Explanatory Power of Temperature and Salinity Towards the Phytoplankton, Detritus, and Microzooplankton Communities in the Gulf of Mexico

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Introduction

The Gulf of Mexico Large Marine Ecosystem (GoM, hereafter) is a well-mixed, semi-enclosed water body that has two main hydrographic influences: the Loop Current and the Mississippi River. The Loop Current is a warm-water, equatorial current that introduces oligotrophic, warm water into the GoM from the south (between the Yucatan Peninsula and Cuba), transcends into the northeastern portion, and then exists through the Florida Straits (Hurlburt and Thompson 1981). While in the GoM, the Loop Current creates mesoscale eddies that change the environmental conditions of the surrounding water body (Muller-Karger et al. 1991). In the northeastern GoM, the Mississippi River introduces nutrient-rich, low salinity water that advects nutrients offshore (Damien et al. 2018). Seasonally, the productivity increased by the influx of nutrients into the GoM has created a hypoxia region in the neritic zone surrounding the Mississippi delta, which has become more pronounced in recent years (Scavia et al. 2017). Other rivers have a smaller-scale impact on the nutrient concentrations in the coastal GoM (Ramos-Vázquez et al. 2017). An absence of major hydrographic sources in the western basin of the GoM means this region is less dynamic in terms of its water masses when compared to the east (Johnston et al. 2019). Offshore regions (seaward of the 200-m isobath) are also less prone to the significant influx of nutrients brought by the Mississippi River relative to neritic zones (Damien et al. 2018). Hypothetically, regional differences exist in the GoM to the extent that seasonal changes in environmental parameters will have varying influences on the low-trophic level productivity in different regions.

The spatial distribution of marine organisms is often related to the environmental conditions of the water masses in that habitat (Su et al. 2020). Due to the ease and efficacy of data collection from satellites, parameters such as water temperature, salinity, sea surface height, and current velocity are typically associated with the spatial distribution of marine organisms (Su et al. 2020). Based on these environmental characteristics, the GoM can be divided into hydrographic regions on a basin-wide scale (Johnston et al. 2019). These environmental conditions influence the diel vertical migration of mesopelagic organisms, as they must expend energy to move into shallower depths, a process that is made more costly by higher temperatures (Boswell et al. 2020). Apex predators (e.g., tunas and billfishes) utilize certain portions of the GoM for their foraging and spawning grounds, which have been attributed to specific environmental conditions (NOAA NMFS 2017). Pelagic predators will also congregate towards current boundaries that are hotspots of productivity at lower trophic levels (Bakun et al. 2006), which is often used by fishermen. The environmental characteristics of a water mass have an influence on the biota of the GoM on a basin-wide scale, but an understanding of the parameter that most influences biological productivity in different regions would help define the GoM on a more localized scale.

In this study, a dataset introduced by Fennel et al. (2011), which was the first basin-wide biogeochemical model for the GoM, has been adapted. Satellite data are used to attribute the time series of biological model output towards two key environmental parameters, temperature and salinity. An examination of the parameter that correlates that most with the biological data across grid-space is used to determine which environmental parameter is most important towards the productivity in that location.

Methods

This study is focused on the Gulf of Mexico Large Marine Ecosystem, covering the entire basin (Figure 1). The biogeochemical model output used in this exercise originally spanned the study region on a 267 x 279 horizontal grid (1/25th degree horizontal resolution) for each day from 2010-2011. This model was initially designed track phytoplankton and detritus densities in hypoxic regions of the northern GoM (Fennel et al. 2011), but has been assimilated with Bureau of Ocean Energy Management (BOEM) ARGO float data to refine the open-ocean portion (Katja Fennel pers. comm. Dalhousie University). A third dimension included 36-depth layers on a curvilinear grid, meaning that each horizontal grid space has layers spanning different depths. To eliminate the effect of depth differences (and reduce the amount of data), the average value of each parameter (phytoplankton, detritus, microzooplankton) was calculated for each horizontal grid space per day. For brevity, the horizontal resolution was also reduced to form a 23 x 24 horizontal grid (0.5 degree horizontal resolution). The resulting grid spanned the same total area as the original dataset. To relate trends in low-trophic level production to environmental parameters, six variables were chosen: surface temperature, mixed-layer depth temperature (~75 m), temperature below the thermocline (deep layer), surface salinity, mixed layer depth salinity, and salinity below the pycnocline (deep layer). Daily satellite-integrated environmental data were obtained from the HYCOM consortium (www.hycom.org). Initially, these data fit the same resolution as the original biogeochemical model and the grids did not align, so a matching procedure was developed to fit latitude-longitude pairs from each dataset to create a new data array with matching grids.

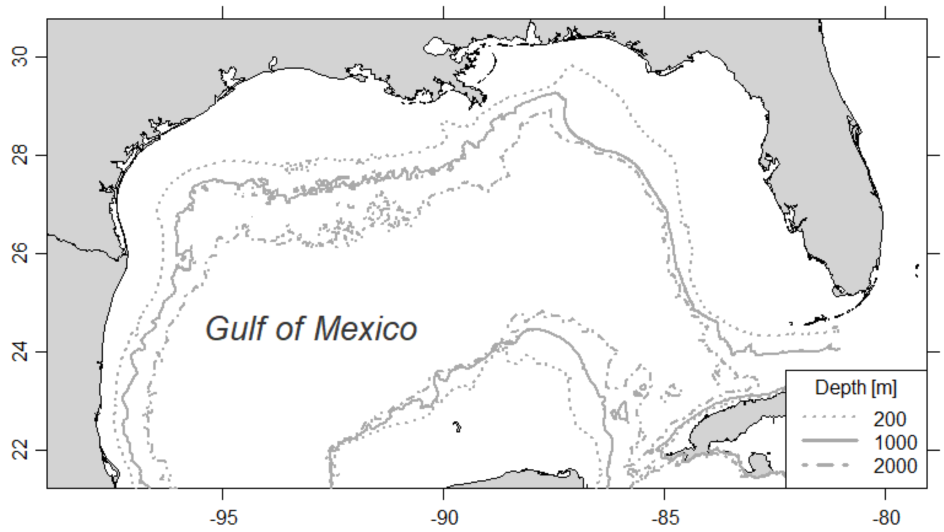

Figure 1. A map of the Gulf of Mexico Large Marine Ecosystem. Contour lines are shown at 200 m, 1000 m, and 2000 m.

Once the datasets were matched together, a series of ARIMA models were developed to examine the time series of the low-trophic level biomass concentrations and environmental variables. For each grid space and each environmental parameter, the low-trophic level time series was decomposed and outliers were removed. The new time series was fit to an ARIMA model, and the Akaike's Information Criterion value was stored. This initial time series was compared to the six environmental parameters, which individually were checked for outliers, fit to an ARIMA model, and each model was compared to the other models for that grid space. Using an AIC selection criterion, the best-fit model was chosen for that grid space, resulting in a new grid showing which parameter was most effective at predicting changes for each low-trophic level parameter in each grid space. Each model was checked for stationarity and residual effects using a p-value of 0.05 as a critical value. This process was completed for phytoplankton, zooplankton, and detritus densities individually.

Results

Overall, the methodology employed during this exercise was successful in finding a parameter that improved the fit to the ARIMA model when compared to the original time series for phytoplankton, detritus and microzooplankton. However, the assumptions of stationarity and residual effects are violated in many grid cells, but these results are reported to maintain consistency with the grid cells that assumptions are not violated.

For phytoplankton, results from the ARIMA model suggest that the eastern portion of the Gulf of Mexico is more prone to the predictability by surface parameters, as opposed to deep-water environmental conditions (Figure 2). In the western Gulf of Mexico and entry waters into the Gulf of Mexico, deep-water parameters have the greatest ability to predict trends in the phytoplankton abundance over time. For the original ARIMA model, the residual assumption appears to be violated for most grid cells, indicating that white noise is a large contributor to the time series.

(Figure 3). For stationarity, the eastern Gulf of Mexico does not have many grid cells that violate the assumptions of the model, but the western Gulf of Mexico does. As for the environmental parameter that best fit the phytoplankton time series, the residual effects were heavily impacted by noise in many areas, particularly the open ocean (Figure 5).

As with phytoplankton, the detritus time series was best explained by surface parameters in the eastern portion of the GoM, and deep parameters in the western GoM (Figure 2). Compared to the phytoplankton time series, less grid cells in the original ARIMA model violate the residual assumption, particularly in the southwest portion and middle of the GoM (Figure 3). The stationarity grid is nearly identical to the phytoplankton time series, but performs a bit worse near the entrance of the southeast GoM (Figure 4). As with the original time series, the environmental parameter that best fits the ARIMA time series performs better than the phytoplankton time series (Figure 5).

The zooplankton time series is not as well explained by either temperature or salinity parameters compared to phytoplankton and detritus (Figure 1). However, the trend of surface parameters explaining more of the eastern portion of the GoM than deep-water parameters still persists. Deepwater parameters were more important towards the explanation of time series trends in the southeastern portion of the Gulf of Mexico for zooplankton, as with the two other parameters. The residual effects for the zooplankton ARIMA suggest there is more noise in this model than the detritus ARIMA, but not the phytoplankton (Figure 3). The stationarity test for zooplankton is nearly identical to that of detritus, suggesting the time series is not time-invariant (Figure 4). The residual effects of the best-fit environmental parameters suggest there is a greater amount of noise in the zooplankton-derived ARIMA than the phytoplankton and detritus ARIMA models.

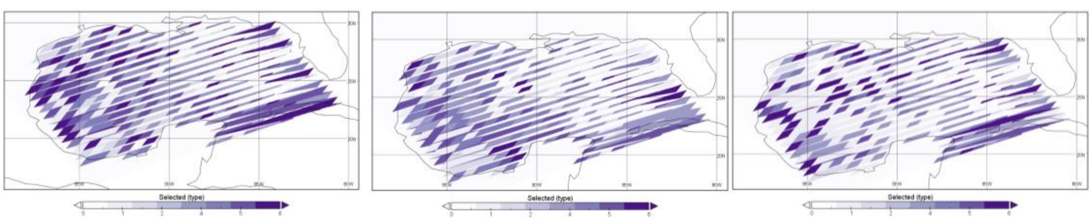

Figure 2. Environmental parameters that were selected as the best fit for each low-trophic level parameter (left = phytoplankton, middle = detritus, right = zooplankton) by the ARIMA models. 0 = No environmental parameter, 1 = surface temperature, 2 = surface salinity, 3 = MLD temperature, 4 = MLD salinity, 5 = deep temperature, and 6 = deep salinity.

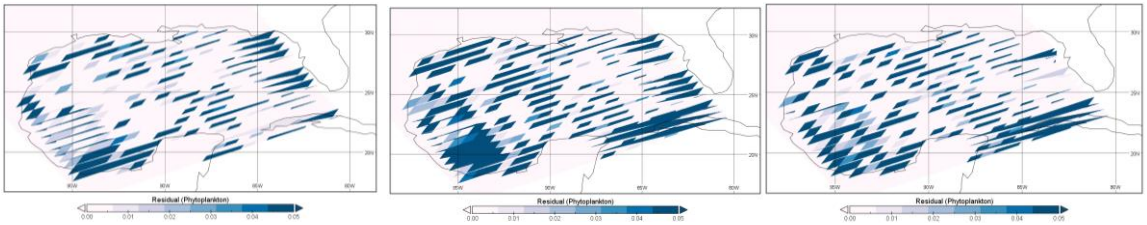

Figure 3. P-values for the residual effects of the original low trophic level ARIMA models (left = phytoplankton, middle = detritus, right = zooplankton). Values less than 0.05 (light green) indicate that noise may be a large part of the model.

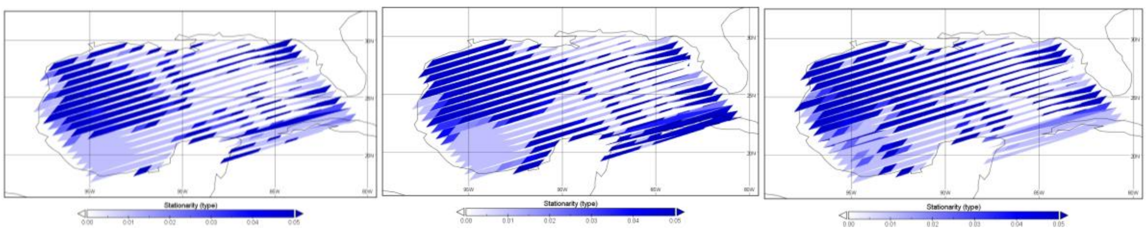

Figure 4. P-values for the stationarity test of the original ARIMA models (left = phytoplankton, middle = detritus, right = zooplankton). Values greater than 0.05 (dark blue) indicate that the model is non-stationary.

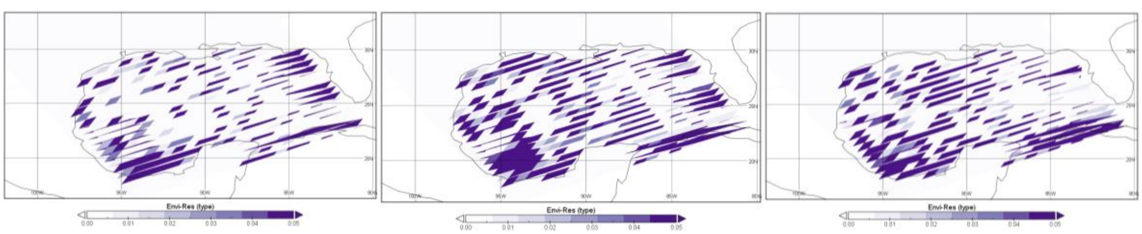

Figure 5. P-values for the residuals of the ARIMA model for the environmental parameters that best fit the ARIMA model (see Figure 1) organized by grid cell.

Discussion

In this study, the predictability of trends in the density of low-trophic level organisms (phytoplankton, detritus, and zooplankton) were examined in relation the temperature and salinity time series at three depth intervals. There was no clear trend in the importance of temperature versus salinity, but depth differences did appear among regions. The western portion of the GoM was paired better with deep-water parameters and the eastern GoM was influenced more by shallow-water parameters. The presence of the Loop Current may explain the influence of shallow water parameters in the eastern basin as this fast-moving current has a greater impact on the near-surface waters and less of an effect deeper than 600-m depth (Johnston et al. 2019). The western basin is more stable, and is thus a less stratified water column than the eastern basin (Damien et al. 2018). Deep-water parameters may have a greater effect on the time series of this region simply because there is not a major hydrographic source that is driving differences in the water masses at various depths. Temperature and salinity likely have the greatest influence on productivity in marine systems, but more advanced models that include other environmental parameters, such as current velocity, may produce results that are more reliable.

This exercise utilized a two-year time series that had a daily time step (n=730) and had a significantly reduced horizontal resolution. Although this is a suitable time-series length for an ARIMA model, the Gulf of Mexico is experiencing rapid changes in terms of hypoxia (Scavia et al. 2018) and harmful algal blooms (Ulloa et al. 2017) that would have a localized influence on the modeled parameters. A longer time series may increase the predictability of low-trophic level parameters, but would also increase the amount of noise produced in the model. A finer-resolution may increase the predictability of grid cells in regions that are currently dominated by white noise, but would significantly increase the run time of the model, which complicates any exercise.

Continuing on the topic of model predictability, several grid cells in this model violate one or more of the assumptions of an ARIMA model. Abiding by stationarity and residual assumptions are critical in the effectiveness of the model to produce a reliable result (McCabe and Tremayne 1995). Therefore, an ARIMA model may not be the best tool to examine this type of question because of the spatial structure of the dataset. The assumption of stationarity assumes that the next step in a time series can be explained by a previous lag in the time series, suggesting a one-dimensional relationship with time (McCabe and Tremayne 1995). Spatially dependent coefficients (e.g., advection of nutrients) will likely have an effect on the production at low trophic levels in a given grid cell at the next time step (Hoffman and Murphy 2004). Future iterations of this project should include spatial-autocorrelation procedures, such as a conditional autoregressive model or spatial eigenvector mapping (Dormann et al. 2007).

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