EEB313 Final Report – Silas Peters and Naveen David

Abstract

Plankton are integral to marine ecosystems and past studies show they may be affected by acidification. However, studies that span across geographic ranges or taxonomic groups are lacking. Our study addresses how plankton in the north Atlantic are affected by acidification, using plankton diversity and partial pressure of CO_2 as measures. Time series analysis and linear modelling show diversity is increasing alongside pCO_2. This does not fit our initial predictions. Our study shows that, at its current trajectory, ocean acidification is not largely affecting the overall diversity of plankton in this geographic region.

Introduction

Past research has demonstrated that certain taxa of plankton are susceptible to ocean acidification through direct effects (Riesbesell et al., 2017) and indirect effects (Cripps et al., 2016). Prior studies into this topic have largely focused on specific regions and taxa (EX – Spisla et al., 2021); thus, our understanding of how ocean acidification affects plankton across larger geographic scales or taxonomic groups is limited. To work towards filling this gap in our understanding, we chose to investigate how acidification affects plankton in the north Atlantic (focusing on a wide geographic range and taxa). Our hypothesis is that an increase in pCO_2 (i.e., increase in acidification) will affect plankton diversity. As some taxa are susceptible to acidification (Riesbesell et al., 2017; Cripps et al., 2016; Spisla et al., 2021), we predict that increases in pCO_2 will lead to a decrease in diversity as susceptible taxa decrease in abundance.

Methods

The plankton data is from the Continuous Plankton Recorder (CPR) Survey (Helaouet et al., 2024), accessed through the Biological & Chemical Oceanography Data Management Office (BCO-DMO). The dataset contains data from the western North Atlantic Ocean (N: 64.91, E: -23.09, W: -74.74) from 1958 to 2021 (Helaouet et al., 2024). Plankton is collected using Continuous Plankton Recorders which are towed behind ships at a depth of seven metres and plankton are identified by experts (Richardson et al., 2006). The data frame was pivoted longer, and Shannon's Diversity Index was calculated using the package *vegan* in R (Oksanen et al., 2024). The pCO_2 data was obtained from a quality-controlled NOAA database including information from multiple expeditions (Takahashi, Sutherland & Kozyr, 2019). It was first filtered to spatially overlap with the geographic range of the plankton data. Both datasets were then filtered for the years 1991 – 2018 to ensure the longest span of continuous data. Finally, the median pCO_2 observation for each year was taken.

A time series analysis was performed first. With only one observation per year, decomposition was not possible. A cross-correlation was performed to examine how diversity at time t and pCO_2 at time t+h are related (Penn State Department of Statistics, n.d.; Righetti, 2022). An ARIMA model of current diversity and pCO_2 data was auto-fitted with auto.arima(), which cycles through combinations of parameters and chooses the model with the lowest AIC score (Hyndman & Athanasopoulos, 2018). The fit of this model was checked through the Ljung-Box Test and plotting the residuals. The forecast() function (Hyndman et al., 2024) was used to first project pCO_2 values from 2019 – 2035, then these values and the ARIMA model were used to project the diversity index. A linear model analysis was also performed. A model showing how year affected pCO_2 and a model to examine how pCO_2 affected diversity were created. Model diagnostic plots were used to check assumptions (linear relationship, variability of residuals is consistent, observations are independent, and residuals are normally distributed). Size, direction, and significance of effects were examined. pCO_2 values were forecast from 2019 - 2035 using predict(), and these values were used with our second linear model to forecast diversity index values.

Results

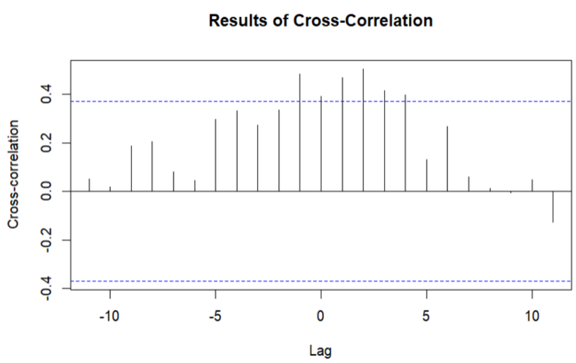

Figure 1: Results of cross-correlation test using ccf(). Lag represents value of h (x is related to y at time + h). Y-axis represents the strength of the cross-correlation. Peaks lie between h = -1 and h = 4.

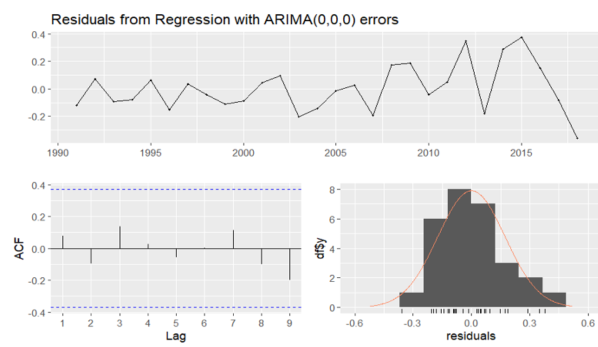

Figure 2: Results of checking the fit of the ARIMA model with the current (1991 – 2018) data. Residuals are uncorrelated and have a fairly normal distribution however there is some variation.

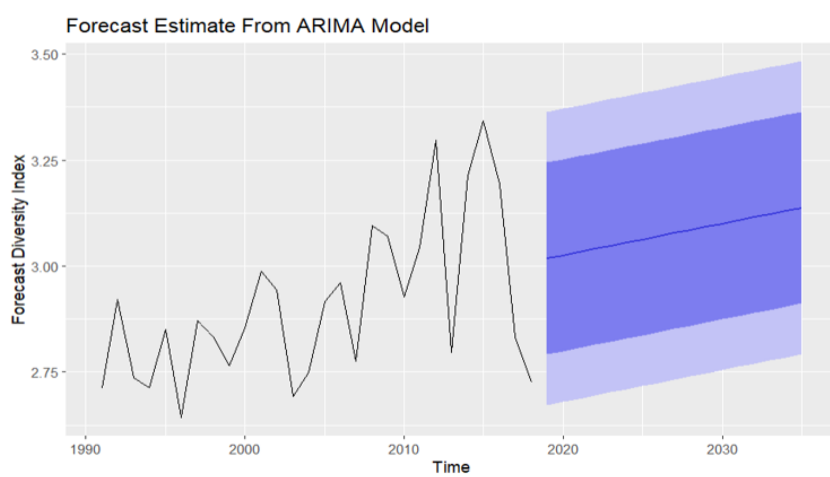

Figure 3: Results of forecasting pCO2 and diversity values from 2019 – 2035. Dark blue shading represents 80% confidence interval, and light blue shading represents 95% confidence interval.

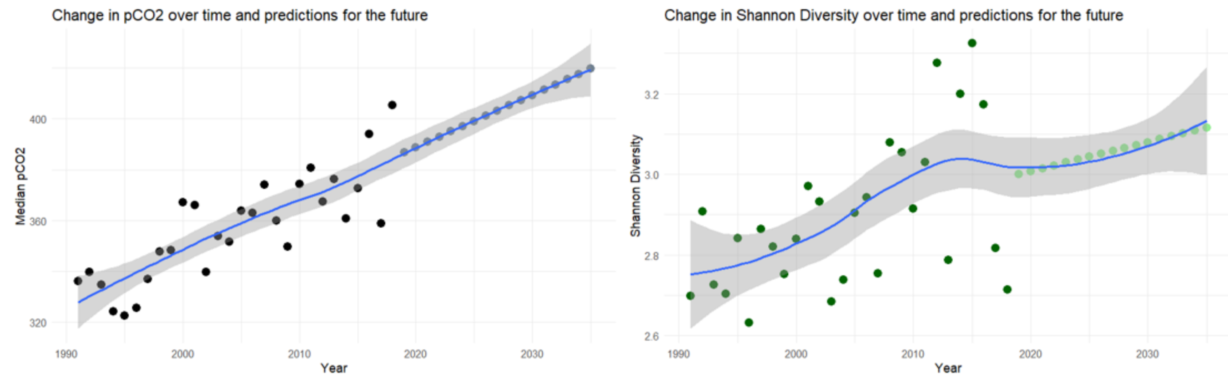

Figure 4: Changes in pCO_2 and plankton diversity (measured as Shannon Diversity Index) in the north Atlantic over time (black dots) and predictions for values from 2019 – 2035 (grey dots in left graph, green dots in right graph). Grey shading represents 95% confidence interval. *p*-value for both models was < 0.05.

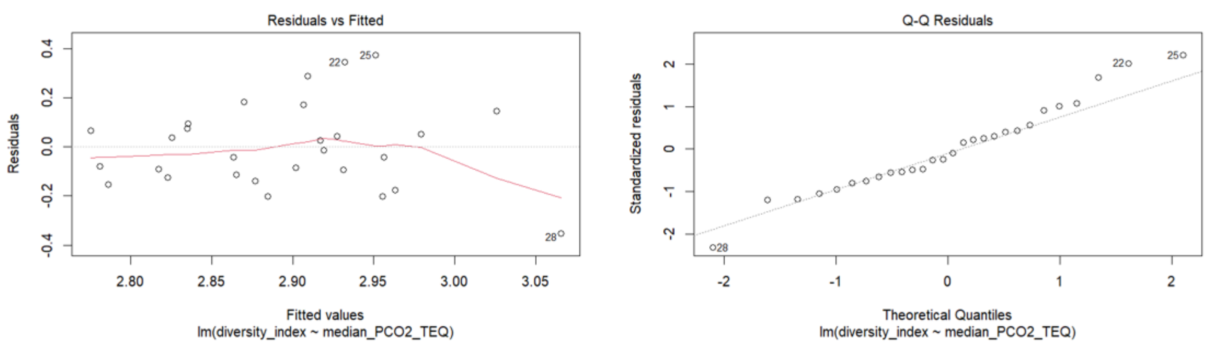

Figure 5: Residuals vs Fitted and Q-Q Residuals from linear model examining how pCO_2 affects plankton diversity (Shannon Diversity Index) in the north Atlantic.

The time series cross-correlation showed that the values of diversity were related to the values of pCO2 between 1 year prior and up to 4 years in the future (Figure 1). The auto.arima function (ARIMA 0,0,0) had an adequate fit based on the Ljung-Box Test, however there was some skew in the distribution of residuals (Ljung-Box Test $p > 0.05$; Fig. 2). The forecast (2019-2035) pCO_2 values increased from approximately 387 atm to 420 atm and the values of diversity are predicted to increase from 3.01 to 3.13 (Fig. 3). The linear model showed significant increases in pCO_2 over time ($p < 0.001$) and increases in diversity with pCO_2 ($p = 0.0422$), fitting with predictions from the time series analysis. Our linear models somewhat meet their assumptions however the data isn't perfectly normally distributed, and the relationship isn't perfectly linear).

Discussion

Both the time series and linear model analysis showed that plankton diversity is expected to increase over time as pCO_2 increases. This does not fit our initial prediction that pCO_2 would negatively affect plankton diversity. As the results were significant, we do see support for our initial hypothesis (pCO_2 affects plankton diversity). It is important to note that while both the

ARIMA model and linear model fit adequately, their diagnostic plots did show some variation in them. There are likely more suitable statistical methods that would allow us to elucidate the effects of pCO_2 more clearly, such as generalized linear models which do not rely on normal distribution or transforming the data to normalize the distribution.

There are also important factors that may influence the positive effect we see in our results. Firstly, using diversity indices is helpful as it allows us to have one measurement to judge the effect of pCO_2, but it does not allow us to elicit why the diversity index is increasing (i.e., presence of new taxa or increasing abundance of previously present rare taxa). It also does not provide information on susceptible or resistant taxa. Moving forward, these would be valuable research avenues to pursue. Moreover, there are various other variables that we did not investigate or control for, such as salinity or temperature. These variables were likely changing alongside pCO_2 and may be affecting plankton diversity or community structure (Röthig et al., 2023; Bendetti et al., 2021). Future research would benefit from investigating these variables alongside pCO_2. Ultimately, our research is an important first step in understanding the effects of ocean acidification across a wide geographic and taxonomic range.

References

Benedetti, F., Vogt, M., Elizondo, U. H., Righetti, D., Zimmermann, N. E., & Gruber, N. (2021). Major restructuring of marine plankton assemblages under global warming. *Nature Communications*, *12*(1), 5226. https://doi.org/10.1038/s41467-021-25385-x

Cripps, G., Flynn, K. J., Lindeque, P. K., & Dam, H. G. (2016). Ocean Acidification Affects the Phyto-Zoo Plankton Trophic Transfer Efficiency. PloS One, 11(4), e0151739–e0151739. https://doi.org/10.1371/journal.pone.0151739

Falkowski, P. (2012). Ocean Science: The power of plankton. *Nature*, *483*(7387), S17–S20. https://doi.org/10.1038/483S17a

Helaouet, P., Sheppard, L., Johns, D. (2024) Continous Plankton Recorder phytoplankton and zooplankton occurrence and count data from The CPR Survey in the Western North Atlantic Ocean from 1958 to 2021. Biological and Chemical Oceanography Data Management Office (BCO-DMO). (Version 5) Version Date 2024-08-29 [if applicable, indicate subset used]. doi:10.26008/1912/bco-dmo.765141.5 [Accessed 15 October 2024]

Hyndman, R. J., & Athanasopoulos, G. (2018). *8.7 ARIMA modelling in R | Forecasting: Principles and Practice (2nd ed)*. OTexts: Melbourne, Australia. https://otexts.com/fpp2/arima-r.html

Hyndman R, Athanasopoulos G, Bergmeir C, Caceres G, Chhay L, O'Hara-Wild M, Petropoulos F, Razbash S, Wang E, Yasmeen F (2024). _forecast: Forecasting functions for time series and linear models_. R package version 8.23.0 <https://pkg.robjhyndman.com/forecast/>.

Oksanen J, Simpson G, Blanchet F, Kindt R, Legendre P, Minchin P, O'Hara R, Solymos P, Stevens M, Szoecs E, Wagner H, Barbour M, Bedward M, Bolker B, Borcard D, Carvalho G, Chirico M, De Caceres M, Durand S, Evangelista H, FitzJohn R, Friendly M, Furneaux B, Hannigan G, Hill M, Lahti L, McGlinn D, Ouellette M, Ribeiro Cunha E, Smith T, Stier A, Ter Braak C, Weedon J (2024). _vegan: Community Ecology Package_. R package version 2.6-8, <https://CRAN.R-project.org/package=vegan>.

Penn State Department of Statistics. (n.d.). *8.2 Cross Correlation Functions and Lagged Regressions | STAT 510*. Retrieved December 8, 2024, from https://online.stat.psu.edu/stat510/lesson/8/8.2

Riebesell, U., Bach, L. T., Bellerby, R. G. J., Monsalve, J. R. B., Boxhammer, T., Czerny, J., Larsen, A., Ludwig, A., & Schulz, K. G. (2017). Competitive fitness of a predominant pelagic calcifier impaired by ocean acidification. Nature Geoscience, 10(1), 19–23. https://doi.org/10.1038/NGEO2854

Righetti, N. (2022). Time Series Analysis With R. Retrieved 23 November 2024, from https://nicolarighetti.github.io/Time-Series-Analysis-With-R/

Röthig, T., Trevathan-Tackett, S. M., Voolstra, C. R., Ross, C., Chaffron, S., Durack, P. J., Warmuth, L. M., & Sweet, M. (2023). Human-induced salinity changes impact marine organisms and ecosystems. *Global Change Biology*, *29*(17), 4731–4749. https://doi.org/10.1111/gcb.16859

Spisla, C., Taucher, J., Bach, L. T., Haunost, M., Boxhammer, T., King, A. L., Jenkins, B. D., Wallace, J. R., Ludwig, A., Meyer, J., Stange, P., Minutolo, F., Lohbeck, K. T., Nauendorf, A., Kalter, V., Lischka, S., Sswat, M., Dörner, I., Ismar-Rebitz, S. M. H., … Riebesell, U. (2021). Extreme Levels of Ocean Acidification Restructure the Plankton Community and Biogeochemistry of a Temperate Coastal Ecosystem: A Mesocosm Study. *Frontiers in Marine Science*, *7*. https://doi.org/10.3389/fmars.2020.611157

Takahashi, Taro; Sutherland, Stewart C.; Kozyr, Alex (2019). LDEO Database (Version 2019): Global Ocean Surface Water Partial Pressure of CO2 Database: Measurements Performed During 1957-2019 (NCEI Accession 0160492). NOAA National Centers for Environmental Information. Dataset. https://doi.org/10.3334/cdiac/otg.ndp088(v2015). Accessed 24 November 2024.