represents 2.5% (97.5 to 99%)</td>
<td>represents 1.5% (97.5 to 99%)</td>
<td>represents 1% most contaminated</td>
</tr>
<tr>
<td>All Alabama Habitats Modeled</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

When “non-detect equals zero” observed-data percentiles exceeded the percentiles estimated from maximum-likelihood parameters, the observed data were used preferentially. The assumption utilized is that a conservative analysis of observed data (nd=0) indicated that a certain percentage of the habitat was exposed to a high level of contamination; therefore, the observed data provides the most accurate estimation of exposure for that habitat/percentile combination.

Table 6. Sediment concentrations in mg/kg for modeled habitats and years, 75th to 99th percentile

<table>
<thead>
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<tr>
<td>99</td>
<td>1,596</td>
<td>13,309</td>
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<td>144</td>
<td>111</td>
<td>1,504</td>
<td>1,140</td>
<td>882</td>
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</table>

\( n = 89 \ 49 \ 157 \ 67 \ 0 \ n/a \ 71 \ 15 \ n/a \ 19 \ n/a \)
For marshes and protected beaches, inadequate samples were available for 2010 sediment estimates to be produced. For marshes, reverse exponential decay was used to estimate 2010 marsh concentrations based on 2011 and 2012 data. For beaches, the same rates of decay estimated in marshes were used to estimate 2010 and 2012 data.
3.2.5 Time-series Application of Sediment Exposure Data

To create a time series of sediment exposures, data for each “year bin” were assigned to the average date collected in that year (approximately 7/15/2010 and 8/15/2011). An exponential decay was then used to calculate sediment concentrations on periods in between those two dates. For most habitats, given a lack of 2012 data, sediment concentrations were conservatively assumed to decay back down to background levels by 8/15/2012.

TPAH in sediment was then broken into the six named Kow bins (Table 4). TPAH was not directly modeled, but calculated as the sum of the six Kow bins for all media. Data were organic-carbon normalized and concentrations of TPAH in sediment organic matter (labile and refractory sediment detritus) were used as driving variables for the perturbed simulations (Figure 46).
Organic carbon content in sediment was estimated at 1.38% which was the mean of 133 samples taken throughout MS Sound (personal communication MDEQ, 2012). The ratio of organic carbon to organic matter was estimated at 0.526 based on stoichiometry data (a standard AQUATOX assumption, see Park and Clough 2014).

### 3.3 Water Column

#### 3.3.1 Data Sets

Query of the NOAA NRDA database for water-column TPAH concentrations during DWH oiling periods indicated that a large quantity of AL water-column data were non-detects. However, many of these tests were screening for a single highly-volatile analyte that was not even present in water-column analyses of weathered source material (i.e. Napthalene). To correct for this, water-column data were screened as to which analytes were tested and the percentage of TPAH 50 that would be expected based on analytes found in source material. Samples that would expect to detect less than 4% of TPAH were excluded from this analysis. TPAH50 results remaining were then scaled up to 100% of TPAH based on the set of analytes tested. (All samples in the final database had an expected sum that was at least 73% of TPAH 50).

The resulting data set consists of 203 samples with a detection frequency of 69%. For conservatism, the non-detect equals zero assumption was used in this analysis. The average water column concentration was 0.27 ug/L TPAH and the maximum value was 16.5 ug/L TPAH. Background levels of TPAH in the water column were set to 2.47 E-5 ug/L.
### 3.3.2 Timing of Water-Column Exposures

The timing of water-column exposures was specified using data derived from ERMA TCNNA/SAR Data grids for Alabama Waters and compiled by Tom Strange and Don Blancher. For each habitat-type being modeled, an appropriate grid cell was selected. Within that surface area, the approximate oil weight in the slick was calculated based on assumptions about the thickness of the oil and also the density of the oil.

Due to the lack of temporally and spatially synoptic data, it was not possible to create a relationship between water-column observed TPAH data in ug/L and estimated oil weight in each cell. Instead, the oil weight in each cell was used to assign the distribution of observed water-column data using a percentile approach. In a particular habitat, for example, the 95th percentile oil weight, would be assigned to the 95th percentile from observed water-column TPAH data. The resulting data set was therefore constrained by observed water-column data, but the timing of exposure was based on observed density of oil at a given location. A summary of the resulting water-column exposure data set is presented in Figure 47.

![Figure 47. Water-column exposure assumptions and timings for each modeled habitat for the 95th percentile exposure regime.](image)

### 3.3.3 Water-Column Partitioning

Measured dissolved water-column TPAH generally represents both truly-dissolved PAH analytes and PAH analytes that are present in oil micelles (microscopic oil droplets) which can be assumed are not bioavailable via direct gill uptake (Viaene et al. 2014).

For this analysis, dissolved water-column TPAH was assumed to partition within four phases in the water column. The solution below discusses how partitioning to the freely-dissolved phase, microdroplets, and dissolved and particulate organic matter were solved simultaneously.
3.3.3.1 Concentration in aqueous solution

The concentration of dissolved TPAH in the water was assumed to consist of the following four phases:

\[
C_{aq,i} = C_{fd,i} + C_{db,i} + C_{md,i} + C_{sp,i}
\]

where:
- \(C_{aq,i}\) = total aqueous concentration of component \(i\) (mol/L)
- \(C_{fd,i}\) = freely dissolved concentration of component \(i\) (mol/L)
- \(C_{db,i}\) = dissolved concentration of component \(i\) bounded by DOC (mol/L)
- \(C_{md,i}\) = microdroplets concentration of component \(i\) (mol/L)
- \(C_{sp,i}\) = particulate concentration of component \(i\) sorbed to POC (mol/L)

➢ The freely dissolved concentration can be estimated as follows:

\[
C_{fd,i} = x_i \cdot S_i
\]

Raoult's Law

where:
- \(x_i\) = mole fraction of component \(i\) in gasoline phase (mol i free microdroplets/Sum of mol i microdroplets)
- \(S_i\) = aqueous solubility of component \(i\) (mol/L)

➢ The dissolved concentration bounded by DOC was calculated:

\[
C_{db,i} = \chi_{DOC} \cdot D_{DOC} \cdot \alpha_{DOC} \cdot K_{ow,i} \cdot C_{fd,i}
\]

(Arnot and Gobas 2004)

where:
- \(\chi_{DOC}\) = concentration of DOC in water (mg/L)
- \(D_{DOC}\) = disequilibrium factor for DOC partitioning
  - Here: \(D_{DOC} = 1\) ; Assumption: solution is in equilibrium
- \(\alpha_{DOC}\) = proportionality constant
  - Here: \(\alpha_{DOC} = 0.1\) ; “EPA (1998) suggests \(\alpha_{DOC} = 0.1\) for deriving freely dissolved contaminant concentrations in the context of a three-phase partitioning model. This value of \(\alpha_{DOC} = 0.1\) for sediment is consistent with the results of Burkhard (2000).” (Final Model Documentation Report Housatonic River)
- \(K_{ow,i}\) = octanol water partition coefficient of component \(i\) (L/mg)

➢ The oil microdroplet concentration:

\[
C_{md,i} = x_i \cdot C_{MD}
\]

(Redman et al. 2012)

where:
- \(C_{MD}\) = concentration of oil microdroplets (mol/L)
And finally, the sorbed particulate concentration:

\[ C_{sp,i} = \chi_{POC} \cdot D_{POC} \cdot K_{oc,i} \cdot C_{fd,i} \]

(Weston Solutions, Inc. 2006)

where:

- \( \chi_{POC} \) = concentration of POC in water (mg/L)
  - Here: \( \chi_{POC} = \chi_{TSS} \cdot f_{oc} \)
- \( D_{POC} \) = disequilibrium factor for POC partitioning
  - Here: \( D_{POC} = 1 \); Assumption: solution is in equilibrium
- \( K_{oc,i} \) = organic carbon water partition coefficient of component \( i \) (L/mg)

### 3.3.3.2 Combined system of equations

- **PAH**

\[
x_i \cdot S_i \cdot (1 + \chi_{DOC} \cdot \alpha_{DOC} \cdot K_{ow,i} + \chi_{TSS} \cdot f_{oc} \cdot K_{oc,i}) + x_i \cdot C_{MD} = C_{aq,i} \; ; \; i = 1, \ldots, n
\]

- **Remaining oil component**

\[
x_n \cdot C_{MD} = C_{aq,n}
\]

Assumption: everything else is in oil microdroplets

- The total oil sums to one

\[
\sum_{i=1}^{n} x_i = 1
\]

- Non-linear system of \( n+1 \) equations and \( n+1 \) unknowns; \( x_i \) with \( i = 1, \ldots, n \) and \( y = C_{MD} \)

\[
\begin{cases}
    a_i x_i + x_i y = c_{aq,i} & ; \; i = 1, \ldots, n \\
    \sum_{i=1}^{n} x_i = 1
\end{cases}
\]

with \( a_i = S_i \cdot (1 + \chi_{DOC} \cdot \alpha_{DOC} \cdot K_{ow,i} + \chi_{TSS} \cdot f_{oc} \cdot K_{oc,i}) \) for PAH components and \( a_n = 0 \) for remaining oil component.

- By solving for all \( x_i \) and substituting one obtains:

\[
\begin{cases}
    x_i = \frac{c_{aq,i}}{a_i + y} & ; \; i = 1, \ldots, n \\
    \sum_{i=1}^{n} c_{aq,i} / (a_i + y) = 1
\end{cases}
\]
• The final equation has only one unknown – “y” the total oil microdroplet concentration -- and is non-linear.
  - One can use a simple Newton-Raphson iterative method to solve the equation \( f(y) = 0 \)
    \[
y_{k+1} = y_k - \frac{f(y_k)}{f'(y_k)}
    \]
    where \( y_k \) is estimation of \( y \) at iteration \( k \) and \( f'(y) \) is the first derivative with respect to \( y \)
  - here:
    \[
y_{k+1} = y_k + \left( \sum_{i=1}^{n} \frac{c_{aq,i}}{a_i + y_k} - 1 \right) / \left( \sum_{i=1}^{n} \frac{c_{aq,i}}{(a_i + y_k)^2} \right)
    \]

• The initial \( y_0 \) can be set equal to the total measured hydrocarbon concentration or total remaining oil concentration (hydrocarbon concentration-PAHs concentration)
  - Once the total oil microdroplet concentration \( y \) is found, PAH and remaining oil component fractions in oil microdroplets phase can be calculated as:
    \[
x_i = \frac{c_{aq,i}}{a_i + y} ; \quad i = 1, ..., n
    \]

4 Bioaccumulation Parameters

4.1 BCF

The bioconcentration factor (BCF) is an important parameter in AQUATOX toxicity studies. BCF is used both to calculate uptake and depuration rates when estimating internal body burdens (see the equation in section 5.2 below). BCF is also used to convert external toxicity parameters into internal toxicity parameters such as the “critical body burden” (Di Toro and McGrath 2000).

An extensive literature search, aided considerably by the EPA Ecotox database was used to estimate BCFs as a function of Kow for PAH components. 625 BCF values were reported for PAH components across the range of modeled Kows (Personal Communication, Bergeron 2015). Separate relationships were derived for game fish (Figure 48), forage fish (Figure 49), and invertebrates (Figure 50).
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Figure 48. Log Kow to Log BCF relationship used for Game Fish

\[ y = 0.1002x + 2.5973 \]

Figure 49. Log Kow to Log BCF relationship used for Forage Fish

\[ y = 0.4223x + 1.4101 \]
Based upon available data, the AQUATOX option to estimate \( K_2 \) (the depuration rate) and \( \text{BCF} \) (the bioconcentration factor) and to calculate \( K_1 \) (the gill-uptake rate constant) was utilized (Park and Clough 2014). As PAH constituents tend to be metabolized within animals, metabolism also needs to be considered in this calculation. The \( K_1 \) was therefore calculated as follows:

\[
K_1 = \frac{\text{BCF}}{K_2 + KM}
\]

where:
- \( \text{BCF} \) = bioconcentration factor (L/kg dry);
- \( K_1 \) = uptake rate constant (L/kg dry day);
- \( K_2 \) = elimination rate constant (1/d); and,
- \( KM \) = metabolism rate constant for each analyte (1/d).

For all animals, the elimination rate constant (\( K_2 \)) was estimated using the method of Barber (2003). Several alternative methods of calculating elimination rates were considered, all which produced the same inverse relationship between \( \text{Kow} \) and \( K_2 \) (Figure 51). The Barber method was chosen for conservatism as it produces the highest elimination rates and therefore the lowest body burdens. \( K_2 \) elimination was considered additive to biotransformation of TPAH components which was also explicitly modeled.
4.3 Biotransformation

Biotransformation was estimated using PAH-specific data from Arnot’s database of fish biotransformation rates (Arnot et al. 2008). From this database a relationship between whole-body $K_M$ and Log Kow was derived that suggests higher metabolism rates for higher Kow analytes (Figure 52). Using the assumption of Viaene (2014) Invertebrates were assumed to metabolize PAH analytes at one tenth the efficiency of fish.
4.4 Bioaccumulation Verification

As the modeling project was undertaken a number of lines of evidence were examined to ensure that bioaccumulation predictions (internal concentrations within organisms) were producing reasonable estimates. NOAA data for AL organism-tissue samples for 2010 were extremely limited. For modeled organisms, only 35 samples were available, 28 of these being “eastern oyster” samples. This limited the capability to perform direct comparisons of PAH levels in tissues, especially given the rapid metabolism that is presumed to take place for PAH components.

Data from literature were reproduced that verified AQUATOX bioaccumulation calculations for PAHs. For example, Synder et al., (2014) found correlations between Donax clam tissue concentrations and the concentrations of PAHs in the sediment they were embedded within, in the beach sands near Pensacola Beach and Perdido Key. Within AQUATOX, the sediment concentrations were approximated, and Donax tissues closely matched observed Donax tissues (Figure 53).

![Figure 53. AQUATOX input sediment concentrations (left) and output Donax tissue concentrations (right) as compared to data from Snyder and coworkers (2014)]](image_url)

Predictions for TPAH body burden for oysters in Alabama compared favorably to NOAA observed body burdens for the dates where these data were available. However, the 95th percentile AQUATOX simulations for Cedar Point Reef predicted a peak would have occurred between the pre-oiling samples and the post oiling samples collected in the fall. It indicates that the fall sampling likely missed the peak TPAH body burdens in oysters. Similar results were observed in Mississippi oysters (Clough, et al. 2015) but sampling by the Mississippi Department of Health during July did manage to derive some elevated levels of oil in oyster tissues (Xia, et al. 2012) which would support the predictions of elevated body burdens in oysters.
Predictions of body burden for surf clams, *Donax* for NOAA derived data with the 95th and 75th AQUATOX predictions bound observed data for these organisms collected by NOAA in 2011. Similar to the oyster observations, samples were not collected by trustees during the periods corresponding to the dates when major beach oiling events were observed. Again, the reader is referred to the Snyder *et al* (2014) results presented above, which indicate that late summer – fall *Donax* tissues in adjacent Florida beaches which did show elevations on the same order of magnitude as the AL-AQUATOX results.
5 Toxicity Parameters

The AQUATOX model requires LC50 parameters for all organisms and for all toxicants being modeled. The primary data source used for this analysis was NOAA data (NOAA, Stratus Consulting 2014). As NOAA data were presented on a TPAH basis rather than reporting on individual analytes, the AQUATOX model summed all individual components of TPAH modeled (see section 4.1.1) and used that estimate of TPAH within the AQUATOX toxic effects calculations.

When TPAH data were not available, data for individual analytes were used, primarily Fluoranthene data. When Fluoranthene data were used, LC50 data were converted for other compounds based on regression to Log Kow (Figure 56).

Information about additional toxicity-data sources follows:

- A meta-analysis of PAH toxicity data was available from (Battelle 2007). Where multiple measurements were available, the mean LC50 was used;
- Rotifer, Amphipod, Grass Shrimp, Trout, Flounder, and Aurelia LC50s for Fluoranthene came from (Spehar et al. 1999);
- Mud, stone, and adult blue-crab toxicity from (Boese et al. 1997);
- Fathead minnow and rainbow trout data were used from (Batelle 2007);
• For mature spot and black drum, in the absence of data, an adult LC50 placeholder LC50 of 2930 ug/L (100 times the measured EC50) was put into place. This was done to allow calculation of non-lethal effects using the AQUATO X “application factor” method. We confirmed that the model has no sensitivity to this high LC50 value and we are calculating no lethal effects on these organisms. A similar procedure was used for Mole Crab.
• Direct effects to algae effects were based on (Hjorth et al. 2008).

Table 7 summarizes sources of LC50 data for all organisms within the AQUATOX simulations. When data about a specific species were not available, a surrogate species was chosen that was the closest biological match to the species being modeled. Depending on the life history of each organism, photo-enhanced toxicity data (UV data) were either “always used,” “used in shallow simulations only (marsh/beach simulations)” or were “never used.”
### Table 7. Sources of LC50 data used

<table>
<thead>
<tr>
<th>Animal name</th>
<th>Additional Representative Species</th>
<th>NOAA LC50</th>
<th>Additional Literature</th>
<th>UV Data</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotifer, marine</td>
<td>N/A</td>
<td>X</td>
<td>Always</td>
<td></td>
</tr>
<tr>
<td>Tanaid Crustace</td>
<td>N/A</td>
<td>X</td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Mediomastus</td>
<td>Scolelepis</td>
<td>N/A</td>
<td>X</td>
<td>no</td>
</tr>
<tr>
<td>Streblospicio (spionid)</td>
<td>Nephtys</td>
<td>N/A</td>
<td>X</td>
<td>no</td>
</tr>
<tr>
<td>Acartia, Copepo</td>
<td>N/A</td>
<td>X</td>
<td>Always</td>
<td></td>
</tr>
<tr>
<td>Aurelia, Large</td>
<td>N/A</td>
<td>X</td>
<td>Always</td>
<td></td>
</tr>
<tr>
<td>Oyster veliger</td>
<td>Non UV only</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Oyster Spat</td>
<td>Used</td>
<td></td>
<td>no</td>
<td></td>
</tr>
<tr>
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<td>Used</td>
<td></td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Sack Oyster</td>
<td>Used</td>
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<td>no</td>
<td></td>
</tr>
<tr>
<td>Mussel</td>
<td>Surf Clam</td>
<td>Used</td>
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<td></td>
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<td>Amphipod</td>
<td>Ampelisca, Haustorius, Lepidactyl</td>
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<td>X</td>
<td>Marsh/Beach</td>
</tr>
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<td>Marsh/Beach</td>
<td></td>
</tr>
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<td>Bubble Snail, Acteon</td>
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<td>X</td>
<td>Marsh/Beach</td>
</tr>
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<td>X</td>
<td>Marsh/Beach</td>
<td></td>
</tr>
<tr>
<td>Brown Shrimp</td>
<td>Ghost Shrimp White Shrimp</td>
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<td>Marsh/Beach</td>
<td></td>
</tr>
<tr>
<td>Mud &amp; Stone Cra</td>
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<td>X</td>
<td>Marsh/Beach</td>
<td></td>
</tr>
<tr>
<td>Blue Crab</td>
<td>zoea only</td>
<td>X</td>
<td>Always</td>
<td></td>
</tr>
<tr>
<td>Grass Shrimp</td>
<td>X</td>
<td>Always</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Anchovy</td>
<td>Larvae (EC50)</td>
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<td></td>
</tr>
<tr>
<td>Menhaden</td>
<td>X</td>
<td>Always</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Goby</td>
<td>Non UV</td>
<td></td>
<td>Marsh/Beach</td>
<td></td>
</tr>
<tr>
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<td>Pompano</td>
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<td>Always</td>
<td></td>
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<tr>
<td>Spot</td>
<td>EC50 non UV</td>
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<td>no</td>
<td></td>
</tr>
<tr>
<td>Killifish</td>
<td>non UV only</td>
<td></td>
<td>Always</td>
<td></td>
</tr>
<tr>
<td>Black drum</td>
<td>non UV emb</td>
<td></td>
<td>no</td>
<td></td>
</tr>
<tr>
<td>Flounder</td>
<td>non UV emb</td>
<td></td>
<td>Marsh/Beach</td>
<td></td>
</tr>
<tr>
<td>Sm. seatout</td>
<td>Used</td>
<td></td>
<td>Marsh/Beach</td>
<td></td>
</tr>
<tr>
<td>Pinfish</td>
<td>N/A</td>
<td></td>
<td>Marsh/Beach</td>
<td></td>
</tr>
<tr>
<td>Toadfish</td>
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<td></td>
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<td></td>
</tr>
<tr>
<td>Seatrout, Deep</td>
<td>Stingray; Kingfish</td>
<td>Embryo</td>
<td>Marsh/Beach Embryo only</td>
<td></td>
</tr>
<tr>
<td>Seatrout, Marsh</td>
<td>Stingray; Kingfish</td>
<td>Embryo</td>
<td>Marsh/Beach Embryo only</td>
<td></td>
</tr>
<tr>
<td>Blue Crab Zoea</td>
<td>Non UV</td>
<td></td>
<td>Always</td>
<td></td>
</tr>
<tr>
<td>Mole Crab</td>
<td>Zoea (EC50)</td>
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<td>Always</td>
<td></td>
</tr>
<tr>
<td>Ladyfish</td>
<td>Embryo</td>
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<td></td>
</tr>
<tr>
<td>Donax</td>
<td>Oyster Vel.</td>
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<td></td>
</tr>
</tbody>
</table>
Table 8 presents the non-NOAA data that were used in this analysis. By far, the largest data set was available for Fluoranthene. Table 9 presents the NOAA data set. Table 10, shows the alternative data sets used when UV data were used for shallow habitats only. Table 11 presents data that were used for modeling reproductive effects (EC50 reproduction parameters).

Table 8. Fluoranthene LC50s used Adults /Size Class

<table>
<thead>
<tr>
<th>Animal name</th>
<th>LC50 (ug/L)</th>
<th>Hours</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rotifer, marine</td>
<td>1.6</td>
<td>48</td>
<td>Spehar et al. (1999), Daphnia UV</td>
</tr>
<tr>
<td>Tanaid Crustace</td>
<td>30.9</td>
<td>240</td>
<td>Battelle (2007), Corophiid Amphipod</td>
</tr>
<tr>
<td>Mediomastus, Po</td>
<td>500</td>
<td>96</td>
<td>Battelle (2007), Nereis arenaceodentata</td>
</tr>
<tr>
<td>Streblospio (spionid)</td>
<td>500</td>
<td>96</td>
<td>Battelle (2007), Nereis arenaceodentata</td>
</tr>
<tr>
<td>Acartia, Copepo</td>
<td>1.6</td>
<td>48</td>
<td>Spehar et al. (1999), Daphnia UV</td>
</tr>
<tr>
<td>Aurelia, Large</td>
<td>2.2</td>
<td>96</td>
<td>Spehar et al. (1999), hydra w UV</td>
</tr>
<tr>
<td>Amphipod</td>
<td>44</td>
<td>96</td>
<td>Non UV Hyallela Azteca Spehar et al. 1999</td>
</tr>
<tr>
<td>Neritina Snail</td>
<td>500</td>
<td>96</td>
<td>&gt;178, Spehar et al. (1999)</td>
</tr>
<tr>
<td>Oyster Drill</td>
<td>500</td>
<td>96</td>
<td>&gt;178, Spehar et al. (1999)</td>
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<tr>
<td>Mud &amp; Stone Crab</td>
<td>74</td>
<td>24</td>
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<td>Blue Crab</td>
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<td>Grass Shrimp</td>
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<td>96</td>
<td>Spehar et al. (1999), UV</td>
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<td>Anchovy</td>
<td>95</td>
<td>96</td>
<td>Battelle 2007 Battelle 2007, fathead minnow</td>
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<tr>
<td>Menhaden</td>
<td>95</td>
<td>96</td>
<td>Battelle 2007, fathead minnow</td>
</tr>
<tr>
<td>Flounder</td>
<td>500</td>
<td>96</td>
<td>&gt;188, Spehar et al. (1999)</td>
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<tr>
<td>Pinfish</td>
<td>187</td>
<td>96</td>
<td>Battelle 2007, Rainbow trout</td>
</tr>
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<td>Toadfish</td>
<td>187</td>
<td>96</td>
<td>Battelle 2007, Rainbow trout</td>
</tr>
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<td>Seatrout, Deep</td>
<td>187</td>
<td>96</td>
<td>Battelle 2007, Rainbow trout</td>
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<tr>
<td>Seatrout, Marsh</td>
<td>187</td>
<td>96</td>
<td>Battelle 2007, Rainbow trout</td>
</tr>
</tbody>
</table>
Table 9. TPAH LC50s used Adults /Size Class

<table>
<thead>
<tr>
<th>Animal name</th>
<th>LC50 (ug/L)</th>
<th>Hours</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Oyster Spat</td>
<td>150.8</td>
<td>168</td>
<td>NOAA, Stratus Consulting (2014), Test 107</td>
</tr>
<tr>
<td>Seed Oyster</td>
<td>2836.4</td>
<td>96</td>
<td>NOAA, Stratus Consulting (2014), Test 305</td>
</tr>
<tr>
<td>Sack Oyster</td>
<td>2836.4</td>
<td>96</td>
<td>NOAA, Stratus Consulting (2014), Test 305</td>
</tr>
<tr>
<td>Mussel</td>
<td>2836.4</td>
<td>96</td>
<td>NOAA, Stratus Consulting (2014), Test 305</td>
</tr>
<tr>
<td>Brown Shrimp</td>
<td>94.8</td>
<td>96</td>
<td>NOAA, Stratus Consulting (2014), Test 283</td>
</tr>
<tr>
<td>Goby</td>
<td>199</td>
<td>24</td>
<td>NOAA, Stratus Consulting (2014), juv. sheepsheard, Test 137</td>
</tr>
<tr>
<td>Spot</td>
<td>2930</td>
<td>96</td>
<td>Placeholder set above level to cause any effects.</td>
</tr>
<tr>
<td>Black drum</td>
<td>2930</td>
<td>96</td>
<td>Placeholder set above level to cause any effects.</td>
</tr>
<tr>
<td>Sm. seatrout</td>
<td>100.8</td>
<td>96</td>
<td>NOAA, Stratus Consulting (2014), Test 142, larvae</td>
</tr>
<tr>
<td>Blue Crab Zoa</td>
<td>2.9</td>
<td>48</td>
<td>NOAA Test ID 117, HEWAF B, from Jeff Morris 2015 Technical Report</td>
</tr>
<tr>
<td>Mole Crab</td>
<td>1000</td>
<td>96</td>
<td>Placeholder set above level to cause any effects.</td>
</tr>
<tr>
<td>Ladyfish</td>
<td>141.3</td>
<td>96</td>
<td>NOAA, Stratus Consulting (2014), seatrout, juvenile</td>
</tr>
<tr>
<td>Donax</td>
<td>500</td>
<td>96</td>
<td>NOAA, Stratus Consulting (2014), Low to no effect on adults, derived from graph</td>
</tr>
</tbody>
</table>

Table 10. Adult Marsh/ Beach Edge LC50s

<table>
<thead>
<tr>
<th>Animal name</th>
<th>LC50 (ug/L)</th>
<th>Hrs</th>
<th>Chem</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Amphipod</td>
<td>14</td>
<td>96</td>
<td>Fluor*</td>
<td>Boese et al. (1997), w/UV, Rheoxynius abronius</td>
</tr>
<tr>
<td>Neritina Snail</td>
<td>82</td>
<td>96</td>
<td>Fluor</td>
<td>Spehar et al. (1999), UV, freshwater pulmonate</td>
</tr>
<tr>
<td>Oyster Drill</td>
<td>82</td>
<td>96</td>
<td>Fluor</td>
<td>Spehar et al. (1999), UV, freshwater pulmonate</td>
</tr>
<tr>
<td>Brown Shrimp</td>
<td>6.6</td>
<td>96</td>
<td>Fluor</td>
<td>Spehar et al. (1999), same as grass shrimp; UV</td>
</tr>
<tr>
<td>Mud &amp; Stone Crab</td>
<td>74</td>
<td>24</td>
<td>Fluor</td>
<td>Boese et al. (1997), UV, sand crab (Emerita)</td>
</tr>
<tr>
<td>Flounder</td>
<td>0.1</td>
<td>96</td>
<td>Fluor</td>
<td>Spehar et al. (1999), 28 days old</td>
</tr>
<tr>
<td>Sm. seatrout</td>
<td>0.2</td>
<td>72</td>
<td>TPAH</td>
<td>NOAA Test IDs 394, 388, Avg HEWAF A&amp;B, Jeff Morris 2015 Technical Report</td>
</tr>
<tr>
<td>Pinfish</td>
<td>7.7</td>
<td>96</td>
<td>Fluor</td>
<td>Spehar et al. (1999), Rainbow Trout, 30-50 days old</td>
</tr>
</tbody>
</table>

Fluor = Fluoranthenone
Table 11. EC50s applied for Reproduction / Gametes and Larvae

<table>
<thead>
<tr>
<th>Animal name</th>
<th>EC50 (ug/L)</th>
<th>Hrs</th>
<th>Chem</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mussel</td>
<td>1.44</td>
<td>96</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), same as Oyster Veliger; Test 106</td>
</tr>
<tr>
<td>Brown Shrimp</td>
<td>2.9</td>
<td>96</td>
<td>TPAH</td>
<td>NOAA Test ID 261, HEWAF A White Shrimp, from Jeff Morris 2015 Technical Report</td>
</tr>
<tr>
<td>Mud &amp; Stone Crab</td>
<td>19.7</td>
<td>96</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), Non UV, Test 144</td>
</tr>
<tr>
<td>Blue Crab</td>
<td>2.9</td>
<td>48</td>
<td>TPAH</td>
<td>NOAA Test ID 117, HEWAF B, from Jeff Morris 2015 Technical Report</td>
</tr>
<tr>
<td>Anchovy</td>
<td>0.07</td>
<td>48</td>
<td>TPAH</td>
<td>NOAA Test ID 926, Slick B HEWAF, from Jeff Morris 2015 Technical Report</td>
</tr>
<tr>
<td>Spot</td>
<td>29.3</td>
<td>72</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), S. ocellatus, embryos, avg. test 380 &amp; 381</td>
</tr>
<tr>
<td>Black drum</td>
<td>29.3</td>
<td>72</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), S. ocellatus, embryos, avg. test 380 &amp; 381</td>
</tr>
<tr>
<td>Flounder</td>
<td>32.5</td>
<td>24</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), Test 635, S. Flounder, embryo</td>
</tr>
<tr>
<td>Sm. seatrout</td>
<td>N/A</td>
<td></td>
<td></td>
<td>Modeled as size class so EC50 not required</td>
</tr>
<tr>
<td>Seatrout, Deep</td>
<td>24.6</td>
<td>72</td>
<td>TPAH</td>
<td>Non marsh-beach habitats. NOAA, Stratus Consulting. (2014), Test 388, seatrout embryo</td>
</tr>
<tr>
<td>Seatrout, Marsh</td>
<td>0.2</td>
<td>72</td>
<td>TPAH</td>
<td>Used for Marsh and Beach only. NOAA Test IDs 394, 388, UV, Avg HEWAF A&amp;B, Jeff Morris 2015 Technical Report</td>
</tr>
<tr>
<td>Blue Crab Zoea</td>
<td>N/A</td>
<td></td>
<td></td>
<td>Modeled as size class so EC50 not required</td>
</tr>
<tr>
<td>Mole Crab</td>
<td>1.7</td>
<td>96</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), U. Longisignals</td>
</tr>
<tr>
<td>Ladyfish</td>
<td>7.4</td>
<td>96</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), Test 291, Coryphaena</td>
</tr>
<tr>
<td>Donax</td>
<td>1.44</td>
<td>96</td>
<td>TPAH</td>
<td>NOAA, Stratus Consulting. (2014), Test 106, Same as Oyster Veliger</td>
</tr>
</tbody>
</table>

Fluor = Fluoranthene

6 Injury Quantification

Models were run from 2010 to 2012 to calculate predicted growth rates for each exposure percentile run (Table 5). These growth rates were then compared to growth rates in simulations with background levels of contamination. Growth rates were exported for all organisms in g/m² y⁻¹. In the case that indirect effects caused one organism to do better under a contaminated simulation (e.g. increased growth rates because oiling killed a key predator) this increased annual growth rate was not considered a credit to offset the injury.

When normalized to surface area, the largest secondary productivity losses over the three-year simulation period were calculated for reef habitats (Figure 57). Beaches, and particularly protected beaches, were also most vulnerable when looking at the percentage of total productivity that is lost for each site (Figure 58). However, the soft-bottom habitat makes up over 90% of the surface area of the study area, and therefore comprises over 85% of the total injury to secondary productivity (Figure 59). Overall, productivity losses by habitat showed losses ranged from about 0.5% to 4% of baseline productivity over 3 years.
Figure 57. Predicted productivity loss by habitat when normalized to surface area

Figure 58. Percentage of total animal productivity lost by habitat
Figure 59. Percentage of predicted secondary productivity injury in kg, by habitat type
Examining the total injury by species predicted by AQUATOX, shrimp were predicted to form a large portion of the total injury, with brown shrimp especially hard hit (Figure 60). This is especially true as shrimp are predicted to make up a large fraction of the soft-bottom injury (Figure 61). Alternatively, for exposed beaches, ghost shrimp, blue crabs and the planktonic copepod *Acartia* have the highest levels of injury with ghost shrimp making up about 70% of the total injury to this habitat (Figure 62). Keep in mind that while these graphics indicate which species showed the greatest injury, the loss in biomass is relatively small compared to overall productivity.

Figure 60. Fraction of total predicted injuries by species.
Figure 61. Soft-bottom injury predicted in AFDW g/m² in Alabama
Breaking down the injury by oil-exposure percentile levels and by year is instructive in that the results reflects the progression of oiling levels at each of the habitat types over time. We present below a few exemplars of this analysis so the impact can be put into the perspective of an injury-recovery time series.
Estimating Productivity Loss Attributed to Deepwater Horizon for AL Nearshore Environments

Beaches at the 75th-95th percentile-levels were predicted to have minor injuries in 2010 followed by nearly complete recovery by 2011 (red through light blue bars in Figure 63). Exposed beaches at the 99th percentile (pink bar) were predicted to have losses in all three years (pink bars in Figure 63). On the other hand, soft-bottom injuries were predicted to occur later in the simulations (Figure 64), based on higher measured sediment concentrations in 2011 than 2010 (Figure 44).

<table>
<thead>
<tr>
<th>Background</th>
<th>75</th>
<th>80</th>
<th>85</th>
<th>90</th>
<th>95</th>
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<th>99</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>386.6</td>
<td>362.0</td>
<td>362.1</td>
<td>362.2</td>
<td>362.6</td>
<td>362.1</td>
<td>357.9</td>
</tr>
<tr>
<td>2011</td>
<td>419.2</td>
<td>419.5</td>
<td>419.5</td>
<td>419.6</td>
<td>419.9</td>
<td>421.0</td>
<td>421.3</td>
</tr>
<tr>
<td>2012</td>
<td>414.4</td>
<td>414.4</td>
<td>414.4</td>
<td>414.4</td>
<td>414.4</td>
<td>414.4</td>
<td>414.3</td>
</tr>
</tbody>
</table>

Figure 63. Exposed Beach Secondary Productivity Predictions by Percentile 2010 to 2012 in (g AFWD)/(m² yr)

<table>
<thead>
<tr>
<th>Background</th>
<th>75</th>
<th>80</th>
<th>85</th>
<th>90</th>
<th>95</th>
<th>97.5</th>
<th>99</th>
</tr>
</thead>
<tbody>
<tr>
<td>2010</td>
<td>293.4</td>
<td>292.5</td>
<td>292.3</td>
<td>292.3</td>
<td>292.3</td>
<td>292.3</td>
<td>292.3</td>
</tr>
<tr>
<td>2011</td>
<td>289.8</td>
<td>289.3</td>
<td>289.0</td>
<td>288.9</td>
<td>288.3</td>
<td>288.3</td>
<td>288.5</td>
</tr>
<tr>
<td>2012</td>
<td>342.7</td>
<td>336.0</td>
<td>336.1</td>
<td>338.1</td>
<td>336.3</td>
<td>336.6</td>
<td>341.2</td>
</tr>
</tbody>
</table>

Figure 64. Soft-Bottom Secondary Productivity Predictions by Percentile 2010 to 2012 in (g AFWD)/(m² yr)
Injury at the oyster-reef habitat perhaps shows the best exemplar of the impacts from DWH oiling over the period 2010-2012 (Figure 65). A clear injury signal is observed in 2010 at the 95th – 99th levels of exposure with some recovery in 2011. The highest oiled levels still showed significant productivity reductions that are related to oiling through 2011 but then show complete recovery by 2012.

![Figure 65. Oyster Reef Secondary Productivity Predictions by Percentile, 2010-2012 (g AFDW/M2-yr)](image_url)
7 Conclusions

This document presents the methodology and results of a comprehensive modeling effort to estimate losses in productivity in Alabama state waters attributed to DWH oiling. This process involved integration of physical and nutrient data for Alabama nearshore waters; the best-available biotic data; site-specific exposure data for Alabama sediment and waters; and creation of a toxicity database for Total PAH and individual PAH analytes for Alabama’s coastal areas. These data sources were integrated within an EPA-peer-reviewed food-web, chemical-bioaccumulation, and chemical-effects model. The model passed through multiple calibration and validation stages and comparison of model-results to observed data. The resulting injury estimate is the best-available calculation of total food-web productivity damages from DWH oil within Alabama nearshore waters.

Overall injuries at the affected habitats, based on the conservative exposure scenarios predicted by observed oil concentrations, ranged from 0.5% to over 4% of baseline productivity across the various habitat types. Soft bottom showed the lowest injury on a percentage basis but since it represents the major habitat type, the vast majority of losses on a kilogram basis occurred in these habitats. However, the greatest productivity losses on a g/m² basis occurred on the oyster reefs habitats, followed by the exposed and protected beaches on the back-side of Dauphin Island and Fort Morgan peninsula.

The oiling of exposed amenity beaches was very visual to the people of Alabama and the associated tourist industry. For this reason, the area was a high priority for clean-up activities ranging from manual removal to large machinery that “deep cleaned” (sifted) down to 6+ feet of sand. This large response effort removed 3.5 million pounds of oil in the form of tarballs and mats from 84 miles of Alabama beach (Michel et al. 2015). Based on the amount of oil removed from Alabama exposed sand beaches, we assume that the near shore sand beach habitat was exposed to more oiling than was reflected in the sampling conducted for the assessment efforts which occurred largely well after the major beach cleaning efforts. We recognize that it is more than likely that the injury to this nearshore habitat is higher than reflected in this study due to lack of representative oil exposure concentrations during the summer of 2010. In addition, the aggressive mechanical clean-up response also significantly impacted beach productivity, especially between the water edge up to the wrack line. Those impacts are not included in our estimates here but are accounted for in other trustee investigations (Michel, et al. 2015).

Restoration efforts, focused in the highly productive coastal environments described in this report, will enhance the overall productivity of the entire ecosystem and will make significant progress towards “Making Alabama Whole.”
8 References


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