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Evaluation and assessment of climate variability in two versions of the BOATS model with different representation of biodiversity

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Riti Shrivastava

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ABSTRACT OF THE THESIS

Evaluation and assessment of climate variability in two versions of the BOATS model with different representation of biodiversity

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Master of Science in Atmospheric and Oceanic Science

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One of the major drivers of ecosystem changes is fishing, with global wild fish harvests increasing four times from the 1950s to 1990s. This spike depleted fish biomass and altered ecosystems. To assess these economic and ecological impacts, projects such as the Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP) have been undertaken. By designing numerical experiments, FishMIP aims to clarify long-term climate impacts on fisheries and marine ecosystems, reducing uncertainties- in model projections. One of the models in FishMIP is the BiOeconomic mArine Trophic

Size-spectrum (BOATS)- that integrates ecology and economics to simulate global fishing history. For the last round of FishMIP simulations focused on model evaluation (ISIMIP3a), I compared BOATS simulations forced by climate reanalysis and forced with historical fishing effort reconstructions to real-world observations. The goal of comparison is to help disentangle the complex interplay between fishing, climate change, and ecosystem health, to strengthen confidence in projections and ultimately aiding in sustainable fisheries management and marine conservation. For this comparison I have worked with two versions of BOATS, the former v1, and a new v2 that includes an improved representation of biodiversity. By analyzing these two versions, I address the following questions: how well the BOATS model performs compared to the observation? What are the effects of climate variability and the effect of human drivers? To investigate climate variability, I generated Empirical Orthogonal Function (EOFs) for the driving variables of BOATS, temperature, NPP, particle flux, and for the modeled consumer biomass. For human drivers, I developed and implemented diagnostics at Large Marine Ecosystems (LMEs) level, including correlation coefficient, root mean square, maximum catch and biomass variation that quantify the biomass decline in each LMEs. The analysis shows that the two model versions provide similar results, both globally and across LMEs. I highlighted coherent patterns of match/mismatch with observations that shed light on remaining model biases in particular at regional scales, and suggest future research directions.

The thesis of Riti Shrivastava is approved.

James C. McWilliams

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1. INTRODUCTION:

Fishing is one of the main activities by which humans appropriate the planet's primary production and reshape ecosystems worldwide (Kroodsma et al. 2018). The global harvest of wild fish from the oceans experienced a significant surge throughout the 20th century, growing by about four times between 1950 and 1990. This surge resulted in a depletion of fish biomass compared to its more pristine state in many regions (Carozza et al. 2017), in some cases leading to changes in ecosystem structures such as reduction of the mean size of catch (Carozza et al. 2016). Notably, fisheries collapse has been observed in 7 to 25% of fish stocks (Hauge et al. 2009). This decline is widely recognized as a factor restricting fishing yields in various parts of the world. On one hand, historical patterns result from a complex interplay of ecosystem dynamics, fish demand, fishing costs, technological advancements. While all these factors will continue to play a role in the future, determining their individual contributions has proven to be a challenging task (Galbraith et al. 2017). On the other hand, environmental change has had profound impacts on marine communities, with potential implications for ocean biogeochemistry and food security (Carozza et al. 2016). Anthropogenic climate change is causing shifts in primary production and temperature patterns on a global scale, affecting the habitats and food web structure of various marine species (Brown et al. 2010).

Recently to understand the respective impacts of fisheries and climate, ecological models have emerged based on broad ecological principles and applicable to a broad range of conditions using scenarios. The Fisheries and Marine Ecosystem Model Intercomparison Project (FishMIP) aims to bring these models together to help evaluate the future ocean states in a changing climate. FishMIP brings together disparate marine ecosystem models that differ in structure, forcing, it designs protocols for numerical experiments that allow improving understanding of long-term impacts of climate change on fisheries and marine ecosystems as well as ranges of uncertainty (Tittensor et al. 2018). Past simulation rounds with FishMIP highlighted the future decline of fish biomass (Lotze et al. 2019; Tittensor et al. 2021), or helped disentangle the relative influence of separate environmental drivers (Heneghan et al. 2021). The last FishMIP Model Evaluation Protocol (ISIMIP3a) plans to understand and reduce uncertainty associated with FishMIP models through model evaluation under historical climate and fishing effort forcings. The objective of the current project is to see how well the model BOATS perform in this last round of simulations.

The BOATS model dynamically couples the ecology and economics of global fisheries to reproduce the historical development of fishing in the global ocean (Galbraith et al. 2018). BOATS successfully reproduced multiple aspects of the historical fisheries (Galbraith et al. 2018, Bianchi et al. 2021, Guiet et al. 2021). We here compare two versions of this model (Carozza et al. 2017, Guiet et al. 2024). To evaluate BOATS, we will explore the variability of the model in relation to environmental forcing, and compare the ISIMIP3a simulations with observations. Recently, multiple sets of observations at a scale relevant for global fisheries simulations have been created. 1. Global catch reconstruction as provided by Sea Around Us (SAU) (Palomares et al. 2021). The SAU maintains a comprehensive dataset of global fisheries landings spanning from 1950 to 2015, which includes information on various types of fishing activities as well as catch correction for large scale, small scale, illegal, and unreported fishing, as well as discards at sea. 2. For biomass, FISHGLOB reconstruction provides an unprecedented view of demersal fish biomasses (Maureaud et al. 2023). It is a project that focuses on gathering and integrating data from scientific bottom trawl surveys. To support research on ocean biodiversity at both regional and global scales it has built a comprehensive collection of survey information, data, and standardized biomass estimates in European and Northern American waters. 3. For effort, Global Fishing Watch (GFW) reconstructions provide a high resolution view of the global fishing effort (Kroodsma et al. 2018). These are derived from Automatic Identification System (AIS) signals, initially created to enhance maritime safety by transmitting a ship's information to nearby vessels, including its identity, location, speed, and direction; processed AIS signals can be used to map fishing activity (Saravannan et al. 2019) . 4. Other datasets are available at a more local level, like for example the RAM Legacy Stock Assessment Database (Ricard et al. 2012). It is a consolidated collection of stock assessment findings for marine populations that are commercially exploited across the globe. Biodiversity information can also complement the data available for observation, especially data from the Ocean Biodiversity Information System (OBIS) that informs the occurrence of species of different size in the global ocean (Costello et al. 2006). The separate dataset can inform various aspects of simulations, but only catch reconstruction from SAU are global, we focus on these for evaluation.

In this study, we aim to assess how well the BOATS model performs compared to observation in the FishMIP (ISIMIP3a) simulation round. We also aim to understand the relative influence of forced effort and historical climate, at global to regional scale. These goals pose new questions about how to compare simulations with observational data to gauge the level of accuracy (Olsen et al. 2016). For this study we implemented a range of indicators to evaluate the model's performance. After introducing the BOATS model, we detail in the following indicators as well as a protocol of numerical experiments designed to disentangle the relative influence of climate and fisheries development on the historical fishing yields. The study discusses the significant impact of fishing on marine ecosystems and the global decline in fish biomass due to increased fishing activity, climate change, and technological advancements.

Marine ecosystem models are used to understand and predict the dynamics of marine ecosystems. These models simulate the interactions between different species, their environment, and human activities such as fishing. By incorporating various biological, chemical, and physical processes, these models help researchers and policymakers assess the health of marine ecosystems, predict future changes, and develop sustainable management strategies.

We need to evaluate the model performance to understand its reliability and accuracy. While poorly performing models can lead to misguided policy, accurate models can help inform effective management policies. Previous work evaluating results from BOATS v1 by using various empirical datasets including catch records, fish surveys and fish population.

Climate variability affects fisheries by altering productivity of fish stocks, abundance and distribution. Primary patterns such as ENSO and long-term trends such as ocean warming are particularly influential. These climate patterns impact fish populations and fisheries, necessitating adaptive management strategies (Pauterk et al. 2021)**.** Additionally, the interaction between climate variability and fishing practices often exacerbates each other's effects, where overfishing can reduce the resilience of fish populations to environmental changes and climate variability can impact fish availability and economic returns. Understanding these interactions is crucial for developing ecosystem-based management approaches. This research addresses the need to predict the impacts of climate variability and fishing on marine ecosystems by analyzing the BOATS model, chosen for its integration of ecological and economic factors. By comparing two versions of BOATS, we aim to refine the model, enhance its performance, and ensure more reliable predictions, ultimately contributing to more effective and sustainable fisheries management strategies.

2. MATERIAL AND METHOD

2.1 BOATS

The BOATS model serves as a comprehensive tool for simulating the global distribution of fish biomass, particularly focusing on three species groups (Carozza et al., 2016, Carozza et al., 2017, Guiet et al., 2024). The ecological module relies on the McKendrick–von Foerster (MVF) model, a well-known continuous-time model for populations structured by age or size (Carozza et al. 2016). In any given location, it represents the evolution of biomass, organized by size, known as a biomass spectrum (Hatton et al. 2021). Fish start in the smallest size class and grow into larger ones over time. Biomass in each size class changes as a result of biomass growth minus mortality. Growth is influenced by the net primary production from phytoplankton, and particle flux at seafloor when dermersal fish are represented, but cannot surpass the maximum physiological growth rates based on fish mass and temperature, surface or bottom. Natural mortality accounts for losses due to predation and other natural causes, depending on fish mass, asymptotic mass, and temperature. Recruitment of new biomass into the smallest class, determined by net primary production, particle flux, and egg production and survival, also sets the initial biomass levels (Galbraith et al. 2017). On the economic front, the model assumes that fisheries develop under an open-access scenario, meaning there is no active management. This module is coupled with the ecological one through a mortality due to fishing and is controlled by three main parameters, the cost of fishing, the catchability of the resource and the price of selling caught fishes (Carozza et al. 2017). Fleet dynamics and cost per unit effort remain constant globally, as does the price, which does not vary based on species or size, while catchability is globally constant, it may be subject to increase over time. This, in any given place, when enough biomass is available for a given catchability, harvest becomes profitable, fishing effort increases driving an increase in catches. Harvest is indirectly proportional to effort and biomass, and the size structure of the harvest is determined by a selectivity function.

The simulations are conducted at a spatial resolution of 1 degree and a temporal resolution of one month. Each simulation undergoes a phased initialization process that predates 1840, followed by the first simulation period from 1840 to 1960, before simulation on the focus period 1960 to 2010 we are here focusing on. Note that to address the inherent uncertainties in model parameters, each simulation incorporates five replicates. This approach allows for a comprehensive study of the mean, enabling a more robust understanding of the model's behavior and outcomes.

Here we compare 2 versions of the model, BOATS v1 and BOATS v2, which we also refer as v1 and v2 in the following. The models are different in the sense that v2 separates fish into pelagic and demersal and each are supported by a distinct energy pathway, and respond to different environmental drivers. BOATS v1 uses a simplified size-spectrum approach to model fish dynamics and fishing impacts, representing population growth, reproduction and mortality. BOATS v2 separates the fish biomass spectrum into pelagic and demersal fish communities, thus providing an improved representation of ecological diversity. It also incorporates new parameterization of fishing, including spatially variable fishing costs and catchability, which provide a more realistic representation of fishing effort dynamics (Guiet et al. 2024). Despite these differences, versions of the models are comparable in many respects.

Model	Scenarios (1960-2010)	Forcings
BOATS V_1	Nat	Reanalysis
	Histsoc	Reanalysis + observed fishing effort
BOATS V_2	Nat	Reanalysis
	Histsoc	Reanalysis + observed fishing effort

Table 1: List of numerical experiments in the present analysis.

2.2 FISHMIP SIMULATION PROTOCOL

The model is influenced by external climatic factors following a simulation protocol from FishMIP design to assess models, this protocol has been applied to both BOATS versions, we here analyze these simulations.

The protocol focuses on the 1960 to 2010 time period with two distinct forcing from reanalysis : one representing the presence of rivers (obsclim), and the other disregarding rivers outflows (ctrlclim).

The model is run under in two scenarios: one without fishing (nat), and the other with fishing (denoted as histsoc). The purpose of running the model in both scenarios is to discern the impact of fishing from the natural mortality of the biomass and to quantify the decline attributed to fishing activities.

2.3 SIMULATIONS

To assess the BOATS model within the FishMIP framework, we compared simulations from v1 and v2. In order to provide a comprehensive evaluation of our simulations, we have compiled a detailed list of the diagnostics used to assess them in Table 2.

We explore the variability of simulated catch and biomass, globally, and regionally, averaged at Large Marine Ecosystem (LME) level. Large Marine Ecosystems (LMEs) are extensive regions of the world's oceans close to continental margins, typically spanning thousands of square kilometers, characterized by distinct bathymetry, hydrography, productivity, and ecological factors.

These areas include coastal waters and continental shelves, and are important units for managing marine resources and understanding ecological processes because they encompass ecological regions defined by specific environmental conditions and biological communities rather than political boundaries). We use various metrics, focusing on global variation over our the analysis period, 1840 to 2010, with emphasis on the 1960-2010 period. We also delved into the examination of the current state of the fisheries-ecosystem system focusing on the period between 2000 and 2010, and in comparison to 1960-1970.

2.4 ASSESSMENT TOOLS

2.4.1 ANALYSIS

In atmospheric and oceanic sciences, Empirical Orthogonal Function (EOF) analysis is often used to study how variables of interest change under the influence of distinct modes of climate variability (e.g., the North Atlantic Oscillation, NAO, Pacific Decadal Oscillation, PDO, etc), each characterized by temporal and spatial patterns of variability. In statistics, EOF analysis is generally known as Principal Component Analysis (PCA).
Analysis of EOFs is considered as a multivariate statistical technique, lacking a predetermined hypothesis based on a specific probability distribution, and therefore lacking a formal statistical test. It does not depend on physical principles, but a portion of the field

under study is partitioned into independent, or mathematically orthogonal modes of variability. This can be interpreted as atmospheric/oceanographic/climate modes or 'structures'. The EOFs are mainly computed by the eigenvectors and eigenvalues of a spatially weighted anomaly covariance matrix of a field.

Popularly, for better EOF analysis, the spatial weights are the sqrt(cos(latitude)) or even the cos(latitude). The eigenvalues obtained from the spatially weighted anomaly covariance matrix provide a measure of the variance or inconsistency explained by each of the modes. However, they may not be clear due to sampling issues (North et al. 1982, Equations 24-26). Processes in the Atmosphere and Ocean are likely to be 'red' that is most of the variance is shown in the first few modes. Each principal component's time series is determined by projecting the corresponding eigenvectors onto the spatially weighted anomalies, thus showing the mode's amplitude over time.

EOF and principal components are intentionally made independent of each other. There are several factors that limit physical interpretation of the EOFs. First, the orthogonality constraint; second, the derived patterns may be dependent on the domain of analysis. Physical systems are not necessarily orthogonal, and if the patterns change with the region used, they may not be physically meaningful. Despite these limitations, classical EOF (PCA) analysis remains a valuable tool.

Here, we apply EOF analysis to output from BOATS simulations and its drivers (temperature and net primary production fields), in the absence of fishing. Our overarching hypothesis is that variations (i.e., EOF) in fish biomass in the absence of fishing reflect a combination in the variation of temperature and net primary production, which, in turn, are generally influenced by major climate modes of variability, such as the PDO, NAO, and El Nino Southern Oscillation (ENSO).

2.4.2 EVALUATION METRICS

Our investigation also focuses on evaluating the predictive accuracy of the BOATS model aiming to assess its alignment with real-world observations. Additionally, we seek to discern the relative influence of environmental factors and fisheries dynamics in shaping the model's performance. In order to comprehensively gauge the model's skills, we have defined a set of relevant indicators that capture diverse aspects of BOATS's predictions, and compared the model to catch observations from SAU.

Table 1 provides a list of the indicators utilized in our analysis. These indicators provide an evaluation of BOATS's performance, considering the complexity of the interactions within marine ecosystems. By employing multiple indicators, we aim to gain a more nuanced understanding of how well the model aligns with observed data. The indicators consist of:

- The correlation coefficient assesses the degree of correlation between simulated and observed data. A coefficient value of 1 signifies perfect positive correlation, while -1 indicates perfect negative correlation. This indicator helps to evaluate how well the BOATS model captures the overall patterns in the fisheries and ecosystem data across different LMEs. High correlation values suggest that the model is reliable in predicting temporal and spatial variations in biomass and fisheries catch within each LME.
- The root mean square (RMSE) indicator quantifies the proximity of simulated to observed values. A higher value is indicative of a closer alignment between the model's predictions and actual observations. This indicator provides a quantitative assessment of the model’s prediction accuracy, with lower RMSE values indicating

better model performance. RMSE helps to quantify the model's prediction errors, providing insight into the absolute magnitude of the model's deviations from observed data. This is crucial for identifying the model's accuracy in estimating biomass and fisheries yield.

- The maximum simulated catch and relative biomass variation, provide an overall perspective on the model's performance. The maximum value indicator refers to the highest observed or predicted value of a particular variable (e.g., biomass, fish catch) within each LME. This indicator is useful for understanding the peak performance or carrying capacity of the ecosystems as predicted by the model. It also helps in comparing the model's ability to predict extreme values and assess its reliability under maximum biomass conditions.

Indicators	**Relevance**
Coefficient Correlation	Linear relationship between observed data and model predictions.
Root mean square	It quantifies the predictions accuracy, highlighting the model's precision in estimating fisheries yield.
Maximum Catch	This evaluates the model's performance under the peak conditions.
Biomass variation	Helps in the understanding of the model's capacity to reflect the dynamic nature of the marine ecosystem.

Table 2: List of the indicators used in the study and their relevance.

3. RESULTS

3.1 GLOBAL HISTORICAL VARIATIONS

Figure 1 shows the simulated temporal dynamics of biomass and harvest from the year 1840 to 2010, for the two versions of the BOATS model (v1 and v2). Regarding biomass, when considering the scenario without fishing, both models indicate a small biomass decrease (1-2%), but this decline is not significantly different from inter-annual variability. This small decline emphasizes the inherent ecological factors (temperature and NPP variations) affecting biomass even in the absence of anthropogenic activities such as fishing. When considering fishing, the biomass decline is much sharper, amounting to nearly 23% by 2010 for v1, 28% for v2. This contrast in the effect of fishing activities on biomass indicates indirect ecological consequences of the representation of fish communities in both model versions.

Regarding fishing, the lower panel in Fig. 1 shows the global harvest, and harvest within LMEs. Harvest slowly increases from 1840 to 1940, as fisheries start developing, then from 1940 the harvest increases rapidly up to reaching a maximum of respectively tons/y for v1, tons/y for v2, in coastal seas where most of observed fishing is occuring. The values are of similar order of magnitude as observation. i.e. ~110 10^6 tons/y, but shows that the coastal catches are increasing more in v1 than in v2. The reason coastal catch reaches a maximum could be the overexploitation of coastal ecosystems, as fishing increases, fish biomass declines (see upper panel), and there is less and less biomass left to support fisheries. Note that the global catches increase (dotted lines), is much larger for v1 than v2, in agreement with a bias in the model that overestimates High Seas biomass, and thus catch.

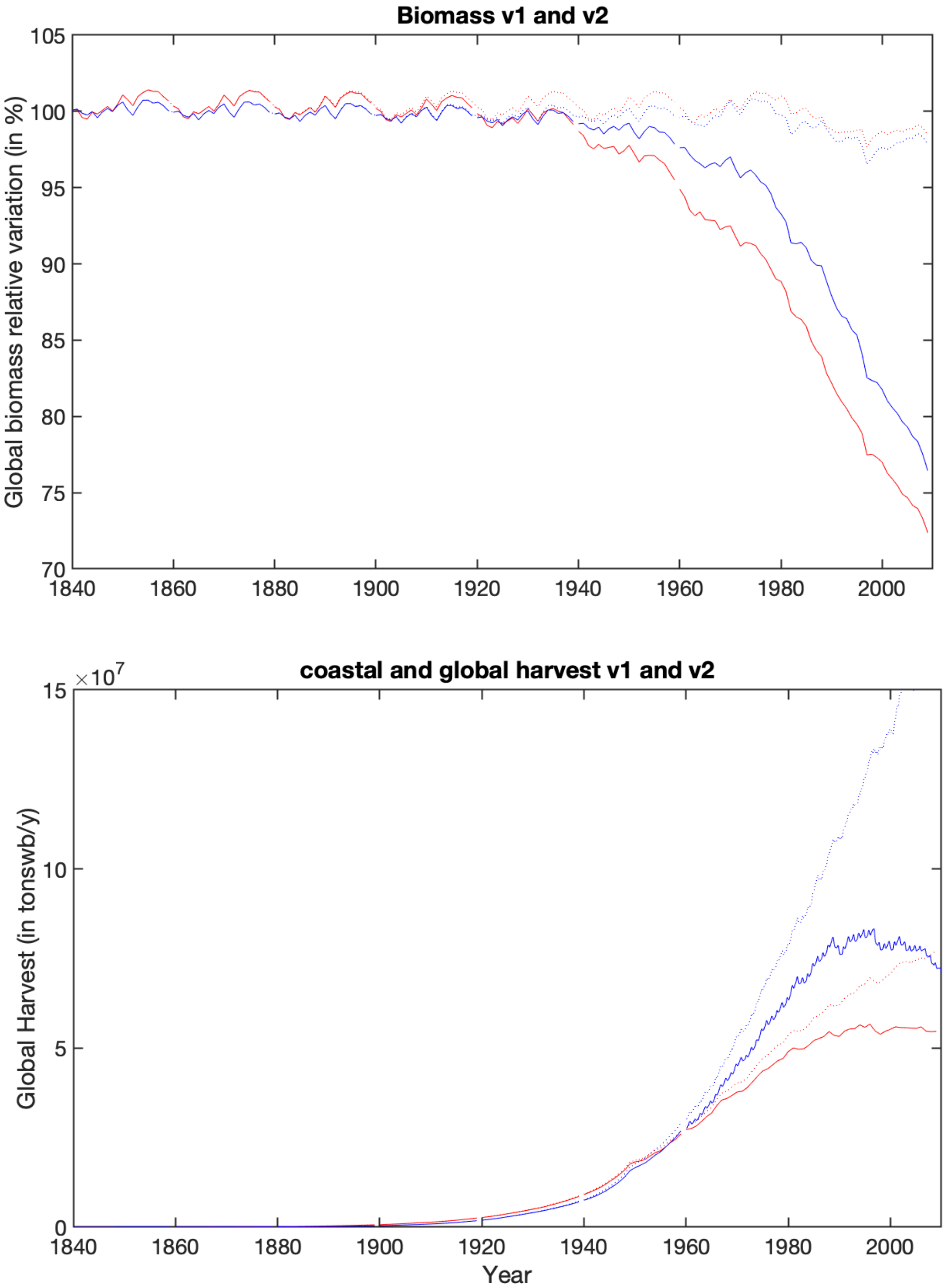

Figure1: Historical variation of commercial fish biomass (top) and fishing harvest (bottom) for BOATSv1 (in blue) and BOATSv2 (in red). Upper panel, the solid lines indicate simulations forced by climate and fishing, dotted lines indicate simulations forced by climate. Lower panel, the dotted lines indicate global catches, solid lines indicate coastal catches summed across LMEs.

3.2 HISTORICAL VARIATIONS IN FISH BIOMASS:

Figure 2 shows the regional biomass variation for BOATSv1 and v2 under the two different scenarios, without and with fishing. Each panel shows the relative biomass variation (mean of 1960 to 1970 vs mean of 2000 to 2010). Without fishing, the maps indicate up to 20% increase or decrease in biomass in the Large Marine Ecosystems (LMEs). Decrease might be associated with natural mortality or increase might be associated with the increased productivity of the regions. Comparing model v1 and v2, we could say that v2 shows a stronger biomass increase in some LMEs like Greenland Sea, Barents Sea and East Siberian Sea, however for some LMEs v1 shows a stronger biomass increase in regions like Arabian Sea, Gulf of Mexico and Caribbean Sea. Regions of increase or decrease of biomass are much comparable between versions, in agreement with the overall trends of total consumer biomass from the EOF analysis. Note main differences in the Gulf of Mexico and Southeast Asia.

In Figure 2, the two maps are for the biomass variation with fishing in all the LMEs for both the versions. As observed from global time series, a strong decrease in the biomass is seen all over the world, up to 80%. Interestingly, v1 shows significantly more decline in most of the LMEs. v2 shows almost 50% decline in the regions like California Current System, Gulf of Mexico, Guinee Current, Arabian Sea and Bay of Bengal, whereas these regions are shown to have almost 70%-80% depleted biomass in v1. Note that these declines are overall stronger than expected from the global time series. The latter are determined on the global ocean biomass that might have been less impacted by fishing overall.

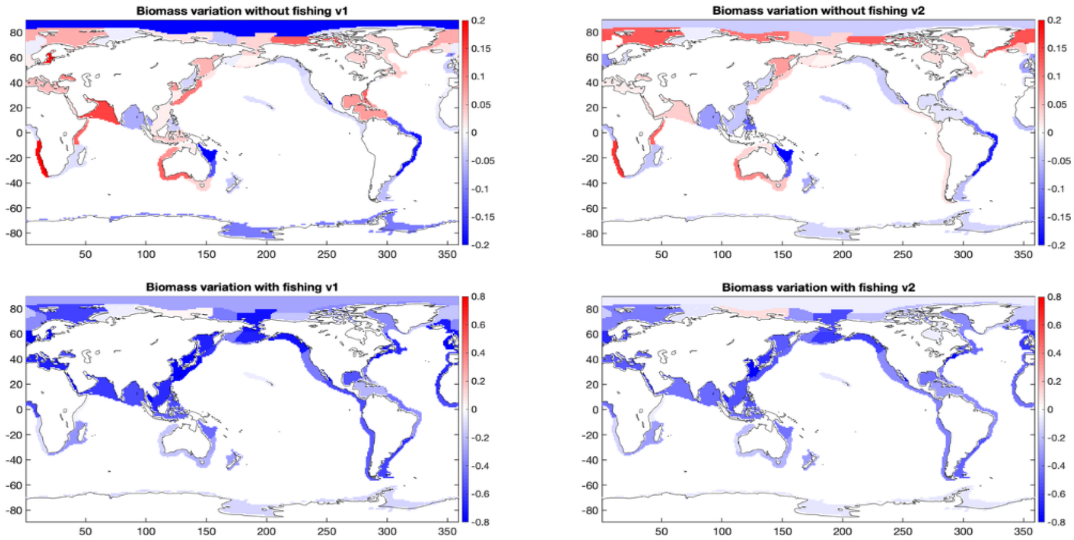

Figure 2: Upper panel describes the biomass variations (1960-2010) without fishing in v1 and v2 in ton/y and the lower panel describes the biomass variation (1960-2010) with fishing in v1 and v2 in ton/y.

3.3 ASSESSMENT OF MODEL CATCHES

Figure 3 shows the correlation coefficients between the simulated catch of BOATS v1 and v2 and the observational data sourced from Sea Around Us, over years 1960 to 2010. The majority of LMEs in v1 exhibit a positive correlation with the observed data, indicating the good prediction of fishing trends by the model. However, exceptions such as the Agulhas Current, Benguela Current, and Yellow Sea show anticorrelation. Correlations in v2 are very similar, despite differences in the representation of ecology and differences in the natural biomass variations (Sections 3.2,3.3). This suggests a strong effect of the forcing of effort on reproducing historical catch. Based on Figure 4, differences in correlation between v1 and v2 reveal local patterns markedly different, in Northeast America, East Asia and around Europe.

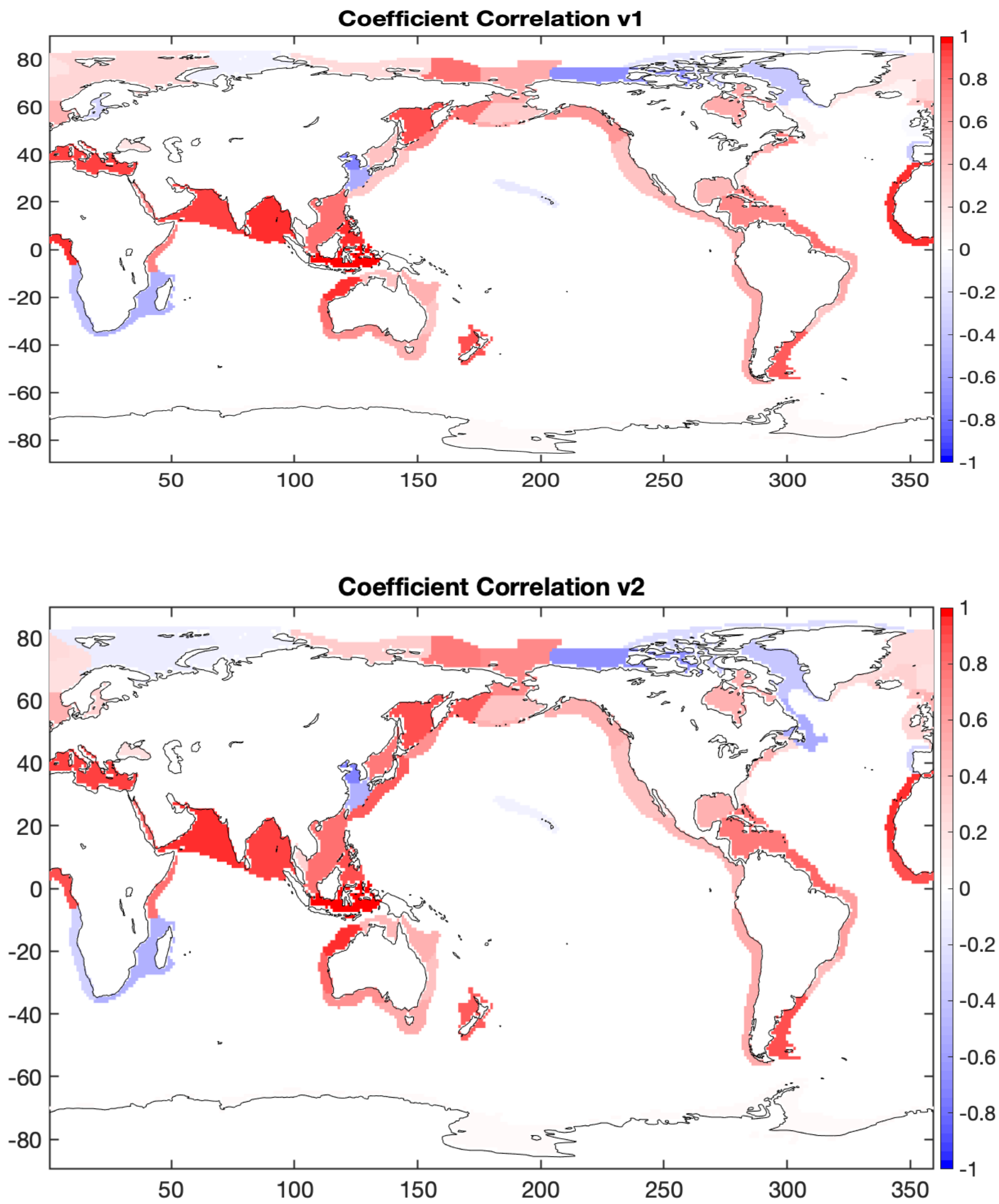

Figure 3: Coefficient Correlation between the simulated data and the observed data. The upper map is for BOATS v1 and the lower map in the panel is for BOATS v2.

Figure 4 shows the difference between coefficient correlation of v1 and v2 (i.e., v1 - v2) that ultimately shows what LMEs are more or less correlated with observations in v1 than v2.

White regions convey the comparable result in both versions. However, red and blue regions indicate that v1 overestimates or underestimates than v2, respectively. For instance, in the

East of Asia LMEs, in v1, the correlation coefficient is almost -0.4 which means that v1 underestimates more than v2. Similarly, east of America/Canada is red that means that v1 overestimates than v2. It is hypothesized that we would see more blue regions but here we see red regions as well.

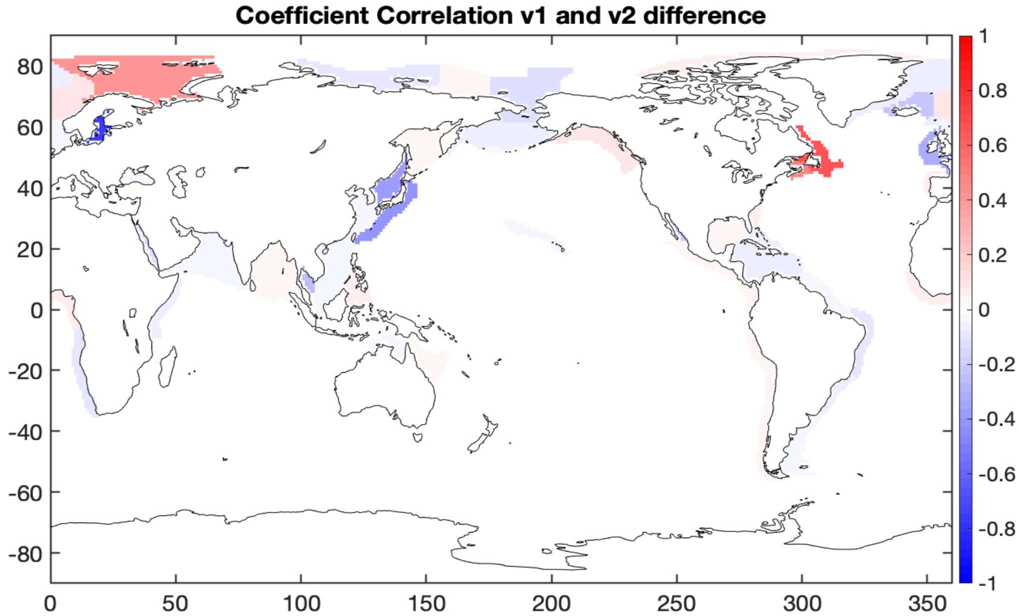

Figure 4: Difference of coefficient correlation of v1 and v2 (v1 - v2).

Figure 5 shows the root mean square error (RMSE) across all 66 Large Marine Ecosystems (LMEs) to compare accuracy of predicted time series. V1 shows the highest accuracy in Australia and Hudson Bay. Similar results have been seen in v2 with a little lower accuracy in the Northeast Australian Shelf-Great Barrier Reef and North Australian Shelf. Overall, the maps for both versions are closely comparable, with a couple of exceptions. The least accurate in v1 is Arabian Sea, and the least accurate in v2 is the Mediterranean Sea.

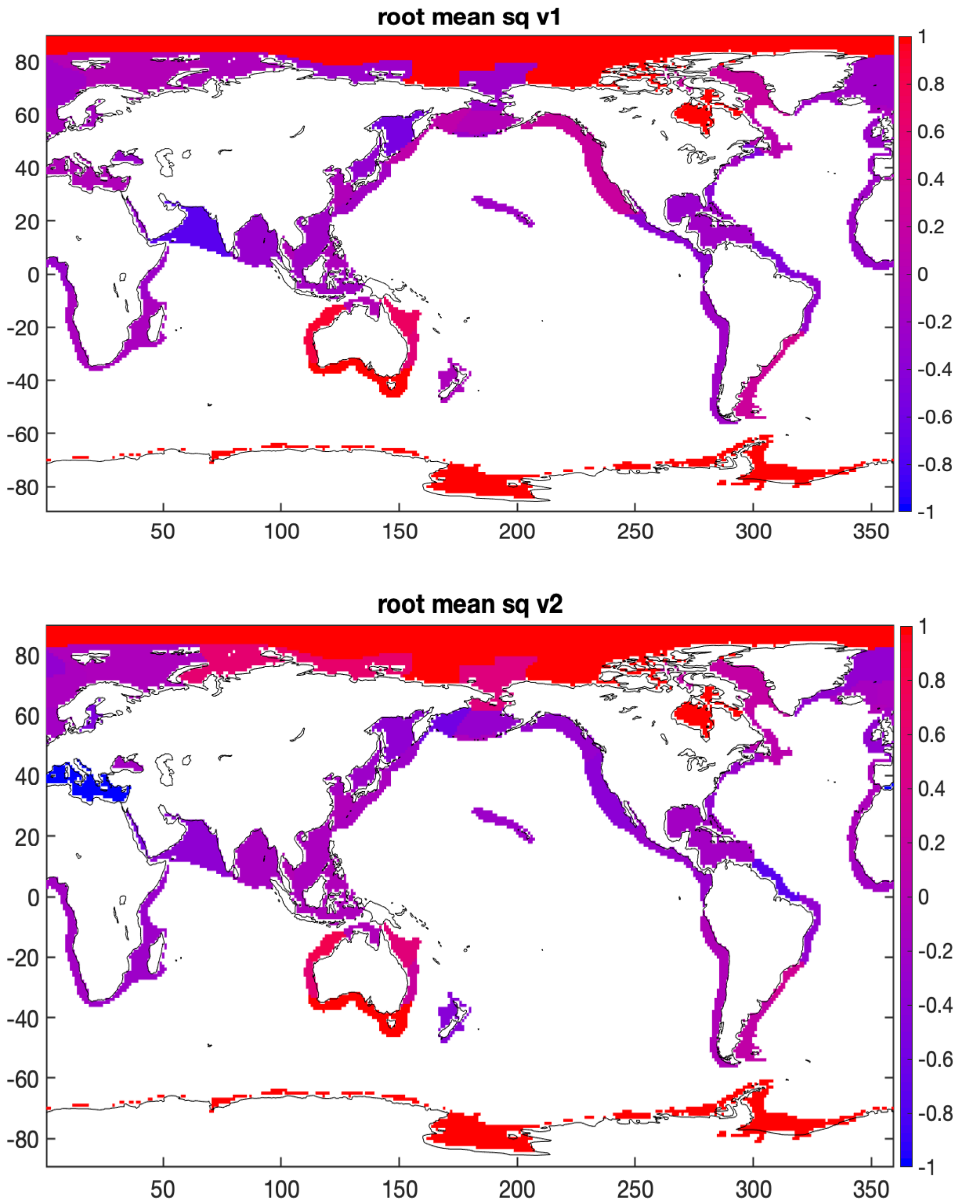

Figure 5: The logged root mean square values for both the versions.

Figure 6 shows differences in the RMSE between v1 and v2. Red regions indicate higher accuracy in v1 and blue regions lower accuracy compared to v2. For example, the California Current System, Europe and somewhat Australia has a higher accuracy in v1 than v2. However, regions like the east of Asia and Agulhas Current have lower accuracy in v1 than v2.

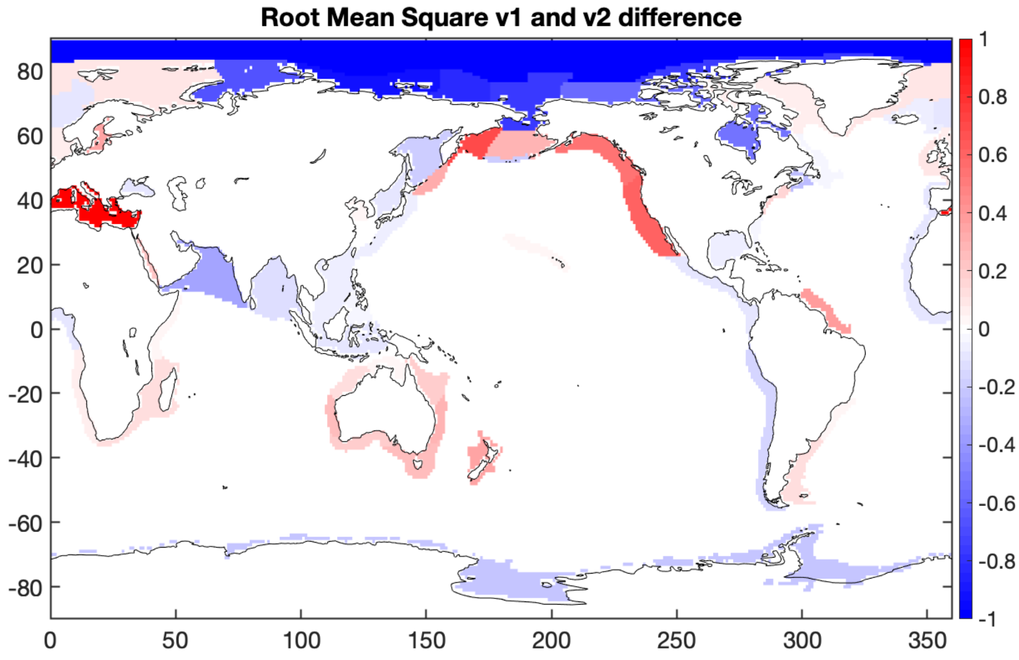

Figure 6: Difference of logged root mean square of v1 and v2 (v1 - v2).

Figure 7 illustrates the maximum values in the simulated data for catch, v1 and v2. The overall trend appears to correlate with the maps depicting correlation and root mean square values. The highest maximum simulations are observed in Asia, the Agulhas Current, the California Current System, and the Humboldt Current in both versions. This aligns with the observational data shown in the lower panel. Beginning with Australia, we observe lower biomass levels at around 4.5 tons per wet weight biomass per year (ton/y). The maximum catch in both versions ranges from 4.5 to 5.5 ton/y. Moving upward, the maps consistently agree with each other for the Benguela Current and Agulhas Current, indicating catches around 6 to 6.5 ton/y. Continuing this trend of agreement, the South American Large Marine Ecosystems (LMEs) in v1 also align with the observational data. However, in v2, there is a slightly lower catch reported in the Humboldt Current. Further north along the American continent, the California Current System (CCS) exhibits lower biomass at around 6 ton/y, with maximum catches ranging between 6.5 ton/y to 7 ton/y in both versions. Moreover, in

East America, the maximum catches are also in this range, indicating consistency between the two versions.

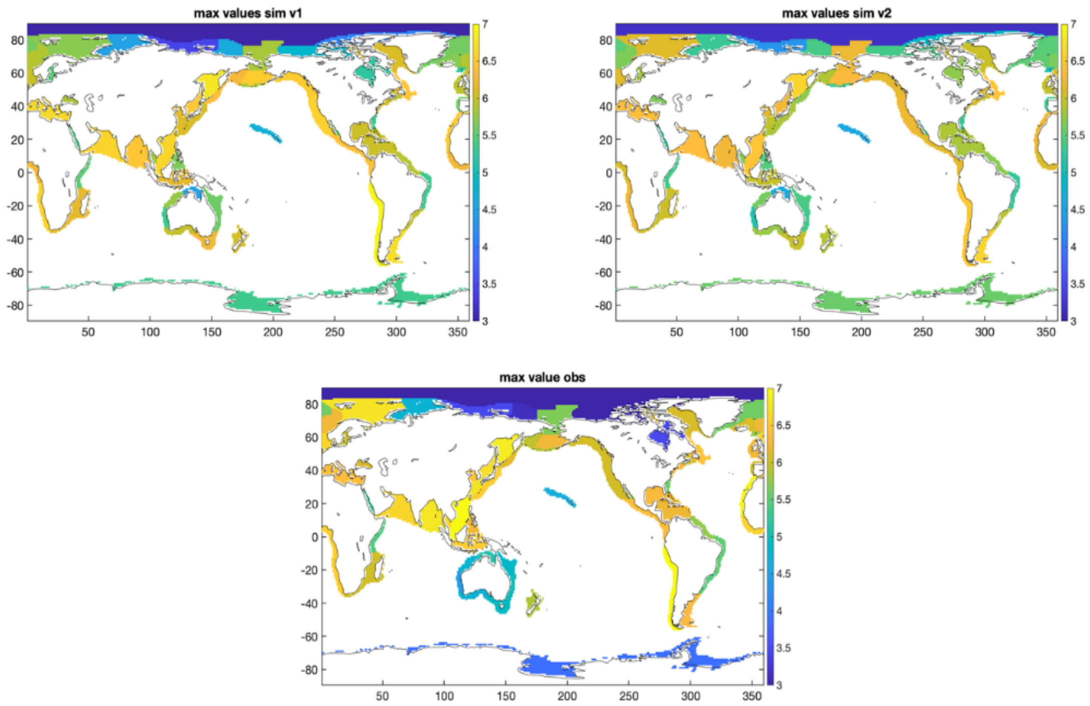

Figure 7: Maximum simulated catch in the two versions v1 and v2. The top panel is the maximum value in the v1 simulated catch (ton/y), the middle panel is the maximum catch in the v2 simulated catch (ton/y) and the bottom panel is the maximum value in the observation (ton/y).

3.4 EFFECTS OF CLIMATE VARIABILITY ON BIOMASS

Figure 8 shows the EOFs of the simulated fish biomass (here labeled Total Consumer Biomass, TCB**).** EOFs, along the principal component time series for both versions from 1960 to 2010, show historical biomass increases in the ‘red’ regions and decreases in the ‘blue’ regions. Looking at the maps it seems like both the EOF1 for v1 and v2 are comparable. The principal component for v2 is smoother than principal component 1. This means version two does not have as much variation as v1. There is more biomass variation along the coasts, which is hypothesized. A latitudinal shift from biomass decline at low latitudes to increase at higher latitudes could indicate climate change / global warming.

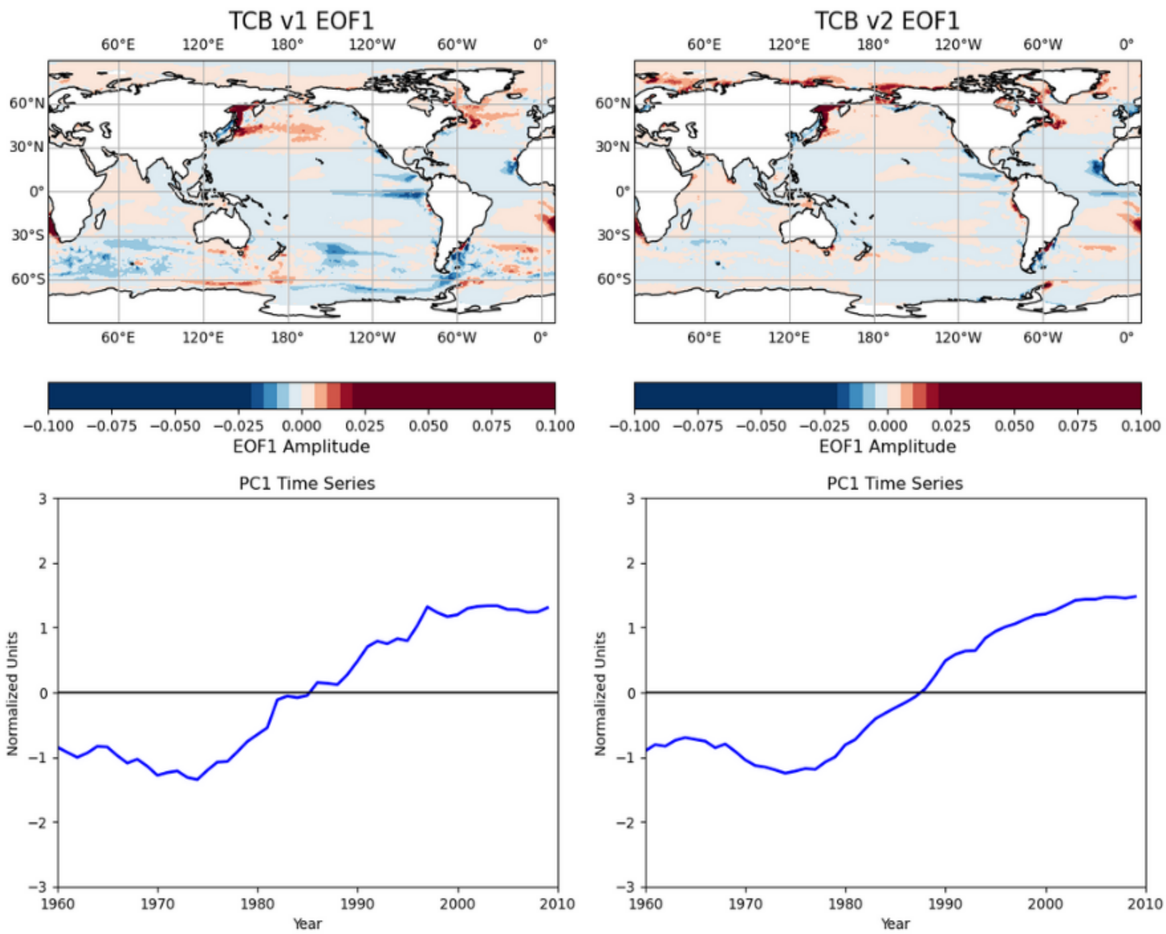

Figure 8: EOF and principal components of total consumer biomass (TCB) v1 and v2. Top left map in this panel is the EOF 1 for v1 TCB and below it is its principal component. The top right map in the panel is the EOF 1 for v2 TCB and below it is its principal component

To understand the variation of fish biomass, Figure 9 shows the EOFs of the forcing, net primary production (NPP), and particle flux at bottom (PFB) that is used to simulate bottom fish communities in BOATSv2**.** EOF of NPP, along the principal component time series, shows higher NPP in the 'red' regions and lower NPP in the 'blue' regions for positive phases of PC1.These patterns are comparable to the El Nino and La Nina. As far as PFB is concerned, the map and principal component shows variations much comparable with what previously described for fish biomass. The principal component of PFB closely relates to the principal component of TCB which suggests that PFB is the main factor of biomass variation, however it is not used in v1.

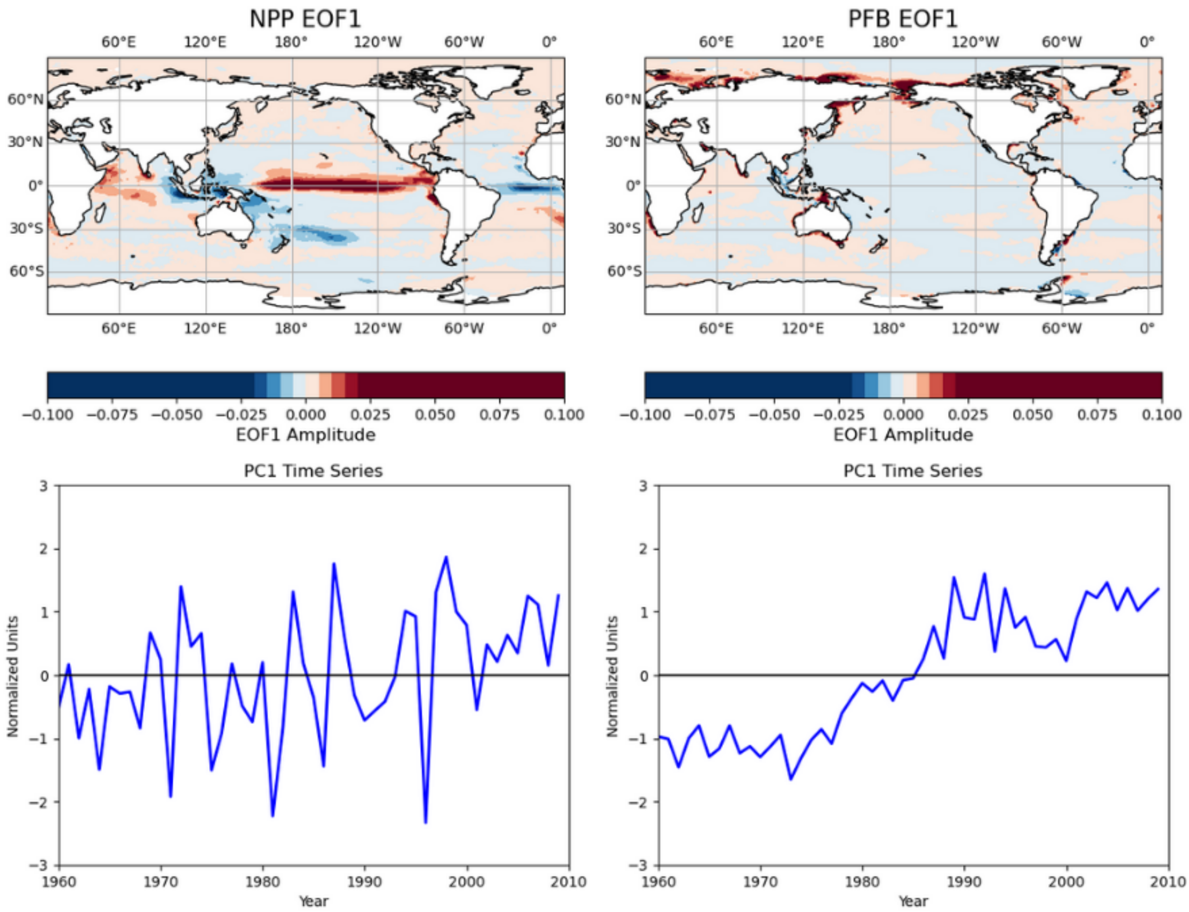

Figure 9: This panel contains the Net Primary Production (NPP) and Particle Flux Biomass (PFB) EOFs and principal component time series. The top left map and the bottom left in the panel is the NPP EOF and principal component and the top right map and the bottom right in the panel is the PFB EOF and principal component time series.

To understand the variation of fish biomass, Figure 10 shows the EOFs of the physical forcing, Temperature at the top 75 mts of the ocean (T75) and the bottom ocean temperature (TBOT). EOF of T75, along the principal component time series, shows higher temperature in the 'red' regions and lower temperature in the 'blue' regions for positive phases of PC1.These patterns are comparable to the El Nino and La Nina (with similar patterns for NPP). As far as TBOT is concerned, the map and principal component shows variations much comparable with what previously described for fish biomass and total consumer biomass (TCB). The principal component of TBOT closely relates to the principal component of TCB and PFB.

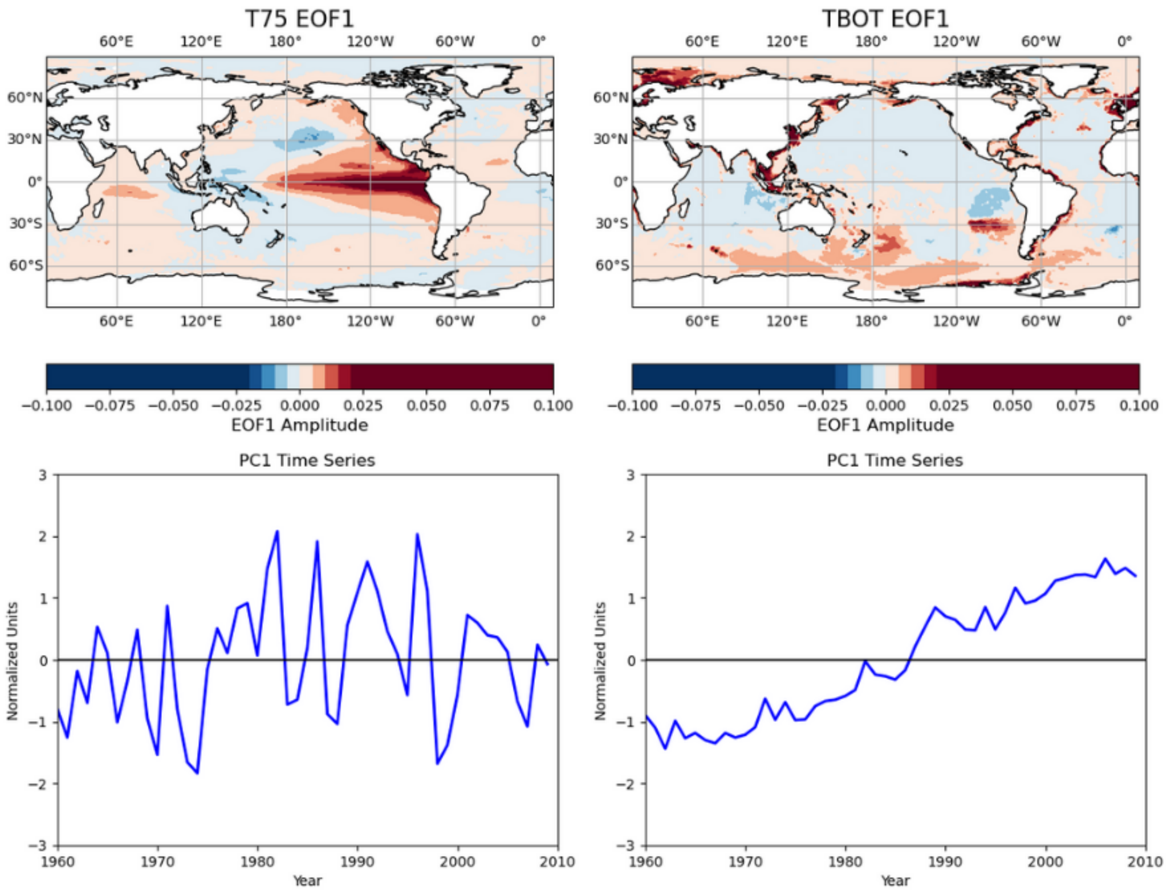

Figure 10: This panel contains the Bottom ocean temperature (TBOT) and Ocean temperature at the top 75 mts (T75) EOFs and principal component time series. The top left map and the bottom left in the panel is the T75 EOF and principal component and the top right map and the bottom right in the panel is the TBOT EOF and principal component time series.

4. DISCUSSION AND CONCLUSION

Historically, human societies have engaged in the harvesting of fish and marine resources since prehistoric times. However, the post-World War II era witnessed a rapid escalation in global wild harvests, propelled by advancements in fish capture technologies and spurred by a burgeoning demand fueled by population growth. This surge in demand for marine resources has exerted profound effects on marine ecosystems, with a significant proportion of fisheries now facing the threat of overexploitation.

Our research is based on a series of simulations that contribute valuable insights to the study. Initially, we embarked on simulating biomass and harvest dynamics, conducting five ensembles for both v1 and v2 of the BOATS model. These simulations revealed the significant impact of fishing on the decline of biomass.

In a subsequent phase of our research, we delved into the examination of the current state of biomass and harvest, focusing on the period between 2000 and 2010. The analysis unveiled a global trend of biomass depletion coupled with an increase in harvest. This global-scale observation was complemented by a localized investigation into specific Large Marine Ecosystems (LMEs), where a notable reduction in biomass was identified. The findings indicate regionally variable interplay between fishing activities and the resultant changes in fish biomass.

Furthermore, our research delved into identifying specific LMEs that exhibited the most substantial declines in biomass over the years. This investigation aimed to pinpoint regions where the impact of anthropogenic activities, particularly fishing, has been most pronounced.

The EOF analysis provides critical insights into spatial and temporal patterns of ocean temperatures and biomass variations by linking climatic events and trends to marine ecosystem dynamics.

The EOF analysis reveals that the climate has a minor influence on the decrease in the biomass in each LME. The Total Consumer Biomass, TCB from 1960 to 2010 in both versions of the BOATS model, reveals that EOF 1 for both versions to be comparable. There is less variation in v1 than in v2 which has a more smoother principal component. This suggests that v2 could be more stable in the face of interannual climatic fluctuations, for example, because the demersal fish respond to bottom temperature and particle fluxes, which are less variable than surface properties. The shift from biomass decline at low latitudes and increase at high latitude could reflect the effects of global climate change. For example, net primary production tends to decline in mid to low latitudes as the ocean becomes more stratified (Bopp et al. 2013, Kwiatkowski et al. 2020), but increases in high latitudes as the more stable stratification reduces phytoplankton light limitation and extends growth season. Similar effects could translate into fish biomass. Along the coast the biomass variation increased that perfectly aligns with the expected patterns. Moreover, the analysis of the forcing net primary production (NPP) and temperature at the surface (T75) suggest correspondence to ENSO phases, or more broadly PDO. The particle flux at the bottom (PFB) suggests significant influence of biomass variation. The temperature at the bottom of the ocean (TBOT) closely aligns with the particle flux. Altogether analysis of the EOFs and principal components suggests that climate has a minor effect on the decrease in the biomass, whereas fishing is the a main reason for the biomass decrease.

In this study, we have aimed to assess how well the BOATS model performs compared to observation in the FishMIP (ISIMIP3a) simulation round. We have also investigated the relative influence of forced effort and historical climate, at global to regional scales. Our analysis poses questions about how to compare simulations with observational data to gauge the level of accuracy [Olsen 2016]. We implemented a range of indicators to evaluate the model's performance. Skill assessment involves comparing model outputs with observational data (Olsen et al. 2016).

The global historic biomass time-scale shows 75% decrease in the biomass while fishing is a factor, in v1. V1 and v2 show a little difference in the decline, as v2 shows a comparable 70% decline. The analysis also highlights the increase in fishing in the coastal regions and indicates that v1 has a higher harvest than v2. In both models, the harvest peaks are followed by a global decrease.

While East Asia and Europe show relatively good correlations with lower RMSE values, regions like the California Current System, East America, Australia, and South Asia display varying degrees of correlation and differences in the observed and simulated paths. These insights provide valuable information on the performance and accuracy of the model simulations across different marine ecosystems that could be relevant for regional resource management.

Biomass variation measures the extent of fluctuations in biomass within each LME over time. This can include temporal variability and spatial heterogeneity in the biomass distribution. Analyzing biomass variation is critical for understanding the stability and resilience of marine ecosystems. It provides insights into how well the model captures the dynamic nature of marine ecosystems, including responses to fishing pressure and environmental changes.

The two versions of the BOATS model have different and distinct strengths for biomass. The biomass variation in the East of Asia has a better performance in v1 than in v2. High latitudes have unreliable data so there the simulations are not that accurate. Regarding coefficient correlation, both the versions are pretty much comparable. Furthermore, the RMSE also looks very similar for both versions. Later, in the maximum value figure, both the versions are again comparable. Our original hypothesis was that of a better performance for v2. However, based on the indicators, v1 is better in some aspects than v2. Despite having a better parameterization for v2, it is still underperforming in regions like Australia, California Current System and Mediterranean Sea, with v1 outperforming. The fact that there are anticorrelated areas and less accuracy calls for a further investigation. Regions with low correlation and low accuracy such as East Asia may also have less reliable data than other regions. The success of v1 in the regions like Australia suggests that model parameterization may be more accurate for this ecosystem. On the other hand, failures of v2 may stem from unaccounted environmental factors or differences in model versions assumptions and limitations of the data. All these factors should be better investigated, given the relevance of regional model discrepancy for marine resource management.

In conclusion, the study provides a new, detailed assessment of the BOATS model v1 and v2. The performance of the model is compared with the observational data, historical fish biomass variation in response to the climate variability and fishing effort. Despite the expectation that the performance of BOATS v2 would exceed v1, the findings indicate that BOATS v2 provides a relatively similar performance as v1. They also show that v2 does not consistently overestimate fish biomass as anticipated. Finally, they show similar and relative muted effects of climate variability. Persisting biases in both model versions suggest common underlying causes. These could be related to similar parameterization of growth, trophic transfer, and mortality, and the use of similar drivers (NPP, T) for both model versions. This overall similarity in model biases between v1 and v2 calls for additional research and better refinement of the model’s parameterization, in particular for regional applications.

The results align with the hypotheses outlined suggesting the crucial need for understanding and predicting the impacts of climate variability and fishing on marine ecosystems. By combining ecological and economic factors, the model, BOATS, helps as an important tool for developing adaptive management strategies. In contrast, the two versions of the model have provided insights into their respective strengths and limitations, although we find that similar biases in both versions. By pointing to model biases, potential improvements, and new research directions, this work ultimately contributes to the broader goal of sustainable fisheries management, and could help ongoing efforts to mitigate the impacts of climate change and human activities on global fish stocks.

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